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Electricity Consumption and Temperature: Evidence from Satellite Data

by Jiaxiong Yao

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Electricity Consumption and Temperature:
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Abstract

Past studies on the relationship between electricity consumption and temperature have primarily focused on individual countries. Many regions are understudied as a result of data constraint. This paper studies the relationship on a global scale, overcoming the data constraint by using grid-level night light and temperature data. Mostly generated by electricity and recorded by satellites, night light has a strong linear relationship with electricity consumption and is correlated with both its extensive and intensive margins. Using night light as a proxy for electricity consumption at the grid level, we find: (1) there is a U-shaped relationship between electricity consumption and temperature; (2) the critical point of temperature for minimum electricity consumption is around 14.6°C for the world and it is higher in urban and more industrial areas; and (3) the impact of temperature on electricity consumption is persistent. Sub-Saharan African countries, while facing a large electricity deficit already, are particularly vulnerable to climate change: a 1°C increase in temperature is estimated to increase their electricity demand by 6.7% on average.

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I. INTRODUCTION

Electricity powers modern economies. Climate change will likely have a fundamental impact on electricity demand. A warming globe could reduce the need for heating in cold seasons and increase the demand for cooling in hot seasons, impacting countries in different geographic locations heterogeneously. Rising temperatures could affect economic growth potential and change electricity demand across multiple economic sectors. The interaction of socioeconomic, demographic, and technological changes, as well as the timing and intensity of temperature changes, will drive electricity demand and, more generally, energy use in the future (van Ruijven, De Cian, and Wing, 2019).

The vast literature on the relationship between electricity consumption and temperature has primarily focused on individual countries and regions where high-frequency micro-level data are available. Many countries are understudied as a result of data constraint, and few studies compare the impact of temperature across countries. However, those understudied countries, mostly in sub-Saharan Africa and facing the electricity access challenge already,[1] are more vulnerable to climate change. The average temperature in those countries has often exceeded the optimal temperature for economic production. A rising temperature would mean increasing electricity demand, making it more challenging for those countries to achieve the sustainable development goals.[2] Understanding how temperature shapes electricity demand in regions like sub-Saharan Africa is thus of great importance.

This paper takes a different approach and investigates the relationship between electricity consumption and temperature on a global scale using grid-level panel data. We focus on annual frequency where identification comes from year-to-year fluctuations in annual average temperature. To overcome the data constraint on electricity consumption, we use night light as its proxy. Mostly generated by electricity and recorded by satellites, night light is available for the entire world at a granular level and it can be a good proxy for electricity consumption.

Night light can be viewed as a normal good with respect to income spent on electricity at annual frequency. In other words, an increase in spending on electricity results in more lights at night, particularly when observed over a long period. Intuitively, lighting is an almost indispensable component for activities at night. Its use would increase as electricity becomes

[1] For example, World Bank (2020) estimates that by 2030, 85% of people without access to electricity would be in sub-Saharan Africa.

[2] Sustainable Development Goal 7, established by the United Nations General Assembly in 2015, aims to ensure access to affordable, reliable, sustainable and modern energy.

more accessible and affordable.[3] For places where electricity access and affordability are not of first-order concern, lighting is often necessary or complementary to activities at night that require electricity consumption. For example, while air-conditioners might be the primary use of electricity for indoor activities in a hot summer, lighting would occur more often with more frequent staying-at-home. When observed at a relatively low frequency such as the annual frequency, night light would be positively linked to total electricity consumption.

We provide some empirical evidence that night light is highly correlated with electricity consumption and reflects both its extensive and intensive margins. We show that at the country level, their functional relationship is linear. Night light is strongly correlated with electricity access, income, and purchase of cooling and heating appliances, indicating that it reflects the number of electric equipments in use, or the extensive margin of electricity consumption. Night light is also positively related to the cooling and heating needs in a year at the grid level, suggesting that it reflects as well the usage pattern of electric equipments, or the intensive margin of electricity consumption.

The monotonic relationship between night light and electricity consumption, at least at annual frequency, means that we could use night light as a proxy to analyze the impact of temperature on electricity consumption. Importantly, the monotonicity implies that the critical point of temperature for night light is also the critical point for electricity consumption. This allows us to find the temperature beyond which electricity consumption would increase.

Because of its granularity—the night light data we use has a resolution of 30 arc second, approximately 1 kilometer—we are able to aggregate it to match grid-level temperature data that cover the entire globe. With nearly 700,000 observations, variation across different locations and over time allows us to precisely characterize the relationship globally between night light and temperature. The cross-region variation is crucial because variation in annual average temperature for a single location is small and only identifies the local relationship.

Using grid-level night light and temperature data, we first examine the relationship nonparametrically degree by degree. We find that the relationship is uncertain below 0° but exhibits a clear U-shape above 0°. The critical point of temperature for minimum electricity consumption is roughly between 10 and 20°C. We then estimate a quadratic function to characterize the relationship and find that 14.6°C is the critical point of annual average temperature. Other things equal, when temperature is below 14.6°C, an increase in temperature would result in less electricity consumption; on the contrary, when temperature is above it, an increase in

[3]The World Bank uses a multi-tier framework to measure access to electricity, task lighting and general lighting belong to the most basic levels of electricity consumption (Bhatia and Angelou, 2015).

temperature would result in more electricity consumption. The 95% confidence interval for the critical point is between 14.1 and 15.3°C. Intuitively, the U-shaped relationship around the critical point of temperature most likely reflects the relative strength of cooling or heating demand.

