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Mapping Poverty Distribution of Urban Area using VIIRS Nighttime Light Satellite Imageries in D.I Yogyakarta, Indonesia

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Abstract

Purpose: This study aims to map the spatial distribution of poverty using nighttime light satellite images as a proxy indicator of economic activities and infrastructure distribution in D.I Yogyakarta, Indonesia. **Research design, data, and methodology:** This study uses official poverty statistics (National Socio-economic Survey (SUSENAS) and Poverty Database 2015) to compare satellite imagery's ability to identify poor urban areas in D.I Yogyakarta. National Socioeconomic Survey (SUSENAS), as poverty statistics at the macro level, uses expenditure to determine the poor in a region. Poverty Database 2015 (BDT 2015), as poverty statistics at the micro-level, uses asset ownership to determine the poor population in an area. Pearson correlation is used to identify the correlation among variables and construct a Support Vector Regression (SVR) model to estimate the poverty level at a granular level of 1 km x 1 km. **Results:** It is found that macro poverty level and moderate annual nighttime light intensity have a Pearson correlation of 74 percent. It is more significant than micro poverty, with the Pearson correlation being 49 percent in 2015. The SVR prediction model can achieve the root mean squared error (RMSE) of up to 8.48 percent on SUSENAS 2020 poverty data.**Conclusion:** Nighttime light satellite imagery data has potential benefits as alternative data to support regional poverty mapping, especially in urban areas. Using satellite imagery data is better at predicting regional poverty based on expenditure than asset ownership at the micro-level. Light intensity at night can better describe the use of electricity consumption for economic activities at night, which is captured in spending on electricity financing compared to asset ownership.

Keywords : Poverty Distribution, Poverty Mapping, Big Data, Satellite Imagery

JEL Classification Code : I30, I32, I38

1. Introduction

As a large country with a population of 275 million people, Indonesia has 27.54 million people living below the poverty line. In addition, there are still 1.5 times people considered vulnerable to poverty living above the poverty line. It is not easy for the Indonesian government amid the covid-19 pandemic to maintain the success of the poverty alleviation program that has been running since 2005. Since 2005, Indonesia has reduced poverty from 17.75 percent (2006) to 9.41 percent (2019) (BPS, Statistic Indonesia, 2021). Therefore, among the 17 Sustainable Development

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Goals (SDGs) targets, poverty alleviation is the main agenda in Indonesia's 2030 development agenda.

The poverty alleviation program SDGs 2030 looks at the problem of poverty in a multidimensional framework. Poverty can be caused by various dimensions and not only in terms of income to meet basic needs (Ministry of National Development Planning, 2022). Multidimensional poverty considers the causes of poverty in terms of education, public health, drinking water, and sanitation facilities. Thus, the initial establishment of an integrated poverty database in 2005 carried out by BPS was based on a multidimensional poverty framework. The poverty database was built to serve as the basis for the provision of assistance by the government.

The provision of economic assistance to poor households requires micro data up to the location of the poor households. Providing data on the location of poor households provided by the poverty database requires many funds. Therefore, in measuring poverty yearly, BPS uses the national socioeconomic survey (SUSENAS) to estimate regional poverty at the macro level. In addition, through SUSENAS, household income is obtained to determine the minimum expenditure limit for poor households. However, the SUSENAS did not find locations where poor households were located.

The location of poor households above the earth's surface can be seen from the spatial coordinates of the satellite image. The development of satellite imagery research in the last decade, it is possible to identify the location of poor households through economic activities from outer space(Chen & Nordhaus, 2011; Doll et al., 2006; Ghosh et al., 2010; Henderson et al., 2012). This study used nighttime light satellite imagery to approach night economic activity. By limiting the area of 1 km x 1 km, it is hoped that the identification of the location of poor households can be more precise, approaching the data in the poverty database. Hence, finding the location of poor areas, especially D.I Yogyakarta Province, through satellite imagery at night can be fulfilled.

D.I Yogyakarta Province is a unique province with the highest human development index and the highest poverty rate in Java. The human development index describes the level of human capital in supporting economic growth. As appropriate, adequate human capital will produce economic growth that will prosper the community and reduce poverty in the area. This condition does not occur in the Province of D.I Yogyakarta, so by finding the spatial location of poverty, development can focus more on human capital to reduce poverty. By using satellite imagery at night, this study predicts the distribution of poverty, especially in urban areas in the Province of D.I Yogyakarta.

