Energy Poverty and Its Determinants at Subnational Level of Indonesia in 2021

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Abstract. In the coming decades, the energy sector will soon be faced with three major transformations, one of which is energy poverty. The World Economic Forum defines energy poverty as people's limited access to modern energy services and products. Access to modern energy has not been fully met for all regions in Indonesia and disparities between regions still occur. For this reason, indicators are needed to measure the level of energy poverty at both the national and district/city levels. This study aims to analyze energy poverty in Indonesia and determine its determinants using the Multidimensional Energy Poverty Index (MEPI) approach. The data used is the March National Socio-Economic Survey and BPS Village Potential in 2021. This research uses Geographically Weighted Regression (GWR) to determine the determinants of Indonesia's multidimensional energy poverty at the district/city level in 2021. It was found that there were still inequalities in energy poverty conditions in most of Indonesia's districts/cities. Analysis using the GWR model resulted in 66 regional groups that were grouped based on the similarity of variables that had a significant effect. The level of influence of the independent variables vary across districts/cities as consequence of spatial heterogeneity in the data.

1. Introduction

Energy is essential for social, economic, and industrial development in every country [1]. Every human being deserves access to energy as stated in Sustainable Development Goal 7 (SDG 7), namely ensuring universal access to affordable, reliable and modern energy services; substantially increasing the proportion of renewable energy in the global energy mix; and doubling the rate of improvement in energy efficiency. In the coming decades, the energy sector will soon be faced with three major transformations, one of which is related to energy poverty [2]. The World Economic Forum defines energy poverty as people's limited access to modern energy services and products that prevent them from enjoying these services for everyday purposes such as lighting or cooking.

Energy poverty has become a serious global problem. The International Energy Agency (IEA) noted that in 2021, there are 2.4 billion people who still cook using pollution-causing solid fuels such as firewood, charcoal, crop waste, animal dung, and coal in open fires and inefficient stoves. 40 percent are in sub-Saharan African countries and 55 percent in developing Asia. The report also states that there are still 754 million people in the world who cannot access to electricity by 2021.

Problems with access to modern fuels have also occurred for a long time in Indonesia [3]. Access to modern energy has not been fully met for all regions in Indonesia and disparities between regions still occur. Based on data from the National Socio-Economic Survey (Susenas), there are still 13.10 percent of households that still use unsafe main cooking fuels such as charcoal/briquettes and wood in 2021. Especially in Eastern Indonesia where the main cooking fuel is still dominated by wood. Central Bureau of Statistics Indonesia, BPS, also noted that there were still families without access to electricity in 2021 in a total of 19,565 villages in Indonesia. Papua Province has the most villages with families without access to electricity with 3,639 villages, followed by North Sumatra with 2,403 villages, and East Nusa Tenggara (NTT) with 2,010 villages.

The availability of access to energy services has a direct influence on dimensions of poverty such as poor health conditions, lack of education, or lack of access to infrastructure services [4]. The burning of traditional fuels such as biomass, coal, and kerosene in traditional stoves, open fires, and wick lamps can produce large amounts of harmful pollutants that cause indoor air pollution. Limited household access to electricity can hinder human development in education. Energy poverty can also prevent a person from getting light to do activities at night, getting information from the media (radio, television, and internet), and hinder teaching and learning activities inside and outside of school [5]. The importance of accessibility to energy services shows that this issue needs to be taken seriously.

The Indonesian government has made various policies to realize the fulfillment of modern energy access to all levels of society, one of which is implementing the kerosene to Liquefied Petroleum Gas (LPG) conversion program based on Presidential Regulation (Perpres) Number 104 of 2007 concerning the Supply, Distribution, and Pricing of 3 kg LPG cylinders. This program significantly increased the percentage of households using LPG as the main cooking fuel from only 10.57 percent in 2007 to 83.36 percent in 2021. However, recent data shows that there are still households that use firewood as cooking fuel at 11.76 percent, especially in rural areas in 2021 [6].

To ensure that every resident has access to modern energy services, indicators are needed that can measure the level of energy poverty at both the national and district/city levels. Energy poverty has a complex and multidimensional concept [7]. Research conducted by Nussbaumer, Bazilian, and Modi [8] has captured the concept of energy poverty that focuses on deprivation of modern energy access using the Multidimensional Energy Poverty Index (MEPI) approach. The multidimensional approach in MEPI uses a similar approach to the Multidimensional Poverty Index (MPI) developed by the Oxford Poverty and Human Development Initiative (OPHI). The MEPI adopts a multidimensional measure of deprivation experienced by an individual with specific cut-offs for combinations of deprivation across dimensions [9]. A person is defined as energy poor if the combination of various deprivations that occur to a person exceeds a specified limit.

Energy poverty can occur due to various aspects, including economic, infrastructure, social, and demographic aspects. The concept of shifting energy use was explained by Leach in 1992, known as the energy ladder theory. The theory explains the relationship between household socioeconomic status that can shift energy consumption patterns. As a family's socioeconomic status increases, they will switch to using more efficient and less polluting energy such as LPG and electricity [10]. Limitations in terms of infrastructure are also an obstacle for people to access modern energy because the provision and distribution of energy to every corner of the community is at a standstill. One of the obstacles in the provision of electricity explained by Ministry of Village, Development of Disadvantaged Regions and Transmigration of Indonesia is the difficulty of road access to the destination location because most rural areas still have poor road conditions [11]. As a result, the supply of electrical energy has not been able to reach remote rural areas far from the growth center.

According to Encinas *et al.* [12], energy poverty has unique characteristics in that it is spatially and territorially located. As a result, the condition of energy poverty varies greatly according to the geographical conditions of the region. As an archipelagic country, geography is one of the factors inhibiting the provision of access to modern energy services in Indonesia. Differences in geographical conditions challenge National Electricity Company (PLN) to expand the electricity network, which takes a long time and costs a lot of money [13]. Especially access to underdeveloped areas. Based on the Presidential Regulation (Perpres) Number 63 of 2020, there are still 62 districts/cities included in underdeveloped areas, most of which are located in the Eastern Indonesia. Households living in these underdeveloped areas tend to find it difficult to gain access to modern energy compared to developed areas. Based on data released by PLN, Papua's electrification ratio is only 53.13% and East Nusa Tenggara's (NTT) is 63.54%. These figures are smaller than those of other provinces which are almost 100%. Therefore, analysis that takes into account spatial aspects is needed as an evaluation tool for the government to adjust policies to the characteristics of each region.

One of the analysis methods that can be used to accommodate spatial aspects of both inter-regional linkages and inter-regional diversity is the Geographically Weighted Regression (GWR) method. In their research, Encinas *et al*. [12] studied energy poverty with a spatial approach in the capital city of Chile, Santiago de Chile. Using Geographically Weighted Regression (GWR), it was found that the percentage of professionals, Normalized Difference Vegetation Index (NDVI), annual thermal amplitude, and housing material quality can affect the temperature in homes that experience energy poverty in winter. A study on energy poverty using a spatial approach was also conducted by Jia and Wu [14] in 30 Chinese provinces from 2008 to 2009. Using the Energy Development Index (EDI) framework designed by the International Energy Agency (IEA), the results showed that reducing inequality in industrial structure, energy prices, and energy investment between regions can effectively narrow the energy poverty gap between regions.

In Indonesia, there is not much research on energy poverty at the regional level such as district/city or province. Some previous studies only provide an overview by mapping energy poverty conditions at the district/city or province level. At the micro level, some studies on energy poverty have considered variables related to spatial aspects such as geopolitical zones ([15]; [16]). However, there have not been many energy poverty studies that consider regional aspects at the macro level. Similar research was also conducted by Nasution [9] but without including spatial aspects where using the Multidimensional Energy Poverty Index (MEPI) approach showed that the factors that influence energy poverty conditions at the household level include the status of the area where the household lives, the poverty status of the household, the length of education of the household head, the number of household members, and the age of the household head. Based on the conditions described above, this research will focus on energy poverty studies that consider regional aspects at the macro level. Thus, this study aims to provide an overview of the distribution of Indonesia's energy poverty conditions by district/city and to find out what variables are thought to affect Indonesia's energy poverty in each district/city in 2021.

