A Spatial Econometric Model for Houshold Electricity Consumption in the Philippines

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ABSTRACT

While electricity is regarded as a catalyst for economic development, twelve million Filipinos still do not have access to electricity. Most of the studies relating to energy focused on socio-demographic and economic context. This study seeks to propose a new perspective in the Philippine's household electricity consumption by incorporating space. To determine this, three spatial econometric models were considered: Spatial Error Model, Spatial Lag Model, and Spatially Lagged X model. The result of several model specification tests led to the conclusion that the household electricity consumption in the Philippines exhibits spatial autocorrelation. Spatial Lag Model (SLM) with a spatial distance weight of 150 km is the most appropriate model for the study. The study shows that by decomposing the result of the Spatial Lag Model, a direct effect of Human Development Index, concrete national road, urban population, high electricity cost and low voltage on household's electricity consumption was observed.

Keywords: spatial econometric models, household electricity consumption

INTRODUCTION

For a country that produces the greatest amount of geothermal energy in the world and stores a massive amount of renewable energy, the Philippines' energy level still fails to meet the demand of its own people (IRENA, 2017a) .

The geography of the Philippines, consisting of 7,641 islands (NAMRIA-DENR, 2017) and of remote communities raises unique challenges in terms of accessibility and security to basic services, such as electricity. The government's centralized system prompted cities to be heavily populated. In fact, National Capital Region (NCR) has the highest population density with 20,785 persons per square kilometer, which is approximately 60 folds higher compared to the overall national level population density which is only 337 persons per square kilometer (PSA, 2015). This has driven both private and government sector to turn its vital ventures to capital region and urban areas. Likewise, due to country's topography, Philippine power system sustains two different grids (main grid-based and Off-grid based) to accommodate both main group and isolated islands. Unfortunately, many off-grid based islands, especially powered by NPC-Small Power Utilities Group, still do not get reliable 24-hour electricity services (Asian Development Bank, 2018). These conditions, and amongst others, have caused wide disparity in the quality of services across the country.

Several studies have already established that electricity is indeed a catalyst for economic development. Electricity is one of the basic component to secure fundamental human needs such as food production, clean water, sanitation, education, health care, and social serves. (Niu, Jia, Ye, Dai, & Li, 2016; Dahodwala, 2014; Ding, et al., 2016)

A considerable number of studies have been conducted to analyze the household electricity consumption using several approaches. These methods include Regression analysis (Sardianou, 2007; Lin, Chen, Luo, & Liang, 2014; Kozlova, 2012; Chen, 2017; Pachauri, 2003; Niu, Jia, Ye, Dai, & Li, 2016), Input-output analysis and structure decomposition analysis (Supasa, Hsiau, Lin, Wongsapai, & Wu, 2017), Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model (Ding, et al., 2016) , Probit models (Balta-Ozkan & Le Gallo, 2016), and Floor Area Ratio Model (Dawodu & Cheshmehzangi, 2017).

The said studies, however, are framed in the socio-demographic and economic context, and do not account for spatial influence. Just a fair number of foreign energy-related studies have been carried out using spatial approach. These spatial models include: Spatial Error Model (Tian, Song, & Li, 2014) , Spatial ARIMA (de Assis Cabral, Legey, & de Freitas Cabral, 2017), Spatial autoregressive model with autoregressive disturbances (SARAR) (Blazquez Gomez, Filippini, & Heimsch, 2013), Spatial Durbin Model (Ojede, Atems, & Yamarik, 2018)

It is worth mentioning that key element in spatial analysis is spatial autocorrelation (Anselin, 1988b). The term spatial autocorrelation refers to neighboring locations which demonstrate similar characteristics. (Anselin & Florax, 2004). Such occurence is highly associated with Tobler's First Law of Geography -- "Everything is related to everything else, but near things are more related than distant things." (Tobler, 1970).

Spatial visualization of the Philippine household electricity consumption per capita is presented in figure 1. It can be observed that electricity consumption exhibits clustering patterns, however it should be emphasized that visualization is just an initial step in spatial analysis, Spatial data should be examined and analyzed accordingly.

