

Spatial Analysis of The Suitability In Number of TPS at Kelurahan Based on Area And Number of DPT In DKI Jakarta Election 2017

Nur Iman Santoso, Chotib
Universitas Indonesia, Indonesia

Email: nurimans@gmail.com, chotib@hotmail.com

*Correspondence: nurimans@gmail.com

ABSTRACT

Keywords:
TPS; Pilkada; suitability

The number of TPS, in the 2017 DKI Jakarta Pilkada, was designed to suit the number of DPTs in one sub-district. There is a spatial relationship in the number of TPS, total DPT and the area between neighboring sub-districts which are processed using the Geoda application. The purpose of the study is Spatial Analysis of The Suitability In Number of TPS at Kelurahan Based on Area And Number of DPT In DKI Jakarta Election 2017. This research is based on data from the 2017 DKI Jakarta Regional Election Voters, which was conducted using quantitative research methods by describing the findings with the help of Geoda software. The results of the analysis on this conclusion show that the number of DPT and area area have a positive effect on the number of polling stations in Kelurahan in DKI Jakarta. In addition, there is a spatial relationship in the number of polling stations and the total DPT between neighboring villages.



Introduction

The basic element in elections is voters. Voters according to Law No. 7 articles 348-350 of 2017, voters are Indonesian citizens who are 17 years old or older, whether married or not and have been married. General election activity is to gather all voters who are in one election activity room to be able to cast their votes in the available ballot boxes (Nugraha, 2019).

The Permanent Voter List (DPT), is a product provided by the Election Organizer to all citizens who are recorded in voter finalization which is usually carried out routinely before the election date (Kaliraj & Malar, 2012). The DPT is managed in a decision of the Election Organizer which groups the call to attend the election in one polling station. In terms of the DKI Jakarta Regional Election in 2017, there were 13,023 polling stations distributed in 267 urban villages (Özkan, Süer, Keser, & Kocakoç, 2020).

Commission II of the House of Representatives of the Republic of Indonesia at the RAKER on December 6, 2016 with the Minister of Home Affairs of the Republic of Indonesia, Minister of PAN and RB RI, Chief, National Police of the Republic of Indonesia, Chairman of the KPU RI, Chairman of Bawaslu RI and Chairman of KASN supported the efforts of the Ministry of Home Affairs of the Republic of Indonesia to

increase voter participation. The government made the decision to suspend voting days in the 2017 simultaneous regional elections, in order to increase voter participation (Watson, 2013).

The number of voters registered in one Polling Station (TPS), is the starting point for this study to answer the effectiveness of the formation of polling stations based on the number of DPT in one Kelurahan where they live or domicile. The Central Election Commission sets the maximum number of voters at 500 polling stations (Ikechukwu, Ebinne, Idorenyin, & Raphael, 2017).

Theoretical Framework

The population density in an area affects the number of voters, which is carried out by the KPU by finalizing voters in one kelurahan area. PILKADA DKI Jakarta has 267 Kelurahan which become a unified region in the election of Governor and Vice Governor (Farhadian Azizi, Kazemi, & Soltani, 2019). The existence of voters in one kelurahan placed in polling stations with the same kelurahan, will facilitate affordability in participating in the DKI Jakarta Regional Election.

The scheme for preparing the Voter List in international discussions is divided into:

- Citizen Registration versus Voter Registration;
- Compulsory registration versus voluntary registration;
- Active Registration versus Passive Registration;
- Periodic Registration versus Continuous Registration.

The total area and population in one kelurahan in DKI Jakarta varies. In 2015, DKI Jakarta Province had a high population density, averaging 23 thousand people per square kilometer (Bell, Hoskins, Pickle, & Wartenberg, 2016). Jelambar Baru sub-district in Grogol Petamburan sub-district is the most populous area with 307 thousand people per square kilometer. In addition, South Grogol also has a population density of more than 100 thousand per square kilometer. According to the Central Bureau of Statistics (BPS), Jakarta had the highest population density in Indonesia at the time (Jackson, 2020).

The distribution of voters in polling stations which later became DPT became very important in order to carry out the activities of the DKI Jakarta Regional Elections which became a barometer of the success of the 2017 Simultaneous Regional Elections, this is because DKI Jakarta became the capital of the Unitary State of the Republic of Indonesia (Waller & Gotway, 2014).

