



## Spatial Analysis of Immunization Coverage in Serang Regency, Indonesia in 2021

Laelatul Fitri<sup>1\*</sup>, Martya Rahmaniati Makful<sup>1</sup>

<sup>1</sup>Department Biostatistik dan Ilmu Kependudukan, Fakultas Kesehatan Masyarakat, Universitas Indonesia  
\*Corresponding Author: laelatulfitri1902@gmail.com

### Abstract

The incidence of deaths of children under five years of age in low- and middle-income countries due to imperfect immune system was estimated to increase, which actually can be prevented and reduced by immunization. In 2021, Banten Province received the highest immunization rating in Indonesia with coverage of 94.8%. However, in its Serang Regency, complete basic immunization coverage was only 89.2%. The aim of this study was to find out the spatial distribution of complete immunization coverage in Serang Regency, Banten Province, Indonesia in 2021. This research used an ecological study design with spatial analysis to estimate and analyze the distribution of immunization coverage in 29 districts in Serang Regency by looking at the number of integrated health post (Ina. *posyandu*) and the number of midwives spread across them. The analysis results showed a negative spatial autocorrelation of immunization coverage in Serang Regency in 2021. There was 1 district included in quadrant II (low-high), namely Bandung District and 1 district included in quadrant IV (high-low), namely Padarincang District.

**Keyword:** immunization coverage, spatial analysis, Moran's Index, vaccine-prevented diseases

### ***Analisis Spasial Cakupan Imunisasi di Kabupaten Serang, Indonesia di Tahun 2021***

#### ***Abstrak***

*Kejadian kematian anak berusia bawah lima tahun (balita) pada negara berpenghasilan rendah dan menengah karena sistem imun yang tidak sempurna diperkirakan meningkat, yang padahal dapat dicegah dan dikurangi dengan imunisasi. Pada tahun 2021 Banten mendapatkan peringkat imunisasi tertinggi se-Indonesia dengan cakupan 94,8%. Namun di Kabupaten Serang cakupan imunisasi dasar lengkap hanya 89,2%. Tujuan studi ini adalah ingin mengetahui sebaran spasial cakupan imunisasi lengkap di Kabupaten Serang Tahun 2021. Penelitian ini menggunakan desain studi ekologi dengan menggunakan analisis spasial untuk mengestimasi dan analisis sebaran cakupan imunisasi di 29 kecamatan di Kabupaten Serang dengan melihat jumlah posyandu dan jumlah bidan yang tersebar. Hasil analisis menunjukkan adanya autokorelasi spasial negatif terhadap cakupan imunisasi di Kabupaten Serang di tahun 2021. Terdapat 1 Kecamatan yang termasuk dalam kuadran II (rendah-tinggi), yaitu Kecamatan Bandung dan 1 Kecamatan yang termasuk pada kuadran IV (tinggi-rendah), yaitu Kecamatan Padarincang.*

**Kata Kunci:** cakupan imunisasi, analisis spasial, Indeks Moran, PD3I

## Introduction

The process of immunization has emerged as a remarkable accomplishment in the realm of worldwide health and progress, effectively preserving the lives of numerous individuals annually. Specifically focusing on the measles vaccine, a staggering 23 million fatalities were successfully prevented between the years 2010 and 2018 (Patel, *et al*, 2019). The incidence of deaths of children under five years of age (toddlers) in low- and middle-income countries is estimated to increase. Child deaths are caused by many factors, one of which is the child's imperfect immune system. In China, the number of under-five deaths between 1996 and 2015 was 181,600 under-fives and as many as 93,400 under-fives (51%) of deaths occurred in neonates. The main causes of death for children under five are congenital abnormalities, complications of premature birth, injuries and pneumonia (He, *et al*, 2017).

The World Health Organization's (WHO) expanded program on immunization (EPI), initiated in 1974, was designed with the goal of diminishing the incidence of childhood morbidity and mortality. Nonetheless, immunization rates in numerous developing countries persistently remain below the desired level (Chu dan Rammohan, 2022). Immunization has been proven to prevent and reduce the incidence of illness, disability and death due to vaccine-prevented diseases (PVDs), which is estimated at 2 to 3 million deaths each year.

