Multiscale Estimation of Electrification Rate Using Night-Time Light Imagery

Miao He, Qiang Xu, Wenlong Wang, Zixuan Shao, and Xi Li

***Abstract*—Electrification rate is an internationally accepted index for electric power access. However, electrification rate data are only commonly available at the national level in underdeveloped countries. In this article, we proposed a power stability method to estimate the electrification rate using night-time light data. The essence of this method is constructing a power stability index viewed as a key parameter, which is derived from daily night-time light data, and the method considers both the reliability of electricity supply and the average power supply which is represented by the annual night-time light luminosity. We assumed that areas with unstable night-time light had no reliable power supply, and the Landscan population map was overlaid to estimate electrification rates in different regions. As a study case, we used the method to estimate the multispatial scale electrification rates in Zimbabwe. We validated the estimated province-level electrification rates using the statistical data. The overall accuracy was 85.42% with an R-Square of 0.98, indicating the method is accurate for estimating the electrification rate. Consequently, we generated an electrification rate map at the district-level, which provides rich spatiotemporal information of the electrification. This research highlights the potential of using multisource night-time light imagery to locate population without a stable electricity supply.**

***Index Terms*—Electrification rate, multispatial scale, night-time light, power stability, visible infrared imaging radiometer (VIIRS).**

I. INTRODUCTION

ELECTRIFICATION is important to measure regional economy [1], as electric popularization supports better lives of human beings [2]. Therefore, electrification has been ranked in the first place for development in a number of countries. The United Nations Sustainable Development Goal 7 (SDG 7) aims to ensure that all people have access to affordable, reliable, sustainable, and modern energy by 2030 [3]. Electrification is a key priority under the SDGs [4], [5], [6]. Over the next decade, global energy demand will grow exponentially [7]. Power outages occur frequently in underdeveloped countries when demand for electricity exceeds supply [8]. Lack of access to reliable and stable energy will be a severe constraint on the achievement of SDG 7.

According to International Energy Agency's World Energy Outlook report in 2019 [9], there is a gap between the promise of energy for all and the fact that nearly a billion people still do not have access to electricity. It was predicted that 36% of the population in sub-Saharan Africa will still be without electricity by 2030 [10], [11]. For cities, governments are more concerned about power stability than power supply [12]. Compared with rural areas, higher population density and illegal connection to the grid have led to electricity theft and power outages [13]. Take Zimbabwe as an example, power outages caused by planned or unplanned load shedding or faults in the country seriously affect people's lives and the economic development of the country [14], [15], [16]. Therefore, understanding the electricity status in countries such as Zimbabwe is of great significance as a case to track the electrification process in sub-Saharan countries.

However, existing electrification data are available mostly at the national-level, such as the data from the World Bank [17]. The Demographic and Health Surveys (DHS) program has provided electrification data at the province-level [18], but its coverage is too limited in both time and space [19]. Therefore, accurate electrification data at the subnational level is required for monitoring the electrification process. Remote sensing is an important means to estimate the electrification rate at a fine-scale [20]. Human-related light at night can be monitored through night-time light remote sensing, which provides a way for estimating the electrification rate.

Studies have estimated the electrification rate based on night-time light imagery and empirical statistical methods. Min and Gaba [21] built a regression model based on night-time light imagery and ground survey data to evaluate the influence of streetlights and electrified homes on the radiance in night-time light imagery, and they proved the potential of night-time light remote sensing to evaluate electricity. Falchetta and Noussan [22] collected five-year panel data sets from night-time light images and used panel regression to evaluate whether night-time light data can capture the inter-annual changes in electricity consumption in different countries around the world. Dugoua et al. [23] built a multiple regression model based on the night-time light imagery and the detailed rural electrification data of the Indian census and

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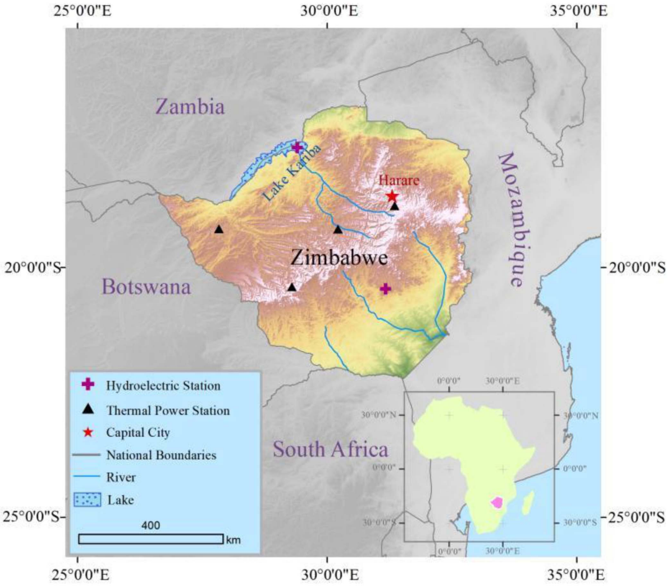


Fig. 1. Geography of Zimbabwe.

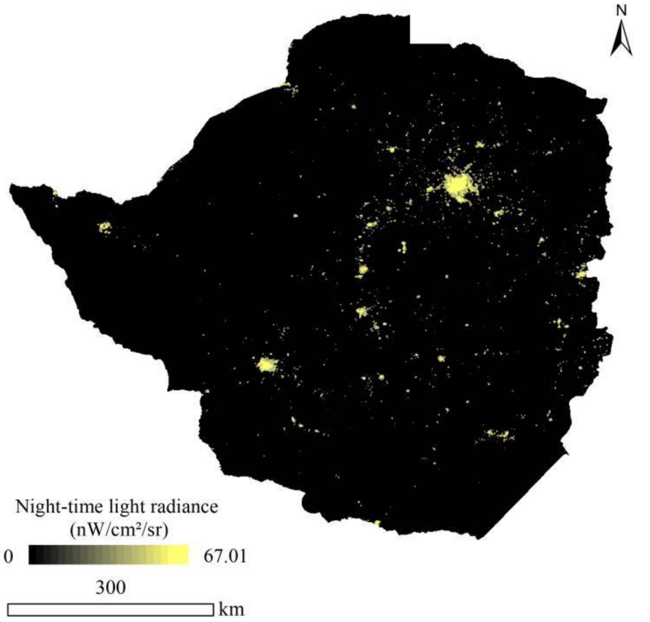


Fig. 2. Annual composite of night-time light from EOG for Zimbabwe in 2015.

evaluated the accuracy of estimated electricity. Elvidge et al. [24] combined night-time light data with population density maps to calculate the ratio of the population in illuminated areas to the total population to obtain the electrification rate, and they generated the first global electrification rate map.