Next we explore the heterogeneous impact of temperature on electricity consumption. The heterogeneity exists at multiple levels. For example, the impact can differ in rich and poor countries (Dell, Jones, and Olken, 2012) and in residential and industrial sectors (Auffhammer and Mansur, 2014). The grid-level data allow us to analyze the spatial heterogeneity at subnational levels. We distinguish between urban and rural areas and between more industrial and less industrial areas. Based on the resolution of gridded data, we focus on the first-level administrative regions (states and provinces).

Using gridded population data to sort the first administrative regions of all countries by population density, we examine the critical point of temperature for minimum electricity consumption in each quartile. We find that in more densely populated areas, the critical point of temperature is higher. For the top quartile of first-level administrative regions, such temperature is close to 16°C. In a similar vein, we examine the difference between more and less industrial regions based on average tropospheric nitrogen dioxide density, a major pollutant of industrial production. We find that more industrial regions tend to have a higher critical point of temperature. This implies that electricity consumption in urban and more industrial areas may react more slowly to climate change. Rural and less industrial areas, on the contrary, may be more sensitive and vulnerable to climate change.

Climate change is a long-term challenge. Beyond the level effect, it is natural to ask whether temperature has any long-lasting impact on electricity consumption. Augmenting the empirical relationship between them by allowing for both level and growth effects to be present, we find evidence that temperature increase appears to raise electricity consumption growth, but the growth effect is small relative to the level effect.

With average annual temperature at 24°C, sub-Saharan Africa is the hottest region in the world and is well beyond the critical point of temperature for minimum electricity consumption. A warming climate could only mean increasing electricity demand. Using the composite functional relationship between electricity consumption, night light and temperature, we estimate that a 1°C increase in temperature will drive up electricity demand in the region by 6.7%. This is roughly equivalent to adding the electricity consumption of the third largest country in sub-Saharan Africa. Already facing a large electricity deficit, sub-Saharan African countries are particularly vulnerable to climate change. The need for building power infrastructure is more urgent than ever to reach their sustainable development goals.

The rest of the paper is organized as follows. Section II briefly reviews the literature. Section III describes the data and the framework for using night light as a proxy for electricity consumption. In section IV, we present findings on the relationship between electricity consumption and temperature, including the heterogeneous impact of temperature on urban and rural areas, evidence on level and growth effects on electricity consumption, and the challenge for sub-Saharan African countries. Section V concludes.

II. Literature Review

This paper is related to a large literature on the impact of climate change on electricity consumption, which primarily focus on individual countries and regions that have high-frequency micro-level data. For example, recent studies have analyzed places such as Brazil (Trotter and others, 2016), China (Li, Yang, and Long, 2018; Fan, Hu, and Zhang, 2019), Cyprus (Zachariadis and Hadjinicolaou, 2014), India (Gupta, 2012), Europe (Bessec and Fouquau, 2008, Cassarino, Sharp, and Barrett, 2018), Hong Kong and Singapore (Ang, Wang, and Ma, 2017). Auffhammer and Mansur (2014) provides a review of the earlier literature. However, many countries and regions lack detailed electricity consumption data. To overcome such constraint and study the relationship on a global scale, we focus on a relatively low frequency and use satellite-recorded night light as a proxy for annual electricity consumption, which is widely used in the remote sensing literature (e.g., Elvidge and others, 1997a, Chand and others, 2009, Min and others, 2013) and the energy literature (e.g., Townsend and Bruce, 2010, Shi and others, 2016, Hu and Huang, 2019). Night light has also been used to identify electrified populations and estimate electrification strategies for sub-Saharan African countries (Mentis and others, 2017).

In characterizing the relationship between temperature and electricity consumption, the literature typically assumes a U-shaped curve, with the minimum point as the balance temperature between heating and cooling needs (e.g., Gupta, 2012, Li, Yang, and Long, 2018). As the relationship is potentially non-linear, heating and cooling degree days[4] are often used as the temperature variable, dating back to Al-Zayer and Al-Ibrahim (1996). Sometimes a comfort zone is allowed where electricity consumption is not sensitive to temperature variations

[4] Heating (cooling) degree days is defined as the sum of degrees below (above) a threshold over a period of time, such as a month or a year.

within a temperature range (e.g., Moral-Carcedo and Vicéns-Otero, 2005; Fikru and Gautier, 2015). As those studies typically use data of daily or monthly frequency and focus on regions in a particular climate zone, it is not immediately obvious that the relationship can be generalized to annual data on a much larger geographic scale. In this paper, we show that at annual frequency, the relationship is uncertain below 0° but exhibits a clear U-shape above 0°.

The response of electricity consumption to temperature variations is shaped by many factors, including socio-economic changes (Hekkenberg, Moll, and Uiterkamp, 2009) and climate zones (Auffhammer and Aroonruengsawat, 2011). Temperature can also have an impact on economic growth (Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015), which in turn affects electricity consumption . The literature has distinguished between the intensive and extensive margins of response to temperature shocks and finds that people adjust along the intensive margin in the short run and along the extensive margin over time (Davis and Gertler, 2015; Auffhammer, 2018). We show that night light is related to both the intensive and extensive margins of electricity consumption. Given the annual frequency of this analysis, however, the extensive margin is likely to dominate in our results. We also show that the U-shaped relationship and the critical point of temperature differ across regions and across different degrees of urban development, highlighting the heterogeneous impact of climate change.

Persistent electricity scarcity has hampered sub-Saharan Africa's growth (Avila and others, 2017), led to more poverty, and contributed to carbon emissions (Koçak and others, 2019). Our findings suggest that climate change will add to the energy challenge the region faces. More broadly, we contribute to the literature that aims to understand the detrimental impact of climate change, particularly on sub-Saharan African countries (e.g., Calzadilla and others, 2013; Abidoye and Odusola, 2015; Moore and Diaz, 2015; Serdeczny and others, 2017; Baarsch and others, 2020).

