# Annual Electricity Access Rate Dataset for Africa from 2000-2021

**Tam Kemabonta***
Ira School of Engineering, Arizona State University, AZ, USA
tkemabon@asu.edu

**Abdulrahman Alsanad**
Ira School of Engineering, Arizona State University, AZ, USA
asanad@asu.edu

**Brighton Mogaka**
Ira School of Engineering, Arizona State University, AZ, USA
bmogaka@asu.edu

**Nathan G. Johnson**
Ira School of Engineering, Arizona State University, AZ, USA
nathanJohnson@asu.edu

*Corresponding Author

**Keywords:** Electricity Access Rate; Nighttime Luminosity; Remote Sensing; Geospatial Data; Africa

## Preprint Statement

This manuscript is a non-peer-reviewed preprint submitted to EarthArXiv.

The manuscript has also been submitted for peer review to *Scientific Data* and is currently under review.

Associated dataset:

Kemabonta, T., Alsanad, A., Mogaka, B., & Johnson, N. (2026). *Africa Electricity Access Rate (EAR) Dataset for Africa from 2000-2021*.
Figshare. https://doi.org/10.6084/m9.figshare.32411700

# Annual electricity access rate dataset for Africa from 2000-2021

**Tam Kemabonta*, Abdulrahman Alsanad, Brighton Mogaka and Nathan G. Johnson**
*Corresponding author: tkemabon@asu.edu

**Abstract –** Accurate and spatially explicit electricity access data are essential for electrification planning and policy evaluation in Africa, yet existing data are often survey-based, infrequent, and temporally inconsistent. This study presents a harmonized Electricity Access Rate (EAR) dataset for Africa spanning 2000-2021, derived from satellite-based nighttime luminosity observations and gridded population data at 1 km² resolution. EARs are estimated at grid-cell level and aggregated to national and subnational administrative units. Validation against the World Bank Global Electrification Database for Sub-Saharan Africa demonstrates strong agreement across multiple luminescence thresholds, with the highest correspondence observed for DN > 7 across both DMSP/OLS and VIIRS nighttime luminosity datasets spanning the study period. The EAR dataset is made publicly available to provide a transparent, reproducible resource for analyzing long-term electrification trends, spatial disparities, and development outcomes across Africa.

**Background and Summary**

Nighttime luminosity (NTL) data have been widely used to measure human activity across spatial and temporal scales due to their global coverage, high spatial resolution, and temporal consistency (Jiang et al., 2021; Min & Gaba, 2014). With a spatial resolution of approximately 1 km², NTL datasets enable high-fidelity analysis of phenomena such as urbanization, economic agglomeration, and electricity access. Unlike household surveys, which are costly, infrequent, and prone to sampling bias, NTL observations are collected systematically by satellite sensors that image the entire Earth at regular intervals, making them particularly well suited for large-scale and longitudinal analysis.

Historically, NTL data have been collected using two satellite systems: the Defense Meteorological Satellite Program's Operational Line-scan System (DMSP/OLS), available from 1992 to 2013 (Jiang et al., 2021; Min et al., 2013; Min & Gaba, 2014), and the Visible Infrared Imaging Radiometer Suite (VIIRS) Day–Night Band (DNB), available from 2012 to the present (Elvidge et al., 2021; Mills et al., 2013; Zhao et al., 2020). Differences in sensor sensitivity, radiometric calibration, and spatial resolution between these systems have created a discontinuity in NTL time series, leading most studies to analyze pre-2012 trends using DMSP/OLS data and post-2012 trends using VIIRS data. This discontinuity has limited the ability to conduct long-term trend analyses, particularly those needed for retrospective evaluation of electrification policies and infrastructure planning. Recent methodological advances have addressed this by harmonizing DMSP and VIIRS nighttime luminosity data by applying a sigmoid transformation that converts VIIRS radiance values into DMSP-like digital number (DN) values (Li et al., (2020, 2023)). This produces a temporally consistent NTL time series to enable robust analysis of long-term nighttime luminosity dynamics across multiple decades. However, this harmonization across datasets has not been calibrated and applied globally.

