# SPATIAL ECONOMETRIC ANALYSIS OF ENERGY ACCESS INEQUALITIES IN AFRICA USING PANEL DATA

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**Abstract**:

This paper examines energy access inequalities in Africa during the Covid-19 pandemic and the role of innovative public policies in reducing poverty and promoting sustainable development. The study was conducted using a spatial econometric panel data methodology to compare trends across countries. The data set includes socio-economic indicators from the World Bank databases, such as Gross Domestic Product, Government Final Consumption Expenditure, Employment-to-Population Ratio, Primary School Enrollment Rate, Poverty Rate at 2.15 dollars a day, and Gini Index. The dependent variable is Access to Electricity. The results show that the GDP growth rate and the final consumption expenditure of public administrations have a negative and positive effect on access to electricity respectively. Additionally, the poverty rate, the Gini index, the employment-to-population ratio, and the primary school enrollment rate all have a significant effect on access to electricity. The Hausman test showed that the fixed-effects SDM model was the optimal model. The results suggest that African governments should consider the importance of public policies to reduce inequalities and poverty, and create decent job opportunities in order to improve access to energy in the continent.

**Keywords:** energy access inequalities; spatial econometric; panel data methodology; public policies; Hausman test; fixed-effects SDM model

## INTRODUCTION

Access to energy is a key issue for African countries. Poverty and inequality are two of the main problems that have prevented the continent from developing. The Covid-19 pandemic has exacerbated this situation, exacerbating poverty and inequality. To support sustainable development and create decent jobs for African populations, innovative public policies play a crucial role. Access to energy is a key factor for sustainable development and the creation of decent jobs for African populations (Belaïd, 2022 ; Fagbemi, 2021 ; De Groot and Lemanski, 2021).

Unfortunately, the Covid-19 pandemic has hindered African households' access to energy, leading to inequalities that could have detrimental social and economic consequences for the continent. It is therefore necessary for African countries to put in place innovative and sustainable public policies to support the continent's economic and social development and reduce inequalities and poverty. These policies should encourage access to energy and provide decent jobs for the population. (Van Barneveld et al, 2020 ; Hamann et al, 2020 ; Mupatsi, 2020).

One of the solutions to address these inequalities and poverty is access to affordable and clean energy sources. For example, technologies such as solar energy, hydroelectricity, and wind energy can contribute to providing African populations with sustainable and affordable energy supply. In addition, innovative technologies such as micro-grids and off-grid energy systems can enable African populations to access clean and affordable energy. These technologies can also help to create decent jobs for the most vulnerable people (Quitzow, 2016 ; Niyibizi, 2015).

In addition, training, awareness, and entrepreneurship support programs can also help to reduce poverty and make energy access affordable for all. These programs can help to promote the creation of innovative energy access-focused businesses and encourage the integration of clean and affordable technologies into rural communities. Furthermore, these programs can help to create decent jobs and strengthen the capacity of rural communities to access energy technologies that can help reduce poverty and combat inequalities (Ban, 2016).

This paper focuses on inequalities in energy access in Africa and the innovative public policies that can help reduce poverty and inequalities in Africa in the era of COVID-19. To conduct this paper, we used a spatial econometric panel data methodology that allowed us to compare trends across countries on the continent.

By analyzing energy consumption data and socio-economic indicators to determine that access to energy is unevenly distributed in Africa and the role of innovative public policies in reducing poverty and inequalities and creating decent job opportunities in Africa.

To do this, this paper is divided into four sections. Section I present a literature review on inequalities in energy access in Africa and innovative public policies. Section II describes the methodology used. Section III presents the data and variables. Finally, the results are analyzed in Section IV.

## I. **Literature Review**

Access to energy is a major concern for developing countries, particularly in Africa. The disparities in access to energy in Africa are very large and this is even more troubling when looking at the figures on access to electricity and the use of cleaner fuels. These disparities between different countries and different population groups are crucial for social and economic development and access to basic services such as education and healthcare. The literature review on energy inequalities in Africa and innovative public policies focuses on the different obstacles to energy access in developing countries and ways to overcome them. In this context, Dika Elokan (2021) explored the role of electricity in development in Africa. He looked at how access to electricity is linked to income growth, improved working conditions, and improved living conditions. He also examined the role played by different factors, including electricity prices, economic policies, and foreign investment, in implementing cost-effective electricity solutions. The aim is to understand how access to electricity can contribute to economic growth and sustainable development in Africa.

Furthermore, Krupa and Burch (2011) showed how South Africa can benefit from the renewable energy movement by adopting policies that, if sufficiently funded and politically supported. The authors conducted interviews with key informants and examined the obstacles and opportunities for transitioning to low-carbon renewable energy in South Africa. They argue that the majority of the stakeholders consulted prefer the development of a renewable energy manufacturing cluster, rather than the three other policies suggested by the authors. The results of the study suggest that South Africa can approach the future of renewable energy with optimism, knowing that there are still challenges to be faced.

Additionally, Sokona et al. (2012) studied ways to improve access to energy in Africa. They looked at various strategies to promote wider and better access to energy and discussed the implications of the energy transition for national energy systems in Africa. The aim is to define ways to promote wider and better access to energy in Africa and to analyze the implications of the energy transition for national energy systems in Africa.

Moreover, Chivanga (2023) focused on inequalities in access to energy in informal settlements in South Africa. She examined the impacts of inequalities in access to energy on the living conditions of people living in these settlements and explored ways to promote equity in access to energy. She also looked at how political, economic, and social systems, as well as non-governmental initiatives, can be used to improve access to energy for people living in informal settlements. Her main goal is to discuss policies and initiatives that can be put in place to ensure that all people have equitable access to energy.

Davidson and Mwakasonda (2004) examined access to electricity for the poor in South Africa and Zimbabwe. They explored how access to electricity can contribute to reducing poverty and improving the quality of life of the inhabitants of both countries. They also discussed policies and strategies to improve access to electricity for the poor. The authors believe that access to electricity can be a powerful tool to improve the economic and social well-being of the poor in South Africa and Zimbabwe. They concluded that new strategies are needed to improve access to electricity and promote social inclusion of the poor populations.

Plagerson (2023) examined public policies in the context of social development in South Africa. He was particularly interested in issues of poverty, inequality, and social exclusion and their integration into major social development programs. He analyzed the nature and content of public policies, focusing on how they help to better understand and respond to problems of poverty, inequality, and social exclusion in South Africa. He also discussed the challenges the country is facing and the strategies that can be adopted to address these issues. His aim was to provide an overview of how South Africans approach problems of poverty, inequality, and social exclusion and to contribute to the implementation of effective policies to face these challenges.

Casati et al. (2013) provided a multidimensional analysis of the social considerations of access to clean electricity in Sub-Saharan Africa (SSA). They examined the main social dimensions of access to clean electricity and identified the most suitable SSA countries for financing and implementing decentralized renewable energy systems and highlighted the opportunities for improving social conditions through clean electrification. They developed a Social Access to Clean Energy (SACE) index, which captures the state of social factors such as health, education, economic development, gender equality, and quality of life related to access to electricity. They also examined the synergies between access to electricity and social development, as well as the progress of these synergies over time.