Research Methods

This research is based on data from the 2017 DKI Jakarta Regional Election Voters, which was conducted using quantitative research methods by describing the findings with the help of Geoda software. Starting with data held at the village level consisting of: the number of male residents; female population; number of voters; fixed voter turnout; permanent voter list; number of polling stations; and area. All of these data are carried out quantitative tests with Geoda software which will later describe the form of *Classic Spatial Regression*, *Spatial Error Regression*, correlation graphs between variables, *Natural Break* maps, and *Lisa Scatter Plot*.

Results and Discussion

Correlation tests between variables are performed by classical regression. The results of the classical regression test in this study are shown in Table 1 below. The results show that the independent variables of regional area and the total number of DPT are positively correlated significantly with the number of polling stations in each urban

village in DKI Jakarta. A P-value smaller than 0.01 indicates the variable significance of the area area and the number of polling stations is very significant (Iván, Stevenazzi, Pollicino, Masetti, & Mádl-Szőnyi, 2020).

Table 1. Regression Statistics, Area and DPT variables per Kelurahan

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,98567662							
R Square	0,971558398							
Adjusted R Square	0,971342932							
Standard Error	4,819991631							
Observations	267							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	2	209513,1846	104756,5923	4509,088861	8,3548E-205			
Residual	264	6133,332301	23,23231932					
Total	266	215646,5169						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0,953581878	0,608518758	-1,567054205	0,118299839	-2,151749529	0,244585773	-2,151749529	0,244585773
LUAS	0,458258126	0,156971717	2,919367478	0,003810043	0,149182307	0,767333946	0,149182307	0,767333946
dpt_t	0,001797488	2,18152E-05	82,39604813	2,3144E-190	0,001754534	0,001840442	0,001754534	0,001840442

```

classic-Luas_dpt_TPS.txt
>>12/12/23 11:31:37
REGRESSION
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set : dpt-L_P
Dependent Variable : t_tps Number of Observations: 267
Mean dependent var : 48.7753 Number of Variables : 3
S.D. dependent var : 28.4194 Degrees of Freedom : 264

R-squared : 0.971558 F-statistic : 4509.09
Adjusted R-squared : 0.971343 Prob(F-statistic) : 0
Sum squared residual: 6133.33 Log likelihood : -797.278
Sigma-square : 23.2323 Akaike info criterion : 1600.56
S.E. of regression : 4.81999 Schwarz criterion : 1611.32
Sigma-square ML : 22.9713
S.E of regression ML: 4.79284

Variable Coefficient Std.Error t-Statistic Probability
-----
CONSTANT -0.953582 0.608519 -1.56705 0.11830
LUAS 0.458258 0.156972 2.91937 0.00381
dpt_t 0.00179749 2.18152e-05 82.396 0.00000

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 4.639475
TEST ON NORMALITY OF ERRORS
TEST DF VALUE PROB
Jarque-Bera 2 42.8479 0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST DF VALUE PROB
Breusch-Pagan test 2 106.1671 0.00000
Koenker-Bassett test 2 56.7848 0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : DKI_Kelurahan_queen
(row-standardized weights)
TEST MI/DF VALUE PROB
Moran's I (error) 0.3088 8.6542 0.00000
Lagrange Multiplier (lag) 1 1.2585 0.26194
Robust LM (lag) 1 0.2364 0.62681
Lagrange Multiplier (error) 1 69.2528 0.00000
Robust LM (error) 1 68.2307 0.00000
Lagrange Multiplier (SARMA) 2 69.4892 0.00000
===== END OF REPORT =====
    
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Figure 2. Spatial Classic Regression, Area and DPT variables per Village

The results of classical spatial regression management with the GeoDa application resulted in a value of $R^2 = 0.97$ and a probability value for the variable area of the village and total DPT less than 0.01 (Aditya & Kraak, 2016). The results show that both significant variables affect the number of polling stations in each village in DKI Jakarta in the first round of the DKI Jakarta Regional Election (Okabe & Sugihara, 2022). These results show that the lagrange multiplier (lag) test produces a probability that is too large, which is 0.26. While the lagrange multiplier (error) test produces a very low probability

close to zero. This suggests that there are significant residual spatial effects that are not explained by regression models (Sakizadeh, 2020).

From that result, based on the Geoda Workbook if the LM (error) value is significant and LM (lag) is not significant, what is done next is a spatial error test. Here are the results (Bont, Fraefel, & Fischer, 2018).