One of the most important applications of NTL data is in monitoring and planning of electrification in developing regions where electricity access remains limited. Min et al. (2013) compared DMSP/OLS nighttime luminosity data in Senegal and Mali with ground surveys from 232 electrified and 899 unelectrified villages, demonstrating that electrified settlements are consistently brighter than non-electrified ones, primarily due to public lighting infrastructure. A parallel study in Vietnam confirmed similar patterns, reinforcing nighttime luminosity as a reliable proxy for village-level electrification despite limited sensitivity to household electricity consumption intensity (Min & Gaba, 2014). Falchetta et al. (2019) developed a high-resolution electrification dataset for sub-Saharan Africa by integrating VIIRS nighttime luminosity with gridded population and land-cover data and validated their estimates against province- and national-level statistics as well as survey-based consumption tiers.

Despite these advances, few studies have leveraged harmonized NTL data to produce long-term, spatially explicit electricity access rate (EAR) estimates for the entirety of Africa. Such datasets are critical for informing electrification planning and policy evaluation in regions with persistent access gaps. This study generates a continent-wide EAR dataset for Africa covering the period 2000-2021 with resolution down to administrative level 2, with higher resolutions possible in certain regions such as Nigeria as shown in prior work by the authors (Kemabonta et al., 2026).

## Methods

### *Data Collection*

The primary data sources used in this study are harmonized NTL data and gridded population data. Harmonized NTL data were obtained from Li et al. (2023) through Figshare, an open-access digital research data repository (https://doi.org/10.6084/M9.FIGSHARE.9828827.V8). Population data were taken from the LandScan dataset produced by Oak Ridge National Laboratory, which provides annual population estimates at approximately 1 km² resolution (https://landscan.ornl.gov/). All geospatial analyses were conducted using ArcGIS, a commercial geographic information system developed by Esri.

### *Geospatial Boundary Selection*

EAR estimates were produced at administrative levels 0 (national), 1, and 2. Accurate geospatial administrative boundary definitions are critical to prevent population-weighted EAR estimates from bleeding across jurisdictional boundaries. Lower-level administration boundaries are available for certain countries, such as Nigeria, but not for the entirety of Africa.

Two boundary datasets were evaluated for use in this study: (1) the Database of Global Administrative Areas (GADM), and (2) administrative boundary data provided through Esri as sourced from the Michael Bauer Research Institute (MBRI). GADM is an open-access geospatial database that provides standardized, high-resolution administrative boundary shapefiles globally (https://gadm.org/). MBRI provides a geospatial database with global administrative boundary datasets integrated into Esri basemaps (https://www.english.mb-research.de/).

While GADM provides complete and internally consistent coverage across administrative levels, its boundaries do not perfectly align with Esri basemaps, as illustrated in Figure 1. This misalignment can introduce minor spatial discrepancies when aggregating raster-based data from nighttime luminosity images. Esri's boundary data – derived from the Michael Bauer Research Institute – lacks complete coverage of administrative level 2 boundaries across many African countries and still exhibits some boundary inconsistencies, as illustrated in Figure 2. Of the two options, the GADM dataset was selected because it permitted greater geospatial granularity, a core purpose of this study and the resulting high-resolution EAR dataset for Africa. The GADM version 4.1. (GADM41) was used.