The aforementioned electrification rate estimation methods using night-time light data have common limitations, as they ignore power stability, which is important in SDG 7 to ensure reliable energy. This study proposed an electrification rate estimation method, named Power Stability Method, which introduced daily night-time light images to represent the stability of electricity supply. Therefore, we used this method to estimate the multiscale electrification rate in Zimbabwe and validated the accuracy. Finally, an electrification map at the district-level in Zimbabwe was generated to locate less electrified regions.

II. Study Area and Data

A. Study Area

Zimbabwe, officially named the Republic of Zimbabwe, with Harare as its capital, is located in the southeast of Africa (see Fig. 1). The whole territory of Zimbabwe is in north of the Tropic of Capricorn, bounded by the Zambezi River and Limpopo River with Zambia and South Africa. Zimbabwe is a part of the South African Plateau. The country is divided into 10 first-level administrative divisions, including 8 provinces and 2 cities with provincial status (provincial municipalities). The provinces are subdivided into 59 second-level administrative divisions (districts) and 1200 third-level administrative divisions (wards).

In general, the electricity generation capacity in Zimbabwe is too limited to meet demand from the industry and residents. The power supply of Zimbabwe mainly relies on the Kariba Hydroelectric Station on the Zambezi River and four thermal power stations, which mainly include Hwange Thermal Power Station [25]. The Zambezi River has a tropical savannah climate, with obvious flood periods and dry periods [26]. Abundant precipitation provides the possibility of hydroelectric power, but relying too much on the weather conditions can easily lead to power shortages during the dry season. Furthermore, the difficult economic situation of Zimbabwe has deteriorated the power shortage to some extent, since power stations sometimes face the problem of insufficient coal supply. On the other hand, the economy is also hampered by an unforeseen energy situation [27].

B. Data

Areas with electricity access normally have bright artificial lights at night (ALAN), which is evidence of economic and human activity. Many studies have proved night-time light data can record ALAN under cloudless weather [28]. At present, the main night-time light data are mainly acquired from Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) and National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer (NPP/VIIRS) [28], [29]. The DMSP/OLS product has been no longer available since 2013, while NPP/VIIRS has been more widely used in recent years. The spatial resolution of NPP/VIIRS is higher than that of DMSP/OLS, and the quantization level is 16 bit. NPP/VIIRS is free from issues such as data saturation and blooming [30].

The critical data of our study is night-time light data. The Annual VNL V2 product is provided by Earth Observation Group (EOG). It can reflect the average night brightness level of each location in a year [31]. The annual composites contain rich spatial information related to the electrification. For example, this annual composite image from EOG (see Fig. 2) shows the night-time light of Zimbabwe in 2015.

The Black Marble night-time light product VNP46A2 is provided by the National Aeronautics and Space Administration (NASA). This product takes VIIRS DNB data as input [32]. The temporal and spatial coverage of VNP46A2 product is relatively wide. With this data, our method can take into account the daily fluctuation of electricity supply. In addition, the time series of VNP46A2 also contains long-term trend information, which provides a prerequisite to estimate power stability.

The Black Marble products have been finely preprocessed including atmospheric correction, while the preprocessing steps have screened out much weak light. The Annual VNL V2 product from EOG retains the weak light and records more original information on night-time light, since it has not been over-processed. Therefore, for the Black Marble, we only used daily products instead of the annual products (VNP46A4). We will combine the annual products from EOG and daily data from Black Marble to generate more electricity-related information.

The population distribution data used in our study is LandScan provided by the Oak Ridge National Laboratory in the United States. It is produced using a multivariate population estimation model [33]. The spatial coverage of LandScan data spans the globe and it is updated annually.

The province-level electrification rate statistics used in our study are obtained from the DHS program. The DHS program is responsible to collect accurate and nationally representative data on the health and population in various countries [34]. The electrification rate is one of the indexes. However, because the survey was conducted infrequently in Southern Africa, the electrification rate data is not continuously available, and that is why remote sensing estimation is needed.

The other statistical data on electrification rate used in our study is obtained from the World Bank, which records the electrification rate at the national scale. The World Bank collects large amounts of data and generates them on the basis of economic models [35].

III. METHODS

A. Power Stability Method

The purpose of this study is to estimate the electrification rate (EA), that is, the percentage of the number of people with electricity access in a region ($P_{\text{electrified}}$) to the total number of people in the region (P_{total}). The formula is as follows:

$$\text{EA} = \frac{P_{\text{electrified}}}{P_{\text{total}}}. \tag{1}$$

This study proposed a method to estimate the electrification rate based on the power stability index. The way our method to estimate the electrification rate consisted of two principles. First, we considered the brighter areas in night-time light images as likely to have a power supply. Second, if the power supply was stable enough, the area was considered to be electrified. In other words, the electrified area should not only have an electricity supply but also with stability. Therefore, we introduced a key index into our method, named power stability index (PSI). We defined it as the proportion of the number of days in a year with light emissions (N_{bright}) to the total valid days in that year (N_{total}). The calculation formula is as follows:

$$\text{PSI} = \frac{N\text{bright}}{N\text{total}}. \tag{2}$$

If the brightness of a pixel is larger than a threshold, we view the pixel in that day emit light at night, and the N_{bright} is the summation of all the days with light emission for that pixel. Therefore, each pixel in each year has a PSI value.

The power stability method contains four steps.

1) The radiance threshold for the EOG annual composite was set. We used 0.1 nW/cm^2/sr as the radiance threshold to detect bright region at night. This threshold was used to pre-screen areas without electricity access.
2) Power stability index in each pixel was generated. Before calculating the power stability index at each pixel, a screening step was required: the number of valid days of VNP46A2 product in a year needed to exceed 15. The pixels that did not meet the requirement will be screened out. Then, we calculated the power stability index based on the daily data of VNP46A2, and the threshold was also 0.1 nW/cm^2/sr.
3) An electrification map was generated. We set 0.85 as the threshold for the power stability index. For each pixel, the pixel was considered to have a reliable power supply if the power stability index was larger than the threshold.
4) Finally, the electrification rates were estimated. The above-generated electrification map was overlaid with the Landscan population map. Based on the electrified population from the electrification map in step 3 and the total population from the Landscan population map, the electrification rates of different regions (i.e., provinces and districts) were estimated.

A flowchart of power stability method is shown in Fig. 3.

B. Brightness Threshold Method

Brightness threshold method is a conventional empirical statistical method [36], which is used for comparison in this study. It is based on an annual composite of night-time light, population data, and statistical data to estimate electrification rate. First, this method treats brighter areas in night-time light images as having power supply. Second, it preferentially allocates the population with electricity access to the area with power supply. In this study, the brightness threshold method was used for comparison to evaluate the performance of the power stability method. The brightness threshold method contains three steps.

