Can Africa's electric grids support the energy transition?

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Abstract

Widespread electrification of cooking, cooling, heating, and transport is central to a global clean energy transition that reduces fossil fuel use and mitigates climate change. Low- and middle-income countries, which account for 85% of the world's population, are expected to drive most future growth in electricity demand, yet face a largely unaddressed constraint: poor power quality and reliability (PQR). We use newly generated, utility-independent, high-frequency measurements from thousands of grid-connected customers in urban, peri-urban, and rural Africa to document four constraints to electrification in these contexts. First, electricity supply is characterized by persistent PQR problems that impose costs on customers and limit the performance of electric appliances. Second, load growth—from both new connections and increased consumption—reduces voltage quality for existing customers in the absence of substantial investment in distribution infrastructure. Third, weak grids cannot support widespread adoption of electric cooking, as power quality is lowest during peak cooking hours. Fourth, higher temperatures are associated with lower voltage and increased outage risk, and rising demand for cooling will further strain already constrained systems. These challenges arise in settings where electricity systems are often financially and operationally constrained, limiting the capacity to improve distribution infrastructure. Without substantial investment, power quality constraints may undermine the clean energy transition for billions of people in low- and middle-income countries.

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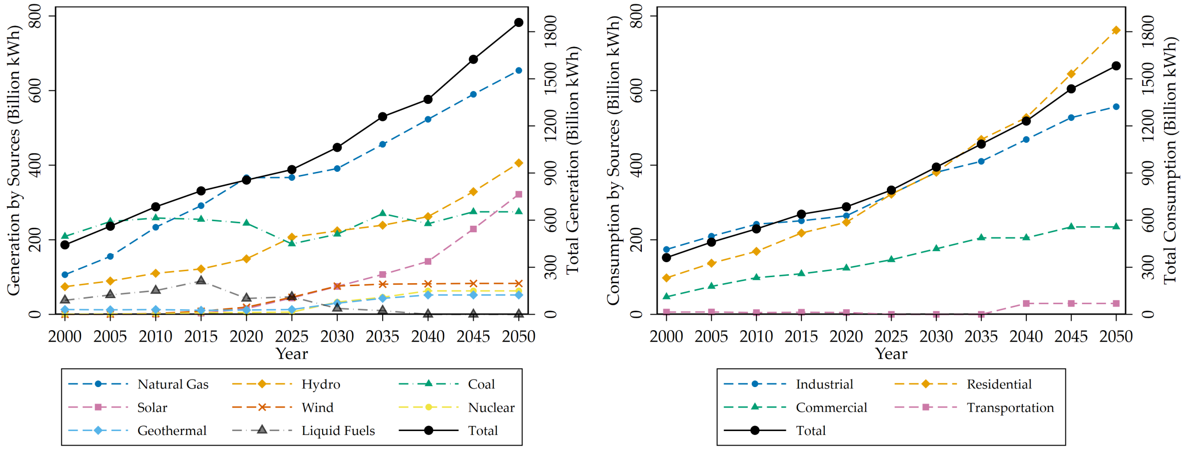
> “[African grids are] old trees growing heavy with fruit.”
> — Rosemary Oduor, General Manager of Commercial Services and Sales at Kenya Power and Lighting Company, the country’s state-owned utility (Bearak 2025)

1 Introduction

The world is on the cusp of a massive global energy systems transition, with large parts of the world’s population shifting from fossil-fuel-based durables to electric substitutes (Bouckaert et al., 2021). Low- and middle-income countries are predicted to drive most global electricity demand growth (IEA, 2021) Africa, where the population is projected to exceed 3 billion people by 2070 and the current energy mix remains dominated by traditional biomass, will be at the forefront of this transition. Electricity consumption in Africa is projected to more than double in the coming decades (Figure 1). Whether existing grids can support this transition depends not only on generation capacity, but on the quality of electricity delivered to end users.

Figure 1: Recent and projected electricity generation and consumption in Africa


(a) Generation

(b) Consumption

Note: Data are summed across all African countries. Historical data on generation is drawn from the U.S. Energy Information Administration (EIA)’s International Energy Information. Historical data on consumption is drawn from the International Energy Agency (IEA)’s Africa Electricity Section. Projections start from 2025 and are drawn from the reference scenario in the EIA International Energy Outlook 2023 (EIA, 2023).

African countries have set ambitious grid expansion targets under initiatives such as Mission 300 (WB, 2025), but decades of rapid and underfunded expansion have left many distribution networks strained, aging, and undersized. Poor power quality and reliability (PQR) from such grids affect an estimated 3.5 billion people globally (Ayaburi et al., 2020). Despite the importance of these constraints, customer-level data on PQR in LMICs remain scarce.

This paper uses high-frequency data from GridWatch sensors deployed with thousands of grid electricity customers across urban, peri-urban, and rural grids across Ghana, Kenya, and Tanzania to analyze variation in PQR across time and space. We document that customer-level voltage is often more than 10% below nominal levels, with frequent sustained drops exceeding 20%, and that outages are both common and more frequent than reported in survey data. These conditions impose hidden costs by damaging appliances, reducing their functionality, and likely suppressing adoption.

We identify three additional ways that electricity distribution issues may constrain the energy transition in similar contexts. First, we find that voltage quality varies systematically within local networks: every 10 additional connections to a transformer results in a 4–5 V drop in average voltage for existing customers, with the largest declines for those farthest from the transformer. This implies that load growth—whether from new connections or higher consumption by existing customers—can degrade quality across the network. Second, voltage is lowest during peak evening hours (6–10 PM), constraining the adoption and performance of electric cooking and other appliances used during diurnal peaks. Third, average voltage decreases with temperature, while the risk of outages generally increases. Rising temperatures directly worsen PQR by hindering power generation and increasing distribution losses. But rising incomes and temperatures will increase demand for cooling (Gertler et al., 2016; Sherman et al., 2022), further straining already weak grids and reducing the effectiveness of these appliances.