Measles immunization coverage in Indonesia is 84% and is a country in the medium category (Kemenkes RI, 2018). Basic Health Research data in 2018 shows that complete basic immunization (CBI) coverage reached 57.9%, incomplete immunization was 32.9% and 9.2% were not immunized (Kemenkes RI, 2018). CBI coverage for babies in Banten Province has reached the national minimum target of 85%. Where in 2019 it reached 89.9% but there was a decline due to Covid-19, only 77% immunization coverage in 2020. In 2021 Banten received the highest immunization ranking in Indonesia with 94.8% coverage. However, in Serang Regency, CBI coverage is only 89.2%.

Spatial analysis is utilized in order to examine the correlation between the human environment and various health factors including nutrition, disease, and the healthcare system, with the aim of

elucidating the spatial interconnections. Spatial analysis is deemed to be more precise when juxtaposed with non-spatial analysis due to the perceived inability of the latter to address numerous inquiries, such as ascertaining the distribution of health issues (Miranda, *et al*, 2018).

Spatial methods commonly employed in health research encompass disease mapping, clustering methodologies, diffusion investigations, the identification of risk factors through map comparison, and regression analysis. The utilization of spatial clustering methods assumes significance when considering statistical techniques as the primary step in the construction of models for forecasting disease risk locations. The immunization coverage, differs depending on both the physical and socio-economic conditions of the individual's residing area and their personal health practices. Consequently, it is imperative to adopt a spatial approach to intervention endeavors for each localized region, particularly when the prevalence remains elevated, by scrutinizing specific area-related factors utilizing district data (Kim dan Park, 2018).

Therefore, it is necessary to carry out a spatial analysis of complete basic immunization coverage to find out which areas can become program priorities so that immunization coverage is more evenly distributed. Hence, spatial analysis emerges as a critical instrument in discerning spatial and spatial-temporal clusters, thereby ascertaining the areas that exhibit heightened susceptibility to health risks (Cunha, *et al*, 2022). In line with government regulation number 12 of 2017, immunization is made a mandatory program that is imposed on a person as part of society to protect against diseases that can be prevented by immunization. The specific objectives of this study are to determine the current state of immunization coverage, analysis and map spatial patterns of immunization coverage and to evaluate the correlation in the level of immunization coverage between different neighboring districts.

## Method

This research used an ecological study design using spatial analysis to estimate and analyze the distribution of immunization coverage in 29 districts in Serang Regency. Ecologic study encompasses the examination of groups rather than individuals as the unit of observation (Younger dan

Xiaoilng, 2016). This research used secondary data collected from several open access data, such as Indonesia Geospatial, Serang Regency health profile for 2022 which can be accessed on each institution's official website. We hereby asserted that the data employed in this study was originated from the public domain health sector and were procured in accordance with the principles of sound research methodology and ethical guidelines. The information was collected and examined in a manner that preserved the anonymity and confidentiality of the participants, aligning with the established protocols. The data analyzed was aggregate data from the number of immunization coverage and population per district.

The dependent variable in this study is the immunization coverage (vaccination coverage). The independent variables in this study were a number of midwives and active integrated health post (Ina. *posyandu*) as included in the data. Public health centers (Ina. *puskesmas*) was not included in this study because each district had one public health center which did not directly affect the immunization coverage. Immunization coverage is divided into three categories based on the provisions of the Ministry of Health regarding complete basic immunization, namely low (immunization coverage <70%), medium (immunization coverage 70-89%) and high (immunization coverage  $\geq$ 90%). Thematic maps were created for the purpose of classifying vaccination coverage according to the aforementioned description. These maps were produced through the utilization of techniques within a geographic information system alongside the spatial analysis techniques. The software used for the aforementioned activities is the QGIS.