1) *Radiance threshold was set:* For any threshold on the radiance of the annual composite of night-time light, the electrified regions were extracted, which was then overlaid with the Landscan population map, and therefore the electrified population was estimated. We adjusted the threshold to find the estimated electrified population closest to the statistical data at the national scale from the World Bank, and the most proper threshold was determined.
2) *Map electrified regions:* For each region, we compared its radiance of the annual composite of night-time light with the radiance threshold determined in step 1. If its radiance

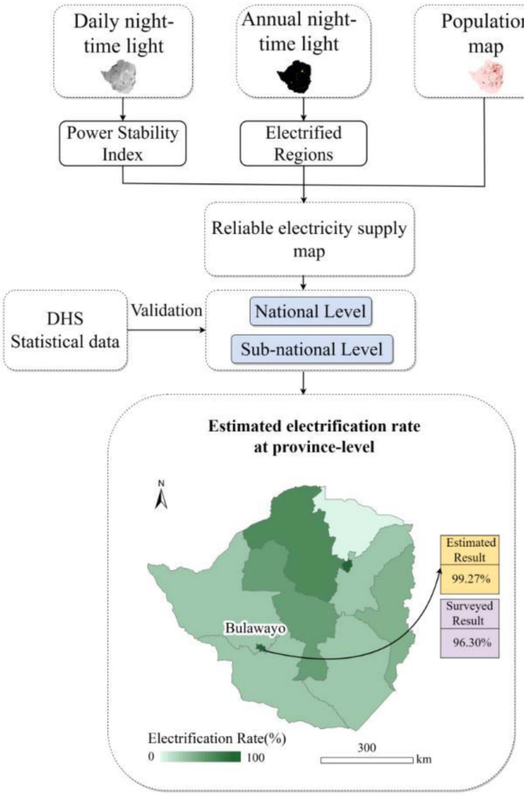


Fig. 3. Flowchart of power stability method to estimate electrification rate.

was greater than the threshold, we mapped this area as the electrified region.

3) *Estimate subnational electrification population:* We aggregated the population with power supply from each region to the subnational level, and estimated the electrification rate.

C. Spatial Autocorrelation Analysis

Spatial autocorrelation refers to the correlation of the same variable at different spatial locations. It is a measure of the degree of clustering of spatial unit attributes [37], [38]. It can be used to estimate whether the characteristics of the object are spatially correlated, and can quantitatively determine the extent of its correlation. Normally, Moran's I can measure the overall clustering of spatial data. It is sensitive to the geographical characteristics and phenomena of continuous distribution. Therefore, we used Moran's I index to analyze the spatial autocorrelation characteristics of the electrification rate in various districts of Zimbabwe. The value is between $[-1, 1]$. Larger than 0 means a positively correlation, less than 0 means a negatively correlation. The larger absolute value of Moran's I indicates more obvious of the aggregation.

To further analyze the detailed spatial distribution pattern of the electrification rate in Zimbabwe, we calculated Local Moran's I index. It was used to detect the place where the spatial aggregation phenomenon existed.

D. Accuracy Assessment

Our study used the DHS statistical data to verify the accuracy of the model at the province-level. We assumed that each province had the same power stability thresholds every year, with the threshold value of 0.85. Then we estimated the electrification rates of all the provinces in Zimbabwe. Finally, we compared the estimation results with the statistical data from DHS to evaluate the model accuracy. Our study used average relative error as the accuracy assessment index for both the power stability method and brightness threshold method. The formula of the relative error E in each province is as follows:

$$E = \frac{|\mathrm{EA}_{\mathrm{statistical}} - \mathrm{EA}_{\mathrm{estimated}}|}{\mathrm{EA}_{\mathrm{statistical}}} \tag{3}$$

where $\mathrm{EA}_{\mathrm{statistical}}$ is the electrification rate from statistical data, and $\mathrm{EA}_{\mathrm{estimated}}$ is the estimated electrification rate.

Then we calculated the average relative errors E_{average} based on the relative error E in each province to estimate the total accuracy of Zimbabwe

$$E_{\mathrm{average}} = \frac{\sum E}{n} \tag{4}$$

where n is the number of provinces in Zimbabwe.

IV. RESULTS

A. Accuracy of Models at Province-Level

We estimated electrification rates in Zimbabwe by power stability method and brightness threshold method respectively. To evaluate the accuracy of power stability method, we calculated the relative errors for ten provinces and used the brightness threshold method for comparison. Table I shows the estimated results and relative errors of aforementioned two methods respectively, where BTM represents brightness threshold method, and PSM represents power stability method. For the PSM, the average relative error reached 14.58%, indicating that the overall accuracy rate was 85.42%. At the provincial scale, the relative error in some provinces reached below 5%. This indicated our method could estimate the electrification rate accurately.

In Table I, Harare has relatively large errors compared to other provinces. One possible reason might be the complex distribution of areas with and without electricity supply in Harare. We used the pixel of remote sensing data as the unit of calculation. Therefore, when we estimated the electrification rate, the areas with and without electricity supply were mixed within a pixel. This may lead to the relatively large errors in Harare.

The comparison between the estimated results by PSM with statistical data is shown in Fig. 4. The electrification rates of Harare and Bulawayo were over 95%, twice of the national average. Provinces with low electrification rate were Mashonaland Central, Matabeleland South and Masvingo, which needed power grid planning and electricity assistance.

By comparing the two methods (see Table I), we found that the average relative error of the BTM was 16.71%, while the average relative error of the PSM was 14.58%. This indicated the proposed PSM was better than BTM. For example, compared with the BTM, PSM reduced the relative errors by 14.04%

TABLE I
COMPARISON OF THE TWO METHODS IN ELECTRIFICATION RATE AT PROVINCE-LEVEL

Province	Statistical data (%)	BTM			PSM		
		Estimated data (%)	Error (%)	Relative error (%)	Estimated data (%)	Error (%)	Relative error (%)
Bulawayo	96.30	98.47	2.17	2.25	99.27	2.97	3.09
Harare	76.50	99.05	22.55	29.47	99.83	23.33	30.50
Manicaland	15.60	16.95	1.35	8.67	17.93	2.33	14.93
Mashonaland Central	11.80	7.61	4.19	35.54	9.26	2.54	21.50
Mashonaland East	16.80	13.81	2.99	17.80	15.64	1.16	6.92
Mashonaland West	25.50	26.41	0.91	3.58	27.97	2.47	9.68
Masvingo	20.00	10.75	9.25	46.23	11.59	8.41	42.05
Matabeleland North	12.40	12.12	0.28	2.24	12.87	0.47	3.81
Matabeleland South	13.10	11.00	2.10	16.05	11.38	1.72	13.10
Midlands	24.30	23.03	1.27	5.24	24.36	0.06	0.25

and 10.89% in Mashonaland Central and Mashonaland East, respectively. In Midlands, the relative error of PSM was as low as 0.25% compared to 5.24% from BTM.