2. Literature Review

Satellite imageries data offers abundant multispectral and multitemporal geospatial information which further can be extracted into valuable spatial features for multidisciplinary applications (Afira & Wijayanto, 2022; Nurmasari et al., 2021; Saadi et al., 2021). With multiple spectral bands, one can construct different specific composite indices for measuring particular land uses, land covers, atmospheric activities, human populations and activities, etc (Wijayanto et al., 2020; Triscowati et al., 2019). Several studies have used nighttime lights from the Defense Meteorological Satellite Program (DMSP/OLS) operational Linescan system to estimate local revenues and economical activities (Putri et al., 2022; Aprianto et al., 2022). Furthermore, the nighttime light image data experienced a significant development from the results of the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite instrument. Nighttime satellite imagery from VIIRS can capture detected urban lighting in the 505-890 nm spectrum. With the resulting increase in resolution, the use of nighttime light satellite imagery data is growing. The utilization of satellite imagery, especially nighttime light, was initially associated with socioeconomic activities (Chen & Nordhaus, 2011). Nighttime lights can quantitatively characterize the intensity of socioeconomic activities and urbanization (Miller et al., 2012), electricity consumption in an area (Doll & Pachauri, 2010; Elvidge et al., 1997) and also measure the income of residents in an area (Ivan et al., 2020). Therefore, based on previous research, this study uses the approach of nighttime light intensity as a description of the income and welfare of the population in predicting the location of poverty in the area.

The nighttime light from VIIRS, compared to DMSP/OLS, is better at capturing the intensity of nighttime light in urban areas than in rural areas with low light intensity. This condition explains that economic activity in urban areas is higher than in rural areas. In addition, more public service infrastructure in urban areas than in rural areas makes electricity consumption at night more in cities than in rural areas. The condition of urban development should not hamper the welfare of the people of D.I Yogyakarta Province. However, this does not occur in the Province of D.I Yogyakarta. Based on BPS data for 2020, the Human Development Index for D.I Yogyakarta Province is 79.97 percent, with the highest poverty percentage in Java at 12.80 percent.

In this study, the highest poverty rate in the province of D.I Yogyakarta is obtained using an income or expenditure approach called macro poverty. The macro poverty level of D.I Yogyakarta Province cannot indicate the location of areas with high human capital, and access to public services can have low poverty levels or vice versa. Therefore, an alternative poverty calculation is needed to predict poverty in the D.I Yogyakarta Province. In this study, regional poverty prediction is made by connecting the intensity of nighttime light with a grid area measuring 1 km x 1 km. Based on previous research, economic activity has a comparative advantage between regions in the size of 1 km x 1 km (Asher et al., 2021). In addition, the Gross Domestic Product (GDP) from several studies correlates with the intensity of nighttime light on a grid area measuring 1 km x 1 km (Elvidge et al., 1997; Ghosh et al., 2010). The use of nighttime light intensity in an area can distinguish the percentage of poverty in an area well. Therefore, this study also used a grid area of 1 km x 1 km, as shown in Figure 1, for modeling poverty predictions.

Identifying the characteristics of poor households to facilitate the Indonesian government in determining poverty alleviation programs has been started since 2000 (BPS Statistic Indonesia, 2005). This activity developed into constructing a poverty database in 2005 and began to be applied as a database for providing direct cash assistance to poor households. The poverty database continued to be developed until the last in 2015. The determination of poor households was carried out using a 14-variable approach. They are the area and type of floor of the house, kind of house wall, facilities for sanitation, source of drinking water, the lighting used, fuel used, frequency of eating in a day, habits of buying meat/chicken/milk, ability to buy clothes, medical treatment health centers, employment for the head of the household, and asset ownership.

Figure 1: Map of Yogyakarta Province Divided by Grid Size 1 km x 1km

3. Research Methods and Materials

This study uses two types of poverty statistical data to compare the extent to which the use of nighttime light levels can predict poverty in an area well. The two poverty data were the macro-level data from SUSENAS data and the micro-level from the household poverty collection database. Several stages were carried out to fulfill the research objectives, from calculating the poverty line to predicting poverty locations using support vector regression (SVR) modeling.

3.1. Poverty Line Calculation and Percentage of Poor Population

Determining the number of poor people based on SUSENAS data is carried out using an expenditure approach for food and non-food consumption compared to the poverty line. The calculation of the poverty line uses equation 1 as follows :

$$Z_j = \sum P_{jk}\, Q_{jk} = \sum V_{jk} \quad (1)$$

where Z_j is the poverty line in area j, P_{jk} is the price of commodity-k in area-j, Q_{jk} is the average quantity of commodity-k consumed in area j, and V_{jk} is the value of expenditure for consumption of commodity k in area j. After calculating the poverty line, the percentage of poor educators is calculated using the Foster Greer Thorbecke (1984) equation as in equation 2 below:

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_i}{z}\right]^\alpha \quad (2)$$

where $\alpha = 0,1,2,$ z is the poverty line, y_i is the average monthly per capita expenditure of the population below the poverty line, q is the number of people below the poverty line, and n is the total population.

