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Spatial Analysis of Seven Islands in Indonesia to Determine Stunting Hotspots

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Abstract

Indonesia is a vast country struggling to reduce its stunting prevalence. Hence, identifying priority areas is urgent. In determining areas to prioritize, one needs to consider geographical issues, particularly correlations among areas. This study aimed to discover whether stunting prevalence in Indonesia occurs randomly or in clusters; and, if it occurs in clusters, which areas are the hotspots. This ecological study used aggregate data from the 2018 National Basic Health Research and Poverty Data and Information Report from the Statistics Indonesia. This study analyzed 514 districts/cities across 34 provinces on seven main islands in Indonesia. The method used was the Euclidean distance to define the spatial weight. Moran's index test was used to identify autocorrelation, while a Moran scatter plot was applied to identify stunting hotspots. Autocorrelation was found among districts/cities in Sumatra, Java, Sulawesi, and Bali East Nusa Tenggara West Nusa Tenggara Islands, resulting in 133 districts/cities identified as stunting hotspots on four major islands. Autocorrelation proves that stunting in Indonesia does not occur randomly.

Keywords: Indonesia, spatial analysis, stunting, stunting hotspots

Introduction

Stunting continues to be a public health problem in Indonesia. Despite a decrease in the national prevalence by 6.4% since 2013, it was still more than 30% in 2018.¹ Furthermore, the distribution of stunting prevalence at the district/city level appears to have increased in some areas from 2015 to 2017. The Government of Indonesia's National Strategy for the Acceleration of Stunting Prevention 2018–2024 includes priority areas of intervention.² Although several studies were used as the basis for this strategy; the method used to determine priority areas did not consider correlations among geographical areas. Studies have shown that stunting does not occur randomly; instead, it is clustered or spatially structured.³⁻⁶

Reducing stunting in Indonesia is a major challenge, considering that Indonesia is a large country consisting of 17,504 islands, 34 provinces, and 514 districts/cities. It is the largest archipelagic country in the Southeast Asia, with an area of 1,904,569 km² and regional and sociocultural characteristics, behaviors, and poverty levels that differ from island to island and among the districts/

cities in a province. Hence, significant resources will be needed if all regions carry out the same intervention, and each region's capacity is different. The spatial analysis could be utilized to generate information for decision-making about allocating limited resources to the most affected areas. Hotspot identification could allow policymakers to design and develop economically viable and effective region-based intervention strategies.^{3,5,7-12}

Although Indonesia is a vast country, spatial analysis in the context of stunting is still not widely used to examine the pattern of stunting across the country, or as a decision support system for developing policies or programs at the national and regional levels. The high prevalence of stunting, large gaps in socioeconomic and facilities in many areas, and limited funds require the central and regional governments to prioritize intervention types and regions and act quickly to meet the national target (19% of children under five by 2024),¹³ and the Global World Health Assembly target (40% of children under five by 2025).¹⁴ Therefore, this study aimed to discover whether stunting occurs randomly or in clusters in Indonesia and, if it occurs in clusters, which areas are

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the hotspots. Identifying the cluster areas (or hotspots) will allow the government to determine and target the priority areas for stunting interventions instead of simultaneously distributing resources across all areas.

Method

This ecological study used aggregate data from the 2018 National Basic Health Research.¹ This nationally representative survey provides data on stunting from all districts/cities in Indonesia for children under five. The units of analysis in this study were 514 Indonesian districts/cities located on seven main islands in Indonesia: Sumatra (10 provinces, 154 districts/cities), Java (6 provinces, 119 districts/cities), Kalimantan (5 provinces, 56 districts/cities), Sulawesi (6 provinces, 81 districts/cities), Bali East Nusa Tenggara West Nusa Tenggara (Bali ENT WNT) (3 provinces, 41 districts/cities), Maluku (2 provinces, 21 districts/cities), and Papua (2 provinces, 42 districts/cities). All data were grouped according to these islands for analysis.

The missing data were calculated using the mean value of the neighboring area prevalence—four statistical assumptions of the stunting prevalence residual needed to be fulfilled before the spatial analysis process. The Anderson–Darling (AD) test was employed to check the normality of the stunting prevalence residual, the Durbin–Watson (DW) test to check the residual independence, the variance inflation factor (VIF) value to check the multicollinearity, and the Breusch–Pagan (BP) test to check the homoscedasticity.¹⁵ The hypothesis of each test successively was that the stunting prevalence residual is normally distributed, independent, and has no multicollinearity if the VIF is less than 10 and the stunting prevalence residual is homogeneous. In each test, the p-value was compared with $\alpha = 0.05$. H_0 was rejected when the p-value was less than the α -value.