Furthermore, we calculated the spatial clustering of errors using Local Moran's I index. As shown in Fig. 5, the errors between the estimated electrification rate and statistical electrification rate were spatially non-autocorrelated (Local Moran's I index is -0.111), indicating that the model satisfied the assumption of independence of the error terms. There were no missing spatial variables in the model, indicating that the model had good performance and could explain the spatial information of the estimated electrification rate.

B. *Results of Temporal Analysis at Province-Level*

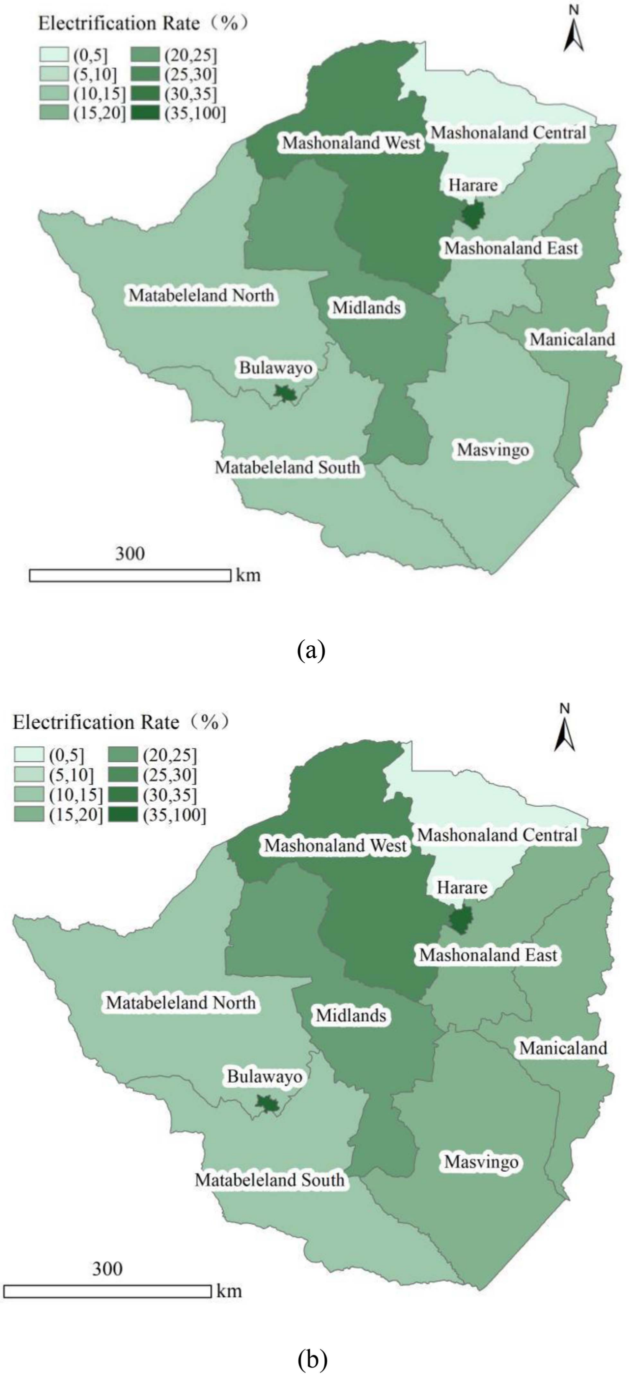
Fig. 6 shows the estimated electrification rates of 10 provinces in Zimbabwe from 2013 to 2019. In general, electrification rates varied greatly among the 10 provinces. The electrification rates of Harare and Bulawayo were much higher than other provinces. The rankings of electrification rates in the rest of the eight provinces did not change much over time. The electrification rate in Harare, the capital, remained almost unchanged over the seven years, with each year above 99%. The electrification rate in Bulawayo decreased slightly in 2014, with each year still above 95%. It was obvious that the electrification rate in almost all provinces showed a trend of decreasing at first and then recovered. It reached its lowest level in 2014 and then gradually returned. This was likely due to the significant drop in the water level of Lake Kariba caused by a drought [39]. This resulted in reducing the power generation capacity of the Kariba Hydroelectric Station, and further exacerbated the existing serious power shortage of Zimbabwe.

After 2015, the interannual variation of the electrification rate in most provinces showed a fluctuating and slowly increasing trend. However, some provinces such as Matabeleland North and Matabeleland South showed a slight decreasing trend. This was probably caused by the El Niño in Zimbabwe in 2019 [40]. Insufficient precipitation led to a sharply drop in power generation of the Kariba Hydroelectric Station. Power cuts became normal that people and companies in Zimbabwe had to face in that year. Hydroelectric station was overly dependent on the weather condition, coupled with factors such as aging equipment, poor management, and technical limitations, causing the electrification rate to fluctuate greatly between years in provinces of Zimbabwe [41].

C. *Estimated Electrification Rate at District-Level*

The electrification rate map at the district-level (see Fig. 7) shows some hidden energy poverty areas. The district with the lowest electrification rate in 2015 was only 1.47%. There were 26 out of all the 59 districts with electrification rates less than 10%. As shown in Fig. 7, some electrified provinces still had districts with low electrification rates. The electrification rate of Wedza (area A) in 2015 was only 4.47%, which was far lower than that of its adjacent districts. For example, the electrification rate of Marondera was 41.59%, which is adjacent to the north of Wedza. Wedza belongs to Mashonaland East and is only 127 km away from the capital Harare. Due to the "Land Reform Policy," the roads in Wedza have depreciated in quality [42]. This leads to serious disruptions in industry and vast amounts of locally employed people lost jobs and livelihoods [43], [44]. Therefore, due to various factors such as geography, transportation, and policies, areas such as Wedza with lower electrification rate appeared in the relatively electrified province.

Interestingly, some provinces with low electrification rate had higher electrified districts. These districts were critical for power grid construction and electricity assistance. For example, Beitbridge (area B in Fig. 7) is a border city located in Matabeleland South. It borders South Africa in the south. It is one of the busiest border cities in Southern Africa. In 2015, the electrification rate of Beitbridge was 32.99%, while the average electrification rate of all districts in Matabeleland South was only 12.39%. Another example is Hwange (area C in Fig. 7) which is located in Matabeleland North. The electrification rate of the whole province was 11.85% in 2015, which was far lower than the national average. However, the electrification rate of Hwange was as high as 54.11%. This was because Hwange borders Zambia, Botswana, and Namibia. As early as the late 1990s, the power grid of Zimbabwe was connected to the Southern African



(a)

(b)

Fig. 4. Electrification rates in Zimbabwe's ten provinces in 2015. (a) Estimated data from PSM. (b) Statistical data.