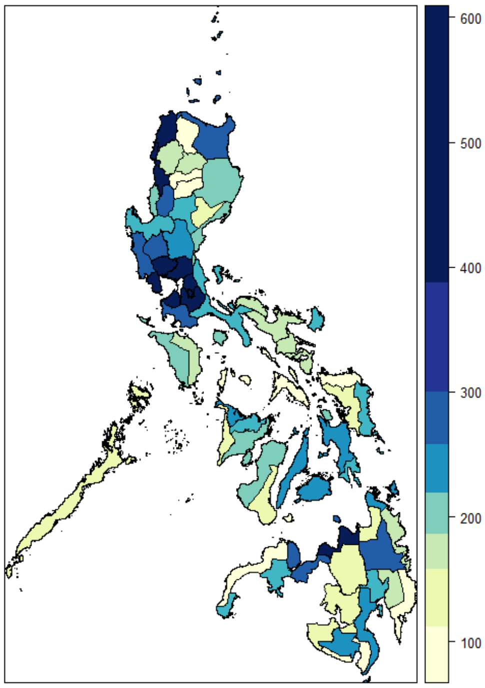

Figure 1. Household Electricity Consumption per capita 2011

Source: Department of Energy

This study provides a new perspective in the Philippine's households electricity consumption by incorporating space. This novel approach aims to examine the level of spatial autocorrelation in household electricity consumption across Philippine provinces and create a model that integrate spatial component and investigate how it correlates with socio-economic and geographical constructs. While doing so, the result of the study could serve as a valuable inputs of local planning committees in anticipation of the energy requirements of various localities particularly in areas where they intend to put up future investments.

MATERIALS AND METHODS

The study consists of information gathered from 74 provinces in the Philippines. Due to inaccessibility of several data, the provinces of Basilan, Lanao del Sur, Maguindanao, Sulu, Tawi-Tawi and Zamboanga Sibugay were excluded from the study. The main data was obtained from the Household Energy Consumption Survey (HECS) 2011 dataset acquired from the Department of

Energy. Missing values were addressed using Predictive Mean Matching (PMM), one of the built-in imputation models of Multivariate imputation by chained equations (MICE). For the purpose of this study, imputation method was computed by province. To achieve estimate stability, five (5) iterations were employed.

Table 1. Variables considered in the study

Variables	Description	Data Source
Household Electricity Consumption per capita	Household electricity consumption over provincial population	HECS 2011, PSA 2011
Landarea	Land Area (square kilometer)	Philippine Statistical Yearbook, PSA
Concrete National Road	Ratio of Concrete National road to Total National Road 2011 (km)	DPWH :2011
Urban population	Percent urban population	PSA : 2010
Human development index	Human Development Index 2009	Philippine Statistical Yearbook, PSA
Labor force participation rate	Labor Force Participation Rate	Philippine Statistical Yearbook, PSA
Young dependents	Young Dependents (0-14yrs)	PSA : 2010
Awareness of energy labeling program	Number of households who are aware of the Energy Labeling Program (yes / no)	HECS : Department of Energy (DOE)
Inflation rate	Inflation Rate 2011	Philippine Statistical Yearbook, PSA
Brownout	Proportion of electricity-using households who encountered brownout (yes/no)	HECS 2011 : DOE
Fluctuating voltage	Proportion of electricity-using households who encountered fluctuating voltage	HECS 2011: DOE
High electricity cost	Proportion of electricity-using households who encountered High Electricity cost	HECS 2011: DOE
Low voltage	Proportion of electricity-using households who encountered low voltage	HECS 2011: DOE
Private investors owned utilities	Proportion of electricity-using households who are connected to Private Investor Owned Utility	HECS 2011: DOE
Internal revenue allotment per capita	Internal revenue allotment per capita (pesos)	Philippine Statistical Yearbook, PSA 2011

PSA: Philippine Statistics Authority
DOE: Department of Energy
HECS: Household Energy Consumption Survey

The study made use of several statistical softwares such as Microsoft Excel, SPSS, R language and Geoda Software. Pearson correlation analysis was performed to determine the strength and direction of non-spatial relationship among the variables under study.

Spatial Autocorrelation

The term spatial effect refers to both spatial autocorrelation and spatial heterogeneity. Neighboring locations which demonstrate similar characteristics is said to exhibit spatial autocorrelation while, while spatial heterogeneity is said to demonstrate structural instability through non-constant error variances (heteroscedasticity) or model coefficients (Anselin & Florax, 2004). The characterization of spatial autocorrelation and spatial heterogeneity heavily depends on a particular distance metric (Anselin, 1988b).