2 Challenges related to power distribution

Despite the importance of distribution-level performance, data on customer-level power quality and reliability (PQR) in LMICs are extremely limited. The majority of losses and failures in electrical grids in Africa arise in the low voltage portion of the network known as the distribution network: all of the wires, transformers, and electrical equipment that connects the grid to customers (CEER, 2017; KfW Development Bank, 2020). But the majority of problems arising in African electrical grids are not quantified and reported in an automated way. Instead, understanding of "typical" grid performance and resilience is based on self-reported customer data, which suffer from reporting biases and inaccuracies, or aggregated data from utilities. We address this gap using GridWatch sensors, which provide high-frequency measurements of voltage and outages directly at the customer level.

We analyze high-resolution customer-level measurements of power quality and reliability (PQR) collected by GridWatch sensors deployed with around 2200 electricity customers in urban and peri-urban Ghana, rural Kenya, and peri-urban Tanzania between 2018 and 2024 (Klugman et al., 2014, 2019). Appendix A1 provides more detail on the GridWatch technology, how it measures PQR, and how it compares to alternative data sources. These high-resolution and high-frequency data elucidate the on-the-ground customer experience of electricity distribution in four very different LMIC contexts in Africa (Table A1).

2.1 Electricity reliability is low

The median site experiences 30, 32, and 68 minutes of outages per day on average in urban Ghana, peri-urban Ghana, and rural Kenya, respectively, which adds up to 181, 194, and 409 annual hours of outages. At the 75th percentile in each context, customers experience 282, 311, and 694 annual outage hours. In Ghana, data from 2019-2024 shows fairly similar average annual customer outage hours over time and no downward trend, consistent with slow changes in reported average outage hours by firms in the World Bank Enterprise Survey (WBES) from 2006-2025 (Figure A2).

Measured outage durations are substantially higher than those reported in survey data, consistent with under-reporting due to recall bias and aggregation. In urban Ghana in 2023, WBES firms reported an average of 146 hours of outages compared to 221 hours detected by GridWatch on the same local networks (Figure A1).

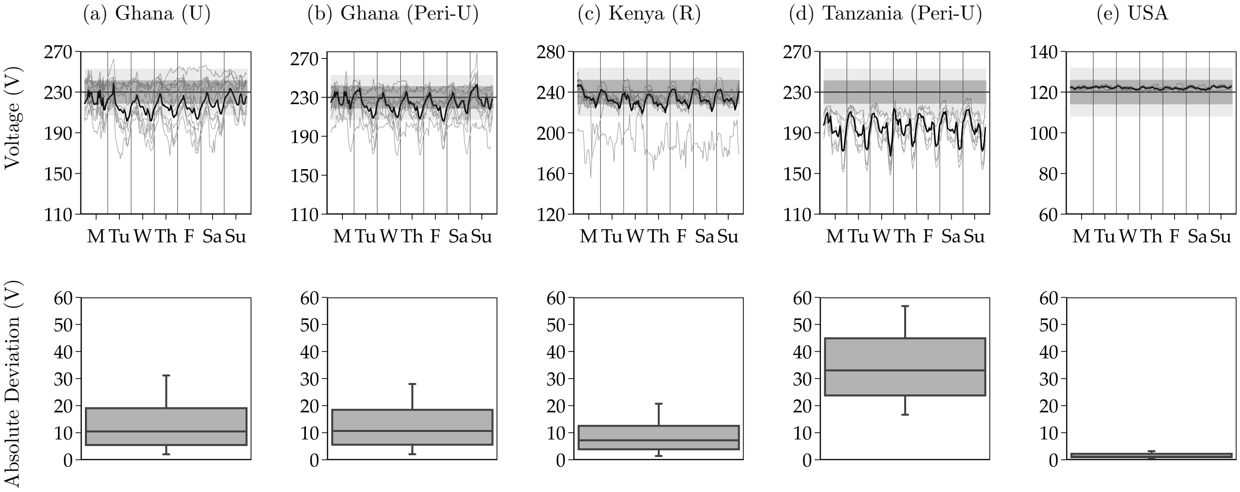
2.2 Voltage quality is highly variable

Voltage fluctuations can damage appliances and reduce their functionality, but direct data on voltage quality are especially limited in LMICs (Berkouwer et al., 2025; Dubey, n.d.; International Bank for Reconstruction and Development / The World Bank, 2021). The few surveys asking about voltage issues find that around one-third of customers report voltage-related appliance damages (Blimpo & Cosgrove-Davies, 2019; Dubey, n.d.). Figure 2 compares data on voltage quality from sensors we deploy in Ghana, Kenya, and Tanzania, alongside voltage data from the U.S. (Pecan Street Inc., 2018).

In the U.S., deviations from nominal voltage are exceedingly rare: the largest fraction of recordings outside ±5% and ±10% within a single month is 1.6% and 0.1%, respectively. Voltage frequently deviates more than 10% below nominal levels in the African study contexts, with substantial variation across locations and time of day. The largest drops occur in the evening hours of peak residential power consumption. Taking all observations together, the median absolute voltage deviation is 6 V in rural Kenya, around 10 V in Ghana, and over 30 V (13% below nominal) in peri-urban Tanzania. At the 75th percentile, these values are 12 V in Kenya, around 20 V in Ghana (9% below nominal), and 45 V (20% below) in Tanzania.

Though there is variation both across and within sites, these voltage issues are widespread rather than concentrated in particular sites (Figure A3). In rural Kenya, voltage is at least ± 10% from nominal voltage 11% of the time on average, compared to 14% of the time in urban and peri-urban Ghana. These voltage deviations can damage appliances and reduce their functionality. In urban Ghana, 25% of grid customers report appliance damages in the past year and one-third of firms report that bad voltage is an important business obstacle (Berkouwer et al., 2025).

Figure 2: Deviations from nominal voltage in Ghana, Kenya, and Tanzania compared with the USA


(a) Ghana (U)
(b) Ghana (Peri-U)
(c) Kenya (R)
(d) Tanzania (Peri-U)
(e) USA

Note: U indicates an urban context and R indicates rural. The top row shows mean hourly voltage for the full sample (in bold) and hourly variation for 10 randomly selected grid customers in each location for a single week with the closest average temperature to the annual mean (April 12-18th 2021 for Ghana; April 11-17th 2022 for Kenya; November 18-24th for Tanzania; Oct 9-15th 2018 for USA). Shaded bands indicate ±5% and ±10% outside the nominal voltage prescribed by the utility regulator (120 V in the USA, 230 V in Ghana and Tanzania, and 240 V in Kenya). The bottom row shows the median, the interquartile range (shaded), and the 10th-90th percentile range (connected line) of the absolute deviations from nominal voltage among all sampled customers and across the sample period of each location. The U.S. data are provided by Pecan Street 2018. All other data are from GridWatch sensors.