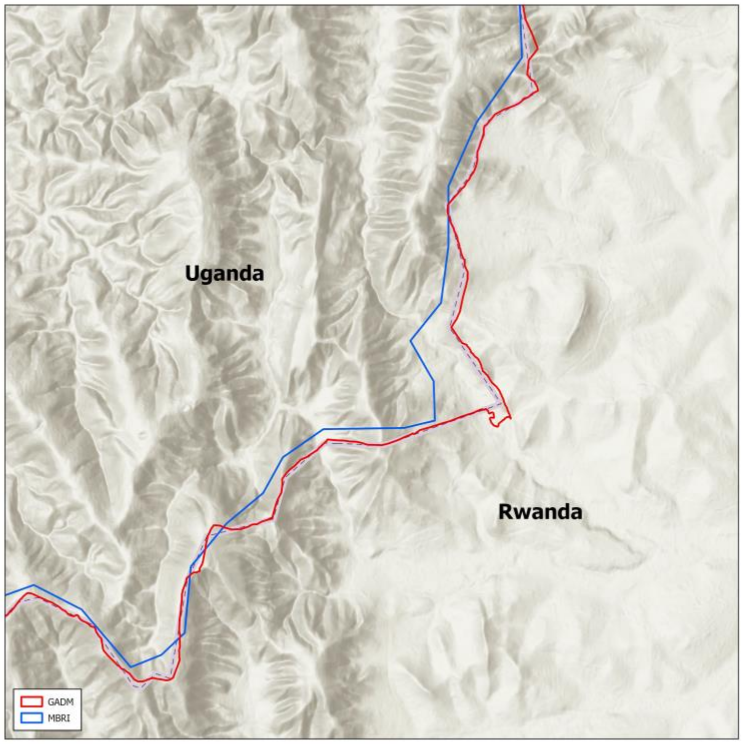

Figure 1: GADM and MBRI shapefile overlayed on Esri's base maps at the border of Uganda and Rwanda in ArcGIS

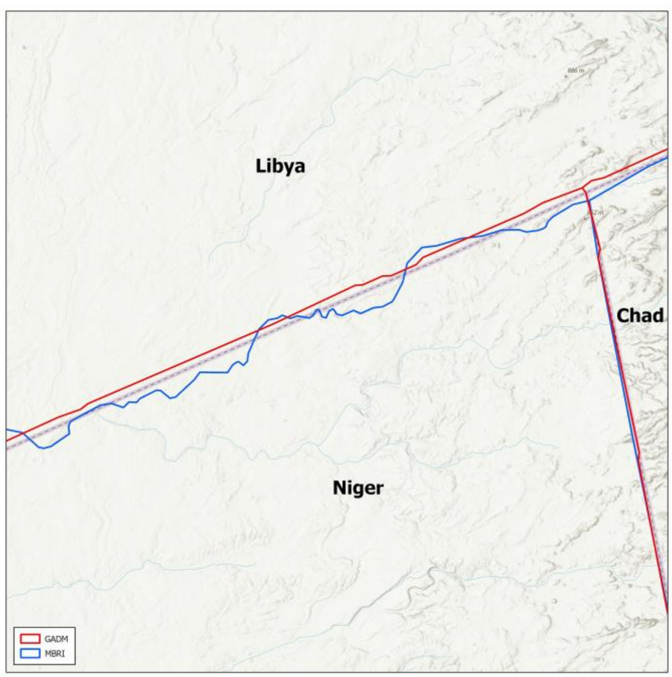

Figure 2: GADM and MBRI shapefile showing deviations from Esri's base maps at the borders of Libya, Niger and Chad in ArcGIS

### *Electricity Access Rates (EAR) Estimation*

We generate the EAR dataset for Africa using Eqs. 1 and 2 applied at different administrative levels. The harmonized NTL and population datasets at 1 km² cell resolution were combined to determine the EAR for each square kilometer in Africa. The EAR estimates for each square kilometer can then be aggregated into larger areas with defined boundaries based on geography and administrative level. Specifically, we aggregate the cell-level EAR to the country level (administrative level 0) and the administrative levels 1 and 2 within each country. The EARs at time $t$ for each area $a$ are calculated by aggregating data from the individual cells $i$ within the selected area $a$. This formulation indicates that all people in the 1 km² cell either have access to electricity or do not, per Eq. 2. There is presently no generalized and validated approach to assign a % electricity access rate within an individual cell based on the DN value.

$$EAR_{a,t} = \frac{\sum_i (Pop_{i,a,t}^{NL})}{\sum_i (Pop_{i,a,t}^{Tot})} \text{ x } 100\% \quad (1)$$

$$Pop_{i,a,t}^{NL} = \begin{cases} Pop_{i,a,t}^{Tot} & \text{if } DN > 7 \text{ (electrified)} \\ 0 & \text{otherwise (unelectrified)} \end{cases} \quad (2)$$

Where:

$EAR_{a,t}$ = Electricity Access Rate (EAR) in % for area $a$ at time $t$

$Pop_{i,a,t}^{NL}$ = Population within cell $i$ of area $a$ that have access to electricity at time $t$

$Pop_{i,a,t}^{Tot}$ = Total population within cell $i$ of area $a$ at time $t$

***Technical Validation***

A primary challenge in defining electrification using NTL data is that low DN values do not always correspond to electricity access. Dim lights detected by VIIRS sensors may originate from non-electric or transient sources such as vehicle headlights, fires, or light spillover from nearby electrified areas. This issue was explicitly addressed by Li et al. (2020) during the development of the harmonized NTL dataset.