The spatial weights serves as a distance metric for various tests for spatial autocorrelation. (Anselin, 2018). Spatial weight matrix creates a neighborhood structure that assesses the degree of similarity among locations. The matrix W is an $n \times n$ positive matrix which contains non-zero off-diagonal elements w_{ij} that corresponds to the spatial weight assigned to each locations(i, j). By definition, the ith observation is not considered a neighbor to itself, a value of zero will then be assigned to the diagonal elements ($w_{ii} = 0$) **Invalid source specified.**. Construction of spatial weight matrix heavily depends on the kind of spatial analysis under study. The said matrix can be made via (1) Contiguity matrix, which assigns 1 if locations (i, j) shares a common boundary, zero otherwise and (2) Distance-based matrix, which fundamentally depends on some distance criterion, such that two locations (i, j) are defined as neighbors when the distance between them is less than a given critical value. This paper, accordingly, applied three (3) distance-based spatial weight matrix to account for the archipelagic characteristic of the Philippine provinces, this include: 150 km, 190 km, and 210 km. Contiguity matrix may not be appropriate for this study, since significant number of provinces have no contiguity neighbors. Row Standardization or the method of rescaling the row of the spatial weights matrix to sum to one was also employed to facilitate different model comparison.

Moran's I served as a statistic to asses the global spatial autocorrelation measure. It identifies and quantifies the degree of (dis)similarity between nearby observations. Its value heavily depends on the spatial weights matrix (W). As a general rule, values of Moran's I near +1 indicates presence of positive spatial autocorrelation. This means that similar values cluster together. While values near -1 indicates negative spatial autocorrelation, this implies that neighboring areas have dissimilar values. Furthermore, a value of 0 indicates no autocorrelation. (Goodchild, 1986).

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_{i=1}^{n}(y_i - \bar{y})^2\right)\left(\sum_{i \neq j} \sum w_{ij}\right)}$$

Local indicator of spatial autocorrelation (LISA) was also employed to identify the significant locations and clustering patterns which contributes to the global spatial autocorrelation. In effect, LISA decomposes global indicators, such as Moran's I into the contribution of each observation.

$$I_i = Z_i \sum_j W_{ij} Z_j$$

Where, z_i is the original variable x_i in $z_i = \frac{x_i - \bar{x}}{SD_x}$ standardized form and w_{ij} is the spatial weight. The summation $\sum_j$ is across each row I of the spatial weight matrix.

Lagrange Multiplier served as a diagnostic test which identifies the kind of spatial autocorrelation processes present in the model. (Anselin, 1988b).

Spatial Econometric Models

This study made a comparative analysis on the performances of four econometric models. Using the OLS model as the benchmark, four models were considered; classical OLS regression model, Spatial Error Model, Spatial Lag Model, and Spatially Lagged X model.

Spatial Error Model (SEM), assumes that the underlying data generating process / spatial covariate that induces spatial autocorrelation was not accounted in the model, thus the burden of spatial autocorrelation is given to the error term. (Cook, Hays, & Franzese, 2015)

$$Y = X\beta + u\,, where\ u = \lambda W u + \varepsilon$$

Where parameter λ is the spatial autoregressive coefficient that mirrors the interdependence between regression residuals; Wu represents the interaction effects among the disturbance term. ε is the error term such as $\varepsilon \rightarrow iid(0, \sigma^2 I_N)$.

Spatial Lag Model (SLM), postulates that the autoregressive processes of the model lies in the response variable, (Fischer & Getis, 2010)

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\beta + \boldsymbol{\varepsilon}$$
$$\boldsymbol{\varepsilon} \rightarrow iid(0, \sigma^2 I_N)$$

Where, $\boldsymbol{Wy}$ is the endogenous lag variable for the spatial weight matrix W; Rho (ρ) is the spatial autoregressive parameter that indicates the strength of interactions present between the observations of y. $\boldsymbol{y}$ represents the dependent variable, $\boldsymbol{W}$ is the spatial weights matrix. $\boldsymbol{X}$ represents the observations on the exogenous variables, with an associated regression coefficient vector β.