2. Theoritical review

2.1. Energy poverty

The concept of energy poverty is variously defined in the literature. Foster classifies households as fuel poor if the energy consumed cannot meet basic energy needs [17]. In line with this, Barnes, Khandker, and A. Samad [18] also stated the concept of energy poverty as the point where people use the minimum energy needed to survive. A number of international organizations have tried to narrow down the concept of energy poverty. In the non-monetary dimensions of multidimensional poverty, two important energy-related indicators are found: cooking fuel and lighting sources. The United Nations Development Program's Human Development (UNDP) explicitly defines energy poverty as the inability to cook using modern fuels and not being able to access electric lighting for reading or productive activities at night [19]. The IEA uses the concept of energy poverty as a state of lack of access to electricity and dependence on traditional biomass fuels for cooking [20]. From the above definitions, energy poverty is a condition where it is difficult to access modern and adequate energy services for daily needs.

2.2. Multidimensional Energy Poverty Index

The concept of energy poverty is not easy to measure through just one indicator [7]. A multidimensional approach is more suitable for complex issues such as energy poverty and sustainable development. The Multidimensional Energy Poverty Index (MEPI) is one of the composite indices proposed by Nussbaumer, Bazilian, and Modi [8]. MEPI captures the concept of energy poverty that focuses on the deprivation of modern energy access so that with the available data, the number and level of energy poverty can be known along with the index [9]. MEPI is composed by five dimensions represented by energy services with six indicators. These dimensions are cooking, lighting, household appliances, entertainment/education, and communication. The weight given to each dimension is not the same. Nussbaumer, Bazilian, and Modi [8] believe that the energy poverty variables considered in these metrics do not have the same importance value.

2.3. Factors affecting energy poverty

There are various factors that contribute to households being in energy poverty. Kowsari and Zerrifi [21] studied household energy choices based on a complex relationship between economic, social, cultural and environmental factors. Then these factors are divided into endogenous factors that come from the characteristics of the household itself and exogenous factors that come from conditions outside the household. Endogenous factors are broken down into household economic and non-economic conditions that reflect household capabilities; and household behavior and culture that reflect household attitudes, preferences, and experiences. Then exogenous factors are broken down into: physical environment such as geographical conditions; government politics and regulations; energy supply; and characteristics of energy-related equipment such as stoves. From this concept, the factors that can cause multidimensional energy poverty can be seen from various aspects. These aspects are economic, social and demographic aspects that come from endogenous household factors, and infrastructure aspects that come from exogenous household factors.

The economic aspects that are considered to be related to energy poverty include per capita expenditure. Per capita expenditure according to BPS is the average expenditure of each resident in an area that has been adjusted to purchasing power parity. Nasution [9] found that poor households whose average expenditure is below the poverty line tend to experience energy poverty much higher than non-poor households.

Social aspects that are considered to be related to energy poverty are education and employment. Kroon, Roy, and Beukering [10] explain the importance of human capital such as education level, knowledge, and professional skills as determinants of fuel switching behavior. Improving the financial capability of households can improve access to resources including energy services to reduce poverty. One indicator to measure employment is the working status of a person, especially the head of the household. Household heads have more responsibility for the daily needs of a household. Murry and Nan [22] introduced the term income effect to explain the relationship between labor and energy consumption. When the economy grows rapidly, the labor participation rate will also increase so that income and domestic demand, especially energy consumption, will also increase.

Furthermore, demographic aspects that are considered to be related to energy poverty are the gender of the household head, the age of the household head, and the regional classification of residence. Gender is likely to have an opposing effect on energy poverty [10]. Since women are often responsible for collecting energy for cooking, they are more likely to abandon time consuming energy sources such as firewood. This assumes that women prefer energy efficiency for their cooking conditions. The age of the household head can also have a countervailing effect on household energy choices [10]. The age of the household head is an indicator of the life cycle of the household. This relates to the more upwardly mobile the life cycle of a household is, the more prosperous the household is and the more able it is to accumulate more financial assets, which would provide financial freedom. On the other hand, older household heads may be more conservative. Hosier and Dowd identified urban areas as an important driver of the energy transition [10]. The problem of access to modern energy services is more concerning in rural areas, especially in remote and low population density areas where the distribution of modern fuels is insufficient and unreliable [21].

The aspects of infrastructure that are considered to be related to energy poverty are distance from the growth center and the type of road surface. Kowsari and Zerriffi [21] studied the problem of access to energy that cannot be collected alone is closely related to regional infrastructure characteristics such as roads, distribution channels, and access to markets. In the technical guidebook for identifying the location of remote villages underdeveloped villages and small islands by the Ministry of Public Works and Housing Indonesia, it is stated that an area is geographically far from the growth center if the distance from the district center/city center/other sub-district is more than 100 km [11]. The area has a low level of accessibility due to limited regional infrastructure, especially transportation, communication, and energy. A study by Chen and Lin [23] found that infrastructure investment and development will increase employment opportunities and income levels of the population, which in turn will increase demand for energy commodities and services. From the literature review, the study contributes to analyzing energy poverty in Indonesia using the MEPI approach and knowing the determinants that are thought to affect Indonesia's energy poverty at the district/city level in 2021 in terms of economic, social, demographic, and infrastructure aspects, by considering spatial aspects.

3. Methodology

This study uses cross section data sourced from the March National Economic Survey (Susenas) and the 2021 Village Potential Data Collection (Podes). The unit of analysis of this study is all districts/cities in Indonesia, totaling 514 districts/cities.

Tabel 1. Research variables and data sources

No	Code	Variable	Data Sources
1	Y	Percentage of Multidimensional Energy Poor Households	Raw Susenas 2021 KOR data across all Indonesian districts/cities for the dimensions of cooking, lighting, household appliances, entertainment/education, and communication.
2	X_1	Expenditure Per Capita	Central Bureau of Statistics Indonesia (BPS)
3	X_2	Percentage of Male Household Heads	Raw Susenas 2021 KOR data across all Indonesian district/cities.
4	X_3	Percentage of Household Heads Ages 60 Years and Above	
5	X_4	Percentage of Working Household Heads	
6	X_5	Percentage of Household Heads with High School Education and Above	
7	X_6	Percentage of Villages with Rural Status	Raw Podes 2021 across all Indonesian district/cities.
8	X_7	Percentage of Villages that are Far from Growth Centers	
9	X_8	Percentage of Villages with Majority Asphalt Roads	

The analysis methods used are descriptive analysis and inferential analysis. Descriptive analysis is used to obtain an overview of the distribution of Indonesia's energy poverty conditions using the MEPI approach at the district/city level as well as the variables that are thought to influence energy poverty at the district/city level in Indonesia in 2021. The descriptive analysis is presented in the form of thematic maps. In this study, the size of the percentage of multidimensional energy poor households is obtained from the aggregation of energy poverty status at the household level. In household level, energy poverty status is determined using the Multidimensional Energy Poverty Index (MEPI) approach developed by Nussbaumer, Bazilian, and Modi [8]. The MEPI calculation is derived from the Alkire-Foster generalized multidimensional energy poverty measure by Oxford Poverty and Human Development (OPHI) which identifies whether a household falls into the multidimensional energy poverty category by calculating the total deprivation score of each unit of analysis (household), with the formula:

$$c_i = w_1 I_1 + w_2 I_2 + \cdots + w_d I_d \tag{14}$$

where c_i is the total deprivation score form various combinations of dimensional indicators. When a person is deprived in indicator i, the score is $I_j = 1$ and otherwise it's $I_0 = 0$. w_j is the weight of indicator i with $\sum_{j=1}^{d} w_j = 1$, the details of which are described in table 2. A unit of analysis is said to be energy poor when the total deprivation score is greater than second cut-off point (k). Second cut-off point is set as 0.3 (energy poor when, $c_i > 0.3$) [8]. Next, the percentage of multidimensional energy poor households is calculated by the formula:

$$Y = \frac{q}{n} \tag{15}$$

where q denotes the number of multidimensional energy poor households and n is the total number of household.