Jean T. (2023) reviewed the effect of unequal access to water and electricity on homicide rates. He used panel data on homicide rates and inequalities for a sample of 21 Sub-Saharan African countries over the period 2000-2015, based on information from the United Nations World Crime Survey, World Bank data, and Global Development Indicators, to analyze the effect of inequalities on intentional homicides. An integrated climate model incorporating inequalities is estimated using the grouped OLS method and the DCM method. These estimators take into account the country-specific unobserved effects, the joint endogeneity of some of the explanatory variables, and the presence of certain types of measurement errors affecting the homicide data. He showed that inequalities in access to water and electricity increase intentional homicide rates. Furthermore, he conducted a long-term fixed-effects analysis, the results showed that inequalities in access to water and inequalities in access to electricity will increase the larger and more robust coefficients of intentional homicide rates if governments do not adopt better strategies.

In conclusion, energy disparities in Africa are very significant and innovative public policies are needed to ensure local population access to basic services such as education and health. Studies on energy inequalities in Africa and innovative public policies have focused on various obstacles to energy access and ways to overcome them. Access to electricity is associated with income growth, better working conditions, and improved living conditions. Moreover, economic policies and foreign investments are needed to promote access to electricity and transition to low-carbon renewable energy. Studies on energy access inequalities in South Africa's informal settlements, access of the poor to electricity, and South Africa's public policies for social development have also been reviewed. They highlighted the importance of public policies to reduce inequalities and improve access to energy and social well-being of the poor population. Finally, access to water and electricity is essential to reduce homicide rates and improve the security of the African population.

## II. **Methodology**

The use of spatial econometrics on panel data is one of the most effective methods for studying questions of energy access inequalities and public policies. It can help to examine the impact of public policies on energy access inequalities in Africa, as well as innovative policies that can help to reduce poverty and inequalities. Furthermore, the use of spatial econometrics on panel data can be very useful for understanding energy access inequalities in Africa and evaluating the effectiveness of public policies in reducing poverty and inequalities. This method can provide valuable information for the development of effective and tailored public policies for African populations. In this context, this section aims to present the theoretical framework of spatial econometrics on panel data.

Data panel is a joint observation of individual cross ( cross section), such as households, companies, regions / locations, and others at some period of time (Baltagi, 2005). Some advantages of using panel data that can control individual heterogeneity, giving data is more informative, more varied, reducing collinearity between variables, increase the degrees of freedom, and more efficient, can assess, construct and model the behavior is more complicated, the better to identify or detect and quantify simple effects which can not be done with the data traffic individuals or time series data from all the above advantages, the panel can enrich the data analysis. Panel data regression model can be written :

$$\boldsymbol{y} = \boldsymbol{\alpha} + \boldsymbol{x\beta} + \boldsymbol{u} \qquad \textbf{(1)}$$

$i = 1,2,3 \dots,$ N; $t = 1,2,3 \dots,$ T, with $i$ is a cross individual unit or object of observation and $t$ is the time series unit,$\alpha$ is a constant, $\boldsymbol{x}_{it}$ is a vector of let $k$ denote the number of explanatory variables in the individual cross $i$ to $i$, $\boldsymbol{\beta}$ is a vector of size $K \times 1$, and $\boldsymbol{y}$ is a cross individual response $i$ for the time period to- $t$ and $\boldsymbol{u}$ is a residual component model. According $(\mathrm{Baltagi}, 2005)$ , a residual component in regression panel data consist of individual effects to- $i(\mu_i)$, time effects to- t$(\lambda_t)$, and residual of individual to- t$(\lambda_t)$, and residual for indivual to- $i$, time to- t$(v_{it})$ can be written in the following equation:

$$\boldsymbol{u_{it}} = \boldsymbol{\mu_i} + \boldsymbol{\lambda_t} + \boldsymbol{v_{it}} \qquad \textbf{(2)}$$

The influence of individual specific $(\mu_i)$ show heterogeinity each individual with other individuals. Meanwhile, the specific effect of time $(\lambda_t)$ is a specific description of the time which presence the characteristics of time. Based on the assumption of residual, data panel model divided on fixed effect and random effect model. Fixed effect model suitable to observase a number N of individuals is fixed by researchers and the final conclusion is limited to the behavior of the observed data (Baltagi, 2005). The estimation of parameter uses Least Square Dummy Variable (LSDV), where coefficient $\mu_i$ is dummy variable which has different value for each individual to- $i$. The regression function of fixed effect model is:

$$\boldsymbol{Y} = \boldsymbol{D\mu} + \boldsymbol{X\beta} + \boldsymbol{v} \qquad \textbf{(3)}$$

with $\boldsymbol{\mu}$ is a vector of individual effect, $\boldsymbol{D}$ is a matrix of dummy variable sized nt × n and $\boldsymbol{v}_{it} \sim N(0, \sigma_v^2)$. Random effect model is selected randomly from large population. The model can be written in the following equation:

$$\boldsymbol{y_{it}} = \boldsymbol{\beta_{1i}} + \boldsymbol{\beta x_{it}} + \boldsymbol{u_{it}} \qquad \textbf{(4)}$$

and intercept value of individual can be written by

$$\boldsymbol{\beta_{1i}} = \boldsymbol{\beta_1} + \boldsymbol{\mu_i} \qquad \textbf{(5)}$$

The assumption of random effect model is (i) $\mu_i \sim N(0, \sigma_v^2), v_{it} \sim N(0, \sigma_v^2)$. (ii) $E(X_{it}, \mu_i) = 0$ and $E(X_{it}, v_{it}) = 0$ for all indivual to- $i$, time to- t, with $u_{it}$ is residual of observation to- $i$ on periode time to- $t$. Estimation of $\boldsymbol{\beta}$ use Generilized Least Square method.

1. **Hausman's Test**

Hausman test is used to choose between random effect with fixed effect model. This hypothesis based on difference of estimation fixed effect $(\widehat{\boldsymbol{\beta}}_{\text{fixed}})$ between random effect $(\widehat{\boldsymbol{\beta}}_{\text{random}})$. Hypothesis used on Hausman test is as follows:

$H_0: E(v_{it} \mid \boldsymbol{x}_{it}) = 0$; there is no correlation between the independent variables with residual
$H_1: E(v_{it} \mid x_{it}) \neq 0$; there is correlation between the independent variables with residual
Statistical tests used were:

$$\begin{gathered} \chi^2_{\text{hit}} = \widehat{\boldsymbol{q}}'[\text{Var}(\widehat{\boldsymbol{q}})]^{-1}\widehat{\boldsymbol{q}} \\ \widehat{\boldsymbol{q}} = \widehat{\boldsymbol{\beta}}_{\text{acak}} - \widehat{\boldsymbol{\beta}}_{\text{tetap}} \end{gathered} \tag{6}$$

The decision rejected of $H_0$ if $\chi^2_{\text{hit}} > \chi^2_{(g,a)}$ with $g$ is a number vector dimension of $\beta$ or $p < \alpha$.