Spatialy Lagged X Model (SLX), specifies that the spatial autoregressive processes rests in the exogenous variables. (Fischer & Getis, 2010)

$$\boldsymbol{Y} = \boldsymbol{X}\beta + \boldsymbol{WX}\theta + \boldsymbol{\varepsilon}$$

Where **Y** represents an $n \times 1$ vector consisting of one observation on the dependent variable for every unit in the sample$i = 1, .., N$. **X** denotes an $n \times k$ matrix of explanatory variables associated with the $k \times 1$parameter vectorβ, and $\boldsymbol{\varepsilon} \rightarrow iid(0, \sigma^2 I_N)$. $\boldsymbol{WX}$, matrix of exogenous lags, and θ represents the spatial spillover effects

Spatial Effect: Direct, and Indirect effect

It should be noted that the coefficient estimate of a spatial model exhibits reflection problem which gives no distinction between endogenous and exogenous interaction effects, hence the model cannot be interpreted directly (Manski, 1993). Given this condition, the final model shall be decomposed and categorized as direct and indirect effect. (Vega & Elhorst, 2013).

Direct effect is the outcome of a region's own explanatory variable together with the feedback effect determined by the spatial coefficient (ρ). (Elhorst, 2014) Indirect effect (spillover effect) is global by nature wherein a change in X at any location will be carried to all other locations following the matrix inverse in the equation, same goes if two locations are unconnected with respect to W. (Vega & Elhorst, 2013) (See table 2)

Table 2. Direct and spillover effects of different model specifications

Spatial Econometric Model	Direct effect	Indirect effect
OLS/ SEM	β_k	0
SAR (SLM) / SAC	Diagonal elements of $(I - \delta W)^{-1}\,\beta_k$	Off-diagonal elements of $(I - \delta W)^{-1}\,\beta_k$
SLX/SDEM	Diagonal elements of $(I - \delta W)^{-1}\,(\beta_k + W\theta_k)$	Off-diagonal elements of $(I - \delta W)^{-1}\,(\beta_k + W\theta_k)$

Source: (Elhorst, 2014)

In relation to diagnostic checking, for the OLS model -- Test for normality, heteroscedasticity, multicollinearity was performed using Jarque-Bera, Breusch Pagan test, Conditional Index, respectively. For spatial models, Test for heteroscedasticity, multicollinearity, test for spatial dependence and model comparison were performed using Breusch-Pagan Test, Likelihood Ratio Test, Akaike Information Criterion (AIC) together with Log Likelihood test, respectively.

RESULTS AND DISCUSSION

Correlation Analysis

Pearson correlation analysis was performed to determine the strength and direction of non-spatial relationship among the variables under study. The results from correlation analysis are presented in Table 3. In contrast with earlier findings (Chen, 2017), the variables: High electricity cost, Awareness to Energy labelling program and Private Investor Owned Utilities (PIOUS) showed positive significant correlation to household electricity consumption per capita.

These findings provide supplementary evidence that Philippine's electricity demand in residential sector is inelastic due to limited alternative energy source for household use. The study may also infer that the government's energy labelling program may not be as effective in reducing the household electricity consumption. Provinces connected to PIOUS may experience higher electricity consumption, since all PIOUs are connected to the main power grid. The main grid power system has an overall load of 74,154 GWh while the Off-grid power system only has an overall load of 1,020 GWh. Therefore, a great volume of electricity consumption is expected in provinces connected to PIOUs

Coherent with the prior report conducted by UK Energy Research Center (2015), the variables: Low voltage and Fluctuating voltage exhibits significant but negative correlation with electric consumption per capita.

As expected, HDI and urban population revealed to have a strong positive correlation with household electric usage per capita. In pursuit of higher paying jobs, better education, and better health care services, people tend to move from rural areas to urban cities, which in turn could translate into higher electricity demand (Balta-Ozkan & Le Gallo, 2016; Campbell, Hanania, Stenhouse, & Donev, 2015; Kozlova, 2012; Niu, Jia, Ye, Dai, & Li, 2016). Conversely, a significant negative correlation was found between land area and household electricity usage per capita, the result may be attributed to Philippine's being an agricultural country. In 2014 it was reported that 47% of the Philippine's 30,000-million-hectare total land area is agricultural land. Therefore, low volume of electricity consumption is anticipated in provinces with greater land area.