Table 2. Modification of energy poverty dimensions, indicators, variable weights, and deprivation cut-offs.

Dimension	Indicator (Weight)	Variables	Deprivation Cut-off (poor if..)
Cooking	Modern cooking fuel (0,4)	Type of cooking fuel	Household uses fuel beside electricity, LPG, kerosene, natural gas, or biogas.
Lighting	Electricity access (0,202)	Has access to electricity	False
Household appliances	Household appliance ownership (0,134)	Has a fridge	False
Entertainment/education	Entertainment/education appliance ownership (0,132)	Has a TV or computer	False
Communication	Telecommunication appliances ownership (0,132)	Has a phone land line or mobile phone	False

Inferential analysis was conducted using the GWR method to obtain the determinants of multidimensional energy poverty of Indonesian districts/cities in 2021. All tests in this research hypothesis use a significance level of 5 percent. The following are the steps of confirmatory analysis carried out in the study:

1. Build a multiple linear regression model
2. Assumption testing

Furthermore, testing the assumptions of normality and non-multicollinearity is carried out. Testing the assumption of normality is done with the Kolmogorov Smirnov test. The hypotheses used in the Kolmogorov Smirnov test are:

$H_0: \varepsilon_i \sim N(0, \sigma^2)$ (*error* is normally distributed)

$H_1: \varepsilon_i \neq N(0, \sigma^2)$ (*error* isn't normally distributed)

The decision will reject H_0 if the Kolmogorov Smirnov statistical test value is more than statistic table $D_{(0,05;514)}$ or the p-value is less than the 5% significance level. From this decision it can be concluded that with a significance level of 5%, the OLS regression model error is not normally distributed. Then, testing the assumption of nonmulticollinearity using the VIF value. If the VIF value generated by each independent variable is more than 10, then there is a multicollinearity problem between the independent variables in the OLS regression model.

3. Spatial aspect testing

Spatial autocorrelation testing was conducted on the dependent variable, percentage of multidimensional energy-poor households, through the Moran's index or Global Moran's I. Before

conducting this test, the appropriate spatial weight matrix is first selected. The hypothesis used is as follows:
$H_0: I = 0$ (no spatial autocorrelation in the data)
$H_1: I \neq 0$ (there is spatial autocorrelation in the data)
The test statistics used are:

$$Z = \frac{I - E(I)}{VAR(I)} \tag{16}$$

The decision will reject H_0 if the test statistic $|Z|$ is greater than the critical value ($|Z| > Z_{\frac{0,05}{2}}$) which means it can be concluded with a significance level of 5%, there is spatial dependence on the percentage of multidimensional energy poor households. Then the spatial heterogeneity test is also conducted using the Breusch-Pagan statistical test. The hypothesis used is as follows:
$H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_{514}^2 = \sigma^2$ (there is no heterogeneity between regions)
H_1: there is at least one $\sigma_i^2 \neq \sigma^2$with $i = 1,2,..,514$ (there is heterogeneity between regions)

The decision will reject H_0 if the value of the Breusch-Pagan test statistic is more than $\chi^2_{0,05;p}$ where p is the number of independent variables or the p-value is less than the 5% significance level. If there is spatial heterogeneity in the observation areas, the GWR model can be build.

4. Building the GWR model

Before building the GWR model, first the selection of the most suitable weighting function and the selection of the optimum bandwidth are carried out. Then the optimum bandwidth combination and the best weighting function will be determined through the comparison of AICc, R^2, adjusted R^2, and residual sum of square.
The GWR model formed is as follows:

$$\begin{aligned} y_i = {} & \beta_0(u_i,v_i) + \beta_1(u_i,v_i)X_{i1} + \beta_2(u_i,v_i)X_{i2} + \beta_3(u_i,v_i)X_{i3} + \beta_4(u_i,v_i)X_{i4} + \\ & \beta_5(u_i,v_i)X_{i5} + \beta_6(u_i,v_i)X_{i6} + \beta_7(u_i,v_i)X_{i7} + \beta_8(u_i,v_i)X_{i8} + \varepsilon_i \end{aligned} \tag{17}$$

where:
(u_i, v_i) : coordinates of the i-th district/city
ε_i : random error of the i-th district/city
i : 1,2,…,514

5. Identify variables that have a significant effect on the percentage of multidimensional energy poor households in each district/city in Indonesia in 2021.

4. Result

4.1. Overview of the energy poverty condition in Indonesia in 2021 and the relationship with the variables that are thought to affect it

Based on the results of calculations using 340,032 Susenas March 2021 household samples, it was found that the national percentage of households experiencing multidimensional energy poverty in Indonesia amounted to 16.89 percent.

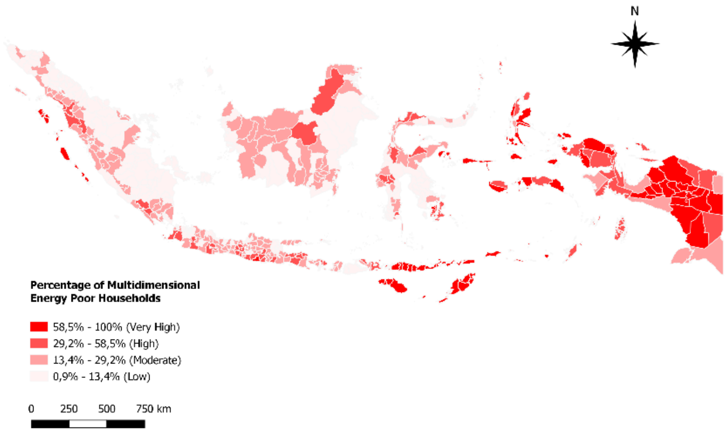


Figure 1. Percentage of multidimensional energy poor households by district in Indonesia in 2021

The darker the red color shown in figure 1, the higher the percentage of energy-poor households in the region. In general, it can be seen that regions with a high percentage of energy-poor households tend to be clustered or close to each other, as well as regions with a low percentage of energy-poor households. Most regions in Sumatra Island have a low percentage of energy-poor households and most regions in Java Island have a medium percentage of energy-poor households. Likewise, Kalimantan Island and Sulawesi Island are dominated by regions with a low to moderate percentage of energy-poor households. In contrast, Nusa Tenggara and Papua Island are dominated by very high percentages of energy-poor households. The districts/cities with the highest percentage of energy-poor households are Deiyai, Intan Jaya, Bintang Mountains, Puncak Jaya, Tolikara, and Yalimo, which reach 100 percent. The district/city with the lowest percentage of energy-poor households is South Tangerang City (0.94 percent).

Tabel 3. Summary statistics.