Li et al. (2020) evaluated multiple DN thresholds (e.g., DN > 7, DN > 20, DN > 30) and found that DN > 7 produced the most stable long-term temporal trends. Higher thresholds reduced interannual variability but systematically underestimated electrification in rural and peri-urban areas, while lower thresholds introduced artificial discontinuities during the transition from DMSP/OLS to VIIRS data between 2013 and 2014. These discontinuities suggest that low DN thresholds are overly sensitive to non-electric light sources, leading to overestimation of electrification.

EAR estimates based on DN thresholds were validated against the World Bank's Global Electrification Database because direct ground-based validation across all African regions would prove logistically and financially infeasible; the World Bank compiles nationally representative survey- and census-based electricity access statistics. This validation approach follows prior work by the authors in which the same methodology was applied and validated for Nigeria using World Bank electrification estimates (Kemabonta et al., 2026). In this study, we replicate this validation procedure for all Sub-Saharan Africa (SSA). This is because SSA is treated separately by the World Bank and electrification statistics for North Africa are reported jointly with the Middle East as part of the Middle East and North Africa (MENA) region. In addition, since most North Africa has been considered to have universal electrification, we select the SSA region for validation as it has the greatest number of people without access to electricity, for validation (IEA, IRENA, UN, World Bank, 2023).

The Pearson correlation coefficient ($r$) is calculated using Eq. 3 to evaluate potential DN thresholds for classifying electrified areas. The t-statistic in Eq. 4 is then used to calculate the p-value ($p$) statistical significance of each Pearson correlation coefficient using Eq. 5 with a two-tailed test. Table 1 provides results of comparing SSA-aggregated NTL-based EAR values to World Bank electrification estimates. Based on empirical evidence, a DN threshold of > 7 was set as the upper limit for classifying electrified areas in the Africa EAR dataset. This is consistent with prior findings by Li et al. (2020, 2023) and the authors in (Kemabonta et al., 2026), in which higher thresholds were found to increasingly underestimate rural and peri-urban electrification. Lower DN thresholds are retained for sensitivity analysis to illustrate the robustness of the results and to allow users to assess if alternative assumptions may be appropriate.

$$r = \frac{\sum(X_t - \bar{X})(Y_t - \bar{Y})}{\sqrt{\sum(X_t - \bar{X})^2 \sum(Y_t - \bar{Y})^2}} \tag{3}$$

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \tag{4}$$

$$p = 2 \times \Pr(T \geq |t|) \quad \text{where } T \sim t_{n-2} \tag{5}$$

Where:

$X_t$ = NTL-based electricity access rate sample points for SSA between 2000 - 2021

$Y_t$ = World Bank electricity access rate sample points for SSA between 2000 - 2021

$n$ = number of observations: 22 (2000-2021)

Table 1: Pearson correlation and p-values for various NTL-derived DN thresholds compared to World Bank electrification estimates for Sub-Saharan Africa

| DN Threshold | Pearson Correlation | p-value |
|---|---|---|
| **DN > 7** | 0.961624 | 1.066868e-12 |
| **DN > 6** | 0.934960 | 1.866197e-10 |
| **DN > 5** | 0.916978 | 1.986469e-09 |

| | | |
|---|---|---|
| **DN > 4** | 0.918826 | 1.598469e-09 |
| **DN > 3** | 0.916389 | 2.126675e-09 |
| **DN > 0** | 0.916228 | 2.166344e-09 |

As shown in Table 1, all DN thresholds in the NTL data create EAR estimates with a strong and statistically significant correlation with World Bank electrification rates, indicating that harmonized NTL data robustly capture long-term electrification trends at the regional scale. However, the strength of the correlation increases with higher DN thresholds, and the highest correlation is observed for DN > 7 (r = 0.96). In addition, visual inspection of the time series in figure 3 reveals that lower DN thresholds exhibit more pronounced discontinuities around the 2013-2014 DMSP-VIIRS transition, whereas DN > 7 yields a smoother temporal trajectory with reduced sensitivity to transient and non-electric light sources.