III. Night Light as a Proxy for Electricity Consumption

A. Night Light, Temperature, and Other Geospatial Data

Night light

Many human activities at night are powered by electricity and emit light. Street lamps, residential buildings, grocery stores, factories, advertising, sports lighting, and numerous other businesses use electricity to operate at night. These nighttime lights, often referred to as night lights, can be seen from outer space and are recorded by satellites. Since night lights are directly linked to electricity consumption,[5] they are a natural candidate as its proxy where electricity consumption data are not available.

The Operational Linescan System (OLS) instruments onboard the Defense Meteorological Satellite Program (DMSP) satellites recorded night lights between 7-9pm local time each day between 1992-2013. Based on DMSP-OLS data, the National Oceanic and Atmospheric Administration (NOAA) provides annual cloud-free composites of night lights (Elvidge and others, 1997b). The night light data are geospatial data of 30 arc second grids, spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude, which we use in this paper. In cases where two satellites were collecting data in the same year, two composites were produced and we use the average of these two composites.

Each grid cell of night light data in a given year has a numeric value between 0 and 63 with larger number indicating higher night light intensity. To calculate the total night lights for a region, we sum the values of all grids within the region's administrative boundary.

Temperature

The University of Delaware Physical Sciences Laboratory hosts global gridded high resolution station (land) data for monthly-mean air temperature and monthly-total precipitation from 1900-2014 (Willmott and Matsuura, 2001). The data are widely used in studies related to climate change. We use the annual average of the monthly data between 1992 and 2013, the period for which night lights data are available, for our analysis. At 0.5 by 0.5 degree grid resolution (about 55.5km), the temperature data are much coarser than night lights, whose resolution is 30 arc seconds (about 1km). To match the two datasets, we take the average of night lights of all grid cells within each grid cell of temperature data.

Population

Because night lights were recorded with noise and not all lights were necessarily artificial lights, we use gridded population data as a mask to exclude cells that are sparsely populated. Specifically, we use Gridded Population of the World (GPW), v4, from the Socioeconomic Data and Application Center of NASA, hosted by Columbia University. The population data are available for every 5 years from 2000 onward. We use 2015, the next available year after DMSP-OLS night light data end, as the mask. We discard cells that have no more than 100 people per grid.[6]

[5] For an estimation of the contribution of public and private sources to night light, see Kyba and others (2020).

[6] The choice of 100 is rather innocuous to our results. To get a sense of the implied population density, a 0.5 by 0.5 degree grid cell is slightly more than two-thirds the size of Rhode Island at its location.

Administrative maps

Throughout, we use first level administrative regions (states and provinces) from the Database of Global Administrative Areas (GADM 2.8) to account for spatial correlation. The choice is based on two factors. First, administrative regions naturally control for institutional and cultural differences. Second, the resolution of the temperature data is about 55km. At this resolution, about 1% of all 2478 first administrative regions contain only one cell of temperature data. At the second administrative level, however, many regions are geographically too small to be in distinct temperature cells.

Other data and considerations

To investigate the heterogeneity across different regions, we also use first-level administrative regions to distinguish areas with different characteristics. To differentiate between urban and rural areas, we sort states and provinces by their population density. We use the year 2000 for calculating population density (people per square kilometer) at the first administrative level as it is close to the middle year night lights data (1992-2013). Higher population density indicates more urbanized areas.

Similarly, to differentiate more industrial areas from less industrial areas, we sort states and provinces by their average nitrogen dioxide density, which we derive from NASA's satellite data.[7] NO_2 is a major pollutant from industrial production. Higher NO_2 density represents more industrial areas. Appendix A provides a graphic illustration of NO_2 distribution across Europe and Africa using more recent data.

To compare night light with variables at the country level, we use electricity access, electricity consumption, and GDP from the World Development Indicators. We use imports of heating and cooling equipments from UN Comtrade database. For comparison with heating and cooling degree days, we use historical global gridded degree-days data from Mistry (2019).

B. Summary Statistics

In total, we have 848340 year-cell observations for which both temperature and night lights data are available, covering 166 countries.[8] Excluding sparsely populated cells, we drop about

[7]Nitrogen dioxide density are calculated as the average of cloud-screened tropospheric NO_2 between 2005 and 2013 at the first administrative level. The NO_2 data are obtained from Level-3 daily global gridded (0.25x0.25 degree) Nitrogen Dioxide Product (OMNO2d) of NASA Goddard Space Flight Center, Goddard Earth Sciences Data and Information Services Center.

[8]Note that temperature data has $360 \times 720 = 259200$ grid cells at a point in time. Since only 29% of the surface of Earth is land and an even smaller fraction is inhabited by humans where night lights are visible, the actual

8% of observations and use the rest of the sample for non-parametric analysis. As will be explained later, our parametric analysis focuses on regions with annual average temperature no less than 0°, which is about 90% of the remaining observations.

Table 1 summarizes temperature and night lights at the grid level by various selection criteria. Our main sample, which is the second block in the table and excludes too sparsely populated cells, have a mean temperature of 13.6°C, a number that we will reference frequently. The average of night lights across cells is 2.2, indicating that a large fraction of lighted areas are very dim at night.

