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Geographically weighted regression analysis of electricity consumption in Indonesian households: aligning with SDG 7

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ABSTRACT

The objective of this study is to establish a thorough comprehension of the interaction of population dynamics, poverty rates, minimum wage levels, and regional GDP in relation to household electricity consumption. The main objective is to improve the precision of electricity demand predictions and prevent planning mistakes, such as the considerable surplus of 6-7 GW in the Java Bali system between 2020 and 2023, resulting in major financial losses. We evaluate and compare the models by employing several approaches, such as ordinary least square (OLS) and geographically weighted regression (GWR) with fixed and adaptive bandwidths. We use modified R-squared and corrected Akaike Information Criterion (AICc) values for this assessment. The GWR with adaptive bandwidth is shown to be the most resilient method and is subsequently chosen for modeling. The results indicate that there is a strong correlation between the number of impoverished individuals and electricity use, with a coefficient range of 0.35-0.55. Furthermore, the correlation between poverty rates and power usage is defined by a coefficient that varies between -0.0010 and -0.0030. There is a direct relationship between regional GDP and power growth, as indicated by coefficients ranging from 1,000,000 to 5,000,000. Moreover, the impact of minimum wage levels differs among different locations.

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1. INTRODUCTION

According to self-actualization theory, not all civilizations have conditions that effectively inspire individuals to perform to their full potential due to a lack of satisfaction of basic requirements in many parts of the world [1]. Abraham Maslow created the hierarchy of needs model in 1943 as a prominent theory of human motivation, to assess various physical and mental demands in a hierarchical structure. Each person has five levels of wants that must be fulfilled, organized in a hierarchy, and represented by a pyramid. The hierarchy consists of five stages in ascending order: physiological, safety, social, esteem, and self-actualization needs. Physiological needs refer to the fundamental requirements for survival, including food, drink, and air [2]-[5]. Safety needs refer to the necessity for a secure and protected environment; social needs involve the desire to belong to a group where one is loved and appreciated; self-esteem needs entail the requirement to be esteemed and respected; and self-actualization need is the aspiration to achieve one's maximum potential, as per the belief that individuals must strive to become the best version of themselves. Efforts to enhance power access and water and sanitation access are closely linked, as they are vital elements of sustainable development. Providing electricity to communities can increase their access to safe water supply and sanitation services, resulting in greater health, improved livelihoods, and overall development. Access to safely managed clean water and sanitation facilities in urban and rural regions grows as access to electricity rises. The findings suggest that having access to electricity helps decrease disparities between urban and rural areas in accessing clean water and sanitation facilities [6]. Indonesia has committed to achieving Sustainable Development Goal 7, namely to ensure access to affordable, reliable, sustainable, and modern energy for all. The Indonesian government improves electricity access through various programs, from the fast-track program for coal-fired power plants to the electricity subsidy for low- income households Given Indonesia's electricity policies and infrastructure, the country has considerably succeeded in improving access to electricity from reaching only 67% of the population in 2010 to 99% of the population in 2019 [7].

In 2022, Indonesia witnessed a substantial electricity consumption of 252,669 gigawatt-hours (GWh). Delving into the specifics, 42% of this energy demand emanated from households, while industrial customers accounted for 33%, business customers 19%, and the remainder originating from social customers and public services. The distribution of household electricity usage within Indonesia exhibits geographic disparities, prominently illustrated in Figure 1. Notably, the island of Java emerges as a significant consumer, overshadowing other regions. Beyond Java, heightened electricity consumption is evident in areas such as North Sumatra and Sulawesi. Given the pivotal role of households as the primary contributors to this energy landscape and the noteworthy regional discrepancies, the imperative arises to construct a model specifically tailored for understanding and managing household electricity consumption [8], [9].

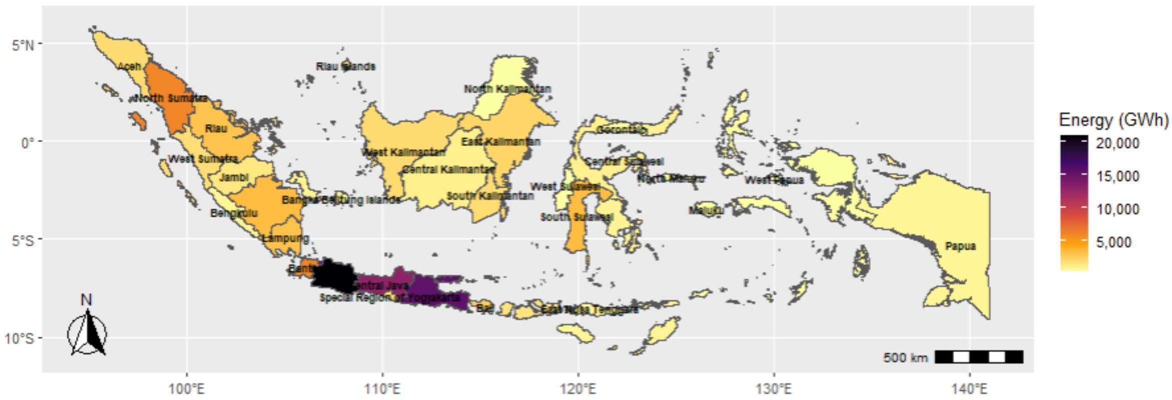

Figure 1. Household electricity consumption in Indonesia in 2022

The imperative to develop an electricity growth model stems from the need for effective planning and forecasting, particularly in light of the challenges posed by past initiatives such as the 35,000 MW program implemented between 2015 and 2019. This ambitious program inadvertently led to a significant overcapacity in electricity generation, totaling 6-7 GW in 2022-2023. The root cause of this overcapacity lies in the overly optimistic assumptions made during the calculation of electricity needs, particularly the assumption of a 7% economic growth rate. This optimistic economic projection led to an 8% anticipated growth in electrical energy demand, resulting in substantial financial losses for both the Indonesian government and the national electricity company [10].