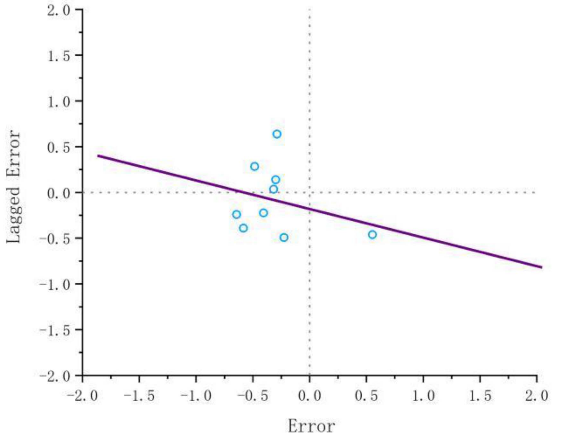


Fig. 5. Moran scatter plot of errors in ten provinces of Zimbabwe. The dashed line indicates the case where the value is 0.

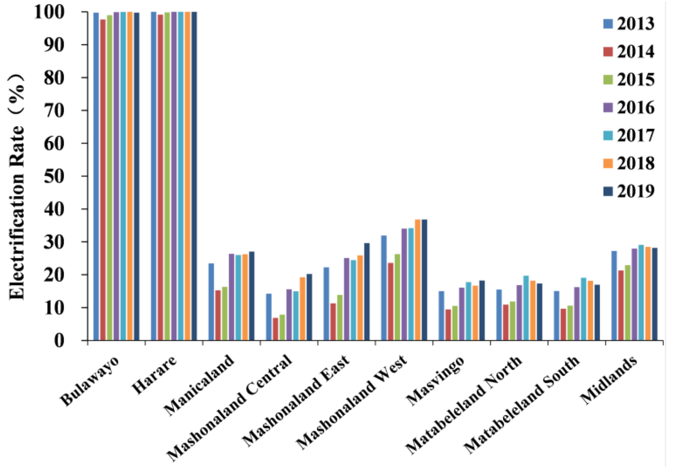


Fig. 6. Estimated electrification rates of the ten provinces in Zimbabwe from 2013 to 2019.

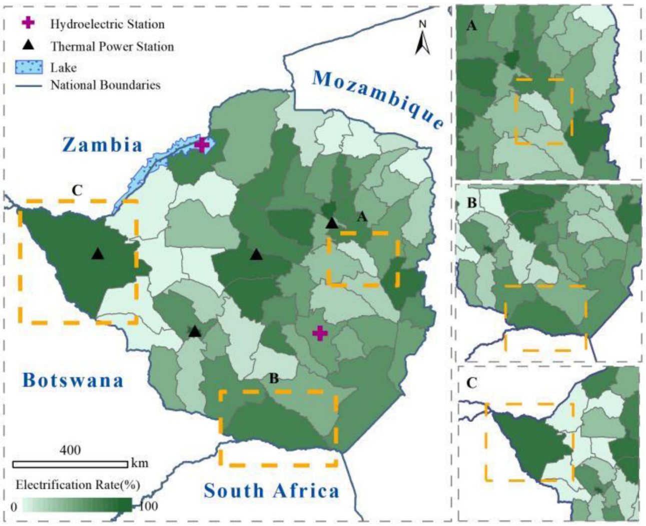


Fig. 7. Spatial distribution of electrification rate at district-level of Zimbabwe in 2015.

power pool for power supply. South Africa is among the major electricity importers of Zimbabwe [45], [46], [47].

We calculated Global Moran's I index to analyze the spatial distribution characteristics of the electrification rate in 59 districts of Zimbabwe. Global Moran's I index was 0.39, with the Z statistic value of 2.53 ($P < 0.05$). The result showed that the distribution of the electrification rate in Zimbabwe had an aggregation pattern, and the spatial correlation among the districts was obvious and positive.

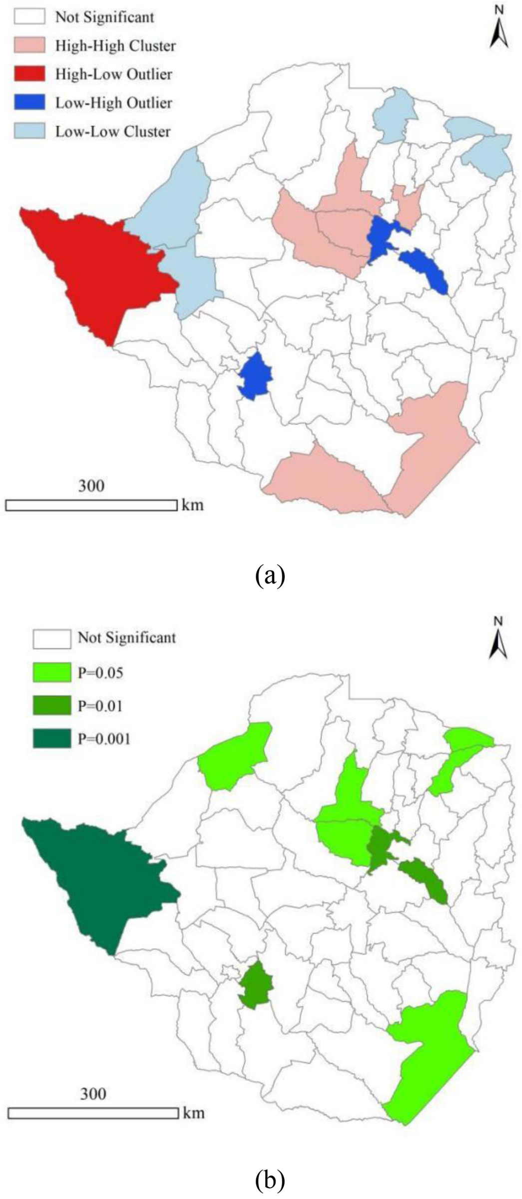


Fig. 8. LISA map of estimated electrification rate at district-level. (a) LISA cluster map. (b) LISA significance map.

To further analyze the spatial cluster heterogeneity of electrification rate at the district-level, we calculated Local Moran's I index. From the Local Indicator of Spatial Association (LISA) cluster map in Fig. 8, the distribution of electrification rate at the district-level had obvious spatial agglomeration characteristics. The High-High Cluster is concentrated in Mashonaland West, where districts with above-average electrification rates were surrounded by districts with above-average electrification rates. The low-low cluster showed the aggregation of districts with below-average electrification rate. These findings suggested that the electrification rate varied widely between districts in Zimbabwe.