3 Challenges related to power demand

3.1 Supporting increased load

Distribution infrastructure such as transformers and low-voltage lines are designed to support a certain sustainable load of electricity consumption. The quality and reliability of electricity received by customers is in large part a function of the overall load on the LV electricity distribution network to which they are connected. Prolonged overloading is an important cause of transformer failures (Carranza & Meeks, 2021; Glover et al., 2012; Singh & Singh, 2010) and also reduces power quality. While a large body of evidence demonstrates how transformer overloading can cause outages, there is less evidence for an effect on power quality, mainly due to data limitations.

Though we do not observe transformer-level loads directly, we combine power quality data from GridWatch sensors in Kenya with detailed information on local network configuration to test whether power quality varies systematically within LV networks. We focus on how voltage changes with the number of customer connections between a sensor and its connected transformer, a proxy for cumulative load along the line.

Table 1 shows that the number of customer connections between a sensor and the connected transformer significantly decreases average voltage. This effect holds even when controlling for physical distance to the transformer along the LV network, which itself does not significantly affect average voltage. These results indicate that it is the current flow along the line, drawn by connected loads, rather than line impedance that drives the decrease in voltage along LV lines.

For every 10 additional connections between a customer and the transformer serving the local LV network, that customer's average voltage drops by 4-5 V. These results show that power quality issues on overloaded transformers are not felt equally by all connected customers. Those closest to the transformer, drawing power first, are somewhat protected while the furthest customers experience the worst voltage on average.

Table 1: Voltage quality deteriorates with additional customers

	(1)	(2)	(3)
Distance to Transformer (m)	-0.003		0.002
	(0.002)		(0.003)
Number of Customer Connections		-0.400^{***}	-0.474^{***}
		(0.114)	(0.133)
Constant	236.587^{***}	237.207^{***}	236.801^{***}
	(1.054)	(0.816)	(1.042)
Observations	507257	494816	492712

Notes: The dependent variable is voltage, measured at the hour-sensor level. Regressions include hour-of-day by day-of-week fixed effects. Distance to transformer is measured in meters along LV lines between the customer connection with the GridWatch sensor and the transformer. Number of customer connections is the count of additional customers connected to the LV line between the sensor and the transformer. Standard errors are clustered by respondent. Data are from GridWatch sensors deployed from June 2021 to June 2022 in rural Kenya, where the nominal voltage is 240 V. $^{*}p < 0.10,^{**} p < .05,^{***} p < .01$.

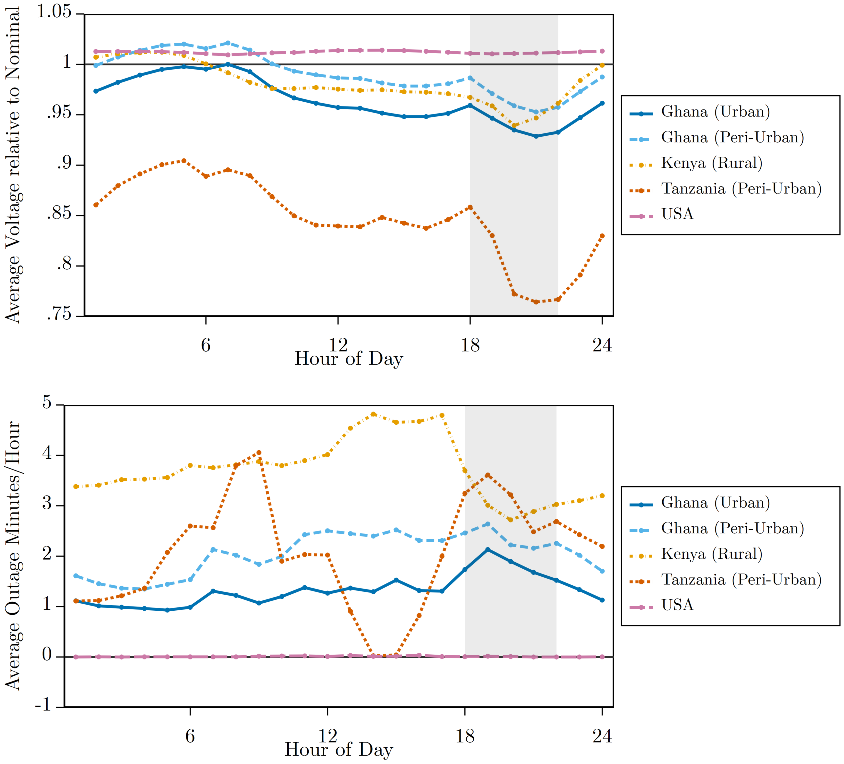
As additional customers connect to the grid, and as those customers increase load through electric appliance adoption, voltage quality can be expected to worsen. This consideration is particularly important for African countries, which with some exceptions generally have more customers per transformer but spend less on repair and maintenance than utilities in higher-income countries (Figure A4).

3.2 Supporting the clean cooking transition

A defining feature of electric cookstove adoption is that it adds load to the grid during mealtimes, which tend to be highly correlated across customers. This increased load from cooking is largest in the evening hours when demand already peaks, and where voltage quality is therefore already worst in grids that are overloaded or not well-maintained (Figure 3).

Average voltage is 7-8 V lower from 6-10 pm compared to other hours in Ghana and Kenya and 14 V lower in Tanzania (Table A2). The trend is most noticeable on weekdays when customers may have less flexibility in their cooking hours (Figure 2). Although increased peak loads could also increase the risk of outages, there is no systematic relationship between outages and time of day (Figure 3, bottom). Average outage minutes per hour are 46% higher from 6-10 pm in urban Ghana and 18% higher in peri-urban Ghana, but are 22% lower in rural Kenya and do not change significantly in Tanzania (Table A3). Without significant investments in the grid, the widespread adoption of electric cookstoves will likely worsen power quality during hours where quality is already low.