The financial setbacks, amounting to 1 trillion rupiah for every additional gigawatt, primarily emanate from private power generation contracts, specifically the adoption of take-or-pay contracts. Even in instances where electricity distribution does not occur, the contractual obligations necessitate payment. Despite efforts by the government and national electricity companies to mitigate risks, these financial losses persist. Therefore, the creation of a comprehensive planning model for electricity consumption projections becomes imperative, incorporating additional factors and methodologies to enhance accuracy and prevent future instances of overcapacity [11]. This research endeavors to explore the potential geographical influences on electrical energy consumption, leveraging indicators such as population, the number of people living in poverty, GDP, and age limits across various provinces.

Against the backdrop of electricity emerging as a fundamental necessity, facilitating a myriad of conveniences through various electrical appliances, this research aims to ensure equitable access to this essential resource for all Indonesian citizens. The prevalence of electricity-dependent devices such as refrigerators, water pumps, cell phones, and lighting underscores its vital role in modern life. To address the imperative of equal access, the research seeks to identify and understand the diverse factors influencing electricity needs in different regions. By doing so, it aspires to contribute to the goal of maintaining a balanced distribution of electricity across diverse areas, catering to the needs of the populace. The global regression model and the spatial regression model with geographic weighted regression (GWR) are utilized to examine factors such as population size, income levels, number of workers, and environmental conditions. By adapting and applying this approach to the Indonesian context, the research seeks to unravel insights into the intricate dynamics influencing electricity consumption across different regions. In essence, this research not only contributes to the academic understanding of geographical influences on electricity consumption but also holds practical significance for policymakers. By identifying key factors shaping electricity needs in specific regions, the findings can inform targeted interventions and policies aimed at achieving a more equitable, efficient, and sustainable distribution of electrical energy throughout Indonesia. This research tries to find out about energy justice there in the distribution of natural gas throughout the Izmir Metropolitan Area using the same approach, namely the global regression model and the spatial regression model with GWR [12]-[14]. The factors studied are population size, income, number of workers, and environmental conditions. This study aims to investigate the impact of additional variables on electricity consumption, such as poverty, regional GDP, and regional minimum wages, building upon prior studies. Studying a greater number of factors leads to the development of a more accurate forecast model.

In terms of energy sources, electrical energy ranks as the second most extensively utilized. This preference is attributed to its efficient transmission capabilities and its eco-friendly nature, characterized by a lack of emissions during utilization. The nexus between the escalating consumption of electricity and economic growth is evident [3] Urbanization also affects electricity consumption in an area [4]. Urbanization, constituting the migration of individuals from rural to urban areas, can significantly alter the demographic composition of a locality. Various factors, encompassing births, deaths, and population mobility, contribute to overall population growth [15], [16]. The migration inherent in urbanization is often driven by the pursuit of enhanced employment opportunities, a rationale substantiated by the higher urban minimum wage (UMR) in Jakarta compared to outlying regions. To comprehensively understand these intricate dynamics, this research aims to scrutinize the influence of population dynamics, poverty rates, regional GDP, and minimum salary levels.

This paper is structured into five distinct sections, each playing a vital role in unraveling the research's narrative and findings. In section 1, the introduction and motivation behind the research are presented, setting the stage for the exploration that follows. Section 2 delves into the methodology employed, focusing on GWR. Here, the intricacies of calculating weighted values, the selection of kernel functions, and the methods used to assess accuracy are discussed. Moving on to section 3, attention is turned to the dataset, providing crucial insights into its composition and characteristics. Section 4 presents the core results and analysis, including discussions on bandwidth selection and a deeper examination of regional influences on electricity consumption. Through this structured approach, the paper navigates through the complexities of its subject matter, offering a comprehensive and coherent exploration of the research topic in section 5. Finally, section 6 offers a conclusive synthesis of the research journey, encapsulating key findings and implications drawn from the study.

2. MATERIAL AND METHODS

2.1. Geographically weighted regression

The backbone of our analytical framework relies on the univariate ordinary least square (OLS) method, a robust statistical technique chosen for its effectiveness in modeling complex relationships. In this study, the dependent variable under scrutiny is the electricity consumption by households, while a comprehensive set of independent variables includes population size, the number of individuals living in poverty, regional minimum wage, and regional GDP. The OLS method, a cornerstone in regression analysis, is adept at producing predictive models by systematically analyzing the impact of multiple explanatory variables on the dependent variable [17]-[19]. Through this approach, we aim to unravel the intricate interplay between household electricity consumption and the socio-economic factors encapsulated by our chosen independent variables. Our methodology involves fitting the OLS model to our dataset, allowing us to derive coefficients that quantify the magnitude and direction of the influence exerted by each independent variable. Subsequently, these coefficients will contribute to formulating a predictive model capable of estimating household electricity consumption based on the nuanced dynamics of population, poverty levels, regional minimum wage, and regional.

The OLS method, a widely acknowledged statistical approach, is employed in this study to construct predictive models elucidating the relationships between various explanatory variables. The OLS model is expressed as (1):

$$y_i = \beta_0 + \beta_i x_i + \varepsilon_i \, , i = 1,2, \dots , n \tag{1}$$

Here, the dependent variable (y_i), electricity consumption—as a linear function of observed variables x_i, such as population, the number of individuals in poverty, regional minimum wage, and regional GDP. The intercept term (β_0) signifies the expected electricity consumption when the observed variable is zero, while the coefficients (β_i) quantify the impact of each observed variable on electricity consumption. The error term (ε_i) encapsulates unobserved factors influencing electricity consumption. By estimating these coefficients, the OLS method minimizes the sum of squared differences between predicted and observed values, allowing us to discern influential variables and create a robust model for predicting household electricity consumption. This statistical approach provides a systematic and rigorous framework for extracting meaningful insights into the intricate dynamics of energy consumption in households.