## 2. Spatial Weighting Matrix

Each nonnegative matrix, $\boldsymbol{W} = (w_{ij})$ with $i, j = 1, \ldots, n$, is possible spatial weight matrix summarizing spatial relation between $n$ spatial units. Here each spatial weight, $w_{ij}$, typically reflects the "spatial influence" of $j$ on $i$. Following standard convention, be assumsed that $w_{ii} = 0$ for all $i, j = 1, \ldots, n$ or $W$ has a zero diagonal. Determination matrix weighted by the inverse of the distance is as follows:

$$\boldsymbol{W} = \begin{pmatrix} \boldsymbol{w_{11}} & \boldsymbol{w_{12}} & & \boldsymbol{w_{1n}} \\ \boldsymbol{w_{21}} & \boldsymbol{w_{22}} & \cdots & \boldsymbol{w_{2n}} \\ & \vdots & \ddots & \vdots \\ \boldsymbol{w_{n1}} & \boldsymbol{w_{n2}} & \cdots & \boldsymbol{w_{nn}} \end{pmatrix} \tag{7}$$

The following weight matrices are based on the centroid distances, $d_{ij}$ is between each pair of spatial units $i$ and $j$. Power distance weights is used as one of weight based on distance (Elhorst, 2010). There is assumed to be no diminishing effect in distance up to threshold $d$. If there are believed to be diminishing effects, then one standard approach is to assume that weights are a negative power function of distance form $w_{ij} = \frac{1}{d_{ij}}$.

## 3. Lagrange Multiplier's Test

Lagrange Multiplier's test were used to estimate the model spatial effect that contained in the data. Model spatial effect be known by a model autoregressive spatial (SAR) and spatial error models (SEM) (Anselin, 1988). Lagrange multiplier test statistic for panel data be explained as follow:

$$\begin{aligned} LM_\rho &= \frac{\left[e'(I_T \otimes W)\mathrm{Y}/\hat{\sigma}^2)\right]^2}{J} \\ LM_\lambda &= \frac{\left[e'(I_T \otimes W)\mathrm{Y}/\hat{\sigma}^2)\right]^2}{T \times T_W} \end{aligned} \tag{8}$$

with $LM_\rho$ dan $LM_\lambda$ each sequence is the Lagrange multiplier test statistics for SAR and SEM. The symbol of $\otimes$ is Kronecker multiplication, $\boldsymbol{I}_T$ is matrix identity sized on $T \times T, \hat{\sigma}^2$ is mean square residual of data panel model, $\boldsymbol{W}$ is spatial weighting matrix which is standardized sized $NT \times NT$, and $e$ is a vector of residual. Then, J and $T_W$ defined as :

$$\begin{aligned} \boldsymbol{A_1} &= (\boldsymbol{I_T W})\mathbf{X}\widehat{\boldsymbol{\beta}} \\ \boldsymbol{A_2} &= (\boldsymbol{I_{NT}} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') \\ J &= \frac{1}{\hat{\sigma}^2}[(A_1^1 A_2 A_1) + TT_w \hat{\sigma}_2] \\ T_W &= \mathrm{tr}(\boldsymbol{WW} + \boldsymbol{W}'\boldsymbol{W}) \end{aligned} \tag{9}$$

with $\boldsymbol{I}_{NT}$ is matrix identity sized on NT $\times$ NT and symbol of "tr" explain trace matrix operation. The decision rejected of $\mathrm{H}_0$ if lagrange multiplier statistic value greater than $\chi^2_{(q)}$ value with $q = 1$ ( $q$ is a number of spatial parameter) or defined by $p -$ value $< \alpha$.

## 4. Spatial Autoregressive Model (SAR)

Spatial Autoregressive Model (SAR) says that level of the dependent variable $y$ depend on the levels of $y$ in neighboring regions. This model expressed in the following equation

$$\boldsymbol{y_{it}} = \boldsymbol{\rho} \sum_{j=1}^{N} \boldsymbol{w_{ij} y_{jt}} + \boldsymbol{x_{it} \beta} + \boldsymbol{\varepsilon_{it}} \tag{10}$$

with $\rho$ is autoregressive spatial coefficient, $w_{ij}$ is spatial weighting matrix elements that have been normalized, $y_{jt}$ is responses variable on location to- $i$ and time to- $t, \boldsymbol{x}_{it}$ is vector sized on $(1, \mathrm{K})$ from explanatary variable, $\beta$ is coefficient vector $(\mathrm{K}, 1)$ from explanatory variable K. K is a number of responses variable. This model is using parameter estimation method of Maximum Likelihood Estimator/MLE (Elhorst, 2010).

## 5. Spatial Error Model (SEM)

Spatial Error Model (SEM) shows that spatial influence only comes from the residual. The formal model is:

$$\begin{aligned} \boldsymbol{y_{it}} &= \boldsymbol{x'_{it} \beta} + \boldsymbol{\phi_{it}} \\ \boldsymbol{\phi_{it}} &= \boldsymbol{\lambda} \sum_{j=1}^{N} \boldsymbol{w_{ij} \phi_{it}} + \boldsymbol{\varepsilon_{it}}, \boldsymbol{i} \neq \boldsymbol{j} \end{aligned} \tag{11}$$

with $\phi_{it}$ is a residual from spatial autocorrelation, $\lambda$ is an autocorrelation spatial coefficient. This model parameter estimation completely with the maximum likelihood function (Elhorst, (2010).

### 6. Goodness of Fit

The method of selection best model is based on Akaike 's Information Criterion (AIC). AIC developed by Hirotsugu Akaike 1974, with the following formula:

$$\boldsymbol{AIC = -2\ln(L) + 2K} \qquad \textbf{(12)}$$

with $K$ is a number of parameter on model, and $(L)$ is maximum likelihood function (Elhorst, 2010).

## III. Data and Variables Used

In this section, we will examine the data and variables used to study energy access inequalities in Africa and innovative public policies that can help reduce poverty and inequalities in Africa under the COVID-19 era. To do this, we collected data on African country socio-economic indicators from the World Bank databases. The explanatory variables included Gross Domestic Product (in current US dollars), Government Final Consumption Expenditure (% of GDP), Employment-to-Population Ratio, 15+, Total (% estimated by the International Labour Organization), Primary School Enrollment Rate (% gross), Poverty Rate at 2.15 dollars a day (PPP 2017) (% of population) and Gini Index. The dependent variable was Access to Electricity (% of population). We then applied a spatial econometric methodology to this panel data in order to compare country trends across the continent and better understand the effects of innovative public policies on energy access and poverty reduction.

The econometric model to explain energy access in Africa in the COVID-19 era can be formulated as follows:

ACEP= f (PIB, DCFI, REMP, SCPRI, TPouv, InGini)

The model can be specified using a basic econometric model expressed as follows:

$$\ln(y)_{it} = \alpha_i + \ln(x)_{it}\beta + \epsilon_{it}, i = 1, .., N, t = 1, ...., T. \qquad (13)$$

Where: ln(y) represents the logarithmic transformation of the dependent variables (access to electricity (% of the population)), $\alpha_i$denotes the fixed effects, ln(x) represents the independent variables, β denotes the coefficient estimation, ϵ is the error term, i represents the units, and t is the period.