Then spatial pattern analysis was carried out using the Global Moran's Index to detect global autocorrelation, and continued with local indicators of spatial autocorrelation (LISA). This analysis was carried out using GeoDa software. The null hypothesis in this study is that there is no spatial autocorrelation between district areas in Serang Regency ( $I = E$ ), while the alternative hypothesis is that there is positive spatial autocorrelation between district areas in Serang Regency ( $I > E$ ). In this research, the significance level used is 95%, so that an area is said to have statistically significant spatial autocorrelation if the significance value (p-value) is less than 0.05 in the results of the Global Moran's Index and LISA analysis.

Global Moran's Index and LISA are statistical analyzes that can measure the relationship between spatial proximity at observation locations with the consideration that areas that are spatially close will have similar attribute values. The results of the Global Moran's Index and LISA range from -1 to +1, where a negative number indicates negative autocorrelation, a value of 0 indicates no autocorrelation, and a positive value indicates positive autocorrelation. If there is negative autocorrelation, then adjacent regions tend to have different attribute values, but in space they will form a pattern like a checkerboard. On the other hand, if there is positive autocorrelation, then adjacent areas will form clusters that have almost the same characteristics and attribute values (Grekousis, 2020).

If the Global Moran's Index assesses autocorrelation in the region in general, in the case of Serang Regency, LISA was used to assess local spatial autocorrelation between districts in Serang Regency. In this case, if a high-high correlation is found, it can be said that there is positive autocorrelation, where the district has high immunization coverage and is surrounded by districts with also high incidence rates. Then, the low-low correlation also shows positive autocorrelation, where district areas with low immunization coverage are surrounded by district areas with low immunization coverage. Furthermore, the high-low correlation shows that the district area has high immunization coverage and is surrounded by districts that have low immunization coverage. Finally, low-high indicates that districts with low immunization coverage are surrounded by districts with high immunization coverage.

The number of babies in Serang Regency in 2021 in Serang Regency was 31,363 babies spread across 29 districts in Serang Regency. The highest number of babies was in Cikande District with 2,128 babies and the lowest was in Gunung Sari with 464 babies. In figure 1 the number of babies were classified by natural break produces 4 categories, namely low, medium, high and very high.

Immunization coverage is divided into three categories based on the provisions of the Ministry of Health regarding complete basic immunization, namely Low (Immunization Coverage <70%), Medium (Immunization Coverage 70-89%) and High (Immunization Coverage  $\geq$ 90%). In Serang

Regency, it can be seen from Figure 1 that immunization coverage was quite good, where medium and high immunization coverage was more dominant than low. The highest immunization coverage was in Bojonegara District with immunization coverage reaching 109.7% and the lowest was in Pabuaran District with 64.2% immunization coverage.

The number of active *posyandu* and the number of midwives in figure 1 are classified using natural breaks. The number of *posyandu* is divided into 4 categories low (<19), medium (19-46), high (47-122) and very high (>=123). Tanara and Pabuaran subdistricts were the subdistricts with the lowest number of active *posyandu*, namely 1 *posyandu*, while Kragilan subdistrict had 123 active *posyandu*. The number of midwives is divided into 4 categories, namely very low (<15 midwives), low (15-21 midwives), medium (22-30 midwives) and high (>=31 midwives). The most midwives were in Kragilan District, namely 35 midwives and the lowest in Gunung Sari District with 6 midwives.

## Results

In this study immunization coverage data was analyzed for Serang District for the year 2021. The results answered the research objectives which were to determine the current state of immunization coverage in Serang district, to analyze map spatial patterns of immunization coverage, and to evaluate the correlation in the level of immunization coverage between different neighboring districts. It was noteworthy that the present study encompassed a whole lot of constraints that had the potential to impact the outcomes of the study. These limitations, discerned within the framework of this research endeavor, included (1) accuracy and reliability- the quality of secondary data depends on the accuracy and reliability of the original data source. If the primary data source has errors or biases, they carry over to the secondary data. (2) Incomplete information - missing variables: secondary data may lack certain variables or information that could be crucial for the research question. Researchers are confined to the variables collected by the original data source and restricted access. Some secondary data sources may have restricted access, limiting the ability of researchers to fully explore or analyze the data. Results analysis is as follows:

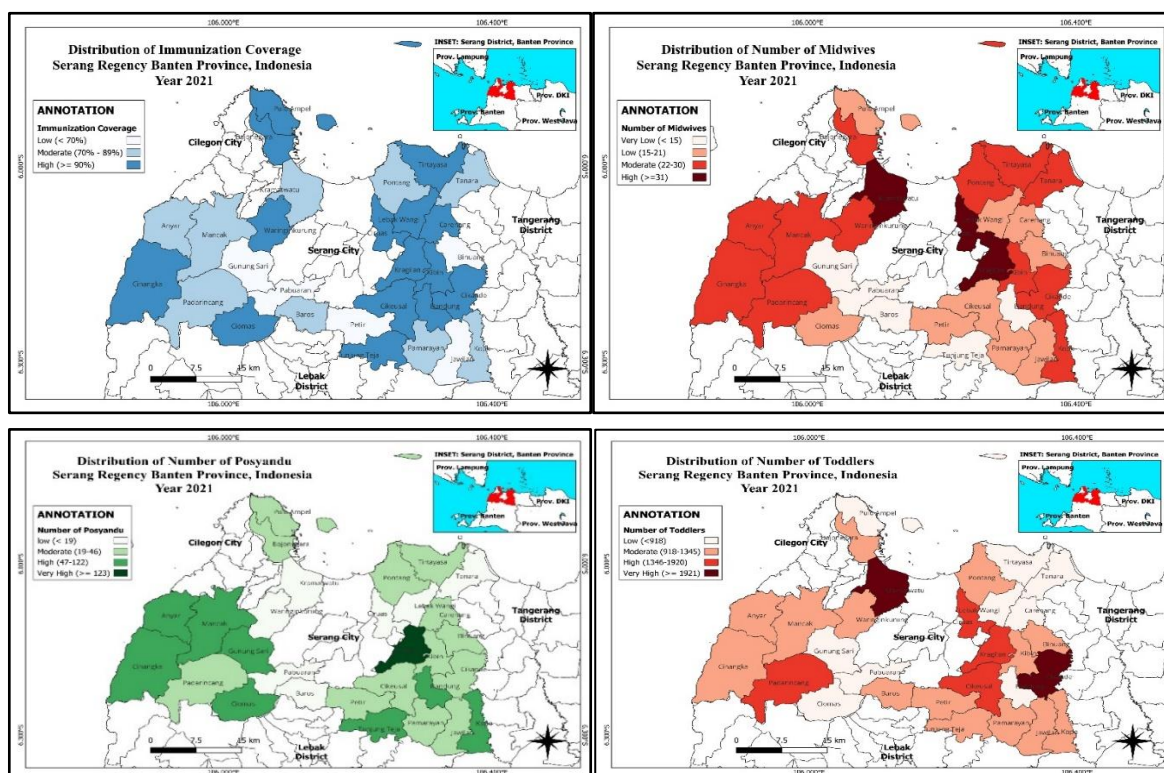


Figure 1. Overview of variables

**Objective 1: Determine The Current State of Immunization Coverage and Spatial Regression**

**Table 1.** Spatial Regression Model

Variable	Coefficient	Std. Error	t-Statistic	Probability
Constant	69.1197	7.3275	9.43292	0.0000
Midwives	0.792837	0.323275	2.45252	0.02121
Posyandu	0.0878716	0.0921006	0.954083	0.34883
R-squared	0.234485			

**Table 2.** Global Moran Index Results 2021

Moran Index	-0,029
Expected Index	-0,0357
P value	0,444

The model generated from the autocorrelation spatial regression output (table 1) shows the coefficient value of the midwives' variable (0.792837). It indicates that if the case of immunization coverage with the number of midwives is positive, it means that the higher the number of midwives in one district, the higher the immunization coverage. Number of midwives has the spatial effect on the immunization coverage (P value 0.02). The coefficient value of *posyandu* is positive (0.0878716), which means the higher number of *posyandu*, the higher the immunization coverage. However, *posyandu* does not have spatial effect on immunization coverage (P value 0.34883). The R squared value in the equation is 0.234485.