The variable Young dependents was also found to have a positive correlation with household electricity consumption per capita. Niu et al (2016) found that time spent at home could have a positive effect to monthly electricity bill. Since young dependents tend to stay at home longer than non-dependents, we would expect high volume of household electricity consumption.

Complementing the above findings, a significant but negative correlation was observed between Labor Force Participation Rate and household electricity consumption per capita, we would expect low household energy consumption per capita in provinces with high Labor force participation rate.

Table 3. Pearson Correlation Analysis Result

KWH per capita	Household Electrical Factors	Economic factors	Geographical Factors
Pearson correlation	Awareness to Energy Labelling Program (0.51)*	Human Development Index (0.66)*	Land area (-0.25)*
	Private Investors Owned Utilities (0.63)*	Labor Force Participation rate (-0.40)*	Urban Population (0.58)*
	Fluctuating Voltage (-0.40)*	Young dependents (0.50)*	
	High Electricity cost (0.37)*		
	Low voltage (-0.30)*		

( ) Statistic value , * p-value < 0.05

Spatial Autocorrelation

Moran's I and Local Spatial Autocorrelation (LISA) tests determined that the household electricity consumption in the Philippines exhibits spatial autocorrelation. Nearby provinces which exhibits similar characteristics was found within the distance of 150 km (Moran's=0.1818 p<0.005), 190 km (Moran's=0.1661, p<0.005), and 240 km (Moran's= 0.08, p<0.024). (See table 4)

Table 4. Moran's Index and Local Spatial Autocorrelation (LISA)

Distance (Km)	Moran's I	P-value	LISA-nonsignificant	Neighborless regions	LISA-significant
150	0.1818	0.005	50	Batanes , Palawan	22
190	0.1661	0.005	47	Batanes , Palawan	25
240	0.08	0.024	49	Palawan	24

After several specification tests, the distance metric of 150 km exhibits the most favorable statistical result compared to other distance metrics with lowest Akaike Information Criterion (AIC=55.77) and the highest log likelihood (-19.886). Please see table 6 for the full model comparison.

Distance weight: 150 kilometers

It can be observed in Figure 2 that the distance of 150 km yields a statistically significant Moran I statistic of 0.1818 (p<0.005). The test revealed that majority (28%) of the provinces belong in upper-right (high-high) quadrant. This implies that majority of these provinces as well as their surrounding neighbors shares similar high electricity consumption per capita. Most of these provinces belong in Region 4-A and NCR region.

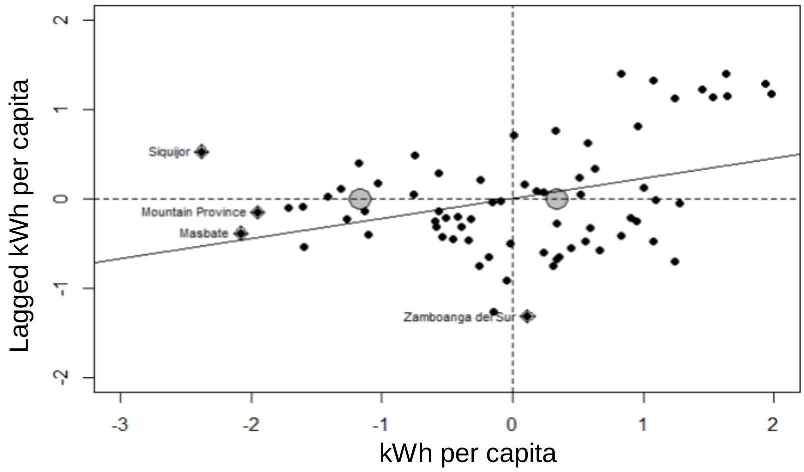

Figure 2. Moran's I scatterplot: δ=150 km

Note: Neighbor less provinces indicated by grey circle: Palawan and Batanes
Provinces with high influence measures are indicated by

Figure 3 illustrates the LISA significance map and cluster map (δ=150 km). The significant provinces that belong in upper-right (high-high) quadrant are the following: Aurora, Bataan, Batangas, Bulacan, Cavite, Laguna, NCR, Nueva Ecija, Pampanga, Pangasinan, Rizal, Tarlac and Zambales. This implies that these provinces as well as its surrounding neighbors have high household electricity consumption per capita. Biliran, Isabela, and Negros Occidental are the significant provinces that lie in the third quadrant (low-low), this denotes that these provinces together with their surrounding region have low household electric usage per capita.