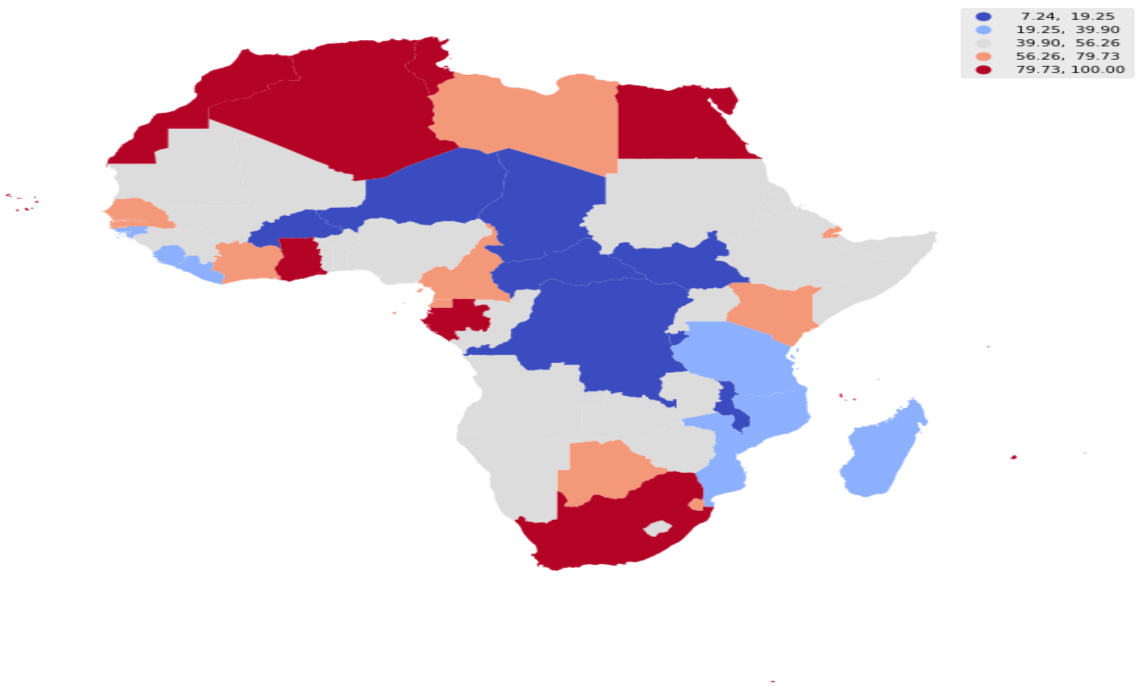
**Table 1: Variable Descriptions**

| Variable | Description | Data Source | Study period |
|---|---|---|---|
| **ACEP** | Access to electricity (% of population) | The World Bank data | 2010-2020 |
| **TXPIB** | GDP growth (annual %) | The World Bank data | 2010-2020 |
| **DCFI** | General government final consumption expenditure (% of GDP) | The World Bank data | 2010-2020 |
| **REMP** | Employment to population ratio, 15+, total (% estimated by International Labor Organization) | The World Bank data | 2010-2020 |
| **SCPRI** | Primary school enrollment rate (% gross) | The World Bank data | 2010-2020 |
| **TPouv** | The poverty rate at $2.15 a day (2017 PPP) (% of population) | The World Bank data | 2010-2020 |
| **InGini** | The Gini Index | The World Bank data | 2010-2020 |

The study is being examined in 46 African countries, namely: Burkina Faso, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Morocco, Mauritania, Senegal, Sierra Leone, Angola, Botswana, Burundi, Congo, Democratic Republic of Congo, Gabon, Kenya, Malawi, Mozambique, Namibia, Rwanda, South Africa, Tanzania, Zambia, Zimbabwe, Algeria, Benin, Cameroon, Central African Republic, Chad, Equatorial Guinea, Libya, Niger, Nigeria, Togo, Tunisia, Djibouti, Egypt, Eritrea, Ethiopia, South Sudan, Sudan, Uganda, and Somalia.

The figure below (Fig. 1 ) shows the percentage of the population with access to electricity in several African countries in 2020. It is evident that there is a great heterogeneity between the different countries. Some countries have a very high access rate to electricity, such as Morocco or Tunisia where 100% of the population has access to electricity. Other countries have much lower rates, such as South Sudan where only 7.2% of the population has access to electricity. The majority of countries that fall into this category are located in Sub-Saharan Africa, where access to electricity is limited due to lack of infrastructure and lack of funding. In sum, this figure shows that access to electricity is highly unequal in Africa. While some countries have very high access to electricity, others face significant challenges in terms of access to electricity. It is therefore important that African countries invest in infrastructure and programs that aim to improve access to electricity for all citizens.

**Fig.1: Access to electricity (% of population) in 2020 in the African continent**




The figure below (Fig.2) shows the annual percentage growth of GDP for each country in 2020. The majority of countries recorded negative growth, which can be attributed to the global COVID-19 pandemic which had negative effects on the global economy. However, there are a few countries that recorded positive growth, including Cote d'Ivoire, Guinea, Togo, and Uganda, which shows that their economies were relatively spared by the pandemic. It is interesting to note that some of the poorest and most fragile countries, such as Burkina Faso, Liberia, and Mali, recorded positive growth, indicating that their economies are recovering from the pandemic. On the other hand, the wealthiest countries, such as Morocco and Egypt, recorded negative figures, which shows that the pandemic had a negative effect on their economies.