Figure 3: Power quality and reliability by hour of day



Note: Average hourly measurements from the U.S., Ghana, Kenya, and Tanzania. Average voltage is relative to nominal voltage (which is 120V in the U.S., 230V in Ghana, 240V in Kenya). Outage minutes are per hour. Typical cooking hours (6pm–10pm) are shaded in gray. The U.S. data are provided by Pecan Street 2018. All other data are from GridWatch sensors.

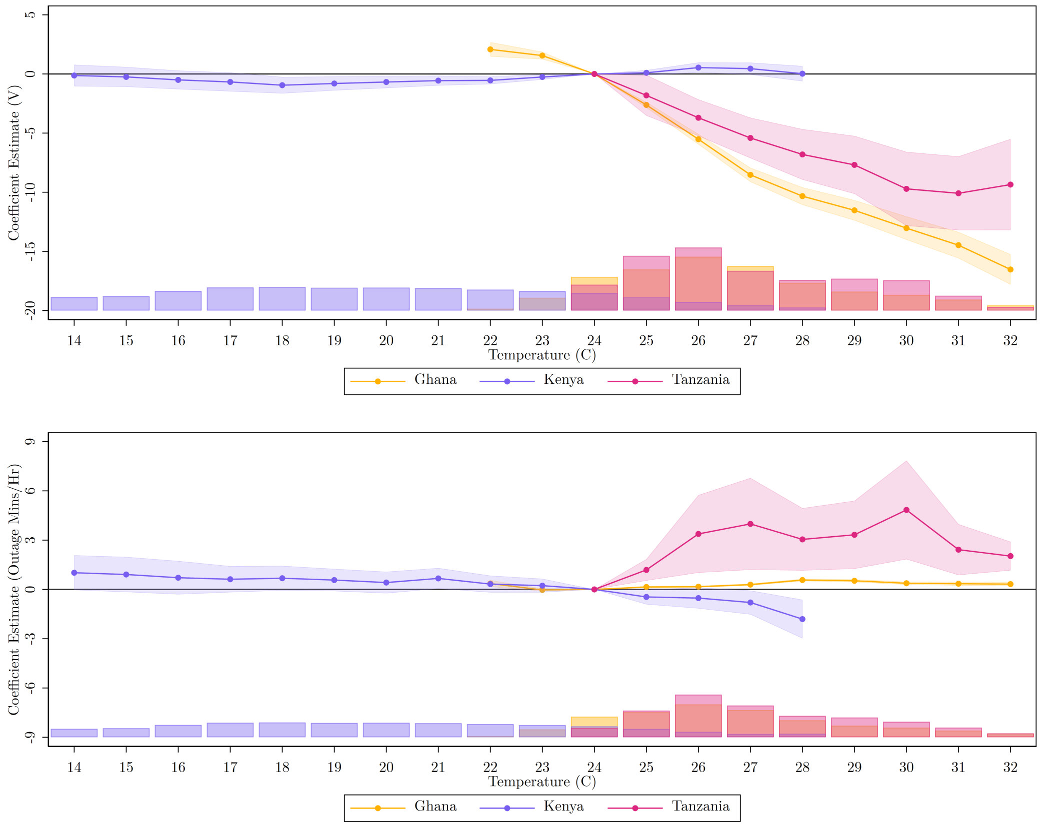
On the other hand, poor power quality during hours in which customers prefer cooking could also undermine the widespread adoption of electric stoves. With voltage often 10% or more below nominal during peak cooking hours, "even the most efficient electrical cooking appliances would not be able to function" optimally (ESMAP, 2023) and there is a greater risk of appliance damage. Power issues during cooking times may cause potential adopters to maintain existing technologies or switch to gas stoves or other cooking technologies instead for their clean cooking transition.

3.3 Supporting adaptation to a changing climate

Higher temperatures increase cooling demand, and meeting this demand will require major investments in electrification and power system resilience (Auffhammer et al., 2017; IEA, 2018; Sherman et al., 2022). Cooling demand will be greatest when temperatures are higher. Using GridWatch sensor data and ERA5 hourly temperature data (Muñoz-Sabater et al., 2021), we test whether PQR are affected by temperature after controlling for location and hour of day.

The top panel of Figure 4 shows that temperature appears uncorrelated with voltage in Kenya but is negatively correlated with voltage in Ghana and Tanzania. Since the regressions include hour-of-day interacted with site fixed effects, this relationship cannot be driven by spurious correlations in the diurnal patterns in load and temperature. The bottom panel of Figure 4 shows that temperature is weakly but positively correlated with outages in Ghana and strongly correlated with outages in Tanzania. The relationship between outages and temperature in Kenya, where the study area is much cooler, is weak but suggests that outages are higher at *lower* temperatures. This could reflect a greater relevance of heating rather than cooling appliances in this setting.

Figure 4: Temperature's effect on power quality and reliability



Note: Coefficients are from separate regressions by country for the effect of hourly temperature deviations away from 24°C on hourly average voltage (top) and hourly outage minutes (bottom) at the customer level. Shaded areas represent 95% confidence intervals. Regressions include fixed effects for hour-of-day interacted with fixed effects for site, capturing most of the predictable diurnal variation in load and power quality. Standard errors are clustered by sensor. The bottom of the figures shows a histogram of the distribution of hourly temperatures by country. Separate figures by country are shown in Figure A5. Power data are from GridWatch devices. Temperature at two meters above the ground is from the ERA5-Land reanalysis dataset.

Several factors can explain the relationship between temperature and PQR. Heat reduces power plant and solar panel efficiency and impairs heat dissipation following generation, potentially decreasing power supply and causing outages (Liang et al., 2025; Saki et al., 2025; Sergio & Colelli, 2025). High temperatures also increase distribution line losses and stress on transformers (Ke et al., 2016; Saki et al., 2025; Santágata et al., 2017), while higher temperatures may also increase load due to use of fans and air-conditioners. Adoption of ACs is low across most of the study areas, suggesting demand factors can explain only a portion of the relationships in Figure 4. In Ghana for example, 83% of customers in the sample have a fan and 9% of customers own an air-conditioning unit. In the mild climate of the rural Kenya study area, none of the customers surveyed owned a fan or an air-conditioning unit, which could explain the lack of relationship between temperature and PQR in this setting.