GWR stands as a robust statistical method that leverages spatial heterogeneity for data analysis. Spatial heterogeneity arises when an independent variable exhibits varying responses to the dependent variable across different locations [12], [13], [20]. GWR is an evolution of the global regression model. In the GWR model, the estimation of the response variable is conducted using predictor variables, each characterized by distinct regression coefficients contingent upon the geographic location where the data is observed [21], [22]. Within the GWR model, the estimation of the response variable is conducted through predictor variables, each exhibiting distinct regression coefficients contingent upon the specific location of data observation. This spatially adaptive approach acknowledges and accommodates the inherent spatial heterogeneity in the relationships between variables across different geographic locations as shown in (2):

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)\, x_{ik} + \varepsilon_i, i = 1,2, \dots , n \tag{2}$$

Within the framework of the GWR model, the estimation of the response variable y_i is intricately linked to the observation values of independent variables x_{ik} at a given location i. This localized approach accounts for the inherent spatial variations, acknowledging that the coefficients of the model are not constant across different geographic locations. The GWR model incorporates the concept that the intercept $\beta_0(u_i, v_i)$ and regression coefficients $\beta_k(u_i, v_i)$ are functions of the coordinates of the observation location, denoted as (longitude, latitude) in the form of (u_i, v_i). Additionally, the error term ε_i encapsulates the discrepancies between the observed values y_i and the values predicted by the model. Assumed to be identical, independent, and normally distributed with a zero mean and constant variance, this error term reflects the stochastic nature of the underlying processes influencing the dependent variable across various observation points. In essence, the GWR model, by considering the spatial context, offers a nuanced understanding of how the relationships between variables vary across different geographical coordinates, providing valuable insights into localized patterns and trends. The selection of the GWR model is grounded in its ability to capture spatial variations and address nuances in covariates that may elude explanation through simple regression [7]. The equation employed to calculate the GWR parameters for each specific location is expressed in (3):

$$\hat{\beta}(u_i, v_i) = (\, X^T W(u_i, v_i) X)^{-1} X^T (u_i, v_i) \tag{3}$$

In (3) signifies the estimation $\hat{\beta}$ of parameters specific to the geographical coordinates (u_i, v_i). Here, X^T represents the matrix of observations, and $W(u_i, v_i)$ is a spatial weighting matrix that accounts for the spatial relationships between observation points. The utilization of this equation allows the GWR model to adapt to the unique spatial characteristics of each location, providing a tailored understanding of the relationships between variables in diverse geographic contexts. $\mathrm{W}(u_i, v_i)$ is a weighting matrix for each *j*-th location from the *i*-th observation location which can be written with (4):

$$W(u_i, v_i) = \begin{pmatrix} w_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{in} \end{pmatrix} = diag\, [w_{i1}, w_{i2}, \dots , w_{in}] \tag{4}$$

This formulation, represented by (4), highlights the diagonal matrix structure of the weighting matrix. Each w_{ij} value corresponds to the weight assigned to the influence of the *j*-th location on the *i*-th observation location. The specific value of w_{ij} is determined by a weighting equation. Notably, there are four commonly used types of weighting functions that govern the assignment of weights in this context. These functions play a crucial role in defining the spatial relationships and influences between observation locations within the GWR model.

2.2. Weighting mechanisms in geographically weighted regression

The choice of weighting function is crucial as it determines how spatial relationships are considered in the GWR model. Depending on the nature of the data and the underlying spatial patterns, researchers select the most appropriate weighting function to ensure accurate and meaningful results in the geographically varying regression analysis. In the context of GWR, the determination of the value w_{i2} is guided by a weighting equation. This equation is pivotal in assigning weights to observation locations, influencing the impact each location has on the estimation at a specific point.

Table 1 outlines the four prevalent kernel functions utilized in GWR. These functions, namely fixed Gaussian, adaptive Gaussian, fixed bi-square, and adaptive bi-square, play a crucial role in determining the weights w_{ij}, and d_{ij} assigned to observation locations based on their distances. The fixed kernels employ a constant bandwidth, whereas the adaptive kernels modify the bandwidth dynamically based on the density of observation sites. This differentiation facilitates a more adaptable representation of spatial interactions, particularly in regions with fluctuating spatial densities. By judiciously choosing the suitable kernel, the precision and comprehensibility of the GWR model can be improved.

Table 1. Kernel function

Types of function kernel	Advantage	Disadvantage	Formulas
Fixed Gaussian	Simple to implement	Assumes uniform influence within the specified bandwidth	$w_{ij} = \exp(-d_{ij}^2/\theta^2)$
Adaptive Gaussian	Adapts to local variations	Requires estimation of varying bandwidths for each observation	$w_{ij} = \exp(-d_{ij}^2/\theta_{i(k)}^2)$
Fixed bi-square	Limits influence beyond a specified distance	Sharp cutoff may lead to sudden changes in weights	$w_{ij} = \begin{cases}(1-d_{ij}^2/\theta^2)^2, d_{ij} < \theta \\ 0, d_{ij} > \theta\end{cases}$
Adaptive bi-square	Adjusts to local variations and bandwidths	Requires estimation of varying bandwidths for each observation	$w_{ij} = \begin{cases}(1-d_{ij}^2/\theta_{i(k)})^2, d_{ij} < \theta_{i(k)} \\ 0, d_{ij} > \theta_{i(k)}\end{cases}$