**Fig.2: GDP growth (annual %) in 2020 in the African continent**

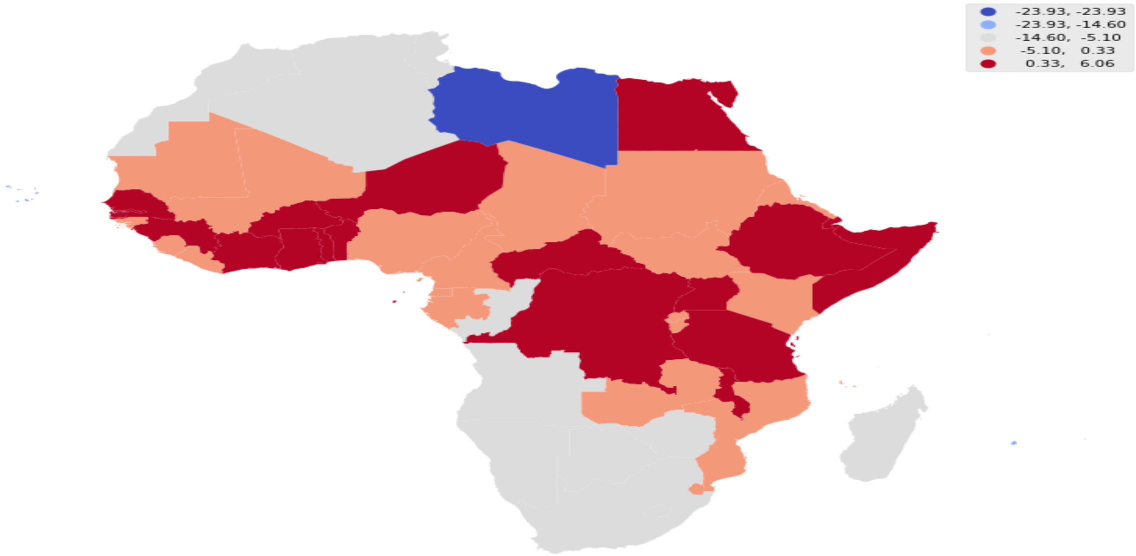



**Table 2:Descriptive analysis of variables**

| Variables | Number of observations | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| **ACEP** | 506 | 3.574377 | 0.7736564 | 0.4054651 | 4.60517 |
| **TXPIB** | 506 | 3.943284 | 0.7401675 | -12.23416 | 4.921186 |
| **DCFI** | 506 | 2.339867 | 0.9204095 | 0 | 4.040495 |
| **REMP** | 506 | 4.032264 | 0.2944128 | 3.114137 | 4.427585 |
| **SCPRI** | 506 | 3.552235 | 1.946456 | 0 | 4.998767 |
| **TPouv** | 506 | 0.4823137 | 1.231335 | -2.302585 | 4.258446 |
| **InGini** | 506 | 0.5771969 | 1.345102 | 0 | 4.149464 |

This table (Table 3) summarizes the statistical characteristics of the six main variables selected for our analysis. The variables are: access to electricity (% of population), GDP growth (% annual), final consumption expenditure of public administrations (% of GDP), employment-population ratio, 15+, total (% estimated by the International Labour Organization), primary school enrollment rate (% gross), poverty rate at 2.15 dollars per day (PPA 2017) (% of population) and Gini index. The average of each variable is between 0 and 4.9, indicating that most countries are relatively prosperous. The highest average is GDP growth (% annual) at 3.9, showing that countries have on average a high standard of living. The lowest average is poverty rate at 2.15 dollars per day (PPA 2017) (% of population) at 0.48, suggesting that poverty is relatively low. The standard deviations are also important to consider. The highest standard deviation is primary school enrollment rate (% gross) at 1.94, indicating that regions have relatively variable levels of prevalence of education. The lowest standard deviation is employment-population ratio, 15+, total (% estimated by the International Labour Organization) at 0.29, showing that the employment ratio is fairly uniform across countries. The minimum and maximum values show that countries vary considerably in terms of living standards and prevalence of poverty. The lowest minimum value is GDP growth (% annual) at -12.2, indicating that some countries are in a state of poverty. The highest maximum value is poverty rate at 2.15 dollars per day (PPA 2017) (% of population) at 4.25, showing that some countries are heavily affected by poverty. In conclusion, this table shows that the countries in the studied country vary considerably in terms of wealth and poverty. The average of the variables is relatively high, but the standard deviation and the minimum and maximum values are very variable, indicating that some countries are in a state of extreme poverty.

**Table 3: Analysis of the correlation of variables**

| | ACEP | TXPIB | DCFI | REMP | SCPRI | TPouv | InGini |
|---|---|---|---|---|---|---|---|
| **ACEP** | 1.0000 | | | | | | |
| **TXPIB** | -0.0285 | 1.0000 | | | | | |
| **DCFI** | 0.4012 | -0.0048 | 1.0000 | | | | |
| **REMP** | -0.5627 | 0.0686 | -0.2011 | 1.0000 | | | |
| **SCPRI** | 0.0064 | 0.0865 | 0.0953 | 0.1439 | 1.0000 | | |
| **TPouv** | -0.1251 | 0.0326 | -0.0664 | 0.1122 | 0.1418 | 1.0000 | |
| **InGini** | -0.0277 | 0.0321 | -0.0320 | 0.0307 | 0.1462 | 0.9203 | 1.0000 |

This table (Table 3) analyzes the correlation between different variables. We observe that the correlation between the variables is weak. For example, the Employment-to-Population Ratio, 15+, Total (% estimated by the International Labour Organization) (REMP) is slightly negatively correlated to Access to Electricity (% of population) (ACEP), meaning that the Employment-to-Population Ratio, 15+, Total (% estimated by the International Labour Organization) is weakly correlated to Access to Electricity (% of population). Similarly, Final Consumption Expenditure of Public Administration (% of GDP) (DCFI) is weakly negatively correlated to Primary School Enrollment Rate (% gross) (SCPRI). This means that the higher the Final Consumption Expenditure of Public Administration (% of GDP), the lower the

Primary School Enrollment Rate (% gross). This suggests that the variables studied are independent of each other and that the correlation between them is weak.

## IV. Results and discussions

In this section, we will present the results of the analysis of energy consumption data and socio-economic indicators to determine that access to energy is unevenly distributed in Africa and the role of innovative public policies in reducing inequalities and poverty and creating decent job opportunities in Africa. To achieve this goal, we used the methodology of spatial econometrics on panel data. In this framework, we will discuss the results of the analysis and their implications for public policies in Africa.

In this regard, the table below (Table 4) shows the intra-individual and inter-individual variations of several variables, including ACEP, TXPIB, DCFI, REMP, SCPRI, Tpouv, and InGini. The mean, standard deviation, minimum, and maximum for each variable are specified, as well as the total number of observations (N) and the number of observations between individuals (n) and the number of observations per individual (T). By analyzing this table, we can see that the mean of the variables ACEP, TXPIB, DCFI, and REMP is respectively 3.57, 3.94, 2.34, and 4.03. The mean of the variables SCPRI, Tpouv, and InGini is respectively 3.55, 0.48, and 0.58. Furthermore, the standard deviation of the variables ACEP, TXPIB, DCFI, and REMP is respectively 0.77, 0.74, 0.92, and 0.29. The standard deviation of the variables SCPRI, Tpouv, and InGini is respectively 1.95, 1.23, and 1.35. Finally, the total number of observations (N) is 506 for each variable, and the number of observations between individuals (n) and the number of observations per individual (T) is 46 and 11 respectively for each variable. The importance of this table lies in the evaluation of the heterogeneity of the different variables and in better understanding the differences between groups. It also provides valuable information on statistical analysis, particularly on tests of means and standard deviations. Furthermore, this table can help to identify variables that are not homogeneous and that might require a different analysis method.