V. DISCUSSION

Electricity is related to the survival and well-being of people [48], [49]. In Zimbabwe, load shedding is routine and some rural areas have no electricity for long time [50], [51]. However, the country is rich in hydropower and thermal power resources [52]. The electricity supply of Zimbabwe mainly comes from the Kariba Hydroelectric Station on the Zambezi River, of which capacity is 750 MW [53], and four thermal power stations, of which Hwange Thermal Power Station is the largest with a theoretical capacity of about 920 MW [54]. The other three at Harare, Bulawayo, and Munyati have a total capacity of 270 MW [55]. This is consistent with our findings of the electrification rate map at the district-level. Districts with power stations had a relatively high electrification rates. In addition, due to deteriorating infrastructure, the capacity of power stations was less than half of the total installed capacity. These facts may explain why the electrification rate did not increase significantly and fluctuated greatly in 2013–2019 of 10 provinces in Zimbabwe. The electrification rates from 2013 to 2019 showed a rising trend in general, which was consistent with the socioeconomic stability in Zimbabwe. We performed a correlation analysis based on the electrification rate and gross domestic product (GDP). The results showed a strong correlation between the electrification rate and GDP, with R-square of 0.62. This indicated that the electrification rate increased as the socioeconomic situation improved in Zimbabwe.

The Kariba Hydroelectric Station had low water levels due to droughts in recent years [56]. Its electricity generation capacity was only 34% of the normal level [57]. The Kariba Dam entered the maintenance period, some units needed to be shut down, and the power generation decreased significantly. Without Kariba Hydroelectric Station, there were about 3 million households facing power outages [58], [59]. However, relying too much on hydroelectricity could easily lead to unstable power supply. Because precipitation decreases during the dry season led to lower power generation from dams. Therefore, we supposed that there may be seasonal variations in the electrification rate in Zimbabwe. This may be a direction for future research to further analyze the temporal variations in the electrification rate in Zimbabwe.

Many underdeveloped countries have low rates of access to reliable energy, with frequent power outages. Some scholars carried out research work on power fluctuation. For example, Min identified outage-prone areas by detecting excess fluctuations in light outputs, and generated the PSI index to estimate the electrical instability of a region, then indicated the areas where the electricity system was unstable in India [60]. Different from that research, we estimated the power stability index, which was derived from the daily night-time light data, and thereby estimated electrification rates.

However, our study also had some limitations. First, although the power stability method had satisfactory accuracy in estimating the electrification rate, it still had the potential to be optimized. It is evident that our method may overestimate the results of some areas with high electrification rate, and may also underestimate the results of some areas with low electrification rate. This might be due to the threshold determined by our current method was not yet optimal. Optimizing thresholds and combining the strengths of multiple models may improve the accuracy of existing estimation models. Second, the quality of raw night-time light data may affect the accuracy of the model. In the future, better algorithms can be developed for the raw night-time light data to remove noises such as fires, thereby improving the estimation method. Third, in the future, we can use the power stability method at finer spatial and temporal scales, making the model more efficient and insightful for the specific area. For example, based on the estimated results of the electrification rate and Google's high-resolution remote sensing images, we found provinces with small changes in electrification rate were mainly composed of residential areas. In the future, land use data can be introduced into the model to further analyze the changes in electrification rate in different land types. In general, there are still many potentials in estimating the electrification rate using night-time light [61], [62], [63], [64].

VI. CONCLUSION

Explicit spatial data on electricity access and usage is critical for effective decision-making and infrastructure planning in low-income and data-poor regions. The SDG 7 aims at ensuring reliable energy for all, which suggests the importance of a stable power supply for global electrification. This study proposed the power stability method for estimating the electrification rate. We constructed a power stability index, and extracted areas without stable power supply. In addition, we introduced daily night-time light images into our method, which recorded more effective information about power stability. We used this method for multiscale estimation in Zimbabwe. The overall accuracy was 85.42% and the R-Square was 0.98, indicating that the proposed method was satisfactory.

Furthermore, we conducted a spatial and temporal analysis of the electrification rate in Zimbabwe from 2013 to 2019 and generated maps of the electrification rate at the subnational level. Through the fine-scale electrification rate map, we could see some detailed information, which helped to gain insight into areas where electricity was scarce and unreliable. Our research could provide support for the decision of electrification plans. Therefore, the proposed methodology provides new opportunities to study the electrification progress under the background of the SDG 7.

REFERENCES

[1] V. Modi, S. McDade, D. Lallement, and J. Saghir, "Energy services for the millennium development goals," *Energy Serv. Millennium Develop. Goals*, 2005.

[2] G. Legros et al., "The energy access situation in developing countries: A review focusing on the least developed countries and sub-Saharan Africa," *World Health Org.*, vol. 142, 2009.

[3] United Nations Department of Economic and Social Affairs, *The Sustainable Development Goals Report 2017*. in The Sustainable Development Goals Report. United Nations, 2017, doi: 10.18356/4d038e1e-en.

[4] A. Brew-Hammond, "Energy: The missing millennium development goal," in *Energy for Development*, vol. 54. F. L. Toth, Ed., in Environment & Policy. Berlin, Germany: Springer, 2012, pp. 35–43, doi: 10.1007/978-94-007-4162-1_3.

[5] D. L. McCollum et al., "Connecting the sustainable development goals by their energy inter-linkages," *Environ. Res. Lett.*, vol. 13, no. 3, Mar. 2018, Art. no. 033006, doi: 10.1088/1748-9326/aaafe3.

[6] F. Fuso Nerini et al., "Mapping synergies and trade-offs between energy and the sustainable development goals," *Nature Energy*, vol. 3, no. 1, pp. 10–15, Nov. 2017, doi: 10.1038/s41560-017-0036-5.

[7] C. Bogmans, L. Kiyasseh, A. Matsumoto, and A. Pescatori, "Energy, efficiency gains and economic development: When will global energy demand saturate?," *IMF Work. Papers*, vol. 20, no. 253, Nov. 2020, doi: 10.5089/9781513561240.001.

[8] F. Riva, H. Ahlborg, E. Hartvigsson, S. Pachauri, and E. Colombo, "Electricity access and rural development: Review of complex socio-economic dynamics and causal diagrams for more appropriate energy modelling," *Energy Sustain. Dev.*, vol. 43, pp. 203–223, Apr. 2018, doi: 10.1016/j.esd.2018.02.003.

[9] "World energy outlook 2019," IEA, Paris, France, 2019.

[10] R. G. Newell, D. Raimi, and G. Aldana, "Global energy outlook 2019: The next generation of energy," *Resour. Future*, vol. 1, pp. 8–19, 2019.

[11] "Tracking SDG 7," World Health Organization, 2021. [Online]. Available: http://hdl.handle.net/10986/38016

[12] P. J. Gertler, K. Lee, and A. M. Mobarak, "Electricity reliability and economic development in cities: A microeconomic perspective," 2017.

[13] A. Burke, L. A. Schultz, O. Omitaomu, A. Molthan, T. Cole, and R. Griffin, "Verification and enhancement of VIIRS day-night band power outage detection product," *Amer. Geophys. Union*, vol. 2017, Dec. 2017, Art. no. IN31C-0093.