3.2. Determination of Poor Households with Proxy Mean Test

Determination of poor households with the Proxy Mean Test (PMT) is the determination of poor households by ranking from the poorest to the wealthiest households. The ranking process is carried out from the modeling results between consumption expenditure and the characteristics of poor households in the data collection or census data. The PMT model used can be written as the following equation:

$$\hat{y} = \alpha + \beta x_{vh} + \eta_v + \varepsilon_{vh} \qquad (3)$$

where $\hat{y}$ is the estimated household consumption, x_{vh} is the household characteristic, and η_v is the community characteristic. The characteristics of the households used are 14 characteristics of poor households. They are the area and type of floor of the house, kind of house wall, facilities for sanitation, source of drinking water, the lighting used, fuel used, frequency of eating in a day, habits of buying meat/chicken/milk, ability to buy clothes, medical treatment health centers, employment for the head of the household, and asset ownership. PMT modeling variables with 14 household characteristics is an approach to measuring poverty in a multidimensional framework that does not only look at the size of poverty from expenditure or income.

3.3. Extraction of Nighttime Light Intensity

This study uses nighttime satellite imagery data from the Suomi-NPP Satellite using the Visible Infrared Imaging Radiometer Suite (VIIRS). The VIIRS sensor can capture the reflection of light on the earth's surface, especially at night, such as urban lights, fires, lightning, volcanic lava, gas flares, and large ship lights called the Raw Data Day Night Band. Day-Night Band Raw data is Raw Data Records (RDR) which is processed (calibrated) into Sensor Data Records (SDR) files. The file has geolocation information for geometric correction purposes and is converted to radians, reflectance, or brightness temperature data. Before extracting the radians data for the nighttime light intensity of an area, a DNB data projection is carried out with a global projection, namely the World Geodetic System (WGS) 84, according to the location of D.I Yogyakarta Province. The extraction equation for the nighttime light intensity value can be written in equation 4.

$$L_{\lambda i} = \left(\frac{LMAX_\lambda - LMI\ \ \lambda}{Q_{calmax} - Q_{calmin}}\right)(Q_{cal} - Q_{calmin}) + LMIN_\lambda \qquad (4)$$

L_λ = spectral radiance at the sensor's aperture $[W/(m^2\ sr\ \mu m)]$ for region-i

Q_{cal} = Quantized calibrated pixel value $[DN]$

Q_{calmin} = Minimum quantized calibrated pixel value corresponding to $LMIN_\lambda[DN]$

Q_{calmax} = Minimum quantized calibrated pixel value corresponding to $LMAX_\lambda[DN]$

$LMIN_\lambda$ = Spectral at-sensor radiance that is scaled to $Q_{calmin}\left[\frac{W}{(m^2\ sr\ \mu m)}\right]$

$LMAX_\lambda$ = Spectral at-sensor radiance that is scaled to $Q_{calmax}\left[\frac{W}{(m^2\ sr\ \mu m)}\right]$

$G_{rescale}$ = Band-specific rescaling gain factor $\left[[W/(m^2\ sr\ \mu m)]/DN\right]$

$B_{rescale}$ = Band-specific rescaling bias factor $[W/(m^2\ sr\ \mu m)]$

3.4. Pearson Correlation

This study used the Pearson correlation to count the relationship between macro or micro poverty and nighttime light intensity. The Pearson correlation equation used can be written as in equation 5 below.

$$r_{xy} = \frac{\sum xy}{(n-1)S_x S_y} \qquad (5)$$

Where r_{xy} is the correlation between x (intensity of nighttime light) and y (percentage of poor people), n is the number of grids in D.I Yogyakarta Province, and S S is the Standard Deviation.

3.5. Support Vector Regression

Furthermore, modeling is done with Support Vector Regression to predict the spatial location. Support Vector Regression is developed from the machine learning method of Support Vector Machine for forecasting, especially in non-linear fields. This study uses SVR to find a function f (x) as a hyperplane regression function to get the smallest possible error (Schölkopf & Smola, n.d.). Another goal in using the SVR model in this study is to overcome the overfitting (Kanevski & Canu, 2000) of poverty prediction using nighttime light. As for getting the parameters that represent the SVR model, a random Search Cross-Validation approach is carried out with validation using Leave One Out Cross Validation, as shown in Figure 2 below.