The results of the analysis of the pattern of distribution of immunization coverage in Serang Regency showed that the distribution of immunization coverage in the region had a clustered pattern because the Moran index (I) > from the expected index (EI). However, the p value is not significant, namely 0.444 above 0.05, so it does not indicate a spatial interaction.

**Figure 2.** Moran Index Scatter Plot of Complete Immunization

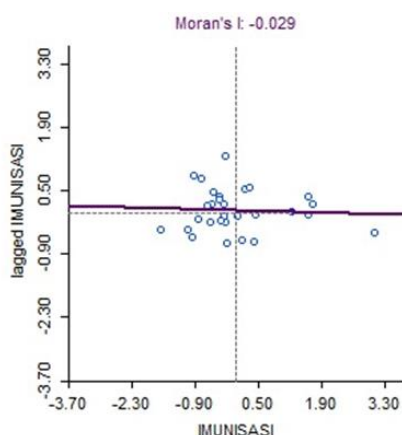
Figure 2 shows a Moran index of -0.029. This shows that the pattern of distribution of immunization coverage in Serang Regency has a negative autocorrelation where adjacent areas tend to have different attribute values, but in space they form a pattern like a chess board.

**Objective 2: Analyze and Map Spatial Patterns of Immunization Coverage 2021 Immunization Coverage Cluster Map**

Based on analysis using LISA, a cluster map of Immunization Coverage in 2021 was obtained as follows. Of the 29 districts in Serang Regency, there were two districts that had a significantly negative spatial correlation with the surrounding districts. Districts that had significance < The 0.05 covered Padarincang District and Bandung District.

**Objective 3: Correlation In the Level of Immunization Coverage Between Different Neighboring Districts**

In Figure 4, it appears that there was one district in quadrant II (low-high), namely Bandung District. This shows negative spatial autocorrelation because Bandung District had a low incidence of immunization coverage rates and was surrounded by other districts that had high immunization coverage rates. Furthermore, Padarincang District was in quadrant IV (high-low), meaning that there was negative spatial autocorrelation. This area had a high immunization coverage rate and was surrounded by districts with low immunization coverage.



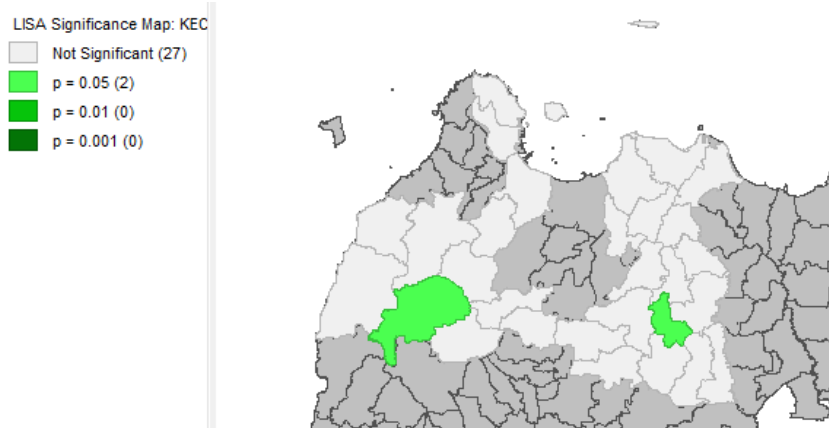


Figure 3. Map of the Significance of LIS LISA Complete Immunization in Serang Regency in 2021