[14] N. Kaseke and S. G. Hosking, "Modelling the cost of electricity outages in Zimbabwe," *Int. J. Econ. Dev. Res. Invest.*, vol. 2, no. 2, 2011.

[15] C. Mbohwa, "Zimbabwe: An assessment of the electricity industry and what needs to be done," *Electric. J.*, vol. 15, no. 7, pp. 82–91, Aug. 2002, doi: 10.1016/S1040-6190(02)00346-9.

[16] R. Samu, F. V. Bekun, and M. Fahrioglu, "Electricity consumption and economic growth nexus in Zimbabwe revisited: Fresh evidence from Maki cointegration," *Int. J. Green Energy*, vol. 16, no. 7, pp. 540–550, May 2019, doi: 10.1080/15435075.2019.1598417.

[17] World Bank, *State of Electricity Access Report 2017*. World Bank, Washington, DC, 2017, doi: 10.1596/26646.

[18] M. Norris et al., "A growing disadvantage of being born in an urban area? Analysing urban–rural disparities in neonatal mortality in 21 African countries with a focus on Tanzania," *BMJ Glob. Health*, vol. 7, no. 1, Jan. 2022, Art. no. e007544, doi: 10.1136/bmjgh-2021-007544.

[19] B. Min, Z. O'Keeffe, and F. Zhang, *Whose Power Gets Cut? Using High-Frequency Satellite Images to Measure Power Supply Irregularity*. Washington, DC, USA: World Bank, 2017, doi: 10.1596/1813-9450-8131.

[20] C. He, Q. Ma, T. Li, Y. Yang, and Z. Liu, "Spatiotemporal dynamics of electric power consumption in Chinese mainland from 1995 to 2008 modeled using DMSP/OLS stable nighttime lights data," *J. Geographical Sci.*, vol. 22, no. 1, pp. 125–136, Feb. 2012, doi: 10.1007/s11442-012-0916-3.

[21] B. Min and K. Gaba, "Tracking electrification in Vietnam using nighttime lights," *Remote Sens.*, vol. 6, no. 10, pp. 9511–9529, Oct. 2014, doi: 10.3390/rs6109511.

[22] G. Falchetta and M. Noussan, "Interannual variation in night-time light radiance predicts changes in national electricity consumption conditional on income-level and region," *Energies*, vol. 12, no. 3, Jan. 2019, Art. no. 456, doi: 10.3390/en12030456.

[23] E. Dugoua, R. Kennedy, and J. Urpelainen, "Satellite data for the social sciences: Measuring rural electrification with night-time lights," *Int. J. Remote Sens.*, vol. 39, no. 9, pp. 2690–2701, May 2018, doi: 10.1080/01431161.2017.1420936.

[24] C. D. Elvidge et al., "Who's in the dark-satellite based estimates of electrification rates," in *Urban Remote Sensing*, X. Yang, Ed., Hoboken, NJ, USA: Wiley, 2011, pp. 211–224, doi: 10.1002/9780470979563.ch15.

[25] "Emergence of electricity crisis in Zimbabwe, reform response and cost implications," *J. Bus. Manage.*, vol. 2, no. 2319, pp. 1–16, 2013.

[26] W. H. Reeve, "Progress and geographical significance of the Kariba Dam," *Geographical J.*, vol. 126, no. 2, Jun. 1960, Art. no. 140, doi: 10.2307/1793954.

[27] C. Mbohwa and S. Fukuda, "Electricity from bagasse in Zimbabwe," *Biomass Bioenergy*, vol. 25, no. 2, pp. 197–207, Aug. 2003, doi: 10.1016/S0961-9534(03)00011-4.

[28] C. Small, F. Pozzi, and C. Elvidge, “Spatial analysis of global urban extent from DMSP-OLS night lights,” *Remote Sens. Environ.*, vol. 96, no. 3–4, pp. 277–291, Jun. 2005, doi: 10.1016/j.rse.2005.02.002.

[29] C. D. Elvidge et al., “Night-time lights of the world: 1994–1995,” *ISPRS J. Photogrammetry Remote Sens.*, vol. 56, no. 2, pp. 81–99, Dec. 2001, doi: 10.1016/S0924-2716(01)00040-5.

[30] S. Mills, S. Weiss, and C. Liang, “VIIRS day/night band (DNB) stray light characterization and correction,” in *Presented at the SPIE Optical Engineering + Applications*, J. J. Butler, X. (Jack) Xiong, and X. Gu, Eds., San Diego, CA, USA, Sep. 2013, Art. no. 88661P, doi: 10.1117/12.2023107.

[31] H. B. Baldwin, M. Klug, K. Tapracharoen, and C. Visudchindaporn, “Utilizing suomi NPP’s day-night band to assess energy consumption in rural and urban areas as an input for poverty analysis,” *Amer. Geophys. Union*, vol. 2017, Dec. 2017, Art. no. IN52B-09.

[32] C. D. Elvidge, K. Baugh, M. Zhizhin, F. C. Hsu, and T. Ghosh, “VIIRS night-time lights,” *Int. J. Remote Sens.*, vol. 38, no. 21, pp. 5860–5879, Nov. 2017, doi: 10.1080/01431161.2017.1342050.

[33] V. Mesev Ed., “LandScan: A global population database for estimating populations at risk,” in *Remotely-Sensed Cities*, 0 ed. Boca Raton, FL, USA: CRC, 2003, pp. 301–314, doi: 10.1201/9781482264678-24.

[34] J. T. Boerma and A. E. Sommerfeltb, “Demographic and health surveys (DHS): Contributions and limitations,” *World Health Statist. Quart.*, vol. 46, pp. 222–226, 1993.

[35] H. O. Bergesen and L. Lunde, *Dinosaurs or Dynamos*, 0 ed. Evanston, IL, USA: Routledge, 2013, doi: 10.4324/9781315071480.

[36] G. Falchetta, S. Pachauri, S. Parkinson, and E. Byers, “A high-resolution gridded dataset to assess electrification in sub-Saharan Africa,” *Sci. Data*, vol. 6, no. 1, Jul. 2019, Art. no. 110, doi: 10.1038/s41597-019-0122-6.

[37] A. Getis, “Reflections on spatial autocorrelation,” *Regional Sci. Urban Econ.*, vol. 37, no. 4, pp. 491–496, Jul. 2007, doi: 10.1016/j.regsciurbeco.2007.04.005.

[38] A. Getis, “A history of the concept of spatial autocorrelation: A geographer’s perspective,” *Geographical Anal.*, vol. 40, no. 3, pp. 297–309, Jul. 2008, doi: 10.1111/j.1538-4632.2008.00727.x.