The fixed Gaussian kernel stands out for its simplicity in implementation, making it a straightforward choice for modeling spatial relationships. However, its notable disadvantage lies in assuming uniform influence within the specified bandwidth, potentially oversimplifying the spatial dynamics. On the other hand, the Adaptive Gaussian kernel addresses this limitation by adapting to local variations, enhancing its ability to capture nuanced spatial patterns [23]-[26]. Nevertheless, its disadvantage surfaces in the need for estimating varying bandwidths for each observation, adding complexity to the modeling process. Moving to the fixed bi-square kernel, its advantage lies in effectively limiting influence beyond a specified distance, contributing to a more focused spatial analysis. However, its disadvantage manifests in the potential for a sharp cutoff, leading to abrupt changes in weights and impacting the smoothness of the model. Conversely, the adaptive bi-square kernel offers the advantage of adjusting to local variations and varying bandwidths, providing a flexible approach to spatial modeling. Yet, similar to the Adaptive Gaussian kernel, its drawback lies in the necessity of estimating varying bandwidths for each observation, introducing computational challenges. The selection of an appropriate kernel function hinges on a careful consideration of these advantages and disadvantages, tailored to the specific characteristics of the spatial data under analysis [27], [28].

In this application, the Gaussian kernel serves as one of the pivotal functions in the GWR model, particularly when the distance function exhibits continuity and demonstrates a decreasing monotone pattern. The corresponding formula for its utilization is (5):

$$w_j(u_i, v_i) = \begin{cases}(1-\frac{d_{ij}^2}{\theta^2})^2;\ d_{ij} \le \theta \\ 0\ ;\ d_{ij} > \theta\end{cases} \tag{5}$$

Here, d_{ij} represents the distance between location *i* and location *j*, and θ is the smoothing parameter, commonly referred to as bandwidth. The d_{ij} value in the equation above corresponds to the Euclidean distance between location (u_i, v_i) and location (u_j, v_j), calculated using (6):

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \tag{6}$$

The bandwidth, akin to the radius of a circle centered at location i, signifies the range within which points continue to impact the formulation of model parameters at that specific location. Optimal bandwidth selection is pivotal for the accuracy of the model in comparison to the underlying data, influencing both variance and bias values. Achieving the optimal bandwidth h involves minimizing the cross validation (CV) value, as expressed by (7):

$$CV = \sum_{i=1}^{n}[y_i - \hat{y}^{(-i)}(h)]^2 \tag{7}$$

Where $\hat{y}^{(-i)}(h)$ is the predicted value of y_i (fitting value) with observations of location i removed from the prediction process [8], [29]. In addition to GWR, our analysis extends to examining the relationship between electrical energy consumption and other factors using OLS. OLS, a method that determines relationships between variables without accounting for spatial variation, is employed for this purpose. We will assess the performance of both models using two indicators: adjusted R-squared and corrected Akaike Information Criterion (AICc), particularly useful for small sample size [4].

3. STUDY AREA

The comprehensive dataset utilized in this research is curated from multiple reputable sources to ensure a thorough and accurate analysis. Key contributors to the dataset include the 2022 publications of electricity data statistics from the state electricity company (PLN/SEC). Additionally, valuable insights are derived from publications provided by the Indonesian Central Bureau of Statistics (BPS) and the Indonesian Ministry of Labour (Ministry of Manpower). This diverse and multi-faceted approach to data collection enhances the robustness of the research findings, incorporating information from authoritative entities within the energy sector and broader statistical landscape as shown in Table 2.

Table 2. Dataset

Label	Variabel	Unit	Description	Source
X1	Population	People	Total population	BPS [30]
X2	Poverty	People	Number of poor people	BPS [31]
X3	Gdp	Million rupiah	Regional GDP	BPS [32]
X4	Wage	Rupiah/month	Regional minimum wage	Ministry of Employment [33]
X5	Energy	Gigawatt-hours	Electrical energy consumed by household customers	State Electricity Company [34]

In this research, a diverse and comprehensive dataset has been curated, encompassing essential variables that play pivotal roles in understanding the dynamics of electricity consumption in Indonesia. The population (X1) provides insights into the demographic landscape, aiding in the assessment of the scale and distribution of energy needs. The variable on poverty (X2) serves as a crucial socio-economic indicator, shedding light on the number of individuals facing economic challenges and potentially vulnerable to energy accessibility issues. Regional GDP (X3) is instrumental in gauging the economic prosperity of different areas, directly influencing electricity consumption patterns. The regional minimum wage (X4) is a key factor influencing household affordability and, consequently, energy consumption behavior. Lastly, the variable on electrical energy consumption by household customers (X5) is the focal point of the study, representing the outcome of interest and reflecting the collective energy demands of households. By incorporating these variables, the research aims to comprehensively analyze the intricate interplay between demographic, socio-economic, and regional factors that shape electricity consumption trends in Indonesia.

4. RESULTS

4.1. Geographically weighted regression models

This section presents the findings and discusses the implications derived from the GWR analysis of electricity consumption in Indonesia, considering various socio-economic and demographic factors. The GWR model reveals spatial variations in the relationships between population, poverty, regional GDP, regional minimum wage, and electrical energy consumption. Localized coefficients obtained from GWR highlight how these factors exert differing influences across distinct geographical locations. For instance, certain regions may exhibit stronger correlations between population growth and increased energy demands, while others may show varying sensitivities. The provinces of Central Papua, Mountain Papua, South Papua, and Southwest Papua are still combined into the Provinces of Papua and West Papua because the expansion of these four provinces occurred in the middle and end of 2022. Data on electrical energy consumption in the Provinces of North Kalimantan and East Kalimantan is the result of interpolation from these two provinces with data on the number of subscribers in both provinces in 2019 because the SEC publications are still combined into one regional data for the provinces of North Kalimantan and East Kalimantan. The results of multiple linear regression calculations obtained the (8):

$$E=-8.792^{+02}+4.410^{-01}population-2.096^{-03}poverty+2.946^{-03}gdp+2.461^{-04}wage \quad (8)$$

where E is electricity consumption households.

