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Analysis of Risk Factors That Affecting Dengue Haemorrhagic Fever in West Sumatra Province with Panel Data Regression

Efriza
Doctoral Candidate, Public Health Faculty, Universitas Indonesia, Depok, Jawa Barat, Indonesia
Tris Eryando
Lecturer, Public Health Faculty, Universitas Indonesia, Depok, Jawa Barat, Indonesia

Abstract:
Dengue haemorrhagic fever (DHF) is endemic disease in Indonesia, including in West Sumatra Province. DHF is found throughout the year in West Sumatra Province. Dengue viruses and their mosquito vectors are sensitive to their environments. The changes of climates (temperature, rainfall, humidity), density of population is a very important factor in the arising and spread of DHF. The aim of this study was to examine the relationship between climate factors, number and density of population with DHF cases in West Sumatra Province in Indonesia to develop a predicting model for dengue's control and prevention purpose. The panel data regression model (Pooled least square) were used to explore associated climate factors, number and density of population are affecting of DHF in West Sumatra from 2012 to 2017.
The result showed that pooled least square model could describe DHF cases in West Sumatra Province with determination coefficient, R2= 64,75. This means that the variation of response variable that can be explained by the model was 64,75%. The predictor variables that affecting the number of DHF cases in West Sumatra Province were humidity, number and density of population in the previous year. That founding makes a contribution towards advancing knowledge with respect to the causality of DHF cases and has policy implications for DHF prevention and control.

Keywords: *Dengue, climate, population, panel data regression, pooled least square*

1. Introduction

The unprecedented surge in dengue epidemics across the globe in recent decades prompted WHO at the start of 2019 to include the virus in its list of the world's top 10 public health threats. The specific goal of the global strategy for dengue prevention and control of 2012 – 2020 is that it can reduce 50% of mortality and 25% of morbidity from dengue. Dengue mortality can be reduced by the application of early detection of cases and proper management in severe cases, healthcare reorientation for early case identification and managing dengue outbreaks effectively (WHO, 2012).

The globally scale of the risk of public health caused by dengue fever because the expansion of the Aedes aegypti to new territories. Dengue fever is still an Indonesian public health problem. This includes West Sumatra with the incidence of DHF per 100,000 population in West Sumatra was greater than 49 per 100,000 population in 2015-2016 (Ministry of Health Republic of Indonesia, 2016, Ministry of Health Republic of Indonesia, 2017, Ministry of Health Republic of Indonesia, 2018)

Climate changes (increase in rainfall, temperature, humidity) may be used to indicate an increased risk of epidemic dengue transmission in early warning systems to highlight the onset of dengue outbreaks. Outbreak definitions based on thresholds of epidemiological data (number of cases or incidence rate) rely on the timely analysis of local surveillance data to establish if cases are above a pre-defined threshold, which varies according the season. The thresholds of case numbers may vary among countries or regions (WHO, 2016).

The climates conditions especially temperature, rainfall and relative humidity also affects the transmission of dengue fever (Simmons et al. 2017, Naish et al., 2014). Some of research show that weather or climate change could potentially increase the epidemic of dengue fever (Liu-Helmersson et al. 2016, Anggraeni et al. 2017, Naish et al., 2014, Choi et al. 2016, Polwiang, 2015). Population density was also a significant explanatory variable for dengue fever outbreak (Atique et al. 2017, Hernández et al. 2017, Simmons et al. 2017, Kim Lien et al. 2015).

Panel data regression model is the regression model using panel data which is a combination of cross section data and time series data. One of the ways to estimate the panel data regression model is pooled least square. Parameters on pooled least square approach be estimated by Ordinary Least Square (OLS) method. Pooled least square is one of the models that can describe the influence independent variables to the number of DHF cases in West Sumatra. In this paper, we examine the relationship between climate factors, number and density of population with DHF cases during 2012-2017 in West Sumatra Province in Indonesia to develop a predicting model for assess the potential risk of DHF. That result can be used as referral base for DHF prevention and control purpose

2. Method

This research was conducted in the 19 districts in West Sumatra Province, in Indonesia in 2012-2017. Response variable (dependent variable) used is the number of DHF cases, independent variables were observed among others, temperature, rainfall, humidity, number and density of population at risk. Data were collected from the Health Office of West Sumatra Province for dengue cases. The climate data were obtained from the National Meteorology, Climatology, Geophysics Agency. The population data over the study period for every district was retrieved from the Central Bureau of Statistics of West Sumatra.