Categorical Variable	Percentage
Multidimensional Energy Poor Household	16.89%
Male Household Head	85.62%
Household Head Ages 60 Years and Above	23.02%
Working Household Head	86.59%
Household Head with High School Education and Above	36.84%
Village with Rural Status	80.55%
Village that are Far from Growth Center	16.09%
Village with Majority Asphalt Roads	78.44%

Variable Interval Scale	Indonesia	Mean	Stad.dev	Min	Max
Expenditure Per Capita (Thousand/People/Year)	11.156	10324.79	2717.14	3976	23888

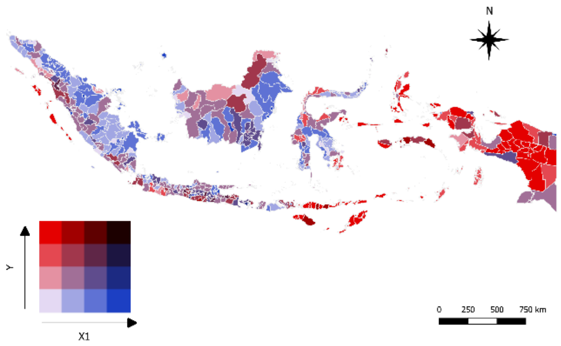


Figure 2. Distribution of the percentage of multidimensional energy poor households and per capita expenditure by district/city in Indonesia in 2021.

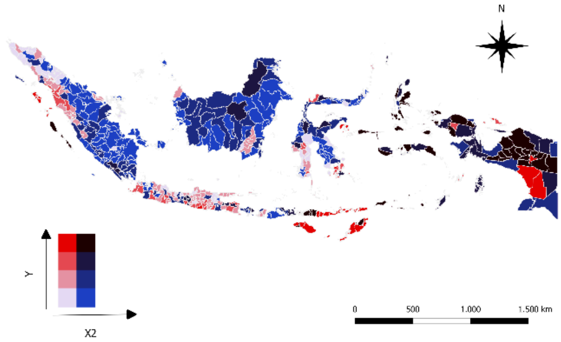


Figure 3. Distribution of the percentage of multidimensional energy poor households and the percentage of male household heads by district/city in Indonesia in 2021

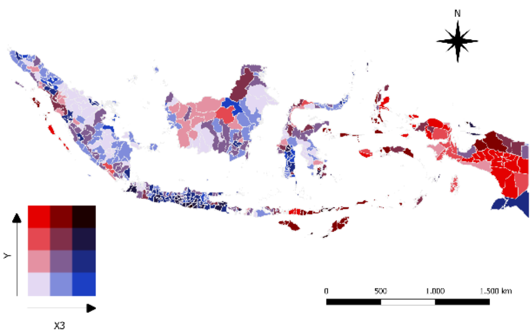


Figure 4. Distribution of the percentage of multidimensional energy poor households and the percentage of household heads aged 60 years and over by district/city in Indonesia in 2021

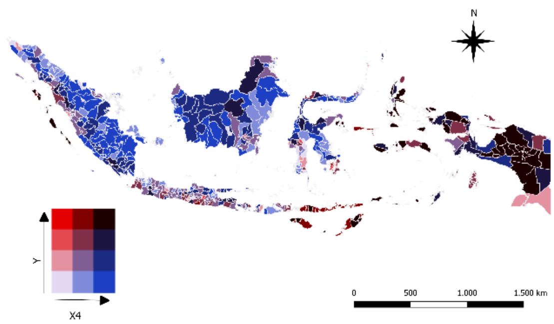


Figure 5. Distribution of the percentage of multidimensional energy poor households and the percentage of working household heads by district/city in Indonesia in 2021

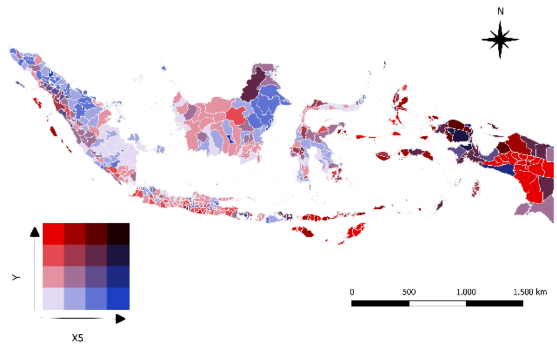


Figure 6. Distribution of the percentage of multidimensional energy poor households and the percentage of household heads with high school education and above by district/city in Indonesia in 2021

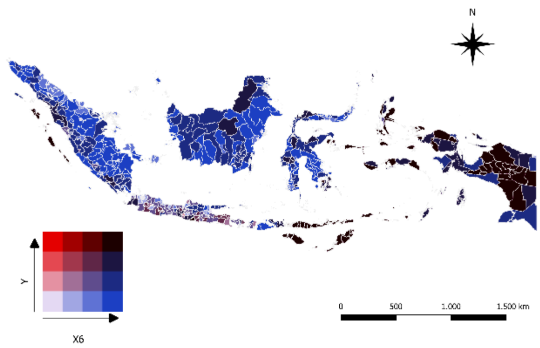


Figure 7. Distribution of the percentage of multidimensional energy poor households and the percentage of villages with rural status by district/city in Indonesia in 2021

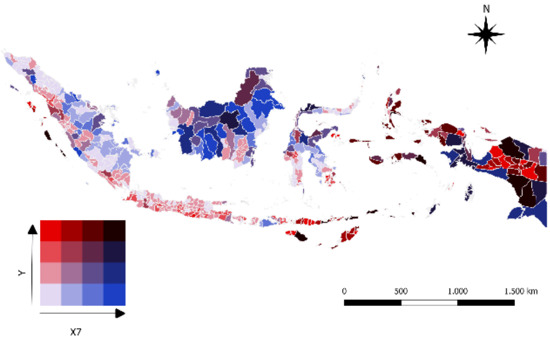


Figure 8. Distribution of the percentage of multidimensional energy poor households and the percentage of villages far from the center of growth by district/city in Indonesia in 2021

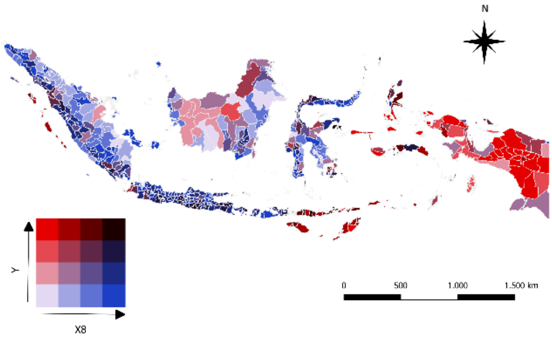


Figure 9. Distribution of the percentage of multidimensional energy poor households and the percentage of villages with majority asphalt roads by district/city in Indonesia in 2021.

Figures 2, 3, 4, 5, 6, 7, 8, and 9 display thematic maps of the relationship between the distribution of multidimensional energy-poor households and the variables that are thought to influence them in each district/city. The combined colors indicate a unidirectional relationship between the percentage of multidimensional energy-poor households and the independent variables in a region. Conversely, non-combined colors indicate an opposite relationship between the two variables. The red color is shown for the percentage of multidimensional energy poor households and the blue color for the independent variables used.

Based on table 3, the per capita expenditure of a person in one year in Indonesia for 2021 is 11.156 thousand rupiah or 11,156,000 rupiah, there are 85.62 percent of household heads that are male; 23.02 percent of household heads are 60 years old and above; 86.59 percent of household heads are working; 36.84 percent of household heads with high school education and above; 80.55 percent of villages have rural status; 16.09 percent of villages are far from the growth center; and 78.44 percent of villages that already have majority asphalt roads.

Figure 2 shows that most districts/cities in Indonesia have medium to high per capita expenditure with a low percentage of multidimensional energy poor households, and vice versa. This is in accordance with the concept of the energy ladder, where the higher a person's welfare, the more they should be able to get out of the energy poverty trap.

If we look at the conditions in Indonesia shown in figure 3, most regions such as Sumatra, Kalimantan, Bali and Sulawesi have a high percentage of male household heads with a low percentage of multidimensional energy poor households. This can be caused by the fact that poor women tend to participate in the informal sector [24]. With a low average income, women tend to face a high risk of experiencing energy poverty [25].