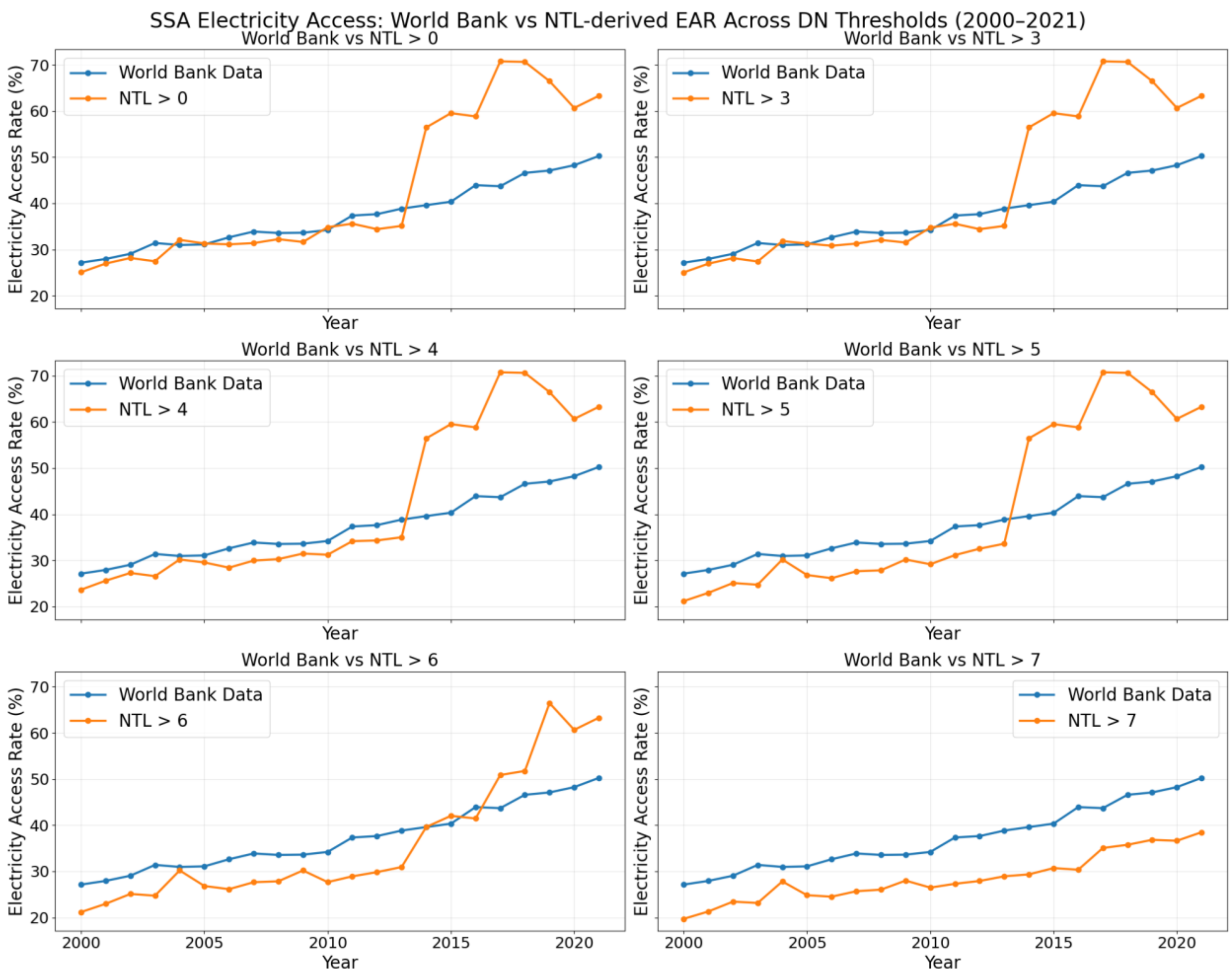


Figure 3: Comparison of World Bank electrification estimates and NTL-based electricity access rates across different DN thresholds (DN > 0, DN > 3, DN > 4, DN > 5, DN > 6, DN > 7).

## Data Records

The Africa EAR dataset consists of annual electricity access estimates for African administrative levels 0, 1, and 2 spanning the period 2000-2021. The dataset is distributed as longitudinal CSV tables organized by administrative level. Separate files are provided for country-level estimates (administrative level 0), first-order administrative regions (administrative level 1), and second-order administrative regions (administrative level 2).