The Euclidean distance method was employed to define the spatial weight. The neighborhood area was defined when the distance between areas was within a radius of 1° or equivalent to 111 km, in accordance with the Euclidean definition.¹⁵ The Moran's index (I) test was used to determine the autocorrelation among the districts/cities on each island, with a significance level of 0.05. Autocorrelation is useful for estimating the level of observed spatial similarity among attribute values of neighboring regions in the research area. Moran's I coefficient is the same as Pearson's correlation coefficient and quantifies the similarity of an outcome variable between regions defined as having a spatial relationship.¹⁶ The null hypothesis for autocorrelation was that there is no autocorrelation among the areas ($I = 0$). H_0 was rejected when the p-value was less than the α -value. The value of Moran's I lay between +1 and -1. A zero (0) value in the Moran's I indicated no spatial clustering or autocorrela-

tion between areas; a positive Moran's I value indicated a positive spatial autocorrelation (a grouping of areas with the same attribute value). In contrast, a negative Moran's I value indicated a negative spatial autocorrelation (neighboring areas tend to have different attribute values). A positive and higher Moran's I value (close to 1) indicated that adjacent districts/cities tend to cluster based on similar stunting prevalence, either high or low.

The hotspot areas were determined using a Moran scatter plot, which was used to describe the spatial autocorrelation statistics. This scatter plot can provide an overview of how similar an attribute value in one area is to its neighboring area. The Moran scatter plot has four quadrants representing four spatial autocorrelation types. In this study, Quadrant 1 (Q1) was a quadrant that described an area with a high prevalence of stunting and surrounded by areas with a high prevalence of stunting. This area was called a high–high area, and the form of spatial autocorrelation was called positive. Quadrant 3 (Q3) described an area with a low stunting prevalence among an area with a low stunting prevalence (low–low); it is a form of positive spatial autocorrelation. Quadrant 4 (Q4) indicated an area with a low prevalence of stunting surrounded by neighboring areas with a high prevalence of stunting; the form of the autocorrelation was negative. Quadrant 2 (Q2) indicated an area with a high prevalence of stunting surrounded by neighboring areas with a low prevalence of stunting; the autocorrelation was negative. In this study, the areas in the high–high quadrant were defined as stunting hotspots, which means that an area with a high prevalence of stunting was surrounded by areas with a high prevalence of stunting.¹⁷ R software version i386 3.6.1 (free version) was used to run the analysis, and Tableau Public 2020 was used to create the map. No patients or public members were involved in this study, so it did not need ethical permission. All the data used in this study are in the public domain.

Results

The results of the normality, independence, homoscedasticity, and multicollinearity assumption tests of stunting prevalence residuals are presented in Table 1, showing significant spatial autocorrelation among the districts/cities based on stunting prevalence in Sumatra, Java, Sulawesi, and Bali ENT WNT Islands. In contrast, no autocorrelation was found among the districts/cities and their neighboring areas in Kalimantan, Maluku, and Papua. The spatial autocorrelation results indicated that stunting was not random in Sumatra, Java, Sulawesi, and Bali ENT WNT.

The Moran scatter plots for Sumatra, Java, Sulawesi, and Bali ENT WNT are shown in Figure 1. The hotspots were the districts/cities located in each Moran scatter plot's high–high quadrant (Figure 1). The authors identi-

Table 1. Statistical Test Results and Moran's Index Values for Each Island

Island	Statistical Test Result (p-value)				Moran's Index Value
	AD	DW	BP	VIF	
Sumatra	0.538 (0.166)	2.052 (0.832)	3.562 (0.829)	VIF of all variables <10	0.299 (1.522e-10)
Java	0.714 (0.0609)	1.754 (0.154)	10.253 (0.419)	VIF of all variables <10	0.105 (1.246e-06)
Sulawesi	0.4696 (0.241)	1.868 (0.48)	6.604 (0.678)	VIF of all variables <10	0.303 (2.038e-09)
Bali ENT WNT	0.669 (0.075)	1.727 (0.34)	11.809 (0.298)	VIF of all variables <10	0.633 (4.127e-15)
Kalimantan	0.420 (0.315)	1.868 (0.56)	4.851 (0.773)	VIF of all variables <10	0.104 (0.073)
Maluku	0.149 (0.956)	2.393 (0.516)	7.608 (0.574)	VIF of all variables <10	-0.128 (0.4103)
Papua	0.243 (0.751)	2.655 (0.02)	5.851 (0.664)	VIF of all variables <10	0.126 (0.55)