These findings imply that rising incomes and temperatures can worsen voltage quality precisely when the grid is most needed. As with electric cooking, grid electricity issues may constrain adoption of cooling appliances. A study in the Kyrgyz Republic finds that randomized improvements to grid reliability led households to purchase more electric appliances, including heating and cooling devices (Meeks et al., 2023), suggesting power quality was a constraint to adoption.

4 Conclusion

Using high-frequency data from African distribution networks, we show that the main constraint to electrification is often not connection alone, but the quality of electricity delivered. Chronic undervoltage, substantial within-network variation, and frequent outages reduce appliance performance, damage equipment, and make electric end uses less attractive precisely when electricity demand is expected to rise.

These constraints directly affect the energy transition. Additional connections and higher demand can worsen voltage for existing customers; evening peaks make electric cooking especially challenging; and higher temperatures are associated with lower voltage and greater outage risk, limiting the effectiveness of cooling as a form of climate adaptation. Worsening reliability and quality may lead wealthier customers to seek alternative or off-grid energy sources, while poorer customers remain limited in their ability to adopt, use, and benefit from electric appliances.

Policies focused only on access or feeder-level outages will miss these distribution-level constraints. Electricity access without quality and reliability is a broken promise. Supporting a durable energy transition will require investment strategies and performance standards that track customer-level power quality and reliability alongside access expansion, so that electrification delivers usable electricity rather than nominal connections.

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A1 Measuring PQR

The lack of discussion of power quality and reliability (PQR) issues in global energy transition discussions results in large part from a scarcity of high-quality quantitative data on grid performance (Taneja, 2017). Existing PQR estimates often use data from household and firm surveys; these tend to be temporally sparse, prone to recall error, and biased towards highly visible grid failures (Moyo, 2013). Customer reports to utilities are furthermore subject to biased selection in who reports issues, with higher-income customers more likely to report (Ayaburi et al., 2020). Direct grid measurements are concentrated in the higher voltage portions of the network, such as those made by Supervisory Control and Data Acquisition (SCADA) systems. Such measurements capture a biased view of the system, entirely missing outages and power quality events emerging in the vast low-voltage distribution network, where significant issues and losses originate (Bhatti et al., 2015). In Senegal, installing sensors on transformers to directly measure outages allowed the utility to respond more rapidly and significantly reduced outages (Cisse, 2026), but deployment of such sensors is very limited in LMICs.

Furthermore, most existing data and targets focus on power outages: there is a dearth on insight into unstable or unusable voltage provided at customers' points of connection. For example, the World Bank's Energy Sector Management Assistance Program (ESMAP) defines Tier 4 energy access as having "no voltage issues;" a single binary measure, originating largely from households surveys (Dubey, n.d.; International Bank for Reconstruction and Development / The World Bank, 2021). The United Nations sustainable development goal on energy access (SDG-7) completely omits any mention of voltage quality ("The Sustainable Development Goals Report 2022 — DISD", 2022).

A1.1 GridWatch technology

To provide granular, continuous PQR data at scale in LMICs, the GridWatch technology suite combines low-cost PowerWatch sensors with cloud data storage and processing (Klugman et al., 2019, 2021). GridWatch's affordable, agile sensing approach has enabled rapid deployment of thousands of sensors across several countries, delivering a generational improvement on the spatial scale and number of measurement points of electricity quality data available anywhere in Africa. The PowerWatch sensor plugs directly into customer wall outlets to measure voltage magnitude, AC frequency, and power state at two minute intervals. With an integrated SIM card, the sensor reports measurements over the cellular network, and has local storage to support a data backlog in case of network failure. Since it is plugged into a wall outlet, the sensor can be installed quickly and cheaply—enabling affordable and rapid deployment at scale—and captures PQR as directly experienced by the customer.

We deploy PowerWatch devices with around 2,300 participants across urban, peri-urban, and rural Africa. 1,538 participants (803 households and 817 businesses) are located across Accra, the capital of Ghana and the 12^{th} largest city in Africa. In Kenya, 598 participants (564 households

Figure 5: A PowerWatch device

A PowerWatch device, part of the GridWatch technologies used to measure customer-level power outages and voltage.

and 34 businesses) are located across rural villages in five counties—Kakamega, Kericho, Kisumu, Nandi, and Vihiga—that were part of Kenya's nationwide rural electrification program. In both countries, devices are deployed in clusters of 3-5 devices per site, defined as a set of households and/or business premises connected to the same distribution transformer. Figure A3 displays a map of deployments in Ghana and Kenya, colored by the fraction of time each site experiences poor voltage. The deployment in Tanzania (11 customers) was smaller in scale.

Algorithms deployed in the GridWatch cloud transform raw PowerWatch data into robust grid performance metrics. A key component of these algorithms is to mitigate noise—inevitably introduced when using an agile, edge sensing strategy—by aggregating data across sensors. To aggregate individual sensor outage reports—which might contain "false outage" noise due to sensor unplugs, loose connections, or a house level meter run out—into coherent grid outages, GridWatch uses the non-parametric spatio-temporal density-based clustering algorithm of applications with noise (ST-DBSCAN)(Klugman et al., 2019, 2021). The algorithm sorts sensor outage reports into clusters based on the spatial proximity of the sensors and the temporal proximity of the reports; hand selected space and time thresholds define the limits for how far apart in space sensors can be and how far apart in time outage reports can be to belong to a single outage. Clustering reflects the physical intuition that a grid outage stemming from a particular piece of infrastructure should affect a contiguous set of sensors deployed under the infrastructure, producing a set of essentially co-incident outage reports from those sensors, while an unplug will affect a single sensor and is unlikely to be co-incident with other outage reports. ST-DBSCAN is a convenient choice of clustering algorithm because it does not require the number of clusters (i.e., outages) present in the data to be specified beforehand; instead this number is discovered through the process of clustering. The algorithm does not require all data points to be forced into a cluster. Consequently, outage reports that are too far in space/time to be assigned to any cluster are marked as outliers, which enables filtering of "false outages."

A1.2 Comparison to other data sources

Researchers have previously attempted to bridge the critical data gap created by the high cost and lack of low voltage network monitoring of SCADA systems, which are the primary source of PQR data in high-income settings. Table 2 compares GridWatch against SCADA and two other approaches.