Each row in the dataset represents a unique administrative unit and year combination. The primary identifier fields are $Country\_Name$, $Adm1\_Name$, and $Adm2\_Name$, corresponding to the national, first-order administrative, and second-order administrative regions, respectively. Additional fields include $EAR$, representing the estimated electricity access rate for the administrative unit and year, and $TotPop$, representing the total population aggregated within the administrative boundary.

The EAR estimates were generated using harmonized NTL and population raster datasets at 1 $km^2$ resolution prior to aggregation to administrative boundaries. The identifier fields allow the EAR tables to be joined to corresponding polygon boundary shapefiles for geospatial visualization and spatial analysis in GIS software such as ArcGIS or QGIS. Figures 4-6 illustrate example visualizations generated from these joined datasets at administrative levels 0, 1, and 2.

Figures 4 shows the geospatial evolution of electricity access rates at the national level over the study period. The maps illustrate variation in electrification across the continent as well as clear temporal trends in increasing electricity access across certain countries. While several countries show steady improvements in access rates over the two decades, large disparities remain between regions of the continent with high electrification levels and those with persistently low access.

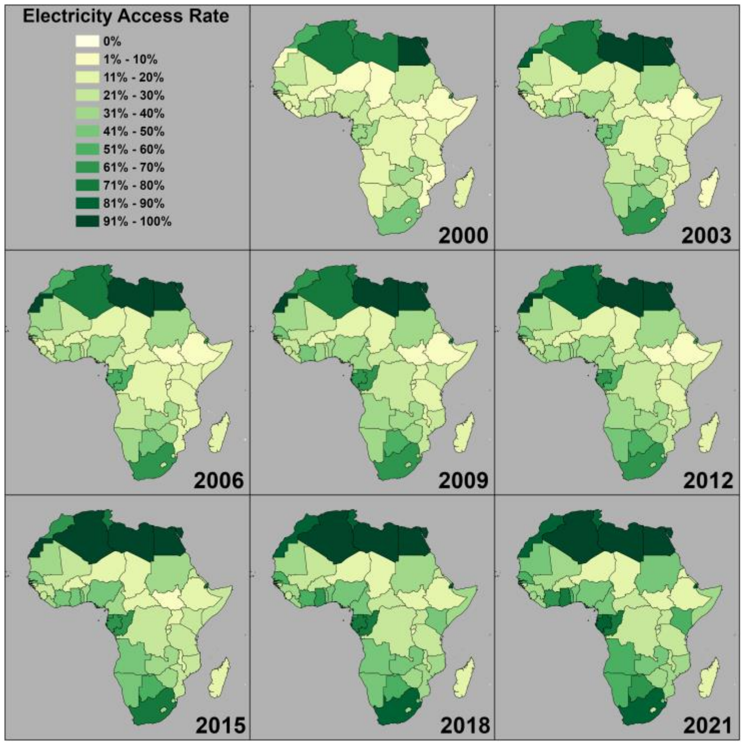


Figure 4: Geospatial evolution of EARs across African countries between 2000 and 2021 as shown in three-year snapshots

Figures 5 and 6 provide higher spatial resolutions of electrification dynamics at administrative levels 1 and 2, respectively. These maps reveal significant subnational heterogeneity in electricity access within countries that is not visible in national-level statistics. The dataset reveals spatial concentration of higher EAR values in urban and peri-urban regions while rural areas exhibit slower growth in electricity access.