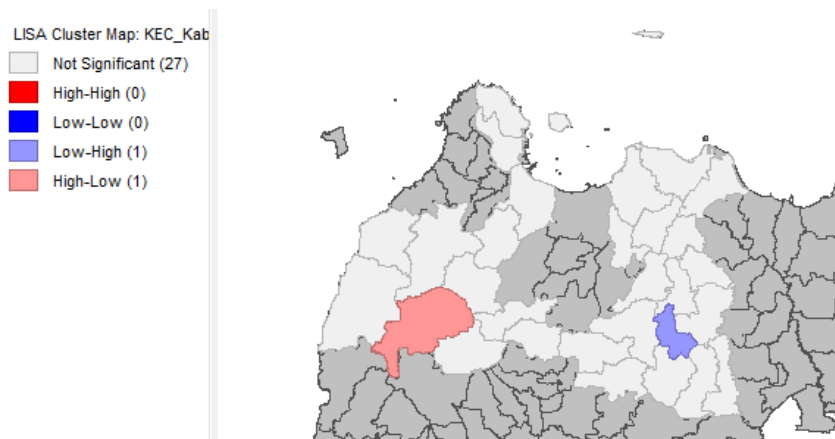


Figure 4. Map of LISA Complete Immunization Clusters in Serang Regency in 2021

## Discussions

In addressing the pivotal objectives set forth in this study, we ventured into a comprehensive discussion that delves into the nuanced landscape of immunization coverage. Our pursuit had been guided by three specific objectives, each tailored to unveil distinct facets of the immunization scenario in our study area. In the ensuing discussion, we navigated through the outcomes, implications, and potential interventions emanating from the pursued objectives.

It had been observed in this study that the coefficient value of the midwives' variable (0.792837) indicated that the case of immunization coverage with the number of midwives was positive. It means that the higher the number of midwives in one district, the higher the immunization coverage. Number of midwives had the spatial effect on the immunization coverage (P

value 0.02). These findings were in agreement with (Lawal, *et al*, 2023) in a study that was conducted in Ethiopia which alluded that the presence of a proficient birth attendant elevated the probability of a child being administered all necessary immunizations immediately after birth. This correlation was similarly observed among women who availed antenatal care, suggesting that previous encounters with the healthcare system may enhance trust.

Although the spatial regression analysis of *posyandu* did not demonstrate any spatial impact on immunization (table 1). It remains crucial for *posyandu* to fulfill its role as a healthcare facility for them to attain high immunization coverage. *Posyandu* plays a significant role in delivering comprehensive services for basic immunization uptake or to make sure that the concept of immunization is well received by everyone. In line

with government regulation number 12 of 2017, immunization is a mandatory program that is imposed on a person as part of society to protect against vaccine-prevented diseases (VPDs).

Furthermore, a Moran index of -0.029 was obtained which shows that the pattern of distribution of immunization coverage in Serang Regency had a negative autocorrelation. Adjacent areas tended to have different attribute values. The p-value obtained was 0.444 which was not significant. However, this finding was not in agreement with Tefal's research in 2013 [10], who determined that the distribution is not random, as indicated by the significant findings of the Global Moran's I statistic ( $I = 0.275696$ ,  $p\text{-value} = 0.000$ ). Specifically, the observed Moran's Index value (0.275696) surpassed the expected Index value (-0.003509), and the p-value was below the threshold of 0.05, indicating statistical significance.

In another study in Peru by Cordova (2022), they found out that the examination of spatial autocorrelation demonstrated a concentrated arrangement of FVC (Global Moran's  $I=0.01$ ,  $p<0.0001$ ). This result was not in line with our study which got a random negative value. Furthermore, based on analysis using LISA, a cluster map of Immunization Coverage in 2021 was found that one of the 29 districts in Serang Regency, two districts had a significantly negative spatial correlation with the surrounding districts (Marek, *et al*, 2021). It also showed negative spatial autocorrelation because Bandung District had a low incidence of immunization coverage rates and was surrounded by other districts that had high immunization coverage rates. Furthermore, Padarincang District was in quadrant IV (high-low), meaning that there was negative spatial autocorrelation. This area had a high immunization coverage rate and was surrounded by districts with also low immunization coverage.

## Conclusions

Based on the analysis, it was found that there was a negative spatial autocorrelation of immunization coverage in Serang Regency in 2021. Then, the distribution pattern of immunization coverage in 2021 showed that there was a negative spatial autocorrelation with a clustered distribution pattern because the Moran index was greater than the expected value. From the cluster mapping, there was 1 district included in quadrant II (low-high), namely Bandung District

and 1 district that was included in quadrant IV (high-low), namely Padarincang District. In order to increase complete immunization coverage in Serang Regency, Bandung Regency can be a priority for the government to study further because it had low immunization coverage while its neighbors had high immunization coverage.