Table 2: Alternative sources for PQR data in low-resource contexts

Data source	**Frequency**	**Granularity**	**Affordability**	**Examples**
SCADA Systems	Very high	Medium	Very low	
Satellite imagery	Low–Medium	Low–Medium	Very high	(Cao et al., 2013; Chand et al., 2009; Correa et al., 2022; Min & Gaba, 2014)
Smart meters	High	Very high	Very low	(Bahmanyar et al., 2016; Kaufmann et al., 2013; Silverstein, 2011; Sovacool et al., 2017)
Phasor Measurement Units	?	?	?	(Hojabri et al., 2019; Stewart & von Meier, 2016; Yuan et al., 2021)
GridWatch	Very high	High	High	

High resolution daytime satellite imagery and low resolution nightlights data can provide estimates of electricity access and large storms (Cao et al., 2013; Chand et al., 2009; Correa et al., 2022; Min & Gaba, 2014), but remote sensing does not capture voltage quality and often lacks temporal frequency and spatial granularity. Conversely, smart meters generate highly precise data, but are prohibitively expensive for many resource-constrained utilities (Bahmanyar et al., 2016; Kaufmann et al., 2013). Smart meter roll-outs also face large technical challenges: the UK's Smart Meter Implementation Program, for example—one of the world's largest and most expensive smart meter roll-outs—has faced software malfunctions, privacy concerns, and concerns about marginalization of low-income populations (Sovacool et al., 2017). Distribution level Phasor Measurement Units (PMUs) are similarly unaffordable and challenging to deploy and operate, in part due to the vast volumes of data they generate (Silverstein, 2011). Comprehensive deployments of smart meters or PMUs will likely remain out of reach to LMICs for decades to come.

Previous research on the use of wireless sensing across generation, distribution, and utilization makes a compelling case for the role of sensor based technology in power monitoring systems (Gungor et al., 2010). Other researchers have developed sensor-based technologies similar to GridWatch to monitor grid behavior. However, unlike GridWatch, these deployments have thus far remained small-scale—a 2020 study from Kenya for example uses the GridAlert system to monitor power blackouts in 18 Kenyan homes (Chidziwisano et al., 2020).

GridWatch is a low-cost, high-accuracy, scaleable measurement technology that can provide actionable insights in service of LMIC utilities, customers, investors, researchers, and diverse energy stakeholders.

A1.3 Analyses using GridWatch data

To analyze the effects of number of connections along the local LV network on average voltage, we estimate fixed effects regressions of the form

$$V_{ist} = \beta_0 + \beta_1 Dist_{is} + \beta_2 NumCust_{is} + \delta_t + \epsilon_{ist}$$

where V_{ist} is voltage quality experienced by customer i at site s at time t. $Dist_{is}$ is the distance in meters along the line between the sensor and the transformer to which it is connected. $NumCust_{is}$ is the number of additional customers along the line between the sensor and the transformer. δ_t are hour-of-day by day-of-week fixed effects. Regressions are only estimated for Kenya as we do not have data on the number of customers along the local LV network in the other study contexts. We cluster standard errors at the level of sensors.

To test for differences in PQR by time of day, we estimate fixed effects regressions of the form:

$$PQR_{ist} = \beta_0 + \beta_1 Prime_{ist} + \delta_t + \lambda_t + \gamma_s + \epsilon_{ist}$$

where PQR_{ist} is power quality and reliability experienced by customer i at site s at time t. $Prime_{ist}$ is an indicator for whether the time of day is between 6-10pm. δ_t, λ_t, and γ_s are day-of-week, week-of-year, and site fixed effects respectively. Regressions are estimated separately by country and we cluster standard errors at the level of sites where GridWatch sensors are deployed.

To explore whether seasonal and diurnal patterns in voltage quality are driven by temperature, we estimate the following fixed effects regressions:

$$PQR_{ist} = \beta_0 + \sum_{b=1}^{B} \beta_n T_{tsb} + \gamma_{ts} + \epsilon_{ist}$$

where PQR_{ist} is power quality and reliability experienced by customer i at site s at time t. T_{tb} is an indicator variable for temperature bin b at site s at time t. $\gamma_t s$ are hour-of-day by site fixed effects, which absorb any predictable diurnal variation at each site that is not caused by temperature. Temperature bins have width $1°C$ and we omit the $24°C$ indicator to serve as the reference temperature. Coefficient estimates can be interpreted as the marginal effect of experiencing a specific temperature for one hour relative to a counterfactual of experiencing $24°C$ for that hour at that site. Regressions are estimated separately by country and we cluster standard errors at the level of sites where GridWatch sensors are deployed.

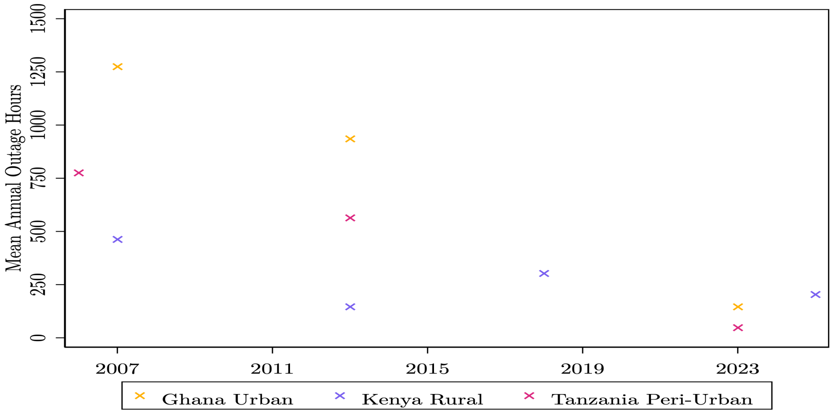
A2 Supplementary Exhibits

Table A1: Basic demographic and socio-economic characteristics of study area households

	Urban Ghana	Rural Kenya	Urban Tanzania
Number of Households (Millions)	5.1	7.38	8.36
Annual Household Consumption (USD)	2,916	2,327	2,815
% Age 0-14	37.5	42.1	36.8
% Age 15-64	57.1	51.6	60.2
% Completed Primary School	63.6	45.15	90.2
% Completed Secondary School	25.6	17.2	31.4
% Households using Electricity for Lighting	99	78.2	92
% Households with Refrigerator	56.3	3.5	17.5
% Households with Television	79.9	38.2	42.5
Sources:	a,b	c,d	e,f