```

spatial Error-Luas_dpt_TPS.txt
>>12/12/23 11:33:01
REGRESSION
-----
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set          : dpt-L_P
Spatial Weight    : DKI_Kelurahan_queen
Dependent Variable : t_tps      Number of Observations: 267
Mean dependent var : 48.775281  Number of Variables   : 3
S.D. dependent var : 28.419445  Degrees of Freedom    : 264
Lag coeff. (Lambda) : 0.497186

R-squared         : 0.977255  R-squared (BUSE)      : -
Sq. Correlation   : -          Log likelihood         : -774.352372
Sigma-square      : 18.3701   Akaike info criterion : 1554.7
S.E of regression : 4.28604   Schwarz criterion     : 1565.47

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Variable          Coefficient      Std.Error      z-value      Probability
-----
CONSTANT          -0.802198        0.775242      -1.03477     0.30078
LUAS              0.329733        0.165066      1.99759     0.04576
dpt_t             0.00180736      2.1127e-05    85.547      0.00000
LAMBDA            0.497186        0.0730999     6.80146     0.00000
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REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST
Breusch-Pagan test          DF      VALUE      PROB
                             2       93.2684   0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : DKI_Kelurahan_queen
TEST
Likelihood Ratio Test      DF      VALUE      PROB
                             1       45.8518   0.00000
===== END OF REPORT =====

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Figure 3. Spatial Error Regression, Area and DPT variables per Village

The parameter used in spatial error analysis in this study is the lambda value. In the Spatial Error test, the lambda (λ) is a parameter that measures the degree of spatial autocorrelation in the model. A lambda number close to zero as in Figure 3, indicates that there is significant spatial autocorrelation in the model. In this case, significant spatial autocorrelation can be interpreted that there are residual spatial effects that are not explained by the variables present in the regression model (Piyatadsananon, Amaratunga, & Keraminiyage, 2020).

The relationship between the number of DPT and the number of TPS with the equation $y = 0.0018x - 0.6288$ with a value of $R^2 = 0.9706$, meaning that the number of TPS is influenced by the number of DPT, the more DPT, the more TPS needed. This is to bring polling stations closer to voters so that the voter participation rate is higher.

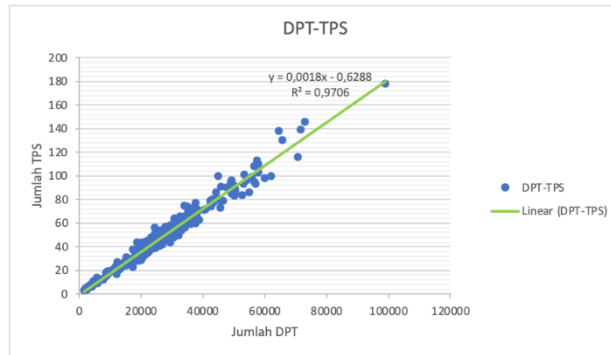


Figure 4. Equation $y = 0.0018x - 0.6288$ with value $R^2 = 0.9706$,

The relationship between Area and the number of TPS with the equation $y = 6.5405x + 32.584$ with the value of $R^2 = 0.2401$. In equation, area is positively correlated with the number of polling stations, but the level of correlation is quite low

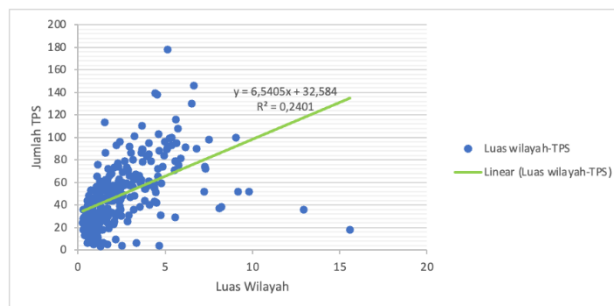


Figure 5. Equation $y = 6.5405x + 32.584$ with value $R^2 = 0.2401$

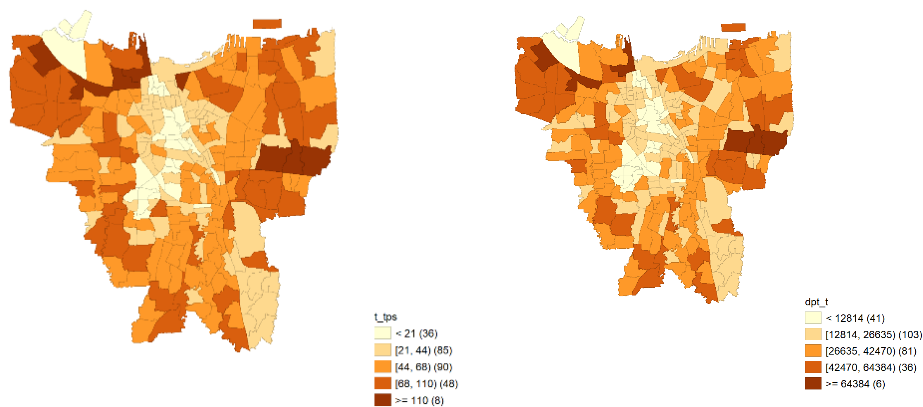


Figure 6. Number of polling stations in Kelurahan, Natural Break Figure 7. Total DPT in Kelurahan, Natural Break