From figure 4, regions that have a low percentage of household heads aged 60 years and above tend to have a low to medium percentage of energy-poor households. However, most districts/cities in Papua Island have a low percentage of household heads aged 60 years and above with a high percentage of multidimensional energy poor households.

In general, as shown in figure 5, districts/cities that have a high percentage of working household heads have a low percentage of multidimensional energy poor households, such as most districts/cities on the islands of Sumatra, Kalimantan, and Sulawesi. When the head of the household works, the household income also increases so that the fulfillment of daily needs including basic energy needs can be fulfilled. This is in accordance with research by Widyastuti and Harotono [26] which found that the employment status of the household head can be a factor in inhibiting household energy poverty.

Based on figure 6, districts/cities with a low percentage of household heads with high school education and above tend to have a medium percentage of multidimensional energy poor households. These districts/cities are found in most parts of Java, Kalimantan, some parts of Sulawesi, and some parts of Sumatra. Some regions indicate that the two variables have a unidirectional relationship such as Tambrauw, South Sorong, Arfak Mountains, and Waropen Regencies which have a high percentage of household heads with high school education and above and a high percentage of multidimensional energy poor households.

In figure 7, it can be seen that most areas such as districts/cities on the islands of Sumatra, Kalimantan, and Sulawesi tend to have the opposite relationship, where the percentage of villages with rural status is categorized as very high and the percentage of multidimensional energy-poor households is categorized as moderate to low. However, the relationship between the two variables is not always consistent. There are districts/cities that have a unidirectional relationship between multidimensional energy-poor households and the percentage of rural villages, such as most districts/cities in Java and Bali.

In figure 8, in general, the relationship between the two variables shown in each district/city tends to have a unidirectional relationship. As in most of Sumatra, Java, Bali, and some areas of Kalimantan and Sulawesi, the percentage of villages far from growth centers tends to be low with the percentage of multidimensional energy poor households in the low to medium category. Functionally, growth centers have a concentration of business groups that can encourage economic growth while geographically growth centers tend to have more facilities [27]. If an area is far from a growth center, then its residents will find it difficult to access existing services, including modern energy services.

In figure 9, the relationship between the two variables is generally the opposite. Districts/cities that have a high percentage of villages with mostly asphalt roads tend to have a low to moderate percentage of multidimensional energy-poor households, as in most of Sumatra, Java and Sulawesi. The availability of adequate connecting facilities is a major support for the economic development process, including the rapid provision of infrastructure to remote areas, especially the entry of electricity to rural areas.

4.2. Modeling the determinants of energy poverty with geographically weighted regression

4.2.1. Building the multiple regression model. The first step in building the GWR model is to build a multiple linear regression model with OLS first. The summary of the OLS model is shown in the following table.

Tabel 4. Parameter estimation of OLS regression model.

Variable	Coefficient	Std.Error	t-statistic	p-value
(1)	(2)	(3)	(4)	(5)
Intercept	626.586	43.190	14.508	< 0.001
Ln Expenditure Per Capita	-62.467	4.106	-10.570	< 0.001
Percentage of Male Household Heads	-0.714	0.227	-3.149	0.002
Percentage of Household Heads Ages 60 Years and Above	0.103	0.160	0.642	0.521
Percentage of Working Household Heads	0.667	0.243	2.742	0.006
Percentage of Household Heads with High School Education and Above	-0.068	0.077	-0.885	0.377
Percentage of Villages with Rural Status	-0.159	0.041	-3.926	< 0.001
Percentage of Villages that are Far from Growth Centers	0.034	0.033	1.008	0.314
Percentage of Villages with Majority Asphalt Roads	-0.167	0.043	-3.925	< 0.001

The data processing results in a calculated F of 92.762 with a p-value of less than 5%, which indicates that at least one independent variable has a significant effect on the dependent variable. Based on the test results, of the eight independent variables, there are five variables that have a p-value of less than 5%, which means that the five variables have a significant effect on the percentage of Indonesia's multidimensional energy poor households in 2021 at the 5% significance level. These variables are ln expenditure per capita, percentage of male household heads, percentage of working household heads, percentage of villages with rural status, and percentage of villages with majority asphalt roads. The adjusted R^2 value in the OLS regression model is 0.589, which means that 50.9 percent of the variation in the percentage of multidimensional energy-poor households can be explained by the eight independent variables in the model.

4.2.2. Assumption testing. For the next step, testing the normality assumption is carried out on the residuals of the OLS regression model. The Kolmogorov Smirnov statistical test value is 0.0572 with a p-value of more than the 5% significance level, resulting in a decision to fail to reject H_0. This means that with a 95% confidence level, the OLS regression model error has followed a normal distribution. The non-multicollinearity test results in all independent variables not having a VIF value of more than 10. So it can be concluded that there is no multicollinearity between the independent variables.

4.2.3. Spatial autocorrelation testing. In spatial data, one of the basic assumptions of classical regression models, namely that observations must be independent of each other, is difficult to fulfill. Since the unit of analysis of the study is the district/city, it is necessary to conduct a test to check the presence of spatial effects, namely spatial autocorrelation on the dependent variable used. This study uses both the contiguity and distance criteria to build a spatial weight matrix, then the resulting moran index value is compared.

Tabel 5. Global spatial autocorrelation test results with Global Moran's I.

Spatial Weighting Matrix	Global Moran's I
Queen Contiguity	0.712*
3-Nearest Neighbors	0.765*
4-Nearest Neighbors	0.743*
*) significant at the 5% level	

It was found that either the weighting matrix using queen contiguity, 3-nearest neighbors, or 4-nearest neighbors, showed significant results at the 5% level. The spatial weighting matrix that will be used in this study is the matrix with 3-nearest neighbors that produces the highest Global Moran's I value. The selection of this spatial weighting matrix is also based on the geographical area of Indonesia which is separated by many waters so that there are several districts/cities that do not intersect or have no neighbors. The result of the autocorrelation test with the 3-nearest neighbors matrix is positive at 0.765, indicating that the multidimensional energy poverty of a district/city tends to play a positive role with other districts/cities in the vicinity, or vice versa.

4.2.4. Spatial heterogeneity testing. Furthermore, the second spatial aspect was examined, namely spatial heterogeneity. Testing the presence or absence of spatial heterogeneity is used to identify the occurrence of geographical variations in the relationship between the independent variable, namely the percentage of multidimensional energy-poor households, and the dependent variable that is thought to affect it. The Breusch-Pagan test statistic value is 83.651 and the p-value is less than the 5% significance level so that the decision to reject H_0 is obtained. From these results it can be concluded that there is spatial heterogeneity in the data because the error variances are no longer identical. The existence of spatial heterogeneity in the data allows for different variations in the effect of the independent variable on the dependent variable in each region. In other words, the influence of the independent variables on the percentage of multidimensional energy poor households in Indonesia in 2021 is not the same for each district/city. Therefore, it is necessary to analyze by considering these spatial aspects, by building a GWR model.

4.2.5. Modeling with GWR. In building the GWR model, there are two things that need to be considered, namely the selection of the optimum bandwidth and weighting function. GWR parameter estimation depends on the chosen weighting function or kernel. The kernel functions that can be used are fixed kernel or adaptive kernel. The difference between the two kernel functions is in the bandwidth used. Fixed kernel has the same bandwidth for all observation areas while adaptive kernel has different bandwidths in each region. The selection of the optimum bandwidth is done with a golden section search process that finds the optimum bandwidth by minimizing AICc, AIC, BIC, or CV. In this study, the AICc criterion is used. Based on the method or formula, the weighting function that can be used is the gaussian weighting function or the bisquare weighting function. In choosing the best model between the two functions, the coefficient of determination (R^2 or adjusted R^2), residual sum of square (RSS), and AICc are used.