Siquijor, however, is the only significant province that belongs in second (low-high) quadrant. Which has low household electricity usage per capita while its surrounding neighbors have high electricity usage. Whereas, Aklan, Davao del Norte, Ilocos Norte, Ilocos Sur and Misamis Occidental are the significant provinces that belong in fourth quadrant (high-low values), whereas these provinces have high electric usage, its surrounding provinces, however, have low household electric usage.

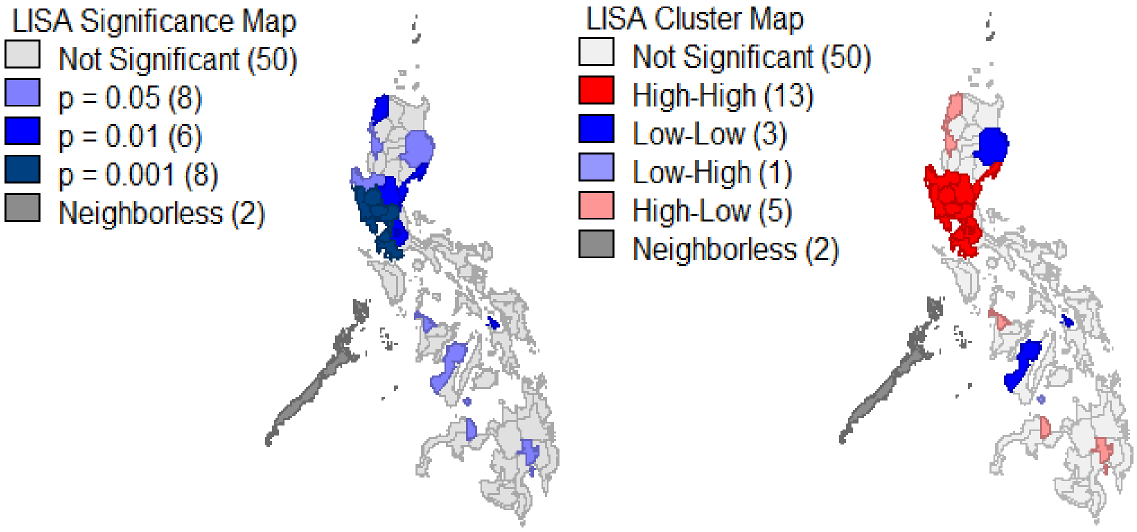

Figure 3. LISA Significance and Cluster Map: 150 km

Neighbor less provinces: Batanes, and Palawan

Spatial econometric models

This section presents the empirical result of the spatial econometric models. Household electricity kWh per capita in natural logarithm form was used as the response variable. The explanatory variables of the initial model include: land area (sq km), concrete national road (natural logarithm form), urban population (natural logarithm form), human development index (2009), labor force participation rate 2011, young dependents 2010 (0-14 yrs old), internal revenue allotment per capita 2011, inflation 2011, number of household who are aware of the energy labeling program, proportion of households connected to PIOUS, proportion of household who encountered brownouts, proportion of household who encountered fluctuating voltage, proportion of household who encountered high electricity cost (natural logarithm form), and proportion of household who encountered low voltage. Correspondingly, 150 km row-standardized distance weight matrices were utilized as the spatial weight.

The results of the initial coefficient estimate of SLM (full model) is presented in Table 5. Bivand (2018) cautioned that omitting variables before incorporating spatial component is not advisable since the response variable and the identified regressors may all have non-negligible spatial processes, which may also be correlated with those of omitted variables. Following the above context, the researcher directly incorporated spatial interaction effect to the full model. The reduced spatial model, presented in table 6, was generated using manual backward selection method.

Table 5. Spatial Lag Model (full model)

SLM FULL MODEL COEFFICIENT	150 KM	
	Estimate	P-value
(Intercept)	5.3125	0.0000
Land area	0.0000	0.7063
Concrete National Road (Natural logarithm)	0.2568	0.0106
Urban Population 2010 (Natural logarithm)	0.0872	0.0384
Human Development Index 2009	1.9020	0.000
Labor force participation rate	-0.0130	0.1431
Young Dependents	0.0000	0.6907
Internal Revenue per capita	0.0000	0.8538
Inflation	0.0181	0.4628
Awareness Energy Labelling	0.0000	0.8210
Private investors owned utilities	0.5010	0.0904
Brownout	0.1885	0.6376
Fluctuating voltage	-0.0608	0.8895
High electricity cost (Natural logarithm)	0.3272	0.0335
Low voltage	-0.5464	0.2046

Condition number: 81.051, Breusch-Pagan = 14.32 p<0.488

The reduced model as shown in Table 6 provided a low condition number (24.17) which implies that the model is now free from multicollinearity. The high probability of Breusch-Pagan test points that the models are free from heteroscedasticity.