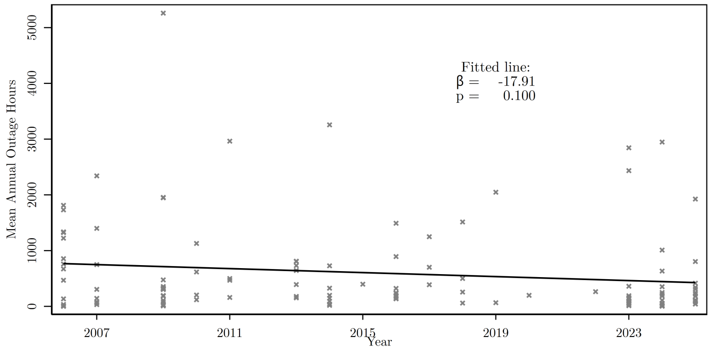
Note: These statistics are from surveys that are representative of the stated populations, and not from the households where GridWatch devices are deployed. Sources: a (Ghana Statistical Service and the DHS Program, 2022), b (Ghana Statistical Service, 2019), c (Kenya National Bureau of Statistics, Kenya Ministry of Health, and the DHS Program, 2022), d (Kenya National Bureau of Statistics, 2022), e (Tanzania National Bureau of Statistics, 2022), f (Tanzania National Bureau of Statistics, 2019).

Figure A1: Average firm-level reported annual outage hours by year in GridWatch deployment areas



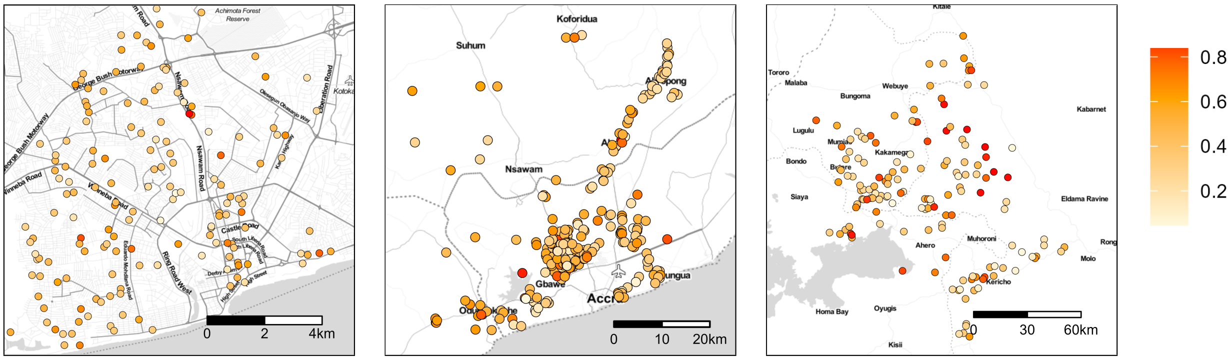
Note: Data are from the WBES, restricting the sample of firm survey respondents in each country to the regions where GridWatch devices are deployed. We calculate reported total monthly outage hours by firm by multiplying the typical number of outages per month by the average outage duration. We multiply this by 12 and take the mean across firms by year in each context, weighted using firm sampling weights, to get the average annual outage hours. WBES survey years vary by country.

Figure A2: Average firm-level reported annual outage hours by country over time in sub-Saharan Africa (WBES)



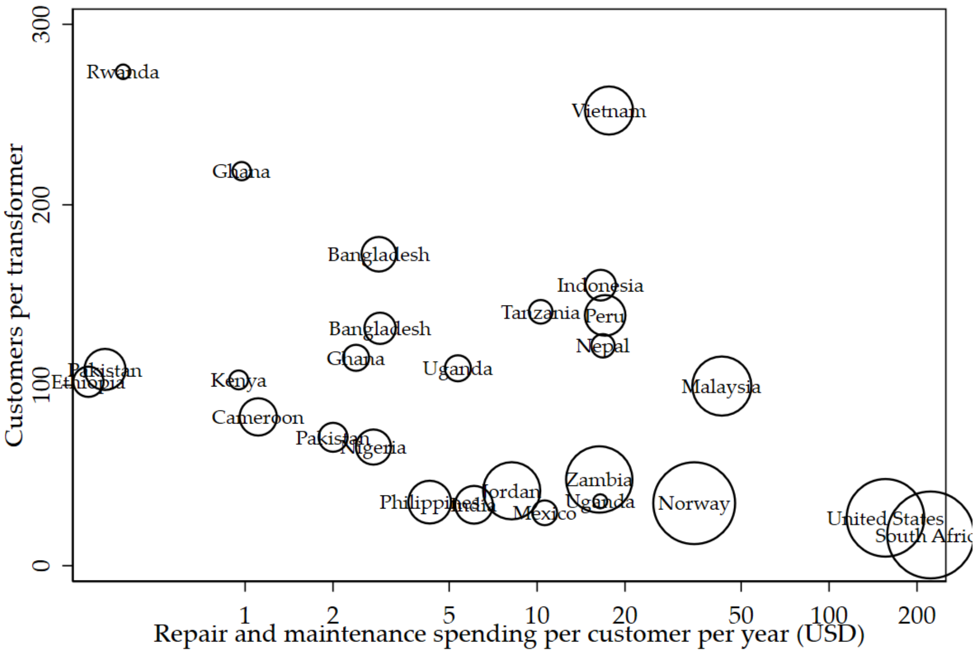
Note: Data are from the WBES, including all sub-Saharan African countries. We calculate reported total monthly outage hours by firm by multiplying the typical number of outages per month by the average outage duration. We multiply this by 12 and take the mean across firms by year in each country, weighted using firm sampling weights, to get the average annual outage hours. The fitted line is from a simple regression of average annual outage hours on survey year. WBES survey years vary by country.

Figure A3: Study sites by fraction of time experiencing bad voltage (outside nominal V± 5%)


(A) Ghana (urban)
(B) Ghana (peri-urban)
(C) Kenya (rural)

Data from GridWatch sensors deployed at 175 urban sites and 270 peri-urban sites in Greater Accra (Ghana) and 150 rural sites in Kakamega, Kericho, Kisumu, Nandi, and Vihiga (Kenya). In each site, we show the share of observations across all sensors and all time periods where voltage is more than ± 5% the nominal level.