Tabel 6. Selection of optimum bandwidth and best kernel function

Weighting Function	Optimum Bandwidth	AICc	R^2	Adjusted R^2	RSS
Fixed Gaussian	189.406	3829.000	0.929	0.884	20931.462
Fixed Bisquare	547.530	3850.278	0.913	0.817	25644.481
Adaptive Gaussian	Various	4034.652	0.787	0.758	62697.638
Adaptive Bisquare	Various	3865.337	0.918	0.872	24109.638

Based on table 6, the best model obtained is the model with the fixed gaussian weighting function because it has the smallest AICc value, the largest R^2 and adjusted R^2, and the smallest residual sum of square than other combinations of kernel functions and optimum bandwidth. The optimum bandwidth used in the model with the fixed gaussian weighting function is 189.406, which means that there are approximately 189 nearest neighbors (districts/cities) that significantly affect a district/city.

The goodness of fit test was then conducted to determine whether the GWR model was better in estimating the percentage of multidimensional energy poor households compared to the multiple linear regression model. The following are the results of the goodness of fit test:

Tabel 7. ANOVA of GWR model.

Source of Variation	SS	df	MS	Calculated F
Global Residuals	119396.291	505.000		
GWR Improvement	98464.829	189.590	519.357	
GWR Residuals	20931.462	315.410	66.363	7.826

Based on table 7, the calculated F statistical value is 7.826. The calculated statistical value is greater than $F_{\alpha(\frac{v_1^2}{v_2};\frac{\sigma_1^2}{\sigma_2})}$ or $F_{0,05(189,590;314,410)}$ which is 1.235. Then the decision obtained is to reject H_0. From this decision, it is concluded that with a significance level of 5%, the GWR model is better than the multiple linear regression model in explaining the relationship between the percentage of multidimensional energy-poor households and the variables that influence it.

To see whether the influence of an independent variable has a diverse effect on each district/city, local parameter variation testing was conducted. An independent variable has spatial heterogeneity if the resulting difference of criterion is negative. Conversely, if the resulting difference of criterion is positive, then the independent variable is global. The following is the difference of criterion value of each independent variable:

Tabel 8. Test results of local parameter variation.

Variable	Difference of Criterion
Intercept	-3884.608
Ln Expenditure Per Capita	-2940.120
Percentage of Male Household Heads	-1.242
Percentage of Household Heads Ages 60 Years and Above	10.887
Percentage of Working Household Heads	-4.758
Percentage of Household Heads with High School Education and Above	-1426.412
Percentage of Villages with Rural Status	4.774
Percentage of Villages that are Far from Growth Centers	9.043
Percentage of Villages with Majority Asphalt Roads	-404.350

Based on table 8, there are five independent variables that have negative difference of criterion values, namely ln expenditure per capita, percentage of male household heads, percentage of working household heads, percentage of household heads with high school education and above, and percentage of villages with majority asphalt roads. These results show that the five independent variables significantly have or local heterogeneity on the percentage of multidimensional energy poor households in districts/cities in Indonesia. There are also three independent variables that have a positive difference of criterion value, namely the percentage of household heads aged 60 years and above, the percentage of villages with rural status, and the percentage of villages far from the growth center. This shows that the three independent variables are global in nature to the percentage of multidimensional energy poor households in districts/municipalities in Indonesia.

The regression equation generated by the GWR method is local and varies between regions so that this study will produce a total of 514 regression equations that correspond to the number of analysis units covered. Next, partial testing of regression parameters is carried out which aims to determine which independent variables have a significant effect on the percentage of multidimensional energy poor households in each district/city in Indonesia in 2021. The decision will reject H_0 if calculated statistical value $|t| > t_{\left(1-\frac{\alpha}{2};\frac{\delta_1^2}{\delta_2}\right)}$ or $t_{(0.975;315.410)}$ and it can be concluded that there is a significant effect of the independent variable on the dependent variable at the 5% significance level.

From the results of the partial testing of parameters, we obtained groups of regions with the same significance of variables. Figure 10 shows the distribution of these groups visually. Regions with the same significant variables are grouped into one color in the thematic map. This resulted in 66 groups of districts/cities. These results can be taken into consideration that each district/city has its own multidimensional energy poverty causal factors so that the government needs to implement policies based on the influential aspects in the region.

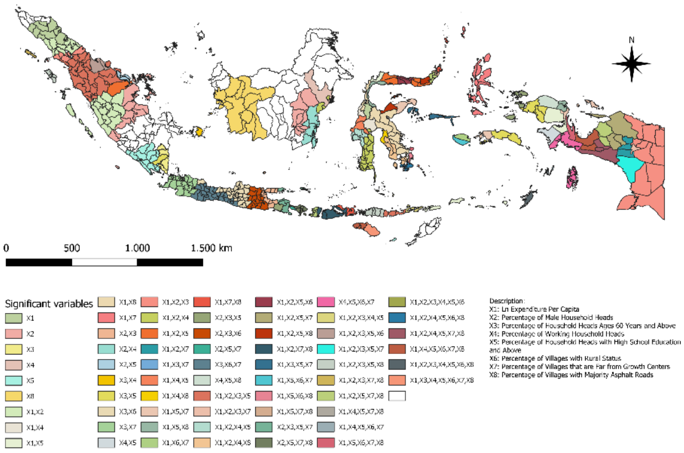
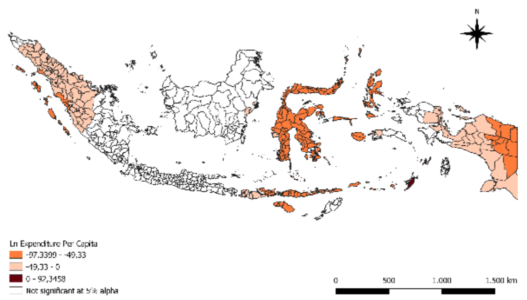


Figure 10. Significance map of variables affecting the percentage of multidimensional energy-poor households.

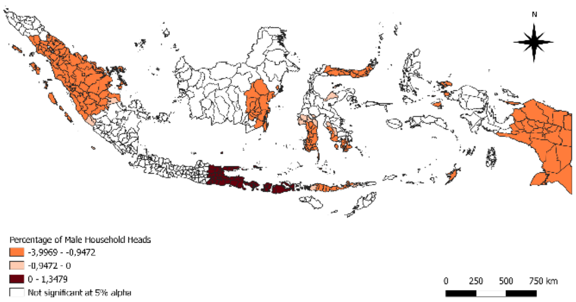
In figure 10, it can be seen that adjacent areas tend to have the same variable significance, marked by the same color around adjacent areas. The group with the most districts/cities is the group of regions with variables that significantly affect the percentage of multidimensional energy poor households, namely the percentage of household heads aged 60 years and above and the percentage of rural villages. This group consists of 32 districts/cities. There are also two regions that have the most variable significance, namely Kabupaten Maluku Tenggara for all independent variables except the percentage of villages far from the growth center and Kabupaten Sumba Timur for all independent variables except the percentage of male household heads. These results indicate that these two districts need special attention in all aspects of the economy, social, demography, and infrastructure in an effort to alleviate multidimensional energy poverty.

There is also a group of 69 districts/cities where all independent variables do not significantly affect the percentage of multidimensional energy poor households. The districts/cities in this group are spread across Sumatra Island, East Nusa Tenggara Province, and Kalimantan Island. Most of the districts/cities in this group have a low percentage of multidimensional energy-poor households.