**Table 4: Intra-individual and inter-individual variations of variables**

| Variables | | Mean | Standard deviation | Min | Max | Number of observations |
|---|---|---|---|---|---|---|
| **ACEP** | **Overall** | 3.574377 | 0.7736564 | 0.4054651 | 4.60517 | N = 506 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | **Between** | | 0.7080631 | 1.589147 | 4.56949 | n = 46 |
| | **Within** | | 0.3272897 | 1.89816 | 5.918897 | T = 11 |
| **TXPIB** | **Overall** | 3.943284 | 0.7401675 | -12.23416 | 4.921186 | N = 506 |
| | **Between** | | 0.2367842 | 2.427054 | 4.090199 | n = 46 |
| | **Within** | | 0.7020622 | -10.71793 | 6.437415 | T = 11 |
| **DCFI** | **Overall** | 2.339867 | 0.9204095 | 0 | 4.040495 | N = 506 |
| | **between** | | 0.7796053 | 0 | 3.561499 | n = 46 |
| | **Within** | | 0.5014026 | -0.4987301 | 4.99853 | T = 11 |
| **REMP** | **Overall** | 4.032264 | 0.2944128 | 3.114137 | 4.427585 | N = 506 |
| | **between** | | 0.2750019 | 3.21596 | 4.361469 | n = 46 |
| | **Within** | | 0.1120283 | 3.274337 | 4.804086 | T = 11 |
| **SCPRI** | **Overall** | 3.552235 | 1.946456 | 0 | 4.998767 | N = 506 |
| | **between** | | 1.327137 | 0 | 4.937534 | n = 46 |
| | **Within** | | 1.436063 | -0.9648533 | 7.894484 | T = 11 |
| **Tpouv** | **Overall** | 0.4823137 | 1.231335 | -2.302585 | 4.258446 | N = 506 |
| | **between** | | 0.3636351 | -0.1724655 | 1.270797 | n = 46 |
| | **Within** | | 1.177529 | -1.647806 | 4.353628 | T = 11 |
| **InGini** | **Overall** | 0.5771969 | 1.345102 | 0 | 4.149464 | N = 506 |
| | **Between** | | .3332866 | 0 | 1.298511 | n = 46 |
| | **Within** | | 1.304001 | -0.7213141 | 4.285589 | T = 11 |

The table shows (Table 5) the results of the non-spatial model used to examine the effects of several variables on electricity access (% of population). The results of this analysis show that the variables (REMP), (DCFI), (InGini) and (TPouv) are significantly related to the dependent variable (ACEP), while the variables (TXPIB) and (SCPRI) are not. The results also indicate that the F-test and R-squared index indicate that the model is statistically significant and explains 42% of the variation in electricity access (% of population). Furthermore, the results show that the highest coefficient is for DCFI at 0.24, followed by REMP at -1.28, InGini at 0.16 and TPouv at -0.20. These coefficients suggest that (DCFI) and (InGini) are positive factors for electricity access (% of population), while (REMP) and (TPouv) are negative factors. The coefficient for GDP growth (% annual) is low at 0.003 and is not significant.

**Table 5: Result of the non-spatial model**

| **Variables** | **Coefficient** | **Standard deviation** | **t** | **P>t** | **[95% conf, interval]** | |
|---|---|---|---|---|---|---|
| **TXPIB** | 0,0031156 | 0,0358179 | 0,09 | 0,931 | -0,067257 | 0,0734881 |
| **DCFI** | 0,2407263 | 0,029556 | 8,14 | 0.000 | 0,1826567 | 0,2987958 |
| **REMP** | -1,276551 | 0,0947547 | -13,14 | 0.000 | -1,462719 | -1,090384 |
| **SCPRI** | 0,020948 | 0,0139922 | 1,5 | 0,135 | -0,006543 | 0,0484389 |
| **TPouv** | -0,2000701 | 0,0561347 | -3,56 | 0.000 | -0,3103596 | -0,0897805 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **InGini** | 0,1620193 | 0,0511535 | 3,17 | 0.002 | 0,0615165 | 0,2625221 |
| **Constant** | 8,074785 | 0,4130821 | 19,55 | 0.000 | 7,26319 | 8,886379 |
| **F (6, 499)** | 60.36 | | | | | |
| **Prob > F** | 0.0000 | | | | | |
| **R-squared** | 0.4205 | | | | | |
| **Adj R-squared** | 0.4136 | | | | | |
| **Number of observations** | 506 | | | | | |

**Table 6: Fixed effects regression results**

| **Variables** | **Coefficient** | **P>t** |
|---|---|---|
| TXPIB | -0,013036 | 0,493 |
| DCFI | 0,172785 | 0.000 |
| REMP | -1,04049 | 0.000 |
| SCPRI | -0,0233548 | 0,014 |
| TPouv | -0,0464103 | 0,134 |
| InGini | 0,0322468 | 0,248 |
| Constante | 7,503753 | 0.000 |
| sigma_u | 0,54614935 | |
| sigma_e | 0,29867877 | |
| Rho | 0,76977615 | |
| F (45, 454) | 33,54 | |
| prob > F | 0.000 | |
| Within | 0,2513 | |
| Between | 0,43 | |
| Overall | 0,3943 | |
| corr(u_i, xb) | 0,1855 | |
| F (6,454) | 25.40 | |

This table (Table 6) shows the results of a fixed effects regression. The obtained coefficients are -0.013036, 0.172785, -1.04049, -0.0233548, -0.0464103, and 0.0322468, respectively. The coefficient of determination (R2) is 0.3943, which means that 39.43% of the variability of the data is explained by the fixed effects regression. The F statistic is 25.40, which means that the model significantly explains the data. The correlation coefficient between the variables is 0.1855, which suggests that the variables are weakly correlated. The estimation results show that the coefficients associated with Final Consumption Expenditure of Public Administration (% of GDP) (DCFI), Employment-population Ratio, 15+, total (% estimated by the International Labour Organization) (REMP), and Primary School Enrollment Rate (% gross) (SCPRI) are statistically significant (their respective p-value < 5%). Furthermore, the effect of

GDP Growth (% annual), Employment-population Ratio, 15+, total (% estimated by the International Labour Organization), and Poverty Rate at 2.15 Dollars a Day (PPA 2017) (% of population) on Access to Electricity (% of population) appears to be negative. Additionally, GDP Growth (% annual), Poverty Rate at 2.15 Dollars a Day (PPA 2017) (% of population), and Gini Index show, on average, a non-significant effect on Access to Electricity (% of population (p-Value > 5%). The F statistic: F (6,454) = 25.40 confirms the heterogeneity of individuals in the form of a fixed effect, since the p-value < 5%. In conclusion, the results of this table show that the model significantly explains the data and that the variables are weakly correlated.

Based on the results of the table below (Table 7), it is clear that all of the explanatory variables are statistically significant, except for TXPIB and SCPRI, which are not statistically significant. DCFI and REMP are the most significant, with P-values of 0.000. The years 2010 to 2019 are also significant, with P-values ranging from 0.007 to 0.760. The constant also has a P-value of 0.000, indicating that the model is well-fitted. The correlation between the errors and the explanatory variables is 0.2111, which is considered to be low. The results of the intra-class variance (0.3651) and between-group variance (0.4389) indicate that most of the variation is explained by the explanatory variables, rather than the errors. Additionally, the intra-class correlation coefficient (rho) is 0.79466771, which is considered to be a good correlation. In conclusion, the main components of the model are well-fitted.