[39] E. M. Makaudze, “Assessing the economic value of El niño-based seasonal climate forecasts for smallholder farmers in Zimbabwe,” in *Climate Change and Multi-Dimensional Sustainability in African Agriculture*, R. Lal, D. Kraybill, D. O. Hansen, B. R. Singh, T. Mosogoya, and L. O. Eik, Eds., Berlin, Germany: Springer, 2016, pp. 591–612, doi: 10.1007/978-3-319-41238-2_31.

[40] P. R. Shukla et al., “Climate change and land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems,” IPCC, 2019.

[41] E. F. Chipango, “Constructing, understanding and interpreting energy poverty in Zimbabwe: A postmodern perspective,” *Energy Res. Soc. Sci.*, vol. 75, May 2021, Art. no. 102026, doi: 10.1016/j.erss.2021.102026.

[42] A. R. Chakhmouradian and F. Wall, “Rare Earth elements: Minerals, mines, magnets (and more),” *Elements*, vol. 8, no. 5, pp. 333–340, Oct. 2012, doi: 10.2113/gselements.8.5.333.

[43] X. Li, L. Ge, and X. Chen, “Detecting Zimbabwe’s decadal economic decline using nighttime light imagery,” *Remote Sens.*, vol. 5, no. 9, pp. 4551–4570, Sep. 2013, doi: 10.3390/rs5094551.

[44] S. Bauer and I. Scholz, “Adaptation to climate change in Southern Africa: New boundaries for sustainable development?,” *Climate Dev.*, vol. 2, no. 2, pp. 83–93, Apr. 2010, doi: 10.3763/cdev.2010.0040.

[45] P. A. Trotter, M. C. McManus, and R. Maconachie, “Electricity planning and implementation in sub-Saharan Africa: A systematic review,” *Renew. Sustain. Energy Rev.*, vol. 74, pp. 1189–1209, Jul. 2017, doi: 10.1016/j.rser.2017.03.001.

[46] F. P. Gudyanga, F. Togara, and R. M. Harlen, “Extraction of alumina from pulverised fly ash: Hwange power station,” in *Proc. 3D Africon Conf. Africon*, 1992, pp. 77–80, doi: 10.1109/AFRCON.1992.624422.

[47] T. Scudder, “The Kariba case study,” 2005. [Online]. Available: https://resolver.caltech.edu/CaltechAUTHORS:20170808-151727675

[48] M. Aklin, S. P. Harish, and J. Urpelainen, “A global analysis of progress in household electrification,” *Energy Policy*, vol. 122, pp. 421–428, Nov. 2018, doi: 10.1016/j.enpol.2018.07.018.

[49] B. K. Sovacool, “The political economy of energy poverty: A review of key challenges,” *Energy Sustain. Dev.*, vol. 16, no. 3, pp. 272–282, Sep. 2012, doi: 10.1016/j.esd.2012.05.006.

[50] L. Chikoko, T. Ngundu, and K. Kupeta, “Economic growth and electricity consumption in a multivariate framework: A case of Zimbabwe 1980 to 2016,” *ACTA Universitatis Danubius*, vol. 14, no. 5, pp. 20–33, 2018.

[51] S. Mhaka, R. Runganga, D. T. Nyagweta, N. Kaseke, and S. Mishi, “Impact of rural and urban electricity access on economic growth in Zimbabwe,” *Int. J. Energy Econ. Policy*, vol. 10, no. 6, pp. 427–434, Oct. 2020, doi: 10.32479/ijeep.10141.

[52] L. Makarichi, R. Kan, W. Jutidamrongphan, and K. Techato, “Suitability of municipal solid waste in African cities for thermochemical waste-to-energy conversion: The case of Harare Metropolitan City, Zimbabwe,” *Waste Manage. Res.*, vol. 37, no. 1, pp. 83–94, Jan. 2019, doi: 10.1177/0734242X18804029.

[53] A. Shumba, S. Togarepi, W. Gumindoga, T. Masarira, and E. Chikuni, “A remote sensing and GIS based application for monitoring water levels at Kariba Dam,” in *Proc. EAI Int. Conf. Res., Innov. Develop. Afr.*, 2018, pp. 159–181, doi: 10.4108/eai.20-6-2017.2270774.

[54] R. Spalding-Fecher et al., “Electricity supply and demand scenarios for the Southern African power pool,” *Energy Policy*, vol. 101, pp. 403–414, Feb. 2017, doi: 10.1016/j.enpol.2016.10.033.

[55] B. Thomas, K. Tendai, P. M. Zororo, and S. Obert, “Employee involvement in change management in organisations: A case of the Zimbabwe electricity transmission and distribution company (ZETDC),” *IOSR J. Econ. Finance*, vol. 10, pp. 14–27, 2019.

[56] T. Murombo, “Climate change in Zimbabwe: Towards a low carbon energy industry,” *Forthcoming Climate Change Law Zimbabwe: Concepts Insights (Konrad Adenauer Found.)*, 2019. [Online]. Available: https://ssrn.com/abstract=3483438

[57] R. H. Campbell and G. G. R. Argent, “Zimbabwe invests in coal power,” *Mod. Power Syst.*, *United Kingdom*, Jun. 1987.

[58] “Independent power producer GZH starts work on a 5-MW mini-hydro facility in Zimbabwe,” *Renewable Energy Monit.*, May 2022.

[59] L. Nyamadzawo and I. Chirisa, “Stalemate, Curse or Priority? A Regional Planner’s Perspective on the Energy Question in Zimbabwe,” 2016.

[60] B. Min, K. M. Gaba, O. F. Sarr, and A. Agalassou, “Detection of rural electrification in Africa using DMSP-OLS night lights imagery,” *Int. J. Remote Sens.*, vol. 34, no. 22, pp. 8118–8141, Nov. 2013, doi: 10.1080/01431161.2013.833358.

[61] C. N. H. Doll and S. Pachauri, “Estimating rural populations without access to electricity in developing countries through night-time light satellite imagery,” *Energy Policy*, vol. 38, no. 10, pp. 5661–5670, Oct. 2010, doi: 10.1016/j.enpol.2010.05.014.

[62] N. Angelou, *Global Tracking Framework*. Washington, DC, USA: World Bank, 2013.

[63] S. Correa, Z. Shah, and J. Taneja, “This little light of mine: Electricity access mapping using night-time light data,” in *Proc. 12th ACM Int. Conf. Future Energy Syst.*, 2021, pp. 254–258, doi: 10.1145/3447555.3464871.

[64] A. C. Townsend and D. A. Bruce, “The use of night-time lights satellite imagery as a measure of Australia’s regional electricity consumption and population distribution,” *Int. J. Remote Sens.*, vol. 31, no. 16, pp. 4459–4480, Aug. 2010, doi: 10.1080/01431160903261005.