In the process of regression testing, two crucial tests are employed to ascertain the significance of parameters and the overall suitability of the model. The first test, known as the model fit test or F test, involves the formulation of hypotheses to assess the influence of independent variables on the dependent variable. The null hypothesis (Ho) posits that there are no independent variables influencing the dependent variable, while the alternative hypothesis (Ha) asserts the presence of such an influence. The rejection criterion is set at Fcount > $F\alpha, v1, v2$, where $v1$ represents the number of independent variables (k) and $v2$ is determined as $(n-k-1)$, with a significance level α of 0.05. If the calculated Fcount exceeds the critical $F\alpha, v1, v2$ value, the null hypothesis is rejected. For instance, with Fcount measured at 363 and the critical $F\alpha, v1, v2$ at 2.70, the rejection of Ho is warranted. Moving on to the second test, the Parameter Significance Test or T-test is designed to evaluate the model's suitability by examining the influence of specific variables, such as tariffs, population, and GDP, on electricity consumption. The null hypothesis (Ho) posits that there is no impact of these variables on electricity consumption, while the alternative hypothesis (Ha) suggests the existence of at least one influential variable. The rejection criterion involves comparing the absolute value of tcount with the critical $t(t\alpha/2, n-k-1)$ value, where $v1$ equals the number of independent variables (k) and $v2$ is determined as $(n-k-1)$, with a significance level α of 0.05. If the calculated | tcount | surpasses the critical t value, the null hypothesis is rejected, indicating the presence of a significant variable affecting electricity consumption. These meticulous tests contribute to a comprehensive evaluation of the regression model's robustness and its ability to capture relevant relationships between variables.

The analysis of predictor variables through T-tests reveals insightful conclusions regarding their impact on the dependent variable. Among the examined variables, population, poverty, and GDP exhibit statistically significant effects, as indicated by t-values of 6.995, 3.697, and 7.678, respectively, all surpassing the critical value of 2.04523 at a significance level of 0.05. Consequently, the null hypotheses for Population, Poverty, and GDP are rejected, signifying their substantial influence on the dependent variable. In contrast, the Wage variable, with a t-value of 0.491 falling below the critical threshold, leads to the acceptance of the null hypothesis. Thus, it can be inferred that Wage does not hold a statistically significant effect on the dependent variable. These findings contribute to a nuanced understanding of the relative importance of each predictor variable, facilitating a more informed interpretation of their roles within the regression model.

4.2. Bandwidth selection and model comparison

In the pursuit of determining the optimal bandwidth for GWR, two approaches were employed: fixed bandwidth and adaptive bandwidth. For the fixed bandwidth method, a bandwidth value of 48.0415 was obtained, resulting in a coefficient of variation (CV) of 96211389. The R square value associated with this fixed bandwidth is notably high at 98.06237%, indicating that approximately 98% of the dependent variable's variation can be explained by the independent variable.

Moving on to the adaptive bandwidth approach, the optimal bandwidth was determined through calculations involving the number of nearest neighbors (M) in specific areas. The resulting q value from this iteration was 0.07377568, with a CV value of 34389959. Subsequently, using this q value, the GWR parameters were estimated, yielding an AIC value of 580.252 and an impressive global R square value of 0.9980483. To assess and compare the models, AICc and R square values were scrutinized. The global regression model exhibited the lowest AICc correction number at 552.7087, suggesting a favorable balance between goodness of fit and computational complexity. However, it's noteworthy that the GWR adaptive bandwidth model achieved the highest R square value of 0.9980483, indicating an exceptional ability to predict 99.8% of the dependent variable from the available independent variables. Consequently, the GWR model with adaptive bandwidth is identified as the preferred model for interpretation, showcasing a remarkable predictive accuracy in capturing the spatial variability of the data.

The comparison of three distinct methods is presented in Table 3. The findings indicate that the global regression model stands out with the lowest AICc number, measuring at 552.7087. This model demonstrates an optimal balance between goodness of fit and computational complexity. Moreover, the adaptive bandwidth GWR model showcases the highest R square value at 0.9980483, suggesting an exceptional predictive capability. This implies that, from this particular model, 99.8% of the dependent variables can be accurately predicted from the available independent variables. Consequently, the GWR model with the identified bandwidth emerges as the preferred choice for subsequent interpretation and analysis.

Table 3. Model comparison

Model	AICc	Rsquare
Global regression	552,7087	0,9804
GWR fixed bandwith	556,1108	0,9806237
GWR adapatif bandwidth	580,2752	0,9980483

4.3. Aligning with SDG 7 and economic development goals

The majority of Indonesia’s population resides on the island of Java, with the province of West Java having the highest population. According to Figure 2, the provinces of East Java and Central Java have a combined population of approximately 40 million people, making them the most populous provinces. Despite their bigger land area, the provinces of Central Kalimantan and West Papua have a comparatively lesser population. Figure 2 demonstrates that the population has a beneficial impact on electrical energy consumption. The provinces of South Sumatra, Bangka Belitung Islands, and Lampung exhibit the highest beta values, indicating a stronger influence. The provinces of Papua and West Papua exhibit the lowest beta values. The increase in population in the Papua region has a much smaller effect on energy usage compared to the regions in Sumatra or Java. The population beta value corresponds to the population density in South Sumatra and its surrounding areas, which ranges from 91-265 people per square kilometer (with an average density of 105 people per square kilometer outside Java). The electrification ratio remains within the range of 97.8% to 99.8%. Additionally, there is still a significant waiting list of 77,718 customers as of the end of 2022.