**Table 7: The results of the two-way fixed effects**

| **Variables** | **Coefficient** | **P>\|t\|** |
|---|---|---|
| TXPIB | -0,0211805 | 0.236 |
| DCFI | 0.155677 | 0.000 |
| REMP | -1.001926 | 0.000 |
| SCPRI | -0,0132389 | 0.152 |
| TPouv | -0,0579829 | 0.047 |
| InGini | 0,0467 | 0.078 |
| **Year** | **Coefficient** | **P>\|t\|** |
| 2010 | -0,2084896 | 0.001 |
| 2011 | -0,1421868 | 0.018 |
| 2012 | -0,0754411 | 0.209 |
| 2013 | -0,0814166 | 0.168 |
| 2014 | -0,0377247 | 0.528 |
| 2015 | -0,0184026 | 0.760 |
| 2016 | 0,0669569 | 0.260 |
| 2017 | 0,095293 | 0.110 |
| 2018 | 0,1499411 | 0.011 |

| | | |
|---|---|---|
| 2019 | 0,1598388 | 0.007 |
| Constant | 7.390032 | 0.000 |
| F (16, 444) | 15,96 | |
| Prob>F | 0.000 | |
| Within | 0.3651 | |
| Between | 0.4389 | |
| Overall | 0.4179 | |
| corr(u_i,Xb) | 0.2111 | |
| sigma_u | 0,54715182 | |
| sigma_e | 0,27812735 | |
| Rho | 0,79466771 | |

The results from Table 8 show that the two-way fixed effects models have significantly lower regression coefficients than the non-spatial and fixed-effects models for the variables TXPIB, DCFI, REMP, and TPouv, suggesting that the two-way fixed effects models are the most appropriate. The two-way fixed effects models are also better than the other models for the InGini variable, with lower regression coefficients and significantly significant. Furthermore, the results for the constant show that the two-way fixed effects model has the lowest regression coefficient and the highest level of significance. Therefore, taking into account the statistical results, the two-way fixed effects models seem to be the best suited for the data analysis.

**Table 8: Model evaluation and selection**

| **Variables** | **Pooled OLS** | **Fixed effects regression** | **Two-way fixed effects** |
|---|---|---|---|
| TXPIB | 0.00 | -0.01 | -0.02 |
| DCFI | 0.24*** | 0.17*** | 0.16*** |
| REMP | -1.28*** | -1.04*** | -1.00*** |
| SCPRI | 0.02 | -0.02** | -0.01 |
| TPouv | -0.20*** | -0.05 | -0.06** |
| InGini | 0.16*** | 0.03 | 0.05* |
| **Year** | | | |
| 2010 | | | -0.21*** |
| 2011 | | | -0.14** |
| 2012 | | | -0.08 |
| 2013 | | | -0.08 |
| 2014 | | | -0.04 |
| 2015 | | | -0.02 |
| 2016 | | | 0.07 |
| 2017 | | | 0.10 |
| 2018 | | | 0.15** |
| 2019 | | | 0.16*** |
| Constant | 8.07*** | 7.50*** | 7.39*** |

| P<.1 ; ** p<.05 ; *** p<.01 |
|---|

The results table of the spatio-temporal fixed-effects SDM model provides a statistical analysis of the variables that help to determine the effects of the variables (TXPIB, DCFI, REMP, SCPRI, TPouv, and InGini) on electricity access (% of population). The coefficients for each variable range from -0.03 to 0.14, and their standard deviations range from 0.01 to 0.11. The Z values for each variable range from -1.39 to 5.97, and the P values range from 0.045 to 0.166. The 95% confidence intervals range from -0.11 to 0.19 for each variable. The neighborhood matrix shows similar coefficients, but the P values are lower and the confidence intervals are wider. The Rho value is -0.052, with a P value of 0.440 and a confidence interval of -0.18 to 0.08. The variance is 0.066, with a P value of 0.000 and a confidence interval of 0.058 to 0.074. Lastly, the R-Squared scores are 0.2550, 0.4505, and 0.4106 for within, between, and overall, respectively, and the log-likelihood is -30.4238. Overall, the results of the spatio-temporal fixed-effects SDM model show that the mean of the fixed effects is 9.35, suggesting that the analyzed variables contribute to some margin to the effects of the model.

From an economic perspective, the model results indicate that GDP growth has a negative effect on access to electricity, meaning that the lower the GDP growth rate, the lower the access to electricity. Final consumption expenditure of public administrations has a positive effect on access to electricity, meaning that the higher the expenditure, the higher the access to electricity. Other variables such as the employment-to-population ratio and primary school enrollment rate also have an impact on access to electricity, although their effects are significant. Furthermore, the poverty rate at 2.15 dollars per day and the Gini index also have an impact on access to electricity, but their effects are statistically significant. Finally, the results show that the neighborhood matrix has a negative effect on access to electricity, but this effect is also not significant.

**Table 9: The results of the Spatial Durbin Model (SDM) with spatial and temporal fixed effects**

| Variables | Coefficient | Standard deviation | Z | P>\|z\| | [95%conf. interval] |
|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| **Mean** | | | | | | |
| **TXPIB** | -0,023009 | 0,0165963 | -1.39 | 0.166 | -0,0555372 | 0,0095192 |
| **DCFI** | 0,1433816 | 0,0240105 | 5.97 | 0.000 | 0,0963218 | 0,1904414 |
| **REMP** | -0,9856594 | 0,1069168 | -9.22 | 0.000 | -1,195212 | -0,7761063 |
| **SCPRI** | -0,0145204 | 0,0086765 | -1.67 | 0.094 | -0,031526 | 0,0024852 |
| **TPouv** | -0,0540406 | 0,0269975 | -2.00 | 0.045 | -0,1069547 | -0,0011265 |
| **InGini** | 0,0441186 | 0,0245605 | 1.80 | 0.072 | -0,004019 | 0,0922562 |
| **Neighborhood matrix** | | | | | | |
| **TXPIB** | -0,0306897 | 0,0289964 | -1.06 | 0.290 | -0,0875216 | 0,0261422 |
| **DCFI** | -0,0896246 | 0,0464359 | -1.93 | 0.054 | -0,1806373 | 0,001388 |
| **REMP** | -0,3284571 | 0,2051464 | -1.60 | 0.109 | -0,7305367 | 0,0736224 |
| **SCPRI** | -0,0408669 | 0,0168806 | -2.42 | 0.015 | -0,0739524 | -0,0077815 |
| **TPouv** | -0,0231165 | 0,0488287 | -0.47 | 0.636 | -0,118819 | 0,072586 |
| **InGini** | 0,0282723 | 0,0417167 | 0.68 | 0.498 | -0,0534909 | 0,1100354 |
| **Spatial** | | | | | | |
| **Rho** | -0,052165 | 0,0675808 | -0.77 | 0.440 | -0,1846209 | 0,0802909 |
| **Variance** | | | | | | |
| **sigma2_e** | 0,0659975 | 0,0041514 | 15.90 | 0.000 | 0,0578608 | 0,0741342 |
| **R-sq:** | | | | | | |
| **Within** | 0.2550 | | | | | |
| **Between** | 0.4505 | | | | | |
| **Overall** | 0.4106 | | | | | |
| **Moyenne des effets fixes** | 9.3498 | | | | | |
| **Log-likelihood** | -30,4238 | | | | | |