## References

- Al-Kassab-Córdova A, Silva-Perez C, Maguiña JL. (2022). Spatial distribution, determinants and trends of full vaccination coverage in children aged 12-59 months in Peru: A subanalysis of the Peruvian Demographic and Health Survey. *BMJ Open* ;12, 1-11 <https://doi.org/10.1136/bmjopen-2021-050211>.
- Chu H, Rammohan A. (2022) Childhood immunization and age-appropriate vaccinations in Indonesia. *BMC Public Health*;22, 2023-2034 <https://doi.org/10.1186/s12889-022-14408-x>.
- Cunha NSP, Fohrat SCL, de Olinda RA, Braga ALF, Barbieri CLA, de Aguiar Pontes Pamplona Y, et al. (2022). Spatial analysis of vaccine coverage on the first year of life in the northeast of Brazil. *BMC Public Health* 2022;22, 1204-1215. <https://doi.org/10.1186/s12889-022-13589-9>.
- Dixon B, Uddameri V. (2016). GIS and Geocomputation for Water Resource Science and Engineering. John Wiley & Sons.
- He C, Liu L, Chu Y, Perin J, Dai L, Li X, et al. (2017). National and subnational all-cause and cause-specific child mortality in China, 1996–2015: a systematic analysis with implications for the Sustainable Development Goals. *Lancet Glob Health* ;5: 186–197. [https://doi.org/10.1016/S2214-109X\(16\)30334-5](https://doi.org/10.1016/S2214-109X(16)30334-5).
- Kemenkes RI. (2018). Hasil-Utama Riskesdas 2018. Kemenkes RI.
- Kim MJ, Park NH. (2018). Analysis of Spatial Distribution of Hypertension Prevalence and Its Related Factors based on the Model of Social Determinants of Health. *J Korean Acad Community Health Nurs* ;29, 414-425 <https://doi.org/10.12799/jkachn.2018.29.4.414>.
- Lawal TV, Atoloye KA, Adebowale AS, Fagbamigbe AF. (2023). Spatio-temporal analysis of childhood vaccine uptake in

- Nigeria: a hierarchical Bayesian Zero-inflated Poisson approach. *BMC Pediatr*;23, 493-500  
<https://doi.org/10.1186/s12887-023-04300-x>.
- Marek L, Hobbs M, Wiki J, McCarthy J, Tomintz M, Campbell M, et al. (2021). Spatial-temporal patterns of childhood immunization in New Zealand (2006-2017): an improving pattern but not for all? *Eur J Public Health*;31, 561–567.  
<https://doi.org/10.1093/eurpub/ckaa225>.
- Miranda, Marie Lynn and Edwards, Sharon E. (2011). Use of Spatial Analysis to Support Environmental Health Research and Practice. *North Carolina Med Journal*:72(2), 132-135.
- Patel MK, Dumolard L, Nedelec Y, Sodha SV, Steulet C, Gacic-Dobo M, et al. (2019). Progress Toward Regional Measles Elimination — Worldwide, 2000–2018. *Morb Mortal Wkly Rep*;68, 1105–1116.  
<https://doi.org/10.15585/mmwr.mm6848a1>.
- Tesfa GA, Yehualashet DE, Getnet A, Bimer KB, Seboka BT. (2023). Spatial distribution of complete basic childhood vaccination and associated factors among children aged 12–23 months in Ethiopia. A spatial and multilevel analysis. *PLoS ONE* ;18, 1-16  
<https://doi.org/10.1371/journal.pone.0279399>
- Tsai P-J, Lin M-L, Chu C-M, Perng C-H. (2009). Spatial autocorrelation analysis of health care hotspots in Taiwan in 2006. *BMC Public Health*;9, 464-473.  
<https://doi.org/10.1186/1471-2458-9-464>.
- Younger, David S., and Chen, Xiaoilong. (2016). Research Methods in Epidemiology. *Neurologic Clinic*;34(4), 815-835,  
<https://doi.org/10.1016/j.ncl.2016.05.003>.