Table 1. Summary Statistics of Grid-Level Temperature and Night Light

	N	mean	min	p25	p50	p75	max
Entire sample							
Temperature	848340	12.86	-23.38	3.57	13.48	23.23	35.77
Night light	848340	2.00	0.00	0.03	0.33	1.95	56.38
population $>$ 100 per 0.5°$\times$ 0.5° grid							
Temperature	777073	13.62	-23.24	4.75	14.43	23.54	35.77
Night light	777073	2.17	0.00	0.05	0.43	2.25	56.38
population $>$ 100 per 0.5°$\times$ 0.5° grid and temperature $\geq$ 0℃							
Temperature	692794	15.77	0.00	7.63	16.63	24.26	35.77
Night light	692794	2.34	0.00	0.06	0.54	2.55	56.38

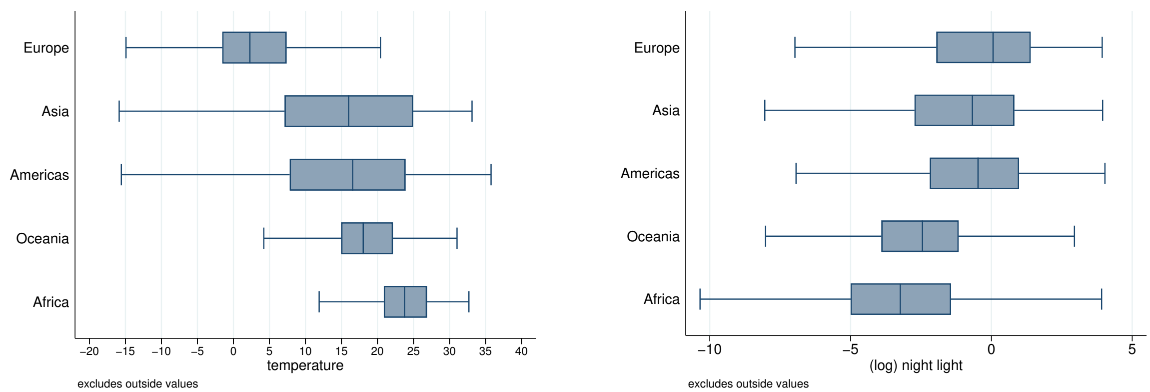
Figure 1 describes the distribution of temperature and night light at the grid level by continental regions[9] between 1992 and 2013. Panel (a) shows that Europe, the Americas, and Asia have a wide range of annual average temperature, ranging from below -15°C to above 30°C. In contrast, Africa has a much smaller temperature range because of its geographic location and its median temperature, at 23.5°C, is much higher than that of other regions. Panel (b) shows that Europe is the brightest continent at night based on the median grid cell luminos-

number of observations is much smaller, averaging $848340/22 \approx 38560$ cells per year between 1992 and 2013. In additional, we use the center point of a temperature grid cell to determine whether it belongs to a country or an administrative region. For some countries, their area is too small to overlap with the center point of any temperature grid and thus is not included.

[9]We use UN Statistics Division's classification of continental regions.

ity, while Africa is the darkest continent. The north-south divide is also evident in Figure 1: colder regions tend to be more developed and brighter at night. Appendix A provides a graphic comparison of night lights between Europe and Africa in 2010.

Figure 1. Temperature and Night Lights by Region



(a) Temperature by Region **(b) Night Lights by Region**

Note: This figure shows the box plots of temperature and night lights by region. The box in the center represents data from the 25th to the 75th percentile of the distribution. The vertical line in the middle of the box is the median. The vertical line on the left (right) is the lower (upper) adjacent line, where the lower adjacent value is defined as the data point right above $x_{25} - 1.5(x_{75} - x_{25})$ (right below $x_{75} + 1.5(x_{75} - x_{25})$).

C. Relationship with Electricity Consumption

We assume lighting at night is a normal good with respect to income spent on electricity at annual frequency. Let E be electricity consumption in a region and L be the total night lights in that region. There is a causal relationship between night light and electricity consumption:

$$\log L = h_X(\log E), \tag{1}$$

where X represents a number of location-specific and time-invariant factors that affect night light, such as local economic growth and habits of using lights at night. $h_X(\cdot)$ is assumed to be a monotonic function, which can be derived from a composite electricity consumption bundle of lighting and other electricity usage.[10]

[10]For example, in the special case of a constant elasticity-of-substitution consumption bundle that consists of lighting L and other electricity usage O,

$$E = \left[\phi^{\frac{1}{\zeta}} L^{\frac{\zeta-1}{\zeta}} + (1-\phi)^{\frac{1}{\zeta}} O^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}},$$

Suppose the impact of temperature change on electricity consumption follows $\log E = g(T)$, then temperature would also affect night lights through:

$$\log L = h_X(\log(g(T))) := f_X(T). \tag{2}$$

Using granular night light and temperature data, one can estimate the function form $f_X(\cdot)$. The monotonicity of $h_X(\cdot)$ implies that we can invert it and obtain:

$$\log E = h_X^{-1}(f_X(T)). \tag{3}$$

Equation (3) allows us to focus on the function $f_X(\cdot)$. Since $h_X(\cdot)$ is monotonic, it preserves the order of $f_X(T)$ as T changes. In particular, if there is a temperature T^* at which $f_X(\cdot)$ is lowest, it is also the temperature at which electricity consumption is lowest. In other words, the critical points of minima and maxima $f_X(\cdot)$ will be preserved.