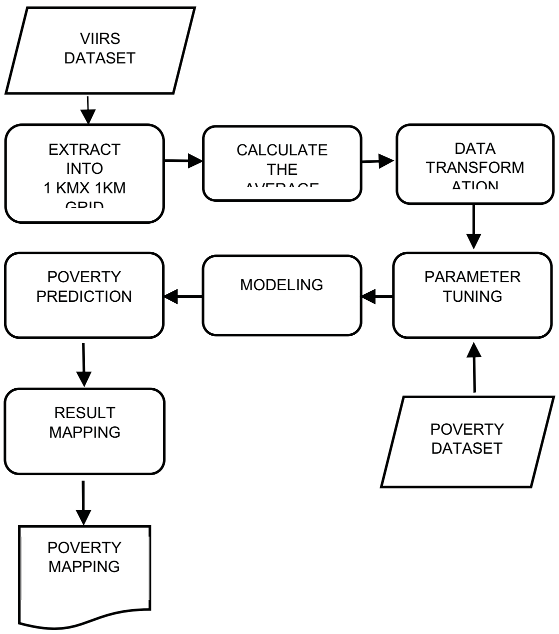

Figure 2: Flowchart Poverty Prediction

4. Results and Discussion

Regional poverty is closely related to economic activities in an area. Increasing economic activity in an area will increase the population's income level and reduce regional poverty (Ivan et al., 2020). The location of poverty can explain the causes of poverty in terms of the environment where poor households live. The nighttime light approach in finding the location of poverty is closely related to the electricity consumption of economic activities at night. In this study, nighttime light observations were carried out in the province of D.I Yogyakarta, Indonesia, to determine the poverty area, especially in urban areas.

Forecasting poverty areas in D.I Yogyakarta Province is carried out in an area measuring 1 km x 1 km. As shown in table 1, an area of 1 km x 1 km divides the D.I Yogyakarta and gets 3,275 grid areas. The division of this area is done to get a more precise poverty area to find poor households by identifying the luminosity of nighttime light. The average luminosity of nighttime light from the 3,275 grid areas in 2020 is 1.73 radiance, with a maximum value of 45.32. In addition, almost 25 percent of the area in D.I Yogyakarta Province is still dark and has not been caught by the VIIRS satellite sensor. Compared to the macro poverty rate, 25 percent of grid areas have 13,5 percent poverty rate, and 75 percent of grid areas still have 17,07 percent poverty rate, below the maximum poverty limit for the Province of D.I Yogyakarta of 18.01 percent. Table 2 shows that there is still 25 percent of areas with poverty above 17.07, indicating low luminosity intensity.

Meanwhile, when compared between the intensity of night light and the 2015 micro poverty rate in table 2.25 percent of dark areas have a micro poverty rate above 23.35 percent, with a macro poverty rate in 2015 of 19.34 percent (column 5). The percentage of micro poverty is greater than the percentage of macro poverty. This condition is caused by differences in the methods of calculating the poor. Micro poverty determines the poor population based on 14 variables characteristic of poor households or a multidimensional poverty framework approach. Meanwhile, macro poverty determines the poor population based on expenditure in meeting consumption for basic needs. Table 2 also shows that the 25 percent of areas with the highest luminosity level have a macro poverty rate of 16.33 percent and a micro poverty rate of 14.73 percent. So, based on table 2, it can be concluded that areas that are dark or have a low level of luminosity will have a lower macro poverty rate than micro poverty and vice versa. Micro poverty can identify poor households in dark areas more than macro poverty.

Table 1: Description Variable Poverty and Average Nighttime Light Luminosity 2020

Description	Average Light Luminosity (Radian)	Macro Poverty 2020	Log Transfromation Average Radian 2020
(1)	(2)	(3)	(4)
Number of Grid	3275	3275	3275
Mean	1.7374	14.9196	0.6936
Standard Deviation	3.2756	3.6423	0.6990
Minimum	0	7.27	0
25 percent	0	13.5	0
50 percent	0.8556	17.07	0.6182
75 percent	1.9143	17.07	1.0696
Maximum	45.3297	18.01	3.8357

Table 2: Description Variable Between Poverty and Annual Nighttime Light Luminosity 2015

Description	Average Light Luminosity (Radian)	Micro Poverty (BDT 2015)	Log Transfromation Average Radian 2015	Macro Poverty 2015 (SUSENAS 2015)
(1)	**(2)**	**(3)**	**(4)**	**(5)**
Number of Grid	3275	3275	3275	3275
Mean	1.0774	19.5614	0.4785	17.0651
Standard Deviation	2.4230	7.2969	0.5954	4.5977
Minimum	0	3.08	0	7.70
25 percent	0	14.73	0	16.33
50 percent	0.4021	20.92	0.3379	19.34
75 percent	1.1064	23.35	0.7449	19.34
Maximum	33.6273	35.44	3.5446	21.4

Macro-poverty 2020 cannot be compared with the value of micro-poverty 2020 due to the unavailability of data on micro-poverty 2020. Therefore, to reach the extent to which the intensity of nighttime light can predict the location of poverty, the 2015 poverty statistics were used. Table 3 shows the relationship between micro and macro poverty levels with nighttime light intensity. Pearson's correlation between the macro poverty level and nighttime light intensity is more significant than micro poverty level and nighttime light intensity. The value of the Pearson correlation between the percentage of poverty and the level of nighttime light is negative. The negative Pearson correlation value indicates that the higher the nighttime light in an area, the lower the poverty rate in that area and vice versa. In addition, the correlation between macro poverty and nighttime light levels in 2020 also shows a negative and robust value of 75.99 percent. The magnitude of this correlation indicates that the nighttime light in an area is proportional to the electricity consumption (Doll & Pachauri, 2010; Elvidge et al., 1997). In line with the determination of macro poverty, expenditure on electricity consumption is one of the consumption expenditures to meet basic household needs. However, electricity consumption is not only carried out by households, public services in an area also require electricity consumption which can be seen in annual trends.