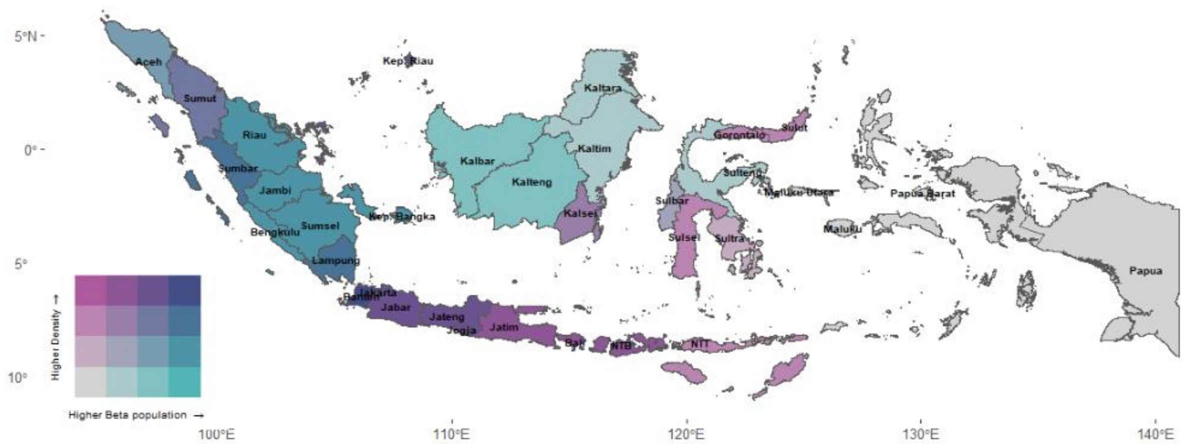

Figure 2. β value of population variables and population density

Regions with a high regional GDP continue to be predominantly located on the island of Java, as shown in Figure 3. The regions of North Sumatra, Riau, East Kalimantan, South Sulawesi, and Papua exhibit elevated scores compared to areas outside Java. These regions are typically abundant in natural resources such as oil, gas, coal mining, and other minerals. The Papua, West Papua, and Maluku areas have the highest GDP beta value, which is 0.50. Figure 3 demonstrates that the South Sumatra region has a GDP beta value that is 0.2 lower than that of other regions. The anticipated increase in GDP development in the Papua region would result in a surge in electricity consumption. Therefore, it is imperative to make enough preparations in terms of electricity generation to fulfill this growing demand. The Papua region’s GDP expansion would lead to a surge in electricity demand, necessitating proactive measures to enhance electricity generation capacity and satisfy this increased demand. The high GDP value in Papua is mostly attributed to the significant contribution of corporate customers, accounting for 25% of the GDP, second only to home customers who contribute 59%. An growth in GDP in Papua leads to a rise in the circulation of money, resulting in increased economic activity such as the establishment of shopping complexes or hotels. This, in turn, directly contributes to an increase in power consumption. Customers belonging to industrial, social, and other groups individually contribute less than 6% of the total value, hence their overall impact is minimal.

The region in Southeast Sulawesi has the largest beta wage value, ranging from ±1.05 as shown in Figure 3. In contrast, the Lampung region has a beta wage value of 0.05. The beta wage value indicates that an increase in the UMR will result in a greater rise in power demand for regions such as Southeast Sulawesi, Central Sulawesi, and Nusa Tenggara compared to other regions. The higher electricity usage in this area compared to others can be attributed to the fact that the average electricity rate in Sulawesi is 1087 rupiah/kWh, which is 1,032 rupiah/kWh lower than the national average electricity tariff. The low mean value of electricity tariffs suggests that a significant number of customers benefit from inexpensive rates, which may be a result of subsidized tariffs or households with power capacities ranging from 900 VA to 2200 VA. Customers with UMR income are included in this tariff group. Customers belonging to the 2200 VA group will face the most significant shift in consumption when there is a change in UMR, compared to other customers.