The study uses a panel dataset where each variable in equation at below refers to districts i at time t, where Xit denotes climate factors (temperature, rainfall, humidity), number and density of population, and $\mathbf{u_{it}}$ is the error term. Pooled Least Square (PLS) model used the results of the transformation data dependent variables. Pooled Least Square model used the results of the transformation data dependent variables and the addition variables one period before (Yi,(t-1)) is a model that can describe the influence independent variables to the number of dengue cases in West Sumatra Province from period 2012 to 2017.

$Y_{it} = ß_0 + ßX_{it} + u_{it}$ (Hsiao, 2014)

i = 1, 2, …, N

t = 1, 2, …, T

Dengue $cases_{it} = ß_0 + ßTemperature_{it} + ß_2Rainfall_{it} + ß_3Humidity_{it} + ß4NoP_{it} + ß5DoP_{it} + u_{it}$

P-values of<0.05 were considered to indicate statistical significance. The goodness-of-fit of the constructed model was determined by *R Square.* All statistical analyses were carried out by using R.

3. Result and Discussion

West Sumatera Province is located between 0^{o}54' North latitude and 3^{o}30' South latitude, and between 98^{o}36' and 101^{o}53' East longitude and lies on equator line located at 0^o latitude line. In term of geographic position Sumatera Barat lies in the middle of the western coast of Sumatera and had an area of 42.2 thousands Km2. During 2017, the average air temperature of West Sumatra ranges from 24.40 to 26.10 with average humidity between 81.0%-86.0%. The population of Sumatera Barat in 2017 consisted of 5.32 million people, with the average population density were total 126 people per square km (Central Bureau of Statistics of West Sumatra, 2018). The panel data regression model (Pooled least square) are affecting of DHF in West Sumatra in 2012-2017 results can be seen in Table 1

Variable	Coefficient	Std. Error	P-value
Intercept	$4.975x10^3$	$1.324x10^3$	0.0002776
Temperature	$-1.24x10^1$	$1.127x10^1$	0.2728484
Rainfall	$3.149x 10^{-3}$	$2.498x10^{-2}$	0.8999283
Humidity	$-5.648x10^1$	$1.458x10^1$	0.0001834
Number of Population (NoP)	$9.988x10^{-4}$	7.357x10-5	$< 2.2x 10^{-16}$
Density of Population ((DoP)	$6.219x10^{-2}$	$1.361x10^2$	$1.313x10^{05}$
R Square	: 0.6475	Adjust R Square	: 0.6134
n	: 19	N	: 114
T	: 6		

Table 1: Results of Panel Pooled Least Square Model DHF Cases in West Sumatra in 2012-2017

The Panel Pooled Least Square Model can be described as follows:

Dengue $cases_{it} = ß_0 + ßTemperature_{it} + ß_2Rainfall_{it} + ß_3Humidity_{it} + ß4NoP_{it} + ß5DoP_{it} + u_{it}$

Dengue $cases_{it} = 4.975x10^3 - 1.242x10^1\ Temperature_{it} + 3.149x10^{-3}Rainfall_{it} - 5.648x10^1Humidity_{it} + 9.988x10^{-4}NoP_{it} + 6.219x10^{-2}DoP_{it} + u_{it}$

This model can be shown R^2 of 64,75. This means that the variation of response variable that can be explained with temperature, rainfall, humidity, number and density of population at risk by the model was 64,75%. Based on the results of the model, the panel pooled least square model estimation result suggest that DHF cases are significantly association with humidity, number and density of population with a p-value <0.05.

The relationship between temperature and rainfall with the dengue cases is no association reported to be in the present study. Our study also supports other findings in Central Visayas in Philippines (Picardal and Elnar, 2012), which found uncorrelated of temperature and rainfall variability on the dengue prevalence. However, this is contrary to many studies reported previously that temperature was significantly association with dengue cases (Sang et al., 2014, Wangdi et al., 2018, Anwar et al., 2019), rainfall was significantly association with dengue cases (Méndez-Lázaro et al., 2014, Dhewantara et al., 2019). Temperature, rainfall, and mean relative humidity demonstrated predictive potential in some countries, but not all. It were inconsistent across the countries (WHO, 2016). The association between dengue incidence with temperature and rainfall factors also apparently varies by locality (Choi et al., 2016). In our analysis, we found that humidity was significantly association with dengue case in West Sumatra. This finding was consistent with those of other studies conducted in Guangzhou, China (Sang et al., 2014, Bouzid et al., 2014) . The humidity are conducive during the rainy season can build-up of the vector population breeding (WHO, 2011).