Table 3: Pearson Correlation Between Nighttime Light Luminosity and Poverty Variable

Pearson Correlation	Micro Poverty 2015	Macro Poverty 2015 (SUSENAS 2015)	Macro Poverty 2020 (SUSENAS 2020)
(1)	(2)	(3)	(4)
Average Radian Nighttime Light Luminosity 2015	-0.3362	-0.5934	
Log Transformation Average Radian Nighttime Light Luminosity 2015	-0.4816	-0.7374	
Average Radian Nighttime Light Luminosity 2020			-0.6117
Log Transformation Average Radian Nighttime Light Luminosity 20152020			-0.7599

The annual trend of changing nighttime light levels could be due to developments in the area. Regional development encourages increased economic activity, which reduces the region's poverty levels. The development of economic activity in D.I Yogyakarta Province from 2015 to 2020 can be seen in changes in lighting levels, as shown in Figures 3 and 4. In the last five years, the annual average nighttime light intensity of D.I Yogyakarta Province has increased due to regional development. The annual average nighttime light intensity in 2020 increased from 2015 by 34.83 percent. Apart from the development of the downtown area of D.I Yogyakarta, the construction of Yogyakarta International Airport also caused an increase in the annual average nighttime light intensity in Temon District, Kulon Progo Regency. This increase in the annual mean nighttime light intensity underlies this study to predict regional poverty. Prediction of regional poverty to find the location of poor households by comparing two different sources of poverty data. Based on two data sources, macro and micro poverty can be mapped, as shown in Figure 5.

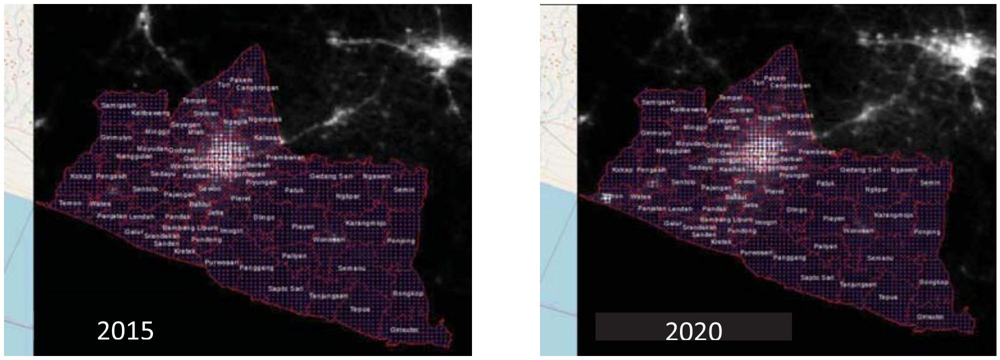

Figure 3: Annual Average Nighttime Light D.I Yogyakarta 2015 and 2020

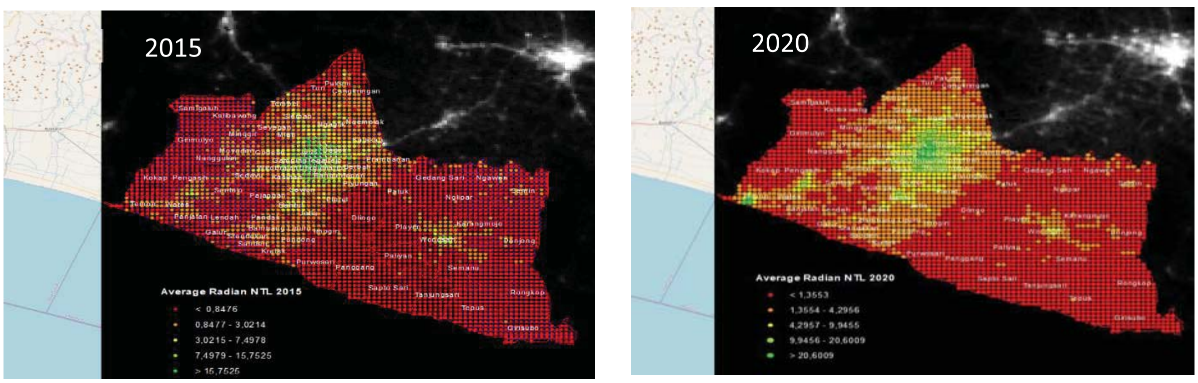

Figure 4: Cluster of Annual Average Nighttime Light D.I Yogyakarta 2015 and 2020 by Grid Area 1 km x 1 km