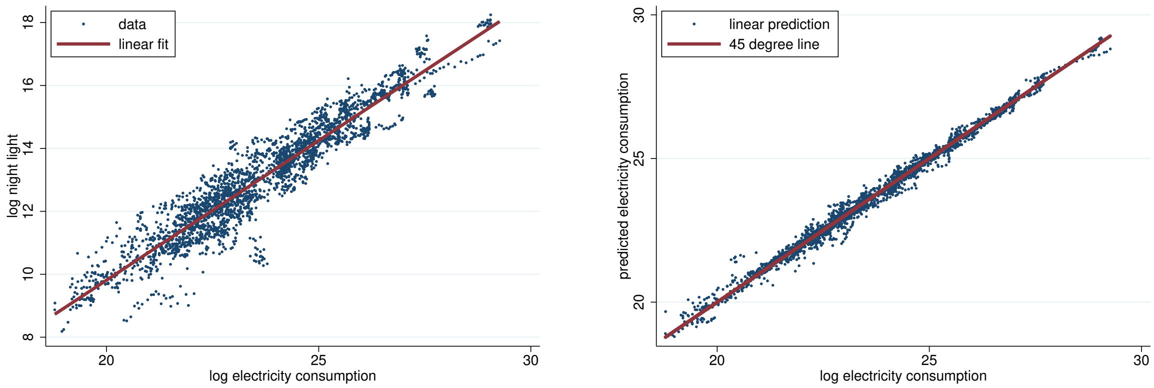
1. Functional relationship

To examine $h_X(\cdot)$ and $h_X^{-1}(\cdot)$, we compare total night lights and electricity consumption at the country level, since most countries do not have subnational level data on electricity consumption. Using electricity consumption per capita and population data from the World Bank, we compute total electricity consumption for a country. Panel (a) of Figure 2 shows that the relationship between night light and electricity consumption is monotonic. Conversely, if we use night lights as a linear predictor of electricity consumption, panel (b) shows that the prediction is well aligned with actual electricity consumption: the adjusted R^2 is 0.99.

Table 2 formally examines the relationship between night lights and electricity consumption at the country level, providing evidence that $h_X(\cdot)$ is monotonically increasing. . Columns (1)-(4) present the results from ordinary least squares regressions of night lights on electricity consumption, adding year and country fixed effects one step at a time. Throughout, the coefficient on log electricity consumption is positive and statistically significant. Without year and country fixed effects, adjusted R^2 is 0.90, indicating a strong correlation between night light and electricity consumption. With both year and country fixed effects, adjusted R^2 is 0.99, suggesting that a linear function that accounts for country characteristics and a common

the optimal lighting follows: $L = \phi E$. Lighting is a constant share of total electricity consumption. As such $\log L = \log \phi + \log E$ and $h_X(x) = \log \phi + x$.

Figure 2. Relationship between Night Light and Electricity Consumption



(a) **Night Light and Electricity Consumption** **(b)** **Night Light Prediction and Electricity Consumption**

Note: The left panel contrasts night lights against electricity consumption at the country level between 1992-2013. The red line is the linear fit of night lights on electricity consumption and a constant. The right panel contrasts linear prediction of electricity consumption by night lights with country and year fixed effects against actual electricity consumption at the country level between 1992-2013.

time trend can broadly characterize the relationship. Column (5) adds the second order term of electricity consumption. While the coefficient on the second order term is statistically significant at the 0.05 level, the domain of electricity consumption data implies that night light falls on the increasing segment of the quadratic relationship with electricity consumption.

Table 2. Night Light and Electricity Consumption

	(log) night light				
	(1)	(2)	(3)	(4)	(5)
(log) electricity consumption	0.888***	0.888***	0.686***	0.488***	1.289***
	(0.00594)	(0.0235)	(0.0445)	(0.0565)	(0.356)
(log) electricity consumption squared					-0.0178*
					(0.00769)
year fixed effects	-	Yes	-	Yes	Yes
country fixed effects	-	-	Yes	Yes	Yes
Obs	2575	2575	2575	2575	2575
Adjusted R^2	0.897	0.901	0.984	0.991	0.991

Note: This table presents results of ordinary least squares regressions of night lights on electricity consumption at the country level. The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered at the country level. Stars indicate significance levels: $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

To analyze the relationship between electricity consumption and temperature, we also need to examine how well night lights can predict electricity consumption. Column (3) of Table 3 shows that the linear prediction by night lights with year and country fixed effects approximates electricity consumption reasonably well, with adjusted R^2 at 0.99. Column (4) adds the second order term. The coefficient before it is not statistically significant and it also weakens the predictive power of the linear term. Note that equations in Table 3 are predictive regressions intended to approximate $h_X^{-1}(\cdot)$, contrary to the causal relationships in Table 2.

Table 3. Predicting Electricity Consumption by Night Light

	(log) electricity consumption			
	(1)	(2)	(3)	(4)
(log) night light	1.010***	0.468***	0.583***	0.645
	(0.00676)	(0.0766)	(0.0798)	(0.396)
(log) night light squared		0.0206***		-0.00264
		(0.00290)		(0.0160)
year fixed effects	-	-	Yes	Yes
country fixed effects	-	-	Yes	Yes
Obs	2575	2575	2575	2575
Adjusted R^2	0.897	0.898	0.990	0.990

Note: This table presents results of ordinary least squares regressions of electricity consumption on night lights at the country level. The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered at the country level. Stars indicate significance levels: $^{*}p < 0.05,^{**} p < 0.01,^{***} p < 0.001$.

Taking the derivative with respect to temperature in Equation (3), we have

$$\frac{d\log E}{dT} = \frac{d\log E}{d\log L}\frac{d\log L}{dT} = \frac{d\log E}{d\log L} f_X'(T). \tag{4}$$

Column (3) of Table 3 shows that the term $d\log E/d\log L$ is 0.583 at the country level.

2. Extensive and Intensive Margins

To gain some insights into what aspects of electricity consumption are captured by night light, we examine the extensive and intensive margins of electricity usage.

The extensive margin reflects the number of electric equipments in use. We consider three factors that shape the extensive margin: income, adaptation to climate change, and electricity access. A rise in income would raise the affordability of electricity, boosting purchases of electric equipments. We use a country's GDP to as a measure of income. Climate change would increase the need for regulating room temperatures, which can be reflected in the adoption of air conditioners and heaters. As it is difficult to obtain data on the number of air conditioners and heaters in use globally, we use imports of heating and cooling equipments as its proxy. For countries with poor electricity coverage, expansion of electric grids would increase the number of electric appliances in use. We use the share of population with electricity access to capture electricity coverage.