This finding found that population density was significantly association with dengue case in West Sumatra Province in 2012-217. Other studies showed that between population density with the incidence rate of dengue has significant relationships (Delmelle, Hagenlocher, Kienberger, & Casas, 2016, Hsueh, Lee, & Beltz, 2012, Gil et al., 2016, Vargas et al., 2015, Martha, Susetyo, & Aidi, 2016, Dhewantara et al., 2019). Mosquitoes have repeatedly bite the ability, if the populous population will then give a great opportunity to contact registered mosquito infected from previous sufferers on the adjacent residents.

4. Conclusion

To implement appropriate control measures, public health organizations and policy makers must rely on accurate and timely predictions of disease for monitoring and analysing them under critical space-time conditions. A better understanding on the space-time signature of infectious diseases such as their rate of transmission and tendency to cluster should help epidemiologists and public health officials better allocate prevention measures.

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5. References

i. Anggraeni, W., Nurmasari, R., Riksakomara, E., Samopa, F., Wibowo, R.P., Condro T., L., Pujiadi, 2017. Modified Regression Approach for Predicting Number of Dengue Fever Incidents in Malang Indonesia. Procedia Comput. Sci. 124, 142–150. https://doi.org/10.1016/j.procs.2017.12.140

ii. Anwar, A., Khan, N., Ayub, M., Nawaz, F., Shah, A., Flahault, A., 2019. Modeling and Predicting Dengue Incidence in Highly Vulnerable Countries using Panel Data Approach. Int. J. Environ. Res. Public Health 16, 2296. https://doi.org/10.3390/ijerph16132296

iii. Atique, S., Chan, T.C., Chen, C.C., Hsu, C.Y., Iqtidar, S., Louis, V.R., Shabbir, S.A., Chuang, T.W., 2017. Investigating spatio-temporal distribution and diffusion patterns of the dengue outbreak in Swat, Pakistan. J. Infect. Public Health. https://doi.org/10.1016/j.jiph.2017.12.003

iv. Bouzid, M., Colón-González, F.J., Lung, T., Lake, I.R., Hunter, P.R., 2014. Climate change and the emergence of vector-borne diseases in Europe: Case study of dengue fever. BMC Public Health 14, 1–12. https://doi.org/10.1186/1471-2458-14-781

v. Central Bureau of Statistics of West Sumatra, 2018. Sumatera Barat in Figures. Central Bureau of Statistics of West Sumatra, Sumatera Barat.

vi. Choi, Y., Tang, C.S., McIver, L., Hashizume, M., Chan, V., Abeyasinghe, R.R., Iddings, S., Huy, R., 2016. Effects of weather factors on dengue fever incidence and implications for interventions in Cambodia. BMC Public Health 16, 1–7. https://doi.org/10.1186/s12889-016-2923-2

vii. Delmelle, E., Hagenlocher, M., Kienberger, S., Casas, I., 2016. A spatial model of socioeconomic and environmental determinants of dengue fever in Cali, Colombia. Acta Trop. 164, 169–176. https://doi.org/10.1016/j.actatropica.2016.08.028

viii. Dhewantara, P.W., Marina, R., Puspita, T., Ariati, Y., Purwanto, E., Hananto, M., Hu, W., Soares Magalhaes, R.J., 2019. Spatial and temporal variation of dengue incidence in the island of Bali, Indonesia: An ecological study. Travel Med. Infect. Dis. https://doi.org/10.1016/j.tmaid.2019.06.008

ix. Farahiyah, M., Nurjazuli, Setiani, O., 2014. Analisis Spasial Faktor Lingkungan dan Kejadian DBD di Kabupaten Demak 42, 25–36.

x. Gil, J.F., Palacios, M., Krolewiecki, A.J., Cortada, P., Flores, R., Jaime, C., Arias, L., Villalpando, C., Alberti DÁmato, A.M., Nasser, J.R., Aparicio, J.P., 2016. Spatial spread of dengue in a non-endemic tropical city in northern Argentina. Acta Trop. 158, 24–31. https://doi.org/10.1016/j.actatropica.2016.02.003

xi. Hernández, L.M., Durán, D.F., Buitrago, D.A., Garnica, C.A., Gómez, L.F., Bados, D.M., Bernal, M.P., Páez, L.M., 2017. Epidemiology and geo-referencing of the dengue fever in a hospital of second level in Colombia, 2010-2014. J. Infect. Public Health. https://doi.org/10.1016/j.jiph.2017.12.005

xii. Hsiao, C., 2014. Analysis of Panel Data, Third Ed. ed. Cambridge University Press, New York.