Figure 5 shows that the downtown areas of the three data sources with the highest light intensity have the lowest poverty rates, marked in red. In comparison, the areas with the highest poverty rates are highlighted in green instead of the color in Figure 4. In contrast, areas outside the city center are colored red with lower light intensity than the city center. However, what is interesting for the sub-district of Temon is that micro poverty is described differently from the SUSENAS data on macro poverty with a high poverty rate. This condition shows the advantages of micro poverty data, which can present data at a lower level at the village level. In addition, this condition also indicates that the inauguration of Yogyakarta International Airport on August 28, 2020, has not had a significant effect on the macro poverty level of the Kulon Progo Regency. The decline in airport activity during the COVID-19 pandemic in Indonesia was not enough to reduce the poverty rate in Kulon Progo Regency, especially in the Temon subdistrict.

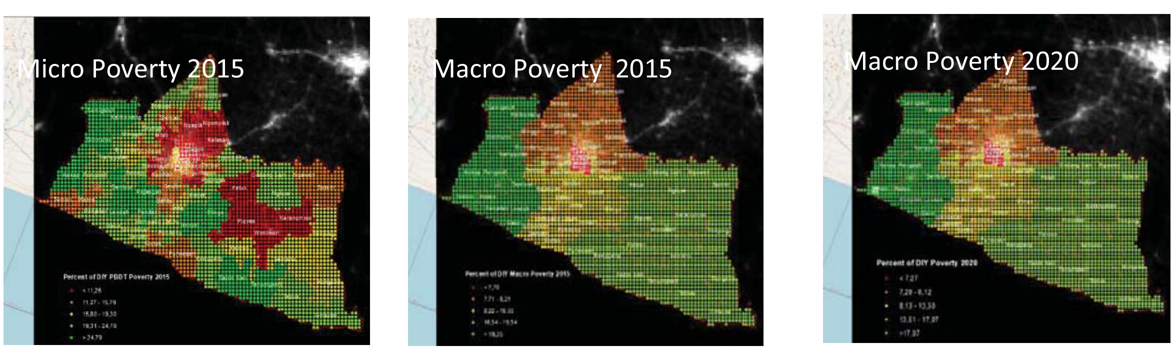

Figure 5: Comparison of Overlay Data Visualization between Poverty and Average Annual Nighttime light intensity

Furthermore, modeling is carried out to predict the location of poverty using Support Vector Regression (SVR). Regional poverty prediction with SVR was carried out to obtain a hyperplane with the smallest possible error (Schölkopf & Smola, n.d.). In addition to overcoming the overfitting of econometric modeling in general. The representative modeling parameters were obtained using the Random-Search Cross-Validation method on the SVR with the model validation stage using Leave One-Out-Cross-Validation. The results of poverty prediction with SVR are obtained as shown in Figure 6.

Based on Figure 6, it can be seen that the downtown area, which has a higher annual average nighttime light intensity than the surrounding area, can be predicted to have the lowest poverty with macro poverty data from 2015 and 2020 SUSENAS. Meanwhile, poverty predictions in the city center are in the range of the second-lowest poverty with micro poverty data. Poverty in the city center based on micro-poverty is predicted with a higher annual average nighttime light intensity than the area around the city center. By comparing the predicted results of micro-poverty and macro poverty, there are differences in predicting poverty in the downtown.

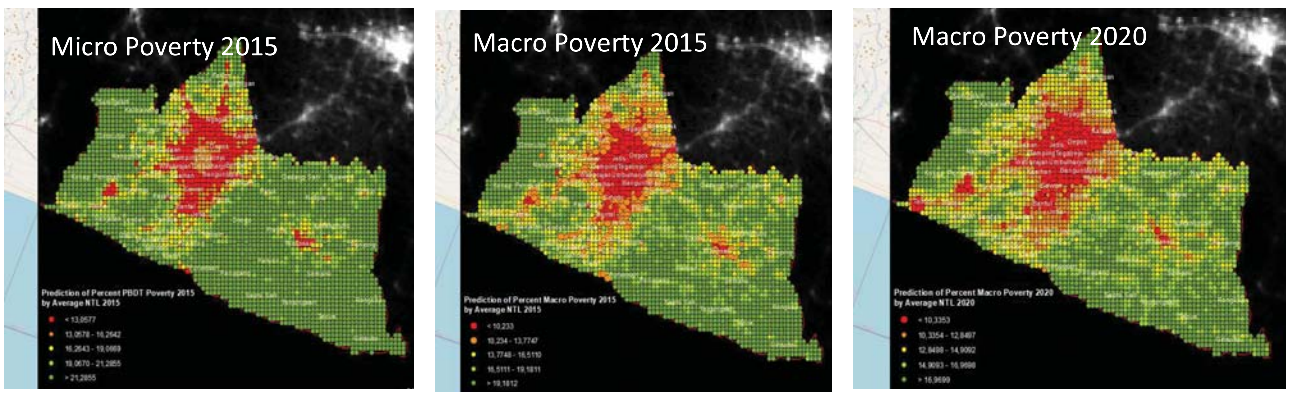

Figure 6: Comparison of Prediction Poverty SVR model Visualisation by Average NTL