Notes: AD = Anderson-Darling, DW = Durbin-Watson, BP = Breusch-Pagan, VIF = Variance Inflation Factor, ENT = East Nusa Tenggara, WNT = West Nusa Tenggara

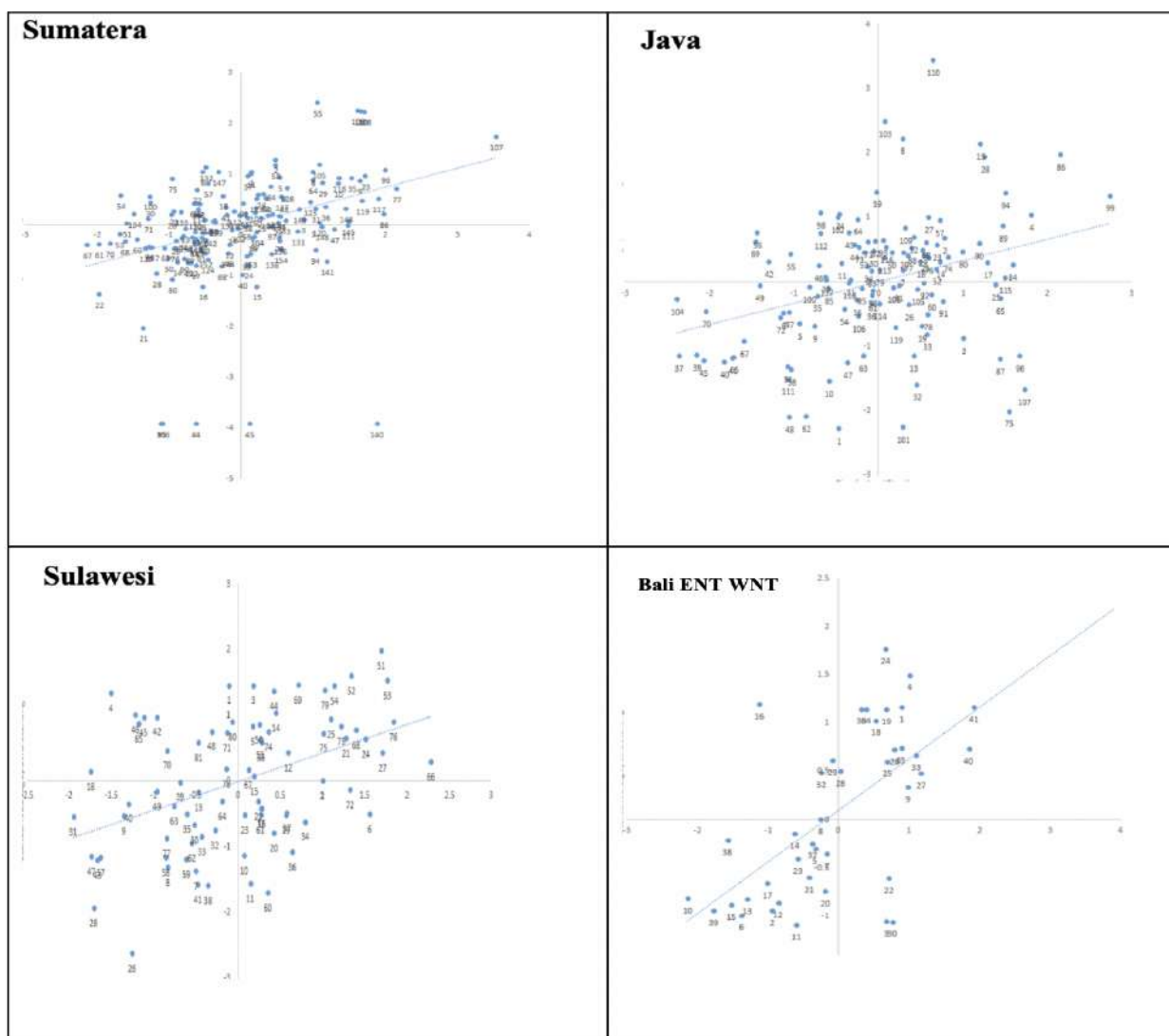


Figure 1. Moran Scatter Plots for Sumatera, Java, Sulawesi, and Bali East Nusa Tenggara West Nusa Tenggara

fied 133 hotspot districts/cities spread across 14 provinces on four islands. Figure 2 shows the geographic

distribution of the hotspots in Indonesia, and Table 2 shows the detailed areas of the hotspots.