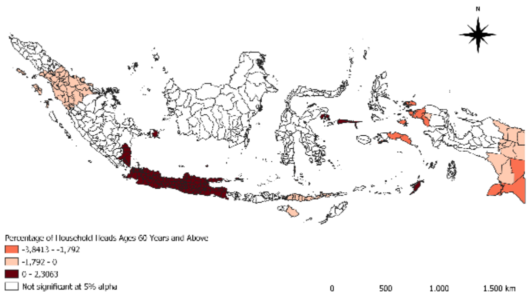
4.2.6. Coefficient Estimation of Independent Variables in GWR model



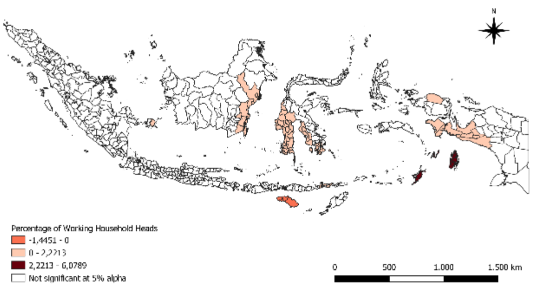
(a)



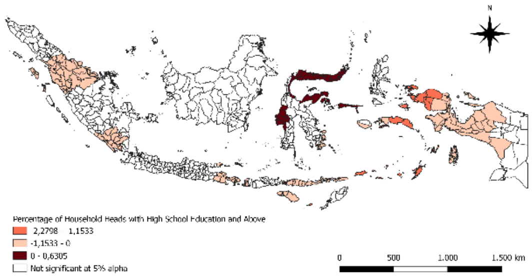
(b)



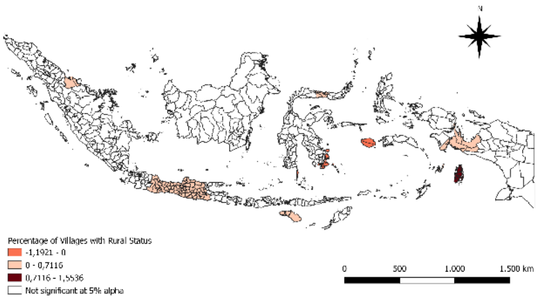
(c)



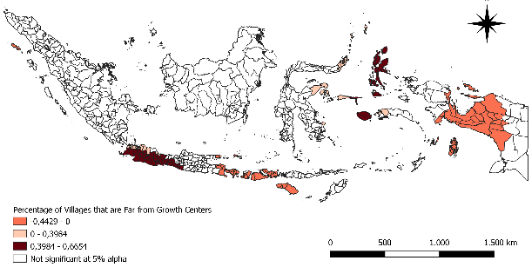
(d)



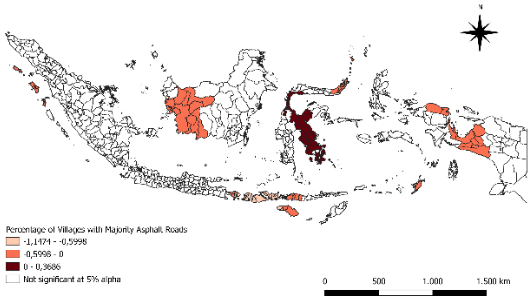
(e)



(f)



(g)



(h)

Figure 11. Local variable coefficient estimates for: a) ln per capita expenditure, b) percentage of male household heads, c) percentage of household heads aged 60 years and above, d) percentage of employed household heads, e) percentage of household heads with high school education and above, f) percentage of villages with rural status, g) percentage of villages far from growth centers, and h) percentage of villages with majority asphalt roads.

When viewed based on the coefficient estimates of each variable, figure 11 (a) shows that the per capita expenditure variable has a significant effect on multidimensional energy poor households in 243 districts/cities. There are 240 regions with negative significance, which means that any growth in per capita expenditure in a household will reduce the percentage of multidimensional energy poor households in the region. This finding is in line with [15] who found that higher total household expenditure will reduce the multidimensional energy poverty score. This finding also confirms the energy ladder theory, that households will switch to using modern energy as their income increases. The negative effect of per capita expenditure on the percentage of multidimensional energy poor households tends to be spread across most of Sumatra Island and Eastern Indonesia.

There are only 3 regions in Maluku Province that have positive significance in the per capita expenditure variable, namely Southeast Maluku, Tual, and West Southeast Maluku. This indicates that growth in per capita expenditure has not been able to increase the ability of households to meet basic energy needs in the region. This phenomenon can also be explained by the expenditure patterns of households from these regions. Given that per capita expenditure consists of food and non-food expenditure, consumption of modern energy services is recorded in non-food expenditure. Based on the March 2021 Susenas data, the percentage of per capita expenditure per month on food in some districts/cities in Maluku is higher than the percentage of non-food expenditure, such as in West Maluku Tenggara District which reached 54.49 percent and an increase from 53.47 percent in 2020. The same thing was experienced by Southeast Maluku Regency with the percentage of per capita food expenditure increasing from 48.88 percent in 2020 to 50.18 percent in 2021. This implies that the increase in household per capita expenditure tends to come from increased expenditure on food, not on consuming energy services.

In various studies that include aspects of household demographics, the influence of gender can be in either a positive or negative direction. Figure 11 (b) shows that the percentage of male household heads has a significant influence on the percentage of multidimensional energy poor households in 235 districts/cities in Indonesia. There are 185 regions with negative significance, which means that any increase in the percentage of male household heads will reduce the percentage of multidimensional energy poor households in the region. This finding is in line with research [15] which found that households with male household heads tend to have lower multidimensional energy poverty scores. This could be due to the high poverty rate of women, which limits access to modern energy services [10]. The negative effect in general tends to be spread across several regions of Sumatra Island and Eastern Indonesia.

There are 50 regions that have positive significance on the percentage of male household heads which tend to be scattered in the provinces of East Java, Bali, and West Nusa Tenggara. This means that any increase in the percentage of male household heads will increase the percentage of multidimensional energy poor households in the region. This finding is in line with [28] who found that male-headed households are more likely to be multidimensionally energy poor than female-headed households.

As with the gender of the household head, age can also have an opposite effect on the energy poverty of a household. Figure 11 (c) shows that the percentage of household heads aged 60 years and above has a significant influence on the percentage of multidimensional energy poor households in 204 districts/cities in Indonesia. There are 71 regions with negative significance, which means that every increase in the percentage of household heads aged 60 years and above will reduce the percentage of multidimensional energy poor households in the region. This finding is in line with [28] who found that the older the household head, the lower the chance of a household experiencing multidimensional energy poverty. The negative effect tends to be spread across Eastern Indonesia and some areas of Sumatra Island.

Then there are 132 regions that have a positive significance on the percentage of household heads aged 60 years and over which tends to be spread in the provinces of Lampung, Banten, Bangka Belitung Islands, Java Island, and some in Maluku and Central Sulawesi. This means that any increase in the percentage of household heads aged 60 years and over will increase the percentage of multidimensional energy poor households in the region. This finding is in line with research by Nasution [9]; Adeyonu *et al*. [15]; and Widyastuti and Hartono [26] which found that an increase in the age of the household head will increase the chances of a household experiencing multidimensional energy poverty.

Another social aspect that is thought to affect the energy poverty condition of households is the percentage of working household heads. Figure 11 (d) shows that the percentage of working household heads has a significant influence on the percentage of multidimensional energy poor households in 68 districts/cities in Indonesia. There are only 4 regions with negative significance, which means that any increase in the percentage of working household heads will reduce the percentage of multidimensional energy poor households in the region. This finding is in line with research by Widyastuti and Hartono [26] which found that a working household head can reduce the chances of a household experiencing multidimensional energy poverty. Research by Ogwumike and Ozughalu [16] also found that the more household members who work, the less likely a household is to experience multidimensional energy poverty. Regions with negative significance are seen in several districts/cities of East Nusa Tenggara, namely Southwest Sumba, Central Sumba, East Sumba, and West Sumba.

There are 64 regions with positive significance on the percentage of working household heads, which tend to be spread across Eastern Indonesia. The relationship means that any increase in the percentage of working household heads will increase the percentage of multidimensional energy poor households in the region. This can be caused by the fact that the jobs they get have not been able to provide enough income to get them out of poverty, which makes it difficult to fulfill the basic needs of the household [29]. A strong positive effect is seen in the districts of Maluku Tenggara Barat, Tual, Maluku Tengah, Aru Islands Regency, and Tambrauw.