Prediction of poverty modeling with SVR, as shown in Figure 6, has a different random mean square error (RMSE). The micro poverty prediction model has an RMSE value of 33.24, which is greater than the RMSE of 2015 macro poverty of 13.20. In addition, the RMSE of poverty prediction modeling with SUSENAS 2020 is worth 8.48. Comparing the visualization of the prediction of the training model with the SVR, it can be shown in Figure 7. The prediction of the micro poverty model produces an overfitting model compared to the poverty training model with macro poverty data. In addition, by comparing the lowest C value in table 4, macro poverty data are better predicted by nighttime light levels than micro poverty data.

Furthermore, in validating the results of poverty predictions, it is done by overlaying the results of the 2020 prediction model with google maps. Google maps can show regional development infrastructure by showing public services in the area. Based on findings from google maps, it was found that downtown D.I Yogyakarta has a higher average annual nighttime light than other areas. Development infrastructure is one of the reasons for the high level of nighttime light downtown, as shown in figures 8 and 9 below.

Table 4: Kernel Radial Basis Function Parameter

Prediction Poverty Model with Average NTL	Kernel RBF Parameter		Random Mean Square Error
	C	γ	
BDT 2015	77.29	0.37	33.24
SUSENAS 2015	88.93	0.12	13.20
SUSENAS 2020	50.30	0.14	8.48

Figure 7: Comparison Model Training Visualisation

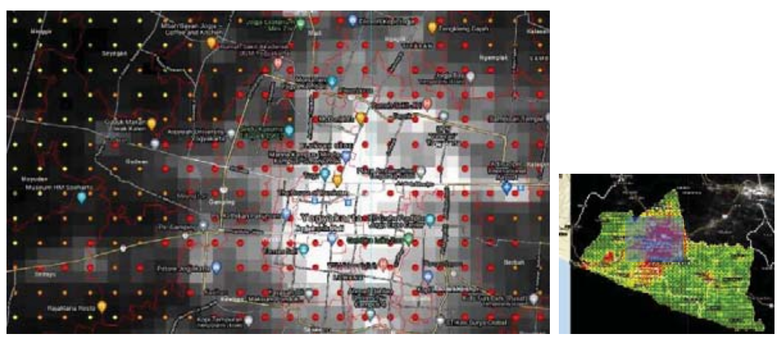

Figure 8: Overlay Public Area in Center of Yogyakarta City with Prediction Macro Poverty 2020 and Average NTL 2020

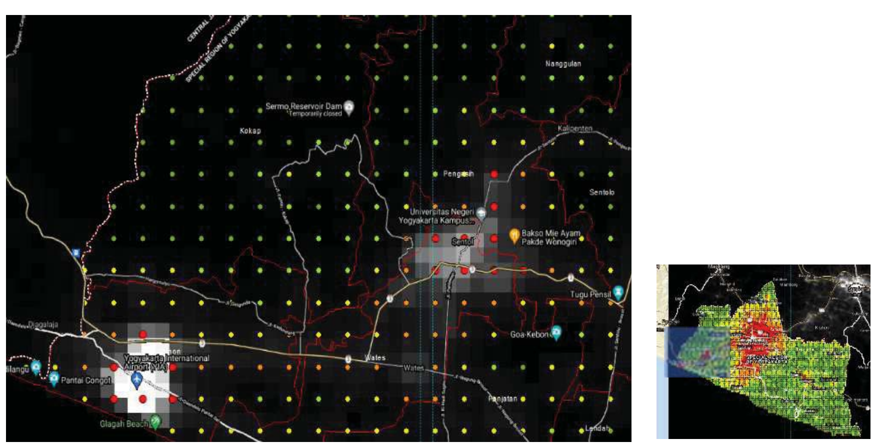

Figure 9.1: Overlay Public Area in Outside of Yogyakarta City (Temon and Sentolo Subdistrict) with Prediction Macro Poverty 2020 and Average NTL 2020