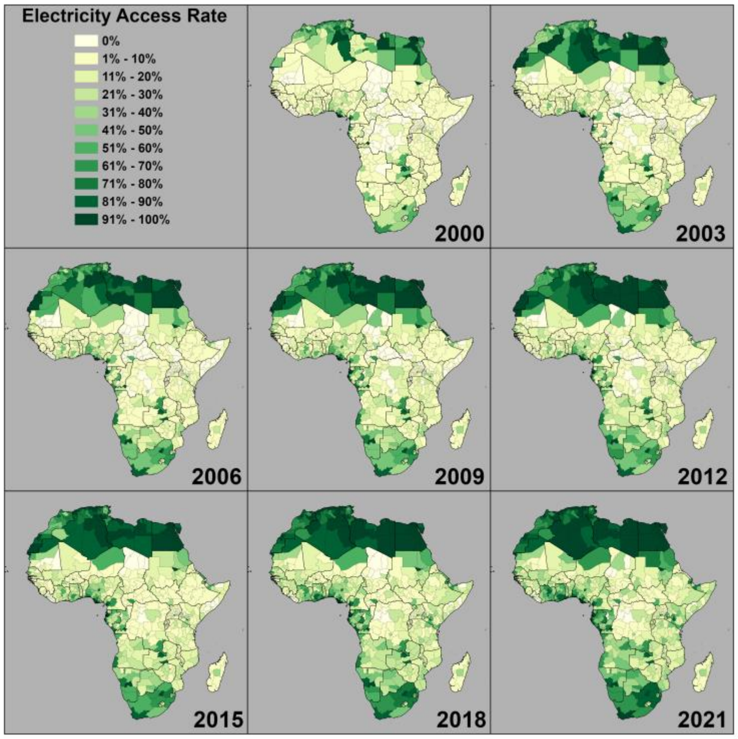


Figure 5: Geospatial evolution of EARs across administrative level 1 in African countries between 2000 and 2021 as shown in three-year snapshots

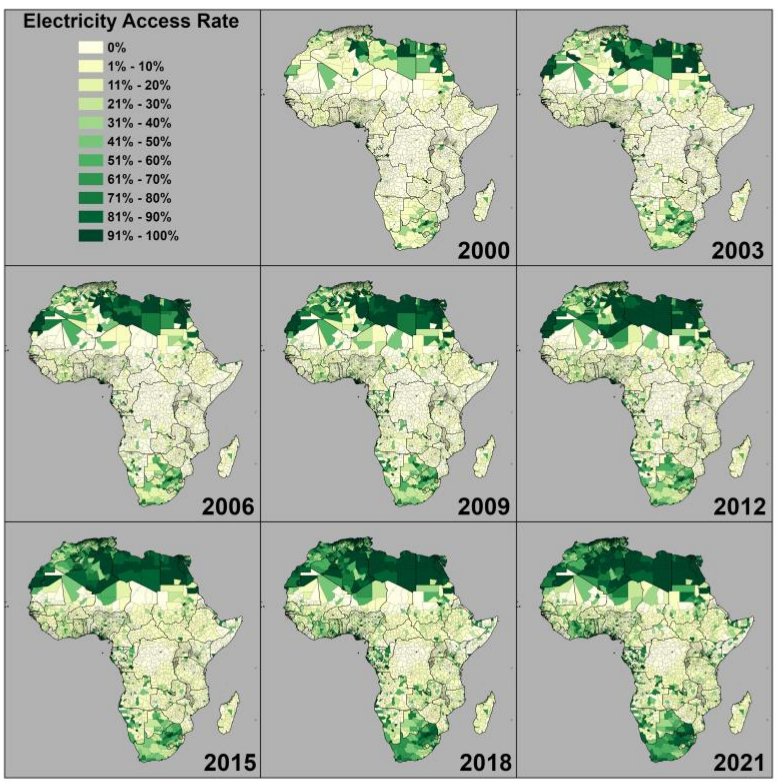


Figure 6: Geospatial evolution of EARs across administrative level 2 in African countries between 2000 and 2021 as shown in three-year snapshots

**Usage notes**

The Africa Electricity Access Rate (EAR) dataset is intended for high-fidelity, large-scale spatial and temporal analysis of electrification patterns across Africa from 2000 to 2021. The dataset provides annual EAR estimates at 1 $km^2$ resolution, with aggregations available at administrative levels 0, 1, and 2, enabling applications at continental, national, and subnational scales.

EAR estimates derived from nighttime luminosity data represent observable and persistent nighttime electricity use, rather than estimates created based on poorly documented formal grid connections or standard engineering measures of service reliability. As such, the dataset is an indicator of any form of electricity access that is sufficiently stable to result in detectable nighttime illumination over time (Min, 2015; Min et al., 2013; Min & Gaba, 2014). Persistent illumination across years may therefore provide indirect evidence of minimum service stability at annual and subnational scales.

However, several limitations should be considered when using the dataset. Nighttime light observations cannot capture short-term service interruptions, outage frequency, or power quality metrics such as SAIDI or SAIFI. Consequently, the EAR dataset should not be used to infer electricity reliability or service quality. In addition, areas with limited or indoor-only electricity use may exhibit weak or undetectable nighttime illumination even when some electricity access exists (Li et al., 2020; Min, 2015).