**Table 10: Random effects results from the Spatial Durbin Model (SDM)**

| **Variables** | **Coefficient** | **Standard deviation** | **Z** | **P>\|z\|** | **[95%conf. interval]** | |
|---|---|---|---|---|---|---|
| **Mean** | | | | | | |
| **TXPIB** | -0,0115954 | 0,0182931 | -0.63 | 0.526 | -0,0474493 | 0,0242585 |
| **DCFI** | 0,1689935 | 0,0257656 | 6.56 | 0.000 | 0,1184938 | 0,2194932 |
| **REMP** | -1,047821 | 0,1115553 | -9.39 | 0.000 | -1,266465 | -0,8291763 |
| **SCPRI** | -0,0126063 | 0,009286 | -1.36 | 0.175 | -0,0308065 | 0,005594 |
| **TPouv** | -0,0531102 | 0,0298583 | -1.78 | 0.075 | -0,1116314 | 0,005411 |
| **InGini** | 0,0396525 | 0,0269243 | 1.47 | 0.141 | -0,0131182 | 0,0924232 |
| Constante | 6,859293 | 0,9888761 | 6.94 | 0.000 | 4,921132 | 8,797455 |
| **Neighborhood matrix** | | | | | | |
| **TXPIB** | 0,0110856 | 0,0302805 | 0.37 | 0.714 | -0,0482631 | 0,0704343 |
| **DCFI** | -0,0512934 | 0,0483288 | -1.06 | 0.289 | -0,1460162 | 0,0434293 |
| **REMP** | 0,0146917 | 0,2072223 | 0.07 | 0.943 | -0,3914565 | 0,42084 |
| **SCPRI** | -0,0391566 | 0,016545 | -2.37 | 0.018 | -0,0715842 | -0,0067289 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **TPouv** | 0,0240096 | 0,0522625 | 0.46 | 0.646 | -0,0784231 | 0,1264423 |
| **InGini** | -0,0210122 | 0,0435009 | -0.48 | 0.629 | -0,1062724 | 0,064248 |
| **Spatial** | | | | | | |
| **Rho** | 0,2190442 | 0,05695 | 3.85 | 0.000 | 0,1074243 | 0,330664 |
| **Variance** | | | | | | |
| **lgt_theta** | -1,627634 | 0,1335053 | -12.19 | 0.000 | -1,889299 | -1,365968 |
| **sigma2_e** | 0,0826591 | 0,0054938 | 15.05 | 0.000 | 0,0718915 | 0,0934268 |
| R-sq: | | | | | | |
| **Within** | 0.2679 | | | | | |
| **Between** | 0.4399 | | | | | |
| **Overall** | 0.4042 | | | | | |
| **Log-likelihood** | -173,5597 | | | | | |

The table above provides a spatial and statistical analysis of the random effects of the SDM model on various variables selected for our analysis. The results indicate that the coefficient of GDP growth was negative (-0.0115954), suggesting that an increase in GDP growth has no significant effect on access to electricity. The coefficients of the other variables are all positive, suggesting that an increase in these variables has a positive effect on access to electricity. Regarding the neighborhood matrices, the results show that all variables have no significant effect on access to electricity. Finally, the R-squared results show that the prediction of all variables is 40.42%, indicating that the model is relatively accurate. The log-likelihood is -173.5597, suggesting that there is a correlation between the variables.

**Table 11 : Hausman test results**

| **Variables** | **(b)** SDM à effets fixes | **(B)** SDM à effets aléatoires | **(b-B)** Difference | **sqrt(diag(V_b-V_B)) Std.err.** |
|---|---|---|---|---|
| | comp1 | | | |
| **TXPIB** | -0,023009 | -0,0115954 | -0,0114136 | |
| **DCFI** | 0,1433816 | 0,1689935 | -0,0256119 | |
| **REMP** | -0,9856594 | -1,047821 | 0,0621613 | |
| **SCPRI** | -0,0145204 | -0,0126063 | -0,0019141 | |
| **TPouv** | -0,0540406 | -0,0531102 | -0,0009304 | |
| **InGini** | 0,0441186 | 0,0396525 | 0,004466 | |
| | comp2 | | | |
| **TXPIB** | -0,0306897 | 0,0110856 | -0,0417753 | |
| **DCFI** | -0,0896246 | -0,0512934 | -0,0383312 | |
| **REMP** | -0,3284571 | 0,0146917 | -0,3431489 | |
| **SCPRI** | -0,0408669 | -0,0391566 | -0,0017104 | 0,0033493 |
| **TPouv** | -0,0231165 | 0,0240096 | -0,0471261 | |
| **InGini** | 0,0282723 | -0,0210122 | 0,0492844 | |

| | | | | |
|---|---|---|---|---|
| comp3 | | | | |
| **Rho** | -0,052165 | 0,2190442 | -0,2712092 | 0,036385 |
| chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 26,03 | | | | |
| Prob > chi2 = 0,0168 | | | | |

This table shows the results of the Hausman test, which is a statistical test used to determine if the explanatory variables in a model are fixed or random. The results show that the explanatory variables comp1, comp2, and comp3 have significantly different results between the two models, the fixed-effects SDM and the random-effects SDM. It compares the fixed-effects and random-effects models for the three components. The (b) column is the coefficient estimated by the fixed-effects model and the (B) column is the coefficient estimated by the random-effects model. The (b-B) column is the difference between the two coefficients. The sqrt(diag(V_b-V_B)) column is the square root of the diagonal of the variance-covariance matrix of the differences between the two coefficients. Finally, the Std.err column is the standard error of the difference between the two coefficients. The result of the Hausman test is that the fixed-effects SDM model is the optimal model. This is determined by calculating the chi2. In this case, the chi2 is 26.03 and the probability is 0.0168, which is less than 0.05, suggesting that the fixed-effects SDM model is statistically significant compared to the random-effects SDM model.

## Conclusion

In conclusion, this paper has explored the inequalities in energy access in Africa and the innovative public policies that can help reduce poverty and inequalities. Through the use of spatial econometric panel data, this paper revealed the uneven distribution of energy consumption in Africa, as well as the role of public policies in reducing poverty and creating decent job opportunities. In addition, this paper provided evidence that innovative public policies can help to promote the integration of clean and affordable energy technologies into rural communities. As a result, this paper has provided valuable insight into the issue of energy access in Africa and the potential for public policies to reduce poverty and inequality.

Overall, this analysis of energy access inequalities in Africa using spatial econometrics on panel data has produced significant results. It has been found that the GDP growth rate and the final consumption expenditure of public administrations have a negative and positive effect on access to electricity respectively. Moreover, the poverty rate, the Gini index, the employment-to-population ratio, and the primary school enrollment rate also have a significant effect on access to electricity. The results of the Hausman test show that the fixed-effects SDM model is the optimal model, with a chi2 of 26.03 and a probability of 0.0168, which is less than 0.05. These results suggest that governments in Africa should take into consideration the importance of public policies to reduce inequalities and poverty, and create decent job opportunities in order to improve access to energy in the continent.

Finally, African governments should consider the importance of public policies to reduce inequality and poverty, and create decent job opportunities to improve access to energy on the continent. With the implementation of these policies, a more equitable distribution of power in Africa can be achieved and the continent can work towards a better future.

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