Columns (2)-(4) of Table 4 show that night light is positively related to income, imports of heating and cooling equipments, and electricity access at the country level at annual frequency. In other words, night light reflects the extensive margin of electricity consumption. Columns (5)-(6) indicate that income and adaptation to climate change have influence on night light beyond total electricity consumption. Such region-specific factors will be captured in $h_X(\cdot)$.

Table 4. Night Light and the Extensive Margin of Electricity Consumption

	(log) night light						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(log) electricity consumption	0.488***				0.433***	0.486***	0.430***
	(0.0565)				(0.0626)	(0.0553)	(0.0551)
(log) GDP		0.373*			0.212**		
		(0.174)			(0.0737)		
(log) imports of heating and cooling equipments			0.0485*			0.0525**	
			(0.0187)			(0.0169)	
electricity access				0.00990***			0.00102
				(0.00244)			(0.00269)
Obs	2575	3134	3231	2825	2493	2481	2206
Adjusted R^2	0.991	0.992	0.991	0.994	0.992	0.991	0.993

Note: This table presents results of ordinary least squares regressions of night lights on electricity consumption, real GDP, real imports of heating and cooling equipments at the country level, and share of population with electricity access. All regressions contain year and country fixed effects. Imports of heating and cooling equipments corresponds to SITC code 7415 (air conditioners) and 7416 (miscellaneous heating and cooling equipment). The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered at the country level. Stars indicate significance levels: $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

The intensive margin reflects the usage pattern of existing electric equipments, or the intensity with which such equipments are used. To investigate the intensive margin, we consider variation of temperature within a year, which drives the intensity for using electric equipments. We use heating and cooling degree days at the grid level, which measure the cumulative degrees below and above a temperature threshold in a year, to quantify the intensity of heating and cooling needs in a certain location. Specifically, we use a threshold of 10°C for heating degree days and a threshold of 25°C for cooling degree days.[11]

Columns (2) and (3) of Table 4 provide evidence that night light is positively related to the intensive margin of electricity consumption at the grid level. When we include annual temperature in Column (4), the coefficient before heating degree days turns negative. One interpretation is that gas might be more important than electricity in heating. As the heating need increases, a switch from electricity to gas might occur. In addition, as we show in subsequent analysis, the correlation between night light and electricity is also weak at low annual average temperatures. Column (5) shows that in capturing the cooling demand at annual frequency, average temperature can be adequate.

Table 5. Night Light and the Intensive Margin of Electricity Consumption

	(log) night lights				
	(1)	(2)	(3)	(4)	(5)
temperature	-0.186***			-0.207***	-0.186***
	(0.0141)			(0.00328)	(0.00241)
temperature squared	0.00634***			0.00678***	0.00634***
	(0.000462)			(0.0000899)	(0.0000804)
heating degree days		0.215***		-0.0752***	
		(0.0328)		(0.00798)	
cooling degree days			0.150**		0.00934
			(0.0478)		(0.00996)
Obs	691626	686973	686973	686973	686973
Adjusted R^2	0.943	0.942	0.942	0.943	0.943

Note: This table presents results of ordinary least squares regressions of night lights on temperature, cooling degree days and heating degree days at the grid level. All regressions contain year and grid-cell fixed effects. Cooling degree days and heating degree days are normalized by 1000 for ease of presentation of the coefficients. The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered by the first administrative region (state/province). Stars indicate significance levels: $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

IV. Electricity Consumption and Temperature

In this section, we focus on the relationship between night lights and temperature. We first investigate the functional relationship between the level of night lights and temperature. Next

[11] A number of thresholds have been used in the literature. A popular one is 65°F, or 18.3 °C. As we want to construct variables that are correlated with the intensive margin strongly, we focus on stricter thresholds where the need for heating or cooling is stronger.

we explore the heterogeneous impact of temperature on night lights with a focus on the urban-rural distinction and the difference between more and less industrial areas. We further analyze the growth effects of temperature on night lights. Finally, we discuss the implications of climate change on electricity demand for sub-Saharan African countries.

A. A U-shaped Relationship

Nonparametric specification

To empirically characterize the global relationship between night light and temperature in equation (2), we start with nonparametric estimation. For each degree, we assume the relationship is locally linear and estimate the coefficient before temperature β_1 in the following equation:

$$\log L_{i,t} = \beta_0 + \beta_1 T_{i,t} + \mu_i + \alpha_t + \varepsilon_{i,t}, \qquad T \in (\omega°\text{C}, \omega + 1°\text{C}]. \tag{5}$$