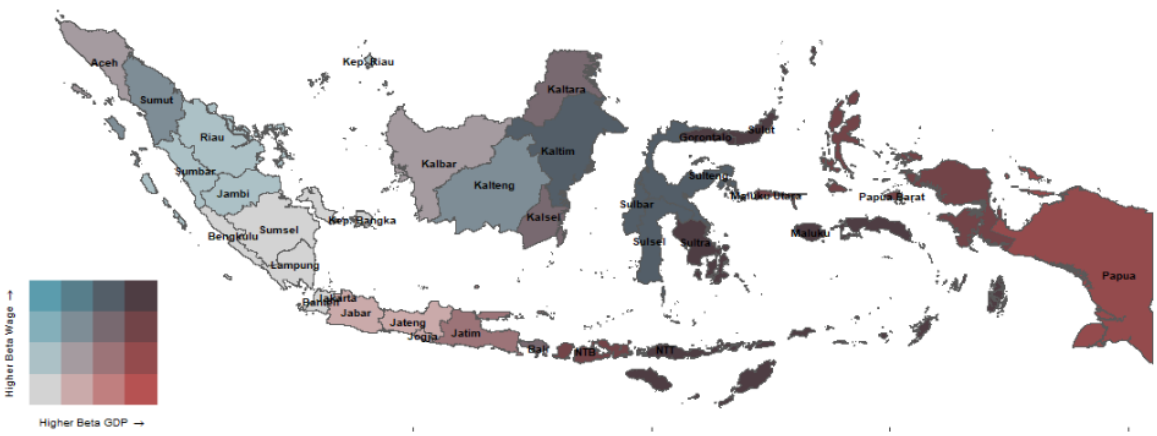

Figure 3. Bivariate clustering β GDP towards β wage/UMR

The wage/UMR values vary significantly across provinces in Indonesia. The low UMR values in regions on the island of Java can be attributed to the affordable prices of essential commodities and other factors contributing to the UMR. Regions outside of Java, such as Aceh, Bangka Belitung, and Kalimantan, have higher minimum wage rates due to the relatively greater cost of products and services in these areas compared to Java. The Papua region has a relatively high minimum wage outside of the major city due to the challenging accessibility of land transportation in this area. Transportation in Papua, particularly in hilly regions, typically relies on single-engine aircraft, resulting in high costs for carrying products and services. Figure 4 depicts the distribution of under minimum requirement (UMR) values throughout Indonesia.

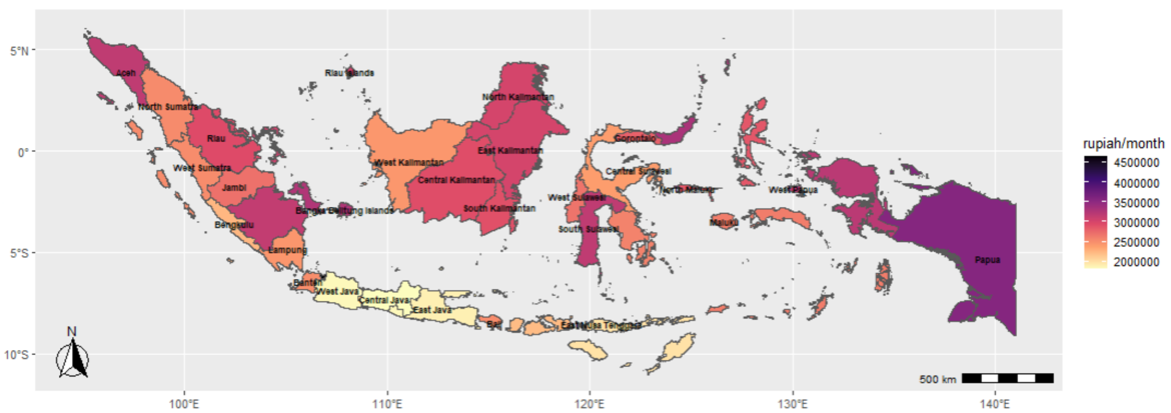

Figure 4. Distribution UMR/wage throughout Indonesia

Figure 5 shows that the average power tariff differs among regions due to variations in customer composition. West Nusa Tenggara, Aceh, and Central Java are the regions with the lowest average electricity tariffs, ranging from 900 to 1000 IDR/kWh. The regions of Papua, West Papua, Riau, Jambi, East Kalimantan, and North Kalimantan have the highest average electricity tariffs, ranging from 1300 to 1400 Rp/kWh. The beta coefficient of the tariff variable is displayed in Figure 5, with the Lampung, South Sumatra, and adjacent areas exhibiting the greatest values. These regions have a beta tariff value ranging from -1.5 to +1.5, with the Papua Region having the lowest Beta Tariff value, which is approximately 0. An escalation in prices does not exert a substantial influence on the electricity requirements in the Papua Region. Figure 5 provides a comprehensive depiction of tariff beta. The price of power in Papua has minimal impact on electricity use due to the relatively higher cost of commodities in the region, which has resulted in people being accustomed to this situation. The electricity prices in Papua are 18% more than the national average electricity price. This condition is consistent with the construction cost index (IKK) published by BPS. The construction expensive index is a price index that quantifies the degree of costliness of construction in a district or city relative to the reference city of Makassar. IKK 2022 demonstrates that the cost of commodities in Papua is 83% more than the national average.