Figure 2. Stunting Hotspots in Indonesia (2018)

Table 2. Hotspot Areas by Island (Total = 133)

Island	Province	District/City	The Number of Hotspot Areas
Sumatra	Nanggroe Aceh Darussalam (NAD)	West Aceh, Southwest Aceh, Aceh Besar, Aceh Jaya, South Aceh, Aceh Tamiang, Central Aceh, Southeast Aceh, East Aceh, North Aceh, Bener Meriah, Gayo Lues, Lhokseumawe, Subulussalam, Pidie, Pidie Jaya, Naganraya	17
		Dairi, Humbang Hasundutan, Gunungsitoli, Padangsidempuan, Labuhanbatu, South Labuhanbatu, Langkat, Mandailing Natal, Nias, West Nias, South Nias, North Nias, Padang Lawas, North Padang Lawas, Pakpak Bharat, Central Tapanuli, North Tapanuli	17
	Bengkulu	South Bengkulu, Kaur, Kepahiang, Seluma, Muko-Muko	5
	South Sumatra	Empat Lawang, Pagar Alam, Muara Enim, Musi Rawas, Penukal Abab, Lematang Ilir, Ogan Komering Ulu, Lahat	7
	Jambi	Sungai Penuh, West Tanjung Jabung, Tebo	3
	West Sumatra	Pasaman, West Pasaman.	2
	Riau	Indragiri Hilir, Indragiri Hulu.	2
Java	West Java	Bandung, Ciamis, Cirebon, Garut, Indramayu, Cirebon City, Tasikmalaya, Majalengka, Pangandaran, Sumedang.	10
	East Java	Bangkalan, Banyuwangi, Bojonegoro, Bondowoso, Jember, Kediri, Pasuruan, Lamongan, Lumajang, Madiun, Magetan, Ngawi, Pamekasan, Pasuruan, Ponorogo, Probolinggo, Sampang, Situbondo, Sumenep, Trenggalek, Tuban.	21
Sulawesi	Central Java	Banyumas, Blora, Brebes, Cilacap, Jepara, Pati, Tegal.	7
	Central Sulawesi	Banggai Kepulauan, Buol Banggai Laut, Parigi Moutong.	3
	South Sulawesi	Barru, Bone, Bulukumba, Enrekang, Gowa, Jeneponto, Kepulauan Selayar, Kota Palopo, North Luwu, Maros, Pangkajene Kepulauan, Pinrang, Sinjai, Soppeng, Takalar, Tana Toraja, North Toraja.	17
	West Sulawesi	Majene, Mamasa, Mamuju, Central Mamuju, North Mamuju, Polewali Mandar.	6
Bali ENT WNT	ENT	Alor, Belu, East Flores, Kupang, Lembata, Malaka, Manggarai, West Manggarai, East Manggarai, Nagekeo, West Sumba, Southwest Sumba, Central Sumba, East Sumba, South Central Timor, North Central Timor.	16

Notes: ENT = East Nusa Tenggara; WNT = West Nusa Tenggara

Discussion

The purpose of conducting spatial autocorrelation was to determine whether the prevalence of stunting in a district/city was whether it occurred randomly.¹⁶ The autocorrelation found in Sumatra, Java, Sulawesi, and Bali ENT WNT indicated that the stunting prevalence,

whether high or low, in one district/city did not occur randomly; rather, it was related to the stunting prevalence in the surrounding districts/cities. The attribute value of a variable from an area tended to be the same or almost the same as the closer region compared to a farther region. This is based on the basic concept of geogra-

phy (Tobler's First Law), which states that "everything is related to everything else, but near things are more related than distant things."¹⁵⁻¹⁹ The highest Moran index value of 0.633 (p-value = 4.127e-15) was found in Bali ENT WNT, followed by Sulawesi, Sumatra, and Java with a Moran index value of 0.303 (p-value = 2.038e-09), 0.299 (p-value = 1.522e-10), and 0.105 (p-value = 1.246e-06), respectively. A positive and higher Moran index value (close to a value of 1) indicated that adjacent districts/cities tend to cluster based on similar stunting prevalence, either high or low.¹⁷ Previous studies in other countries, including India, Ethiopia, and Peru, showed similar results.^{4,6,20} The autocorrelation findings of this study can be used to tailor the stunting interventions designed for these four islands.