The areas with the number of polling stations ≥ 110 are Jatinegara (130), Kapuk (178), Pademangan Barat (113), Pejagalan (110), Penggilingan (139), Penjaringan (138), Pulo Gebang (146), Tegal Alur (116)

Areas with Total DPT $\geq 64,384$ are Jatinegara (65597), Kapuk (98,800), Pejagalan (57846), Penggilingan (71468), Penjaringan (64384), Pulo Gebang (72987), Tegal Alur (70610)

Village Area, based on Natural Break using the Geoda Application is divided into 5 categories. Category with an area above 12,942 (km²) is only owned by 2 Kelurahan. While most are in an area that is covered by less than 1,936 (km²) there are 141 Kelurahan. A total of 124 urban villages are located between 1,936 and 12,942 (km²).

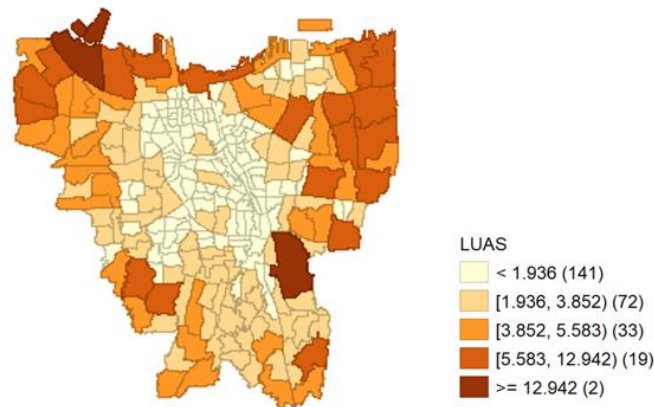


Figure 8. Area per Village in Jakarta, Natural Break

Morrans The TPS Index is positive, indicating that there is a spatial relationship between the number of polling stations, so areas with high polling stations tend to be neighboring with areas with high polling stations, and vice versa.

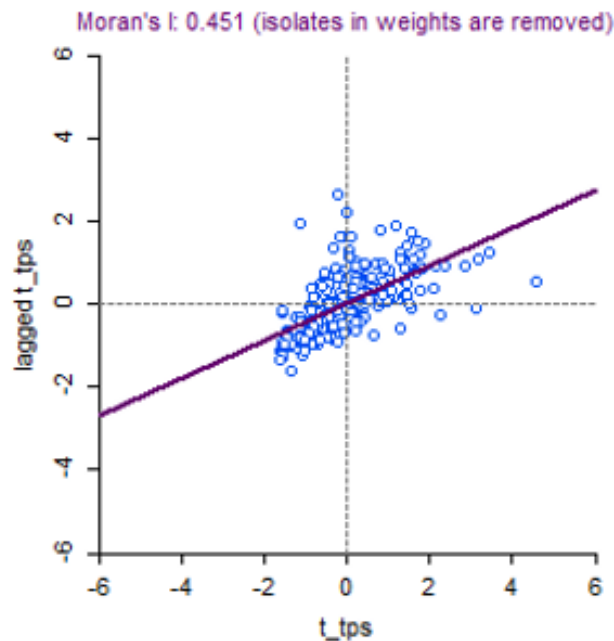


Figure 9. Index Morrans TPS in Jakarta has a positive value

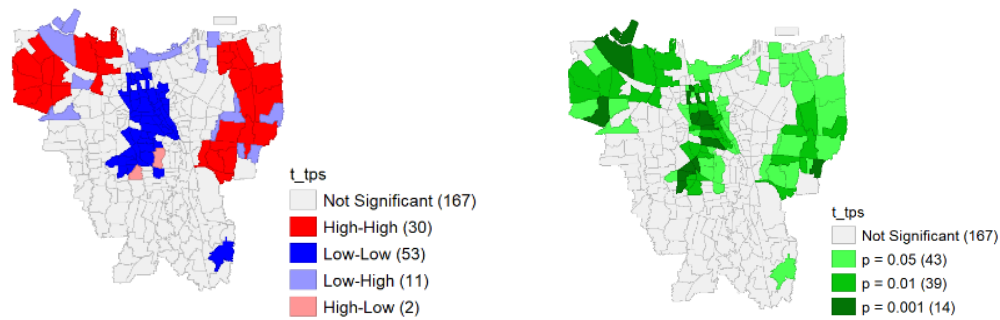


Figure 10. Lisa Scatter Plot, Number of Polling Stations (Polling Stations)