The primary EAR estimates provided in this study are based on a DN threshold of $DN > 7$, which demonstrated the strongest agreement with survey-based electrification statistics and reduced sensitivity to transient light sources. Alternative thresholds are included for sensitivity analysis, allowing users to evaluate how different assumptions about light intensity affect electrification estimates (Li et al., 2020, 2023) .

Researchers using the dataset should also account for the transition between the DMSP/OLS and VIIRS satellite systems. Although the harmonized nighttime luminosity dataset substantially improves temporal consistency, residual artifacts may remain, particularly at lower DN thresholds.

The EAR dataset is well suited for applications including electrification planning, energy systems modeling, planning for businesses and entrepreneurs that require a threshold energy access level, climate-energy-development analysis, and retrospective analysis of electrification policy. The data may help complement other studies that provide a more detailed study of electricity reliability, quality of service, or intra-household access, as these dimensions cannot be resolved from nighttime light observations alone.

**Data Availability**

The Africa EAR dataset generated in this study is publicly available at [https://doi.org/10.6084/m9.figshare.32411700]. The repository contains CSV tables of annual EAR estimates for administrative levels 0, 1, and 2 across African countries from 2000 to 2021. The tables include administrative identifiers that allow users to join the data to corresponding polygon boundary files for mapping and spatial analysis.

**Code Availability**

Custom geospatial processing and statistical analysis code used to generate the EAR dataset is available from the corresponding author upon reasonable request.

**Funding Declaration**

The authors received no specific funding for this work.

**References**

Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F., & Taneja, J. (2021). *Annual Time Series of Global VIIRS Nighttime Lights Derived from Monthly Averages: 2012 to 2019*.

Falchetta, G., Pachauri, S., Parkinson, S., & Byers, E. (2019). A high-resolution gridded dataset to assess electrification in sub- Saharan Africa. *Scientific Data*, 1–9. https://doi.org/10.1038/s41597-019-0122-6

IEA, IRENA, UN, World Bank, W. (2023). *Tracking SDG7: The energy progress report*. The World Bank Group.

Jiang, S., Wei, G., Zhanf, Z., Wang, Y., Xui, M., Wang, Q., Das, P., & Liu, B. (2021). Detecting the Dynamics of Urban Growth in Africa Using DMSP/OLS Nighttme Light Data. *Land*, 1–19.

Kemabonta, T., Alsanad, A., Leonard, B., & Johnson, N. (2026). Nightlights and electricity access: Measuring the effectiveness of electrification policies in Nigeria using satellite images. *Frontiers in Energy Research: Sustainable Energy Systems*.

Li, X., Zhou, Y., Zhao, M., & Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific Data*, *7*(1), 168. https://doi.org/10.1038/s41597-020-0510-y

Li, X., Zhou, Y., zhao, M., & Zhao, X. (2023). *Harmonization of DMSP and VIIRS nighttime light data from 1992-2021 at the global scale* (p. 1210581707 Bytes) [Dataset]. figshare. https://doi.org/10.6084/M9.FIGSHARE.9828827.V8

Mills, S., Weiss, S., & Liang, C. (2013). Mills, S., Weiss. & Liang, C. VIIRS day/night band (DNB) stray light characterization and correction. *Proc. SPIE 8866, Earth Observing Systems*, *XVIII*(88661P).

Min, B. (2015). *Power and the Vote: Elections and Electricity in the Developing World*. Cambridge University Press.

Min, B., & Gaba, K. M. (2014). *Tracking Electrification in Vietnam Using Nighttime Lights*. 9511–9529. https://doi.org/10.3390/rs6109511

Min, B., Gaba, K. M., & Sarr, O. F. (2013). Detection of rural electrification in Africa using DMSP-OLS night lights imagery. *International Journal of Remote Sensing*, (March 2015), 37–41. https://doi.org/10.1080/01431161.2013.833358

Zhao, F., Ding, J., Zhang, S., Luan, G., Song, L., & Peng, Z. (2020). Estimating Rural Electric Power Consumption Using NPP-VIIRS Night-Time Light , Toponym and POI Data in Ethnic Minority Areas of China. *Remote Sensing*.