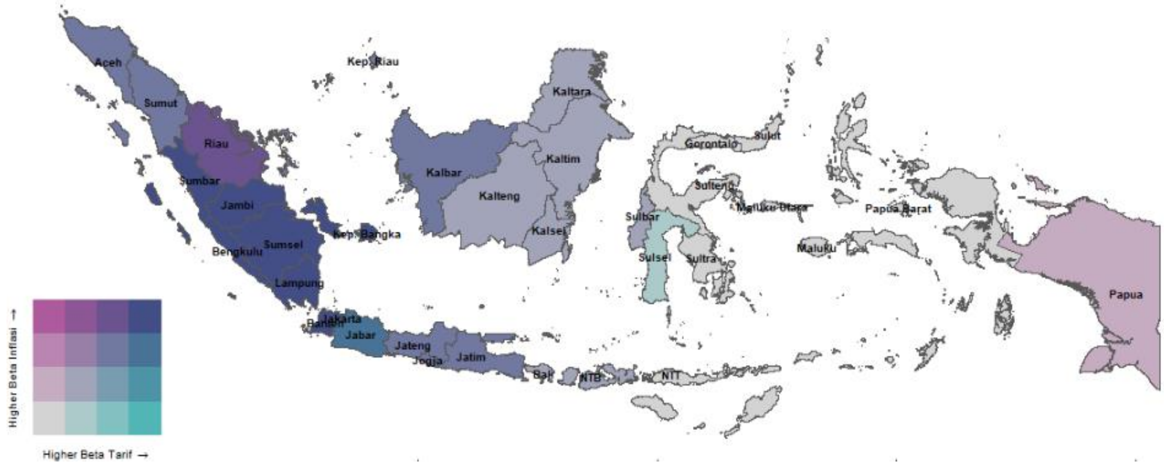

Figure 5. Bivariate clustering of β tariff and inflation β values

The region with the lowest inflation rate is the Sumatra Island area, where the average number is below 4.5%. The distribution of inflation on the island of Java is quite uniform, with the greatest rate seen in East Java at 5.6% and the lowest rate in Jakarta at 5.35%, as indicated by Figure 5. As we travel deeper into the Eastern Indonesia region, the inflation rate increases, reaching a maximum value of 7.19% in the West Papua region, as depicted in Figure 5. The beta coefficient for inflation exhibits a negative value, indicating that an increase in inflation will result in a drop in power usage. The regions of Southeast Sulawesi and East Nusa Tenggara have the largest inflation beta values, which are less than -2. On the other hand, the southern section of Sumatra has the lowest inflation beta values. The inflation beta value in NTT and Southeast Sulawesi is very high compared to the electricity consumption in these regions, which is mostly utilized for basic necessities. This is evident from the fact that the electricity consumption in the NTT region is still at 0.73 MWh/year, but in Southeast Sulawesi it is 1.16 MWh/year. The result is below the national average energy use of 1.48 MWh/year. The reduced usage indicates that electrical energy is solely utilized as a power source for fundamental electronic devices such as light bulbs, rice cookers, and refrigerators. Minimal power use indicates minimal public expenditure. Communities that have expenses of this magnitude are susceptible to the impact of inflation.

5. PRACTICAL IMPLICATION

Conducting a geospatial analysis of socio-economic factors on household electricity energy consumption in Indonesia carries significant practical implications across various domains. Firstly, the insights gleaned from such an analysis can directly inform policy development, enabling policymakers to tailor interventions that address specific consumption patterns prevalent in different regions. This targeted approach can optimize the efficacy of energy-related policies, fostering greater sustainability and efficiency within the sector. Moreover, the findings can guide infrastructure planning initiatives, facilitating the expansion of electricity grids and the implementation of smart technologies to meet evolving demand patterns. By understanding the spatial distribution of consumption and its correlation with socio-economic factors, stakeholders can design and implement energy conservation programs that cater to the diverse needs of communities across Indonesia.

The government can utilize the findings of this research in implementing population transmigration programs on the social aspect. The government can transfer individuals from densely populated regions like Java to locations with lower beta coefficients such as western Sumatra, northern Sulawesi, Maluku Islands, and Papua Province. Relocating to these places will result in lower electricity bills due to the smaller increase in electricity usage resulting from the population change compared to other areas.

Electricity requirements in poverty reduction initiatives should be a key focus for the government. Regions in central Kalimantan, southern Kalimantan, and southwestern Nusa Tenggara will see a rise in energy demand due to the increasing number of people transitioning out of poverty. If the government fails to fulfill the electrical requirements, this society will regress to the former state of poverty. Kalimantan island requires thorough preparations for its electrical requirements as the relocation of the Indonesian capital commences in 2024. These programs may include incentives for energy-efficient appliances, behavioral change campaigns, and subsidies to improve access for low-income households in Indonesia.

Governments can utilize GWR results in the economic sector to analyze how regional GDP affects fluctuations in household electricity demand. Regions like northern Sumatra, Riau, eastern Kalimantan, central Sulawesi, and Papua, which have high regional GDP outside Java, exhibit low beta levels. There is not necessarily a direct relationship between GDP growth and power usage in the area. One cause is the financial resources generated within the area and the influx of officers from outside the region. Local governments have the authority to establish requirements for a minimum number of employees residing in the vicinity of a site. This ensures that resources from the area contribute to enhancing the welfare of the local community. Regional minimum wages vary throughout different regions in Indonesia, with certain areas like Jakarta having higher salaries and others like central Java, eastern Java, and western Java having lesser salaries. Unlike other regions in Indonesia, the high number of tourists in Bali and the southern Nusa areas may explain this phenomenon, although additional research is needed to confirm this hypothesis.

The government can utilize free variable simplification for quicker and more straightforward calculations. Among the free variables examined, the population-free variable has the highest beta value, followed by regional GDP and poverty, which have nearly identical values, and the minimum wage variable, which has a variable beta value for a specific location. The poverty component can be excluded from the equation as it has the least impact compared to the other variables, according to the modeling results.

Furthermore, addressing disparities in electricity consumption can contribute to social equity goals, ensuring that all segments of the population have equitable access to essential services. Finally, leveraging the insights gained from the analysis can support climate change mitigation efforts by promoting renewable energy sources, implementing efficiency measures, and raising awareness about carbon emissions reduction. In essence, conducting a geospatial analysis of household electricity consumption in Indonesia transcends academic inquiry, offering practical guidance that can drive sustainable development and improve quality of life for communities nationwide.

6. CONCLUSION

This study undertook a comprehensive geospatial analysis of the impact of socio-economic factors on household electrical energy consumption in Indonesia, employing multiple methodologies including the multiple linear regression method, GWR fixed bandwidth method, and GWR adaptive bandwidth method. Among these approaches, the adaptive bandwidth GWR method emerged as the most effective, presenting superior results with an AICc value of 580.2752 and an exceptionally high R square value of 0.9980483. The findings underscore the existence of significant relationships between population, poverty, GDP, and wages on household electricity consumption in Indonesia. At a global scale, population exerts a substantial influence on electricity consumption, while poverty and GDP parameters demonstrate non-significant effects. Wages, among the parameters studied, exhibit the smallest influence. The insights gained from this research are of paramount importance for policymakers, providing valuable information to strategically plan power plants and electricity networks to meet the evolving needs of Indonesian society. The robust methodology employed in this geospatial analysis contributes to a nuanced understanding of the intricate dynamics shaping household electricity consumption, paving the way for informed decision-making in the realm of energy planning and infrastructure development.

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