xiii. Hsueh, Y.H., Lee, J., Beltz, L., 2012. Spatio-temporal patterns of dengue fever cases in Kaoshiung City, Taiwan, 2003-2008. Appl. Geogr. 34, 587–594. https://doi.org/10.1016/j.apgeog.2012.03.003

xiv. Kim Lien, P.T., Duoc, V.T., Gavotte, L., Cornillot, E., Nga, P.T., Briant, L., Frutos, R., Duong, T.N., 2015. Role of Aedes aegypti and Aedes albopictus during the 2011 dengue fever epidemics in Hanoi, Vietnam. Asian Pac. J. Trop. Med. 8, 543–548. https://doi.org/10.1016/j.apjtm.2015.06.009

xv. Liu-Helmersson, J., Quam, M., Wilder-Smith, A., Stenlund, H., Ebi, K., Massad, E., Rocklöv, J., 2016. Climate Change and Aedes Vectors: 21st Century Projections for Dengue Transmission in Europe. EBioMedicine 7, 267–277. https://doi.org/10.1016/j.ebiom.2016.03.046

xvi. Martha, Z., Susetyo, B., Aidi, M.N., 2016. Panel Data Regression Model for Case of Dengue Hemorrhagic Fever (DHF) in Bogor. Glob. J. Pure Appl. Math. 12, 741–746.

xvii. Méndez-Lázaro, P., Muller-Karger, F.E., Otis, D., McCarthy, M.J., Peña-Orellana, M., 2014. Assessing climate variability effects on dengue incidence in San Juan, Puerto Rico. Int. J. Environ. Res. Public Health 11, 9409–9428. https://doi.org/10.3390/ijerph110909409

xviii. Ministry of Health Republic of Indonesia, 2018. Indonesia Health Profile 2017. Ministry of Health Republic of Indonesia, Jakarta.

xix. Ministry of Health Republic of Indonesia, 2017. Indonesia Health Profile 2016. Ministry of Health Republic of Indonesia, Jakarta.

xx. Ministry of Health Republic of Indonesia, 2016. Indonesia Health Profile 2015. Ministry of Health Republic of Indonesia, Jakarta.

xxi. Naish, S., Dale, P., Mackenzie, J.S., McBride, J., Mengersen, K., Tong, S., 2014. Climate change and dengue: A critical and systematic review of quantitative modelling approaches. BMC Infect. Dis. 14. https://doi.org/10.1186/1471-2334-14-167

xxii. Picardal, J.P., Elnar, A.R.R., 2012. Rainfall, temperature and the incidence of dengue in Central Visayas, Philippines are not correlated. CNU J. High. Educ. Categ. B 6, 61–70.

xxiii. Polwiang, S., 2015. The seasonal reproduction number of dengue fever: impacts of climate on transmission. PeerJ 3, e1069. https://doi.org/10.7717/peerj.1069

xxiv. Sang, S., Yin, W., Bi, P., Zhang, H., Wang, C., Liu, X., Chen, B., Yang, W., Liu, Q., 2014. Predicting local dengue transmission in Guangzhou, China, through the influence of imported cases, mosquito density and climate variability. PLoS One 9, 1–10. https://doi.org/10.1371/journal.pone.0102755

xxv. Simmons, C.P., Whitehorn, J., Anders, K., Van Nguyen, V.C., 2017. Dengue and Chikungunya, in: Infectious Diseases. Elsevier Ltd, pp. 1119-1122.e1. https://doi.org/10.1016/B978-0-7020-6285-8.00133-7

xxvi. Vargas, W.P., Kawa, H., Sabroza, P.C., Soares, V.B., Honório, N.A., De Almeida, A.S., 2015. Association among house infestation index, dengue incidence, and sociodemographic indicators: surveillance using geographic information system. BMC Public Health 15, 1–12. https://doi.org/10.1186/s12889-015-2097-3

xxvii. Wangdi, K., Clements, A.C.A., Du, T., Nery, S.V., 2018. Spatial and temporal patterns of dengue infections in Timor-Leste, 2005-2013. Parasites and Vectors 11, 1–9. https://doi.org/10.1186/s13071-017-2588-4

xxviii. WHO, 2016. Technical handbook for dengue surveillance, dengue outbreak prediction/detection and outbreak response.

xxix. WHO, 2012. Global Strategy for Dengue Prevention and Control 2012–2020 [WWW Document]. WHO. URL http://www.who.int/denguecontrol/9789241504034/en/ (accessed 2.13.18).

xxx. WHO, 2011. Comprehensive Guidelines for Prevention and Control of Dengue and Dengue Haemorrhagic Fever [WWW Document]. WHO Reg. Publ. SEARO. URL http://www.who.int/iris/handle/10665/204894 (accessed 1.30.18).