In order to identify the appropriate spatial weight matrix for this study, the measure for goodness-of-fit was determined by AIC (Akaike Information Criterion), Log likelihood test and Likelihood ratio test. Among three distance metrics, 150 kilometers has the lowest AIC (55.7730), highest log likelihood (-19.8864) and significant Likelihood ratio test (value=4.211, p-value = 0.0498). The spatial effect or the added indicator (rho) exhibits positive and significant effect to the model (ρ=0.0862, p<0.0498) this concludes that the spatial weight of 150 km is the most appropriate metric for this study.

Table 6. Spatial Lag Model (reduced model)

SLM REDUCED COEFFICIENT	150 KM		190 KM		240 KM	
	Estimate	P-value	Estimate	P-value	Estimate	P-value
(Intercept)	4.4812	0.000 (0.00)	4.4826	0.0000 (0.00)	4.5909	0.0000 (0.00)
Concrete National Road (Natural logarithm)	0.2367	0.0124 (0.012)	0.2344	0.0133 (0.021)	0.2266	0.0182 (0.029)
Urban Population (Natural logarithm)	0.1197	0.0004 (0.0007)	0.1206	0.0004 (0.0007)	0.1289	0.0002 (0.000)
Human Development Index (2009)	2.3076	0.000 (0.00)	2.3059	0.0000 (0.00)	2.1275	0.0000 (0.00)
High electricity cost (Natural logarithm)	0.4463	0.0002 (0.0003)	0.4458	0.0002 (0.0003)	0.4761	0.0001 (0.000)
Low voltage	-0.5900	0.0046 (0.007)	-0.5874	0.0049 (0.0073)	-0.5791	0.0063 (0.009)
Rho (ρ)	0.0862	-	0.0860	-	0.0864	-
Condition Number	24.1709	-	24.1709	-	24.1709	-
Likelihood Ratio Test	4.2110	0.0406 (0.0498)	4.0292	0.0451 (0.0533)	2.0963	0.1498 (0.195)
Log likelihood	-19.8864	-	-19.9773	-	-20.9437	-
AIC	55.7730	-	55.9544	-	57.8874	-
LM test for residual autocorrelation	2.4591	0.1186 (0.1552)	1.8166	0.1787 (0.2112)	0.8492	0.3611 (0.427)
Breusch-Pagan value	7.4027	0.1935 (0.2200)	7.1311	0.2123 (0.2406)	5.86804	0.3209 (0.357)

Note: Values in parenthesis (highest p-value among five (5) regression models)

Table 7 presents the Lagrange Multiplier test. The analysis found that the underlying data generating process are characterized by the following: spatial error (4.09, p<0.0441), spatial lag (4.13, p<0.0424), and spatial autoregressive moving average (6.7530, p<0.0352).

Table 7. LM diagnostic test with respect to the reduced model $\delta = 150\ km$

LM	150 KM	P-value
LMerr	4.0939	0.0441
LMlag	4.1349	0.0424
RLMerr	2.6181	0.1073
RLMlag	2.6590	0.1034
SARMA	6.7530	0.0352

Econometric Model Comparison

Table 8 presents a comparative analysis of the reduced econometric models: OLS, SLM, SEM and SLX. In order to identify the most appropriate (spatial) econometric model for this study, the AIC (Akaike Information Criterion), and the Log likelihood test served as a criterion for goodness-of-fit.