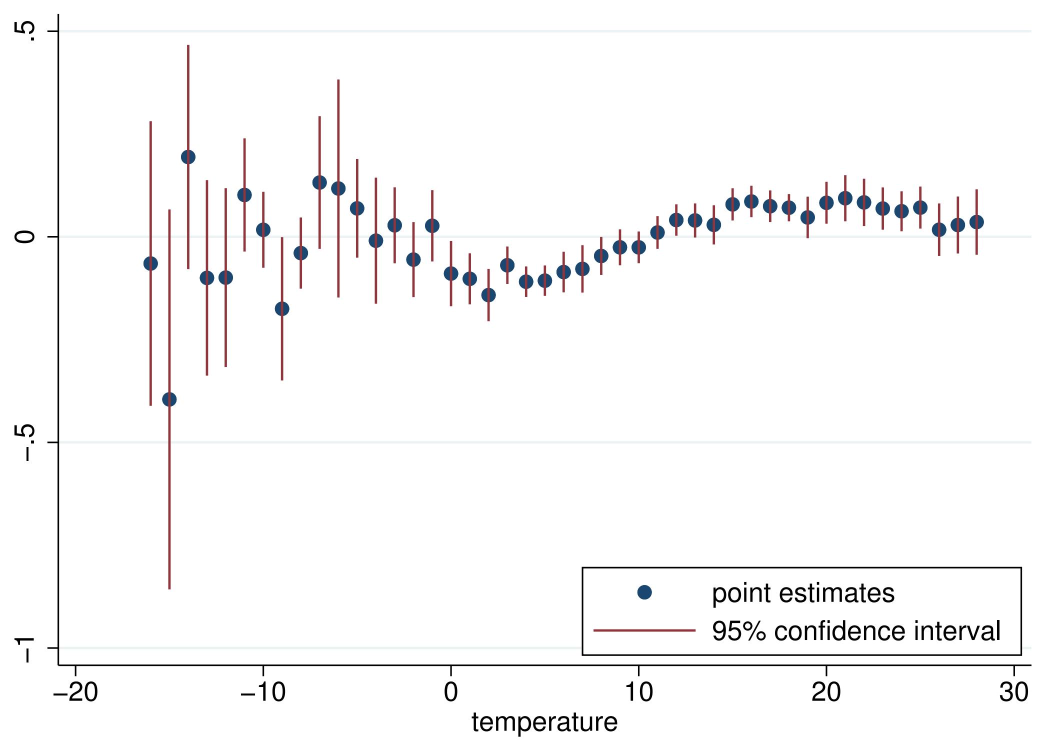
$L_{i,t}$ and $T_{i,t}$ are the level of night lights and temperature in cell i in year t, respectively. μ_i is the grid cell fixed effect that is intended to capture time-invariant location-specific level effect, such as regional level of economic development, average population density, habits of using lights at night, terrain and atmospheric conditions, etc. α_t captures the time fixed effect, including satellite sensors decay over time and the trend in world economic growth. $\varepsilon_{i,t}$ is the residual.

Figure 3 plots the estimated coefficients β_1 along with their 95% confidence intervals. Notably, below 0°C, the estimated β_1 is highly uncertain with wide confidence intervals that almost always contain zero. For temperature between 0°C and 9°C, the 95% confidence intervals of β_1 are below zero; for temperature greater than 14°C, the confidence 95% intervals are mostly above zero. Since β_1 is the local slope of the functional relationship between night light and temperature, this indicates that night light first decreases as temperature increases and then increases, displaying a U-shaped pattern. The critical point of temperature for the minimum of night lights is roughly between 9°C and 15°C.

Parametric specification

The U-shaped pattern motivates us to use a quadratic function to capture the relationship between night light and temperature, which has the additional benefit of having a closed-form expression of the critical values. We focus on cells that have annual average temperature no less 0°C, because the relationship becomes uncertain below 0°C, as shown in Figure 3.

Figure 3. Nonparametric Estimates of the Impact of Temperature on Night Light β_1



Note: This figure presents non-parametrically estimated coefficients of linear regressions of night lights on temperature, degree by degree and controlling for year and cell fixed effects.

Specifically, we consider the following panel regression equation:

$$\log L_{i,t} = \beta_0 + \beta_1 T_{i,t} + \beta_2 T_{i,t}^2 + \mu_i + \alpha_t + \varepsilon_{i,t}. \tag{6}$$

The second order term in equation (6) captures the nonlinear effect of temperature and allows us to compute the critical points of local extreme values. If β_2 is positive, the point for minimum night light is

$$T^* = -\frac{\beta_1}{2\beta_2}. \tag{7}$$

If temperature is above T^*, an increase in temperature would imply an increase in night light or electricity consumption. Conversely, if temperature is below T^*, an increase in temperature would imply a decrease in electricity consumption.

Table 6 presents the results of regression (6). All regressions contain year and grid-cell fixed effects. We cluster standard errors by the first administrative region (state/province) to account for spatial correlations of night lights within a small geographic area.[12] Column (1) shows that β_2 is indeed positive and statistically significant. The implied critical point of temperature T^* is 14.6°C. Column (2) adds precipitation and its square. The estimated coefficients before temperature and its second order term are little changed and the critical point of temperature is 14.5°C, similar to that in column (1). Because temperature and precipitation are correlated, we focus on specifications without the precipitation terms in order to capture the full impact of temperature in subsequent analysis.[13]

Columns (3)-(7) show the results from the same regression with the sample restricted to different continents. For Asia, the Americas, and Africa, the quadratic relationship between night light and temperature is statistically significant. The implied critical point of temperature are slightly higher than that implied by the entire sample. For Europe, the coefficient before the second order term of temperature is statistically significant but the significance level is weaker. The critical point is much more uncertain. For Oceania, the coefficients are not statistically significant and the relationship is essentially flat.

Figure 4 plots the implied functional relationship by region in Table 6, where the functions are normalized to zero at $T = 14.6$°C, the critical point of temperature for the entire sample, for ease of comparison. All continents exhibit a U-shaped quadratic relationship, although Europe and Oceania have much flatter curves—a key reason is that Europe does not have observations for high temperatures and Oceania has a narrower range of temperature than other continents. The regional results highlight that focusing on a single region runs the risk of extrapolating the relationship far beyond the domain of temperature data and underscore the need for analysis on a global scale. For example, examining Europe alone would focus only on the temperature range where heating demand dominates, while excluding Europe would yield higher estimates of the critical point of temperature.

[12]In Appendix B, we discuss clustering by country and two-way clustering by state and year.