Spatial autocorrelation among districts/cities could not be identified in Kalimantan, Maluku, and Papua because Kalimantan and Papua are vast islands with greater distances between districts, while Maluku's geographic situation is slightly different from Papua and Kalimantan, as the districts are separated by water. These unique features and the absence of autocorrelation emphasized that district size, the distance between districts, and the varied geographical conditions between districts significantly affected neighborhood status. In this case, these factors affected the spatial autocorrelation of stunting prevalence. Geographic theories state that the attribute of a variable in a region tends to be the same or almost the same as that of an area closer to it than a farther one.^{17,21,22} In the context of spatial analysis, autocorrelation is the similarity that varies with the distance between locations, and this variation is affected by that distance.²³

On the islands where spatial autocorrelation was identified, 16 hotspot areas in Bali ENT WNT were located in the ENT Province, 26 hotspot areas in Sulawesi were found in three provinces (Central Sulawesi, South Sulawesi, and West Sulawesi), 51 hotspot areas were located in seven provinces (NAD, North Sumatra, Bengkulu, South Sumatra, Jambi, West Sumatra, and Riau), and 38 hotspot areas in Java were located in three provinces (West Java, East Java, and Central Java). Determining the priority areas for stunting interventions in Indonesia is based only on the high prevalence of stunting and is weighted by the percentage of poverty in the region.²⁴ However, the spatial analysis method can determine priority areas by identifying hotspots within a certain period. The rationale is that the stunting prevalence in a district/city is related to nearby areas, interventions should target all districts/cities within a hotspot. The stipulation of priority areas for stunting intervention using spatial analysis has been described in studies conducted in Peru, Pakistan, and Africa.^{4,5,8,9,22,25-30}

There were some limitations to this study. This ecological study was prone to an ecological fallacy, in which

aggregate data representing areas were applied at the individual level.^{18,31} An estimation was performed to fill the gap left by missing data, but the weakness of such a data estimation was it could not completely represent the actual situation. Missing data were often encountered during the data entry process, the missing data were manipulated. The weakness of this treatment was that the data did not precisely represent the actual situation. The issue of secondary data quality became very important during the study process.

The use of Euclidean distance to define neighboring areas as within a radius of 1° led to bias in the autocorrelation definition for a large island/area. The larger the area, the higher the probability of a larger island/area having no neighboring areas, as found in Kalimantan, Papua, and Maluku. It is advisable to use different methods (the most suitable according to the island characteristics) for defining neighboring; for instance, this study used Euclidean distance for Sumatra Island but not in Maluku (an island area), Papua, and Kalimantan (a large mainland area).

Conclusion and Recommendation

Indonesia is making progress toward stunting prevention: to reduce the stunting prevalence to 14% by 2024. Considering the vast size of Indonesia and its different regional characteristics, it is necessary to have priority areas for intervention. Spatial analysis can help determine priority areas by using a Moran scatter plot to identify hotspots (areas located in the high-high quadrant). This study reveals that of the 514 Indonesian districts/cities analyzed, 133 are stunting hotspots spread across four major islands: Sumatra, Java, Sulawesi, and Bali ENT WNT. All these hotspots have been recommended to the government as priority areas for stunting interventions. Given that there is autocorrelation among neighboring districts/cities and that stunting does not occur randomly in the four regions, intervention programs should target these hotspot clusters.

Abbreviations

WNT: West Nusa Tenggara; ENT: East Nusa Tenggara; AD: Anderson-Darling; DW: Durbin-Watson; VIF: Variance Inflation Factor; BP: Breusch-Pagan; NAD: Nanggore Aceh Darussalam.

Ethics Approval and Consent to Participate

This study was based on data available in the public domain; therefore, there are no ethical issues.

Competing Interest

The author declares that there is no significant competing financial, professional, or personal interest that might have affected the performance or presentation of the work described in this manuscript.

Availability of Data and Materials

Data are available online from Statistics Indonesia at <https://www.bps.go.id/pressrelease/2019/07/15/1629/persentase-penduduk-miskin-maret-2019-sebesar-9-41-persen.html> and the Indonesian Ministry of Health at <https://www.litbang.kemkes.go.id/laporan-riiset-kesehatan-dasar-risikesdas>. The data are included in the Statistics Indonesia report and 2018 National Basic Health Research.

Authors' Contribution

TS contributed to all the steps of this study, starting from the concept, design, writing, data interpretation, and review. TE and MPB contributed to the concept, interpretation, and review. All authors made substantial contributions to this study and approved the final manuscript.

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