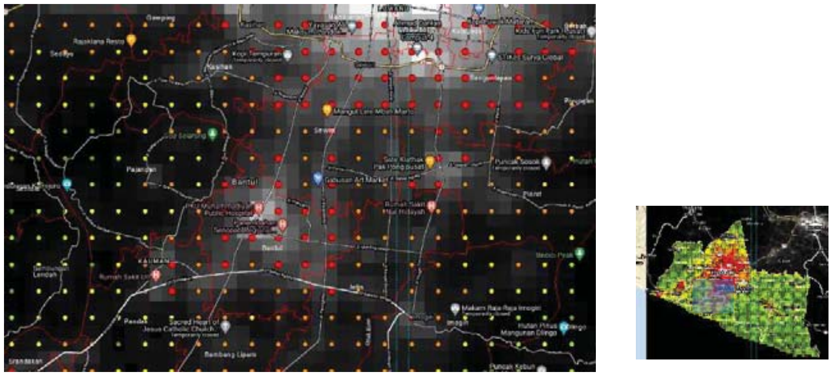

Figure 9.2: Overlay Public Area in Outside of Yogyakarta City (Bantul Subdistrict) with Prediction Macro Poverty 2020 and Average NTL 2020

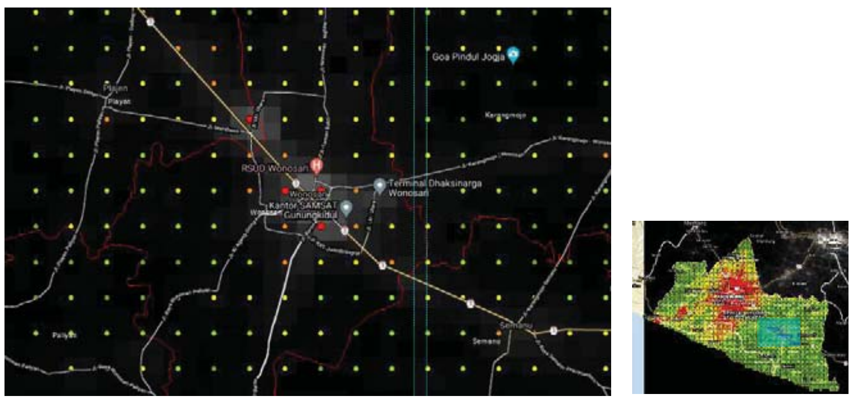

Figure 9.3: Overlay Public Area in Outside of Yogyakarta City (Wonosari Subdistrict) with Prediction Macro Poverty 2020 and Average NTL 2020

Figures 8 and 9 show that areas within and outside the city have a higher average annual nighttime light intensity than other places with public facilities that residents can access. The number of public facilities in an area increases economic activity, which is more significant than in other areas. In addition, the quality of the population in the area with easy access to public facilities has a better human development index than before, especially in the Yogyakarta City area, which is the center of education with various educational facilities in it. The International Airport in Temon Subdistrict, Bantul tourist attraction, Wonosari Hospital, and Samsat Regional of Wonosari, located outside the city of Yogyakarta, encourage the economy in that region. This condition is shown by the prediction poverty 2020 in that area has the lowest poverty range with a red color grid as shown in figure 6.

5. Conclusion

Research in the last ten years has explored economic activity from outer space (Henderson et al., 2012) through satellite imagery, especially with the use of night light intensity. The intensity of light at nighttime can represent the condition of socioeconomic activity (Chen & Nordhaus, 2011a) in an area, measuring the level of urbanization (Miller et al., 2012), the level of income of the population (Ivan et al., 2020), and electricity consumption in the area. (Doll & Pachauri, 2010; Elvidge et al., 1997). This research is also supported by developing observations of light intensity at night (Miller et al., 2012).

Detection of city nighttime light with VIIRS which has better spatial resolution than DMSP, and research on population income estimation with nighttime light motivates this study to compare two sources of poverty data. Two sources of poverty data are micro poverty and

SUSENAS as macro poverty. Micro-poverty comes from 14 characteristics of poor households and asset ownership. In addition, micro-poverty has the advantage of providing poverty data down to the sub-district level. However, the SVR poverty prediction model used in micro poverty data with nighttime light does not accurately predict urban poverty areas with a higher average annual nighttime light intensity than other areas.

Meanwhile, poverty with the expenditure approach through SUSENAS has a correlation above 50 percent and is inversely proportional to the annual average nighttime light intensity. The macro poverty SVR prediction model from SUSENAS can be predicted by the annual average nighttime light intensity on a grid area size of 1 km x 1 km. This is in line with Ivan et al. (2020) which states that the intensity of light at night is related to the income of the population of an area. Meanwhile, the population's income can be an approach to determine the level of poverty in an area. In addition, areas with high annual average nighttime light intensity, both in the city center and outside the city, are supported by infrastructure development that supports economic activities in the area. Based on the results of this study, the Indonesian government can assist in poverty alleviation based on the location of the poverty modeling results, especially in the Province of D.I Yogyakarta, so that it has implications for targeted poverty alleviation programs. In addition, the problem of developing a poverty database that requires large funds can be resolved.

Furthermore, the poverty prediction method can be further developed by using other poverty variables to support the development of a poverty database that is better than before. In addition, the location of poverty in an area of 1 km x 1 km, the results of poverty predictions with macro poverty can be a recommendation for regions that receive poverty assistance from the government.

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