Figure A4: Average customer load and spending on distribution upkeep by electric utilities



Note: Authors' calculations based on information compiled from the websites of utilities in different countries. Each bubble is a utility; some countries have more than one utility. Bubble size is proportional to annual consumption per customer in MWH.

Table A2: Change in average voltage during prime electricity consumption hours

	(1) Ghana (Urban)	(2) Ghana (Peri-Urban)	(3) Kenya (Rural)	(4) Tanzania (Peri-Urban)	(5) USA
6-10 PM	-6.893	-7.293	-7.988	-14.28	-0.168
	(0.278)	(0.262)	(0.490)	(2.723)	(0.376)
Constant	223.3	229.3	237.1	197.7	121.5
	(0.0588)	(0.0555)	(0.105)	(0.592)	(0.0784)
Observations	6967666	6520704	655706	9300	528645
Nominal Voltage	230	230	240	230	120
Grand Mean Voltage	221.8	227.8	235.4	194.6	121.5

Notes: Regression of hour-sensor voltage readings on an indicator of prime electricity consumption hours (6-10 PM), controlling for site, day of week, and week of year fixed effects. The constant is interpretable as the average voltage in the other hours, and the "6-10PM" coefficient as the average change during the prime hours. Each observation is an hour-sensor reading from GridWatch sensors. Standard errors (in parentheses) are clustered by site.

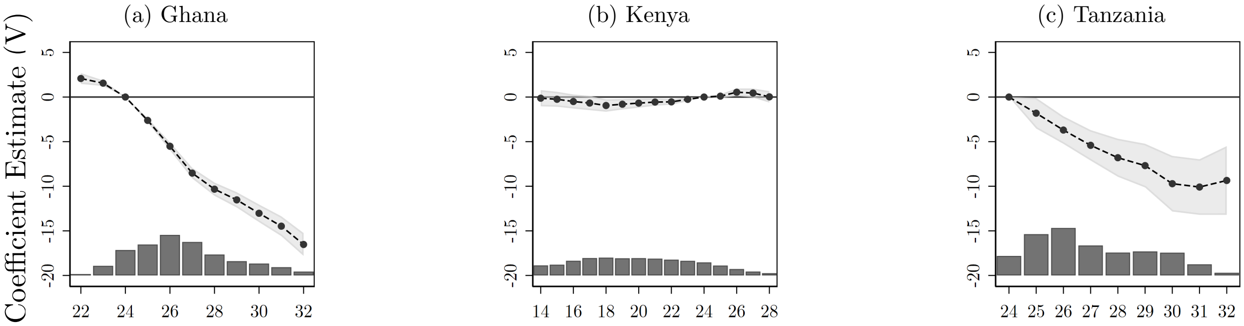
Table A3: Change in outage minutes per hour during prime electricity consumption hours

	(1) Ghana (Urban)	(2) Ghana (Peri-Urban)	(3) Kenya (Rural)	(4) Tanzania (Peri-Urban)	(5) USA
6-10 PM	0.599	0.369	-0.833	1.266	-0.00404
	(0.0463)	(0.0888)	(0.103)	(0.867)	(0.00398)
Constant	1.199	1.973	3.902	1.802	0.0100
	(0.00977)	(0.0188)	(0.0215)	(0.181)	(0.000829)
Observations	6967666	6520704	153696	6438	528645
Grand Mean Outage Mins	1.3	2.1	3.7	2.1	0

Notes: Regression of hour-sensor total outage minutes readings on an indicator of prime electricity consumption hours (6-10 PM), controlling for site, day of week, and week of year fixed effects. The constant is interpretable as the average minutes of outages in the other hours, and the "6-10PM" coefficient as the average change during the prime hours. Each observation is an hour-sensor reading from GridWatch sensors. Standard errors (in parentheses) are clustered by site.

Figure A5: Temperature's effect on grid power quality and reliability, by country

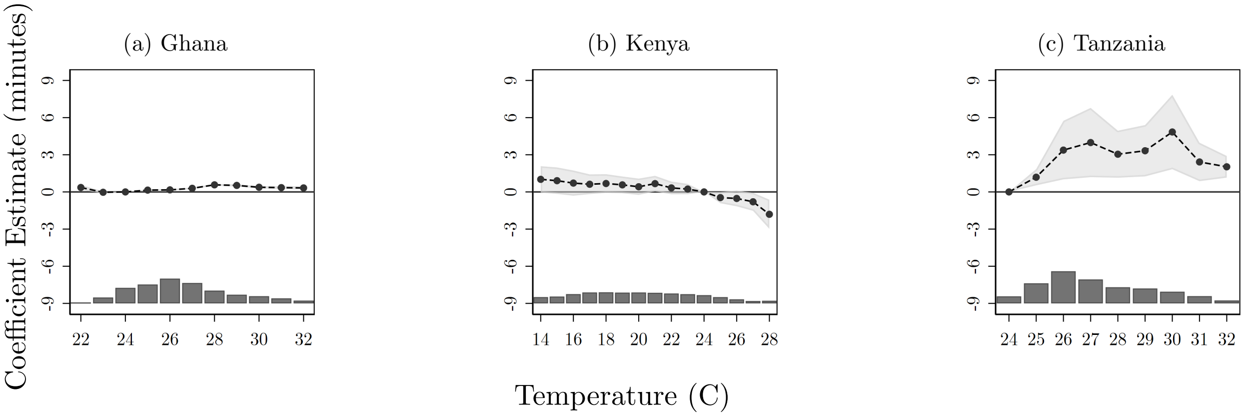
Panel A: Average voltage


(a) Ghana

(b) Kenya

(c) Tanzania

Panel B: Average outage minutes per hour


(a) Ghana

(b) Kenya

(c) Tanzania

Note: Coefficients of how hourly voltage (Panel A) and outage minutes (Panel B) respond to hourly temperature deviations away from 24°C. Regressions include fixed effects for hour of day interacted with fixed effects for site, capturing most of the predictable diurnal variation in load. Standard errors are clustered by respondent. Power data are from GridWatch devices. Temperature at two meters above the ground is from the ERA5-Land reanalysis dataset.