Table 8. Comparative Analysis: Reduced Model Specification (150 km)

150 KM	Base Model: Non Spatial Regression via OLS		SLM		SEM		SLX
	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic
ρ or λ		-	0.0862	-	0.3374	-	-
Condition Number	24.1709	-	24.1709	-	24.171	-	24.171
Likelihood Ratio Test	-	-	4.2110	0.0406	3.6979	0.0555	-
Log likelihood	-21.9919	-	-19.886	-	-20.143	-	-
LM test for residual autocorrelation		-	2.4591	0.1186	-	-	-
AIC	57.9838	-	55.7730	-	56.311	-	63.318
Breusch-Pagan value	5.9730	0.3101	7.4027	0.1935	6.0928	0.2986	-

Among four models, the SLM has the lowest AIC (55.7730), and highest log likelihood (-19.886). Accordingly, rho (ρ=0.0862) or the added spatial effect variable in the model exhibits positive and significant effect to the model (likelihood ratio =4.211 $p<0.041$). The value for Breusch-Pagan test indicates that the four (4) models are free from heteroscedasticity. Based on these findings, the researcher can now conclude, that Spatial Lag Model with a distance weight of 150 km is the most suitable model for this study.

Spatial Effect

The direct and indirect effect of the SLM with δ=150 km is presented in Table 9. A significant positive direct effect was found between concrete national road and household electricity consumption per capita, this entails that we would see increase in household electric consumption per capita in provinces which have longer concrete national road. Ojede (2018) found that efficient highway networks provide economic and social opportunities, and better accessibility to services, such as, electricity. This in turn could translate into higher electricity demand.

Coherent with prior energy studies (Campbell, Hanania, Stenhouse, & Donev, 2015; Hanania, Llyod, Stenhouse, Toor, & Donev, 2015), Urban population and HDI also show significant positive direct impact on household electricity usage per capita, this denote that we would see increased in per capita household electric consumption in provinces with level of HDI and urban population.

These findings may be attributed to rural to urban migration in search of high-paying jobs, better education and better health care services, which can lead into higher electricity demand. Niu et al. (2016) cited that an improvement in quality of life changes household's electricity consumption demand. Starting from basic energy needs such as lighting and cooking to higher-level energy needs such as sanitation, and refrigeration. It was also reported that city residents less likely to acknowledge energy as a national concern and they too are less responsive to electricity price changes compared to their rural counterparts, (Balta-Ozkan & Le Gallo, 2016; Kozlova, 2012).

A significant but negative direct effect was found between Low Voltage and household electricity consumption per capita, we would expect decreased in household electricity usage per capita in provinces with low voltage supply since people will less likely maximize their electricity consumption (Bilton & Carmichael, 2015)

Finally, the variable, high electricity cost exerts a positive direct impact on household electricity usage per capita, suggesting that we would see increased electric consumption in provinces with higher proportion of households which encounter high electricity cost. This finding provides additional evidence that Philippine's electricity demand in residential sector is inelastic due to limited alternative energy source for household use.

It can be observed that none of the variables has significant indirect effect on household electricity consumption, this holds that any changes on the exogenous variables in a particular province will not transmit any effect on household electricity consumption per capita in neighboring provinces.

Table 9. Direct, indirect effects

Impact Variables	DIRECT Estimate	 P-values	INDIRECT Estimate	 P-values
Concrete National Road (Natural logarithm)	0.2370	0.0114	0.0214	0.1548
Urban Population (Natural logarithm)	0.1199	0.0006	0.0108	0.0952
Human Development Index (2009)	2.3106	0.0000	0.2088	0.0762
High electricity cost (Natural logarithm)	0.4469	0.0002	0.0404	0.0704
Low voltage	-0.5907	0.0043	-0.0534	0.1247

CONCLUSION

The result of several model specification tests led to the conclusion that the household electricity consumption in the Philippines exhibits spatial autocorrelation. Spatial Lag Model (SLM) with a spatial distance weight of 150 km is the most appropriate model for the study.

In general, by decomposing the results of the spatial lag model, a direct effect of Human Development Index, concrete national road, urban population, high electricity cost and low voltage on household's electricity consumption was observed. This implies that we would see increased in per capita household electric consumption in provinces with high level of HDI, Urban population, high electricity cost, and longer concrete national road, while a decreased in electricity consumption in provinces with low voltage level. The large direct impact of HDI is consistent with the positive externality of HDI found in the economic literatures. Remarkably, the study also revealed that concrete national road generates more direct effect on electricity consumption than urban population. As anticipated, high electricity cost revealed a positive direct effect on electricity consumption. This finding provides further evidence that Philippine's electricity demand in residential sector is inelastic due to limited alternative energy source for household use.

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