High-High shows that there are 30 Kelurahan areas with a high number of polling stations side by side with high number of polling stations. Low-Low shows that there are 53 villages with a low number of polling stations side by side with low polling stations. Low-High shows that there are 11 villages with a low number of polling stations side by side with high polling stations. High-Low indicates an area of 2 Kelurahan with a high number of polling stations side by side with a village with a low number of polling stations. Not Significant shows an area of 167 villages that do not show significant spatial patterns. There is insufficient statistical evidence to conclude the existence of significant spatial patterns in these regions.

Morrans DPT Index is positive, indicating that there is a spatial relationship between the amount of DPT, so areas with high DPT amounts tend to neighbor with high DPT amounts, and vice versa.

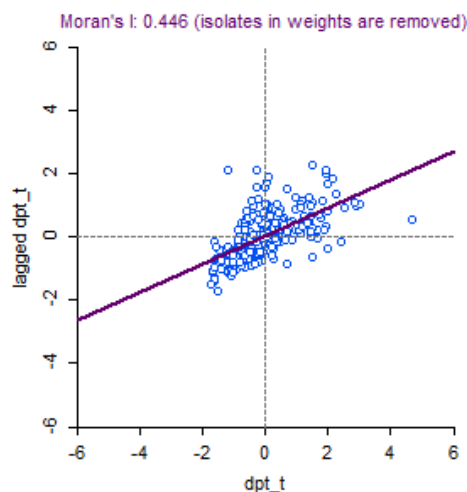


Figure 11. Index Morrans DPT in Jakarta is positive

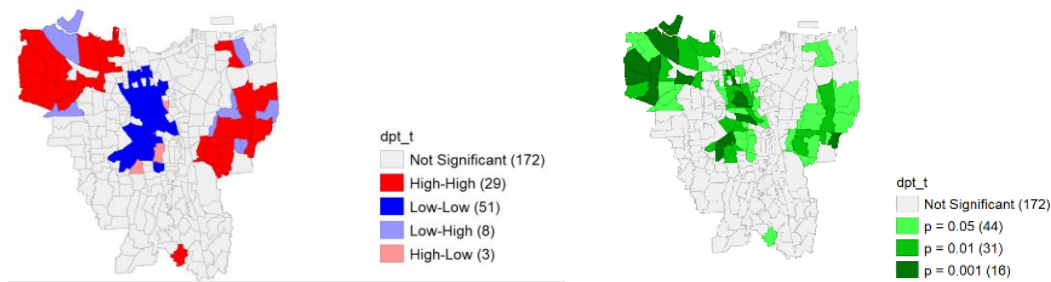


Figure 12. Lisa Scatter Plot, Number of Permanent Voter Lists (DPT)

High-High shows an area of 29 Kelurahan with a high number of DPT side by side with Kelurahan with a number of high DPT. Low-Low shows an area of 51 Kelurahan with a low DPT number side by side with a low DPT number Kelurahan. Low-High shows an area of 8 villages with low DPT numbers side by side with high DPT number villages. High-Low shows an area of 3 Kelurahan with a high amount of DPT side by side with a Kelurahan with a number of low DPT. Not Significant shows the area of 172 Kelurahan that does not show significant spatial patterns. There is insufficient statistical evidence to conclude the existence of significant spatial patterns in these regions.

From the processing of data produced by the Geoda application, it is read that there is a positive correlation and relationship with the determination of the number of TPS and the number of DPT seen in the Morrans Index, with value H-H, L-L, H-L, L-Hand NS Which is not too far off in the comparison of figure 10 and figure 12.

Similarly, it can be seen in data processing using the Geoda application, it reads that there are values that are not too different from those produced with maps Natural Break which is not too far away can be seen in the comparison of figure 6, Number of polling stations in Kelurahan and figure 7, Total DPT in Kelurahan.

Conclusion

The results of the analysis on this conclusion show that the number of DPT and area area have a positive effect on the number of polling stations in Kelurahan in DKI Jakarta. In addition, there is a spatial relationship in the number of polling stations and the total DPT between neighboring villages. This means that villages with a high number of polling stations and the number of DPT tend to be neighbors with villages with a high number of polling stations and the number of DPT and form clustering. Likewise, Kelurahan with a low number of polling stations and the number of DPT tend to cluster with villages with a low number of polling stations and the number of DPT.

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