In the energy ladder theory, the choice of energy service consumption will follow the household income condition, which can be signaled by the education level of the household head. The level of education will usually affect the amount of one's wage. Figure 11 (e) shows that the percentage of household heads with high school education and above has a significant influence on the percentage of multidimensional energy poor households in 161 districts/cities in Indonesia. There are 130 regions with negative significance, which means that any increase in the percentage of household heads with high school education and above will reduce the percentage of multidimensional energy poor households in the region. This finding is in line with [28] and [7] who found that the higher education of the household head will reduce the chance of a household experiencing multidimensional energy poverty. The negative effect is spread across several regions in Eastern Indonesia such as Nusa Tenggara Sulawesi Island, Maluku, Papua and several regions in Western Indonesia such as North Sumatra Province, Riau, Lampung, East Java, and Bali.

Then there are 31 regions with positive significance in the percentage of household heads with high school education and above which tend to be scattered in the Sulawesi Island region such as North

Gorontalo Regency, Gorontalo, Boalemo, Gorontalo City, Bone Bolango, and others. This means that any increase in the percentage of household heads with senior high school education and above will increase the percentage of multidimensional energy poor households in the region. This phenomenon can occur due to the mismatch between available job opportunities and the competencies of job applicants. When job opportunities are not able to accommodate all prospective workers, they will prefer to wait for jobs that match their competencies, which can increase the unemployment rate [30]. For example, in North Sulawesi Province itself, the number of people aged 15 years and over with at least a high school education who are unemployed is 61,177 people, but the number of unemployed people with junior high school education and below is only 24,363 people. With the unemployment of the household head, household income also decreases, which can result in limitations in the fulfillment of modern energy services.

Demographic aspects other than gender and age that are thought to affect household energy poverty are regional status. Figure 11 (f) shows that the percentage of villages with rural status has a significant influence on the percentage of multidimensional energy poor households in 101 districts/cities in Indonesia. There are only 10 regions with negative significance, which means that any increase in the percentage of rural villages will reduce the percentage of multidimensional energy-poor households in the region. Negative significance can be seen in several areas of Southeast Sulawesi, South Sulawesi and Maluku provinces such as Central Buton, North Buton, Konawe Islands, Baubau and others. This can be explained because the characteristics of the ten regions with negative significance tend to have a fairly high percentage of rural areas with a not too high percentage of multidimensional energy-poor households. This causes the high percentage of rural areas to not necessarily worsen the condition of multidimensional energy poverty in these districts/cities.

There are 90 areas with positive significance in the percentage of rural villages that tend to be spread across Java Island as well as several areas of Riau Province, East Nusa Tenggara, Maluku, and Papua. This means that any increase in the percentage of rural villages will increase the percentage of multidimensional energy-poor households in the region. This finding is in line with research [9] that found the tendency for household energy poverty in rural areas to be much greater than in urban areas. A strong positive effect was observed in Aru Islands and Dogiyai districts.

Furthermore, in terms of infrastructure, the distance of an area from the growth center is thought to affect the condition of household energy poverty. Areas that are far from growth centers tend to have low accessibility, making it difficult for residents to access basic services, including energy. Figure 11 (g) shows that the percentage of villages far from the growth center has a significant influence on the percentage of multidimensional energy poor households in 136 districts/cities in Indonesia. There are only 52 regions with negative significance, which means that any increase in the percentage of villages far from the growth center will reduce the percentage of multidimensional energy-poor households in the region.

Negative significance is seen in several areas of Aceh Province, East Java, Bali, Nusa Tenggara Island, Maluku, and parts of Papua Island such as North Lombok District, Klungkung, Buleleng, and others. This indicates that the distance to growth centers is less of an obstacle to accessing basic services in these areas and more about how the economic infrastructure can be spread to remote areas. For example, the provinces of Bali and East Java tend to have a large number of economic facilities such as minimarkets/supermarkets and markets. BPS data shows that the number of minimarkets/supermarkets owned by the provinces of East Java and Bali are 8,375 and 2,972 places in 2021, respectively.

Positive significance can also be seen in 84 regions which tend to be spread across Java, Sulawesi and Maluku. This means that any increase in the percentage of villages far from the growth center will increase the percentage of multidimensional energy poor households in the region. This finding is in line with research by [31] which found that the tendency for households to be multidimensionally energy poor is much greater if the households have a long distance to the nearest group of shops. A strong positive influence is seen in the districts of Pangandaran, Tasikmalaya, Garut, Sukabumi, and other regions.

Another aspect of infrastructure that can be seen is roads, which are one of the economic infrastructures. The limited supply of modern energy due to poor regional infrastructure forces households to use a variety of fuels and switch to firewood collected from nearby neighborhoods [21]. Figure 11 (h) shows that the percentage of villages with mostly asphalt roads has a significant influence on the percentage of multidimensional energy poor households in 94 districts/cities in Indonesia. There are 69 regions with negative significance, which means that any increase in the percentage of villages with majority asphalt roads will reduce the percentage of multidimensional energy poor households in the region. The strong negative effect tends to be spread across the provinces of Bali, West Nusa Tenggara, and several regions of East Nusa Tenggara such as West Sumbawa, Central Lombok, Sumbawa, East Lombok, and other regions.

Then there are 26 regions with positive significance that tend to be scattered in the Sulawesi Island region, especially Central Sulawesi and 1 Central Kalimantan region. This means that any increase in the percentage of villages with mostly asphalt roads will increase the percentage of energy-poor households in multidimensional regions. This phenomenon can occur due to a mismatch in the additional length of roads and the quality of existing road conditions in the region [32]. Data from the Ministry of Public Works and Housing Indonesia shows that only 29.61 percent of national roads in Central Sulawesi Province were in good condition in 2021. This condition will certainly hamper the distribution process and other economic activities. Similarly, the percentage of villages with mostly asphalt roads is not significant to the percentage of multidimensional energy poor households in most districts/cities in Indonesia.

5. Conclusions

Based on the results of the analysis and discussion, the condition of energy poverty in Eastern Indonesia tends to be more worrying. Then from the modeling with GWR, it is found that the variables that affect the percentage of multidimensional energy poor households in districts/cities in Indonesia in 2021 are per capita expenditure, percentage of male household heads, percentage of households aged 60 years and over, percentage of employed household heads, percentage of households with high school education and above, percentage of villages with rural status, percentage of villages far from growth centers, and percentage of villages with majority asphalt roads. Most of the percentage of multidimensional energy poor households in districts/cities in Indonesia is influenced by per capita expenditure. In addition, the level of influence of the independent variables vary across districts/cities as consequence of spatial heterogeneity in the data.

The suggestions proposed by researchers for government policy implications and for further research are that the government needs to consider spatial aspects in the implementation of multidimensional energy poverty alleviation because the factors that cause energy poverty can be different in each region. The government also needs to adjust the policies to be taken by looking at the relationship of the independent variables to energy poverty in a region because the level of influence of the independent variables on energy poverty is different for each region. It is hoped that this can help the government make policies that are right on target in overcoming the inequality of energy poverty in Indonesia. Providing access to modern energy services must also take into account all aspects of the economic, social, demographic and infrastructure aspects of a region. Energy subsidies such as LPG and electricity should be prioritized for low-income and poor communities. At the same time, the government needs to develop regional infrastructure such as the availability of proper energy distribution facilities, public transportation facilities, and roads in order to increase community accessibility to modern energy services. For future research, it is expected to include other variables, especially from the infrastructure aspect, such as the availability of groups of shops, travel time from the nearest market/supermarket, availability of telecommunication facilities, and the presence of other facilities and infrastructure.

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