[13]Note that in Table 6, we only control for time and grid-cell fixed effects, not region-specific time trend. This is because we want to estimate the unconditional relationship between night light and temperature while abstracting from exact channels through which temperature affects electricity consumption. Local economic growth, for example, affects electricity consumption and hence night lights, but temperature has an impact on economic growth (e.g., Dell, Jones, and Olken (2012), Burke, Hsiang, and Miguel (2015)). Adding region-specific time trend would be estimating the relationship conditional on economic growth and we would not capture such impact. Since temperature is exogenous, at least in the short run, there is no concern of simultaneity that drives both temperature and night lights. In Appendix B, we conduct various exercises to examine the role of region-specific time trend.

Table 6. Night Light and Temperature

	(log) night lights						
	World		Asia	Americas	Africa	Europe	Oceania
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
temperature	-0.186***	-0.185***	-0.185***	-0.156***	-0.247*	-0.0963***	-0.0211
	(0.0141)	(0.0141)	(0.0394)	(0.0212)	(0.0963)	(0.0121)	(0.0698)
temperature squared	0.00634***	0.00639***	0.00553***	0.00514***	0.00697**	0.00208*	0.000508
	(0.000462)	(0.000470)	(0.00122)	(0.000667)	(0.00222)	(0.000854)	(0.00188)
precipitation		0.00470					
		(0.00298)					
precipitation squared		-0.0000636					
		(0.0000622)					
Obs	691660	691660	207379	215931	121433	124266	22651
Adjusted R^2	0.943	0.943	0.923	0.956	0.904	0.957	0.928
Average T (℃)	15.8	15.8	16.4	16.1	23.5	6.1	18.3
Critical point T^* (℃)	14.6	14.5	16.7	15.2	17.7	23.1	20.8
95% confidence interval (℃)	$[14.1, 15.3]$	$[14.0, 15.2]$	$[15.1, 18.5]$	$[14.2, 16.4]$	$[14.4, 20.3]$	$[16.5, 42.2]$	$[-40.0, 58.3]$

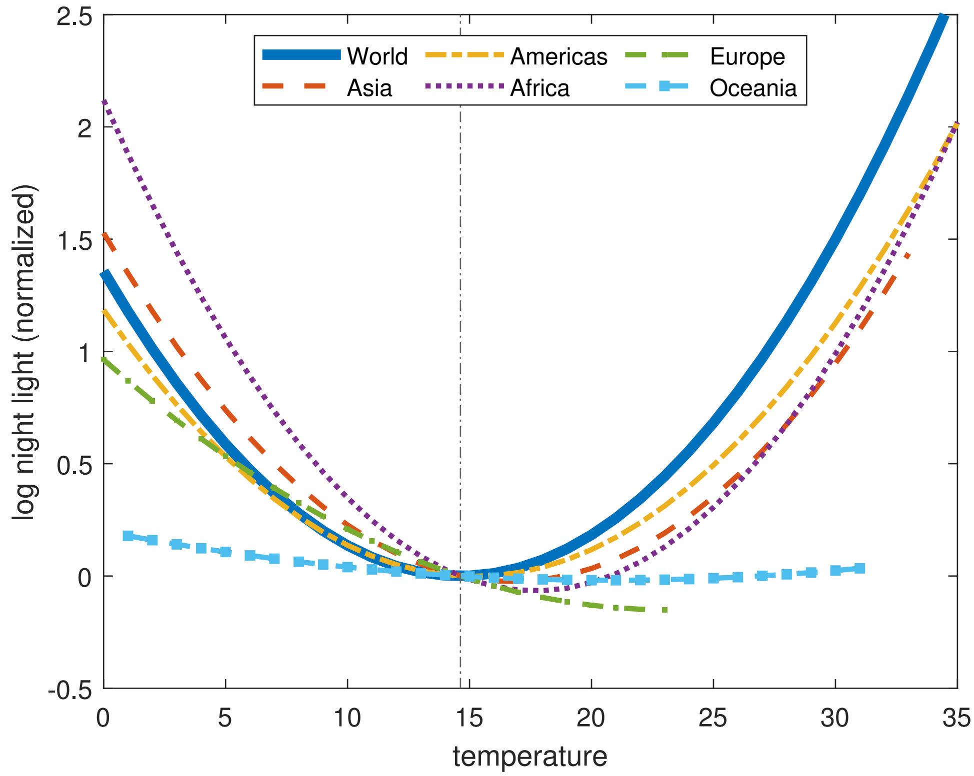
Note: This table presents results of ordinary least squares regressions of night lights on temperature at the grid level. All regressions contain year and grid-cell fixed effects. The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered by the first administrative region (state/province). Stars indicate significance levels: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 95% confidence intervals for the critical point of temperature are based on 400 bootstraps. Each bootstrap draws a random sample with replacement that has one-fifth the size of the original sample and estimates equation (6).

To account for the uncertainty of the sample, we conduct 400 bootstraps of the entire sample and plot the estimated U-shaped relationship between night lights and temperature. Figure 5 presents the 95% confidence interval of the U-shaped relationship. The corresponding critical point of temperature ranges between 14.1°C and 15.3°C. Note that the average temperature across all cells between 1992 and 2013 is 15.8°C (Table 6), already exceeding the critical point. Notably, the average temperature in Africa, 23.5°C, is well above this critical point. It is also above the critical point implied when we use Africa data alone (17.7°C). In fact, most cells in Africa are firmly above this critical point (Figure 1).

B. Heterogeneous Impact of Temperature

Does temperature affect electricity consumption in urban and rural areas alike? What about different types of economy? To differentiate between urban and rural areas, we compare population density across regions. Many cities extend beyondd their jurisdictions with their satellite cities or suburbs more akin to urban areas than to rural areas. For this reason, we focus

Figure 4. Night Light and Temperature by Region



Note: This figure presents the relationship between night lights and temperature for the entire sample and by continent. For comparison purposes, the implied quadratic functions are normalized to zero at $T = 14.6$℃, the critical point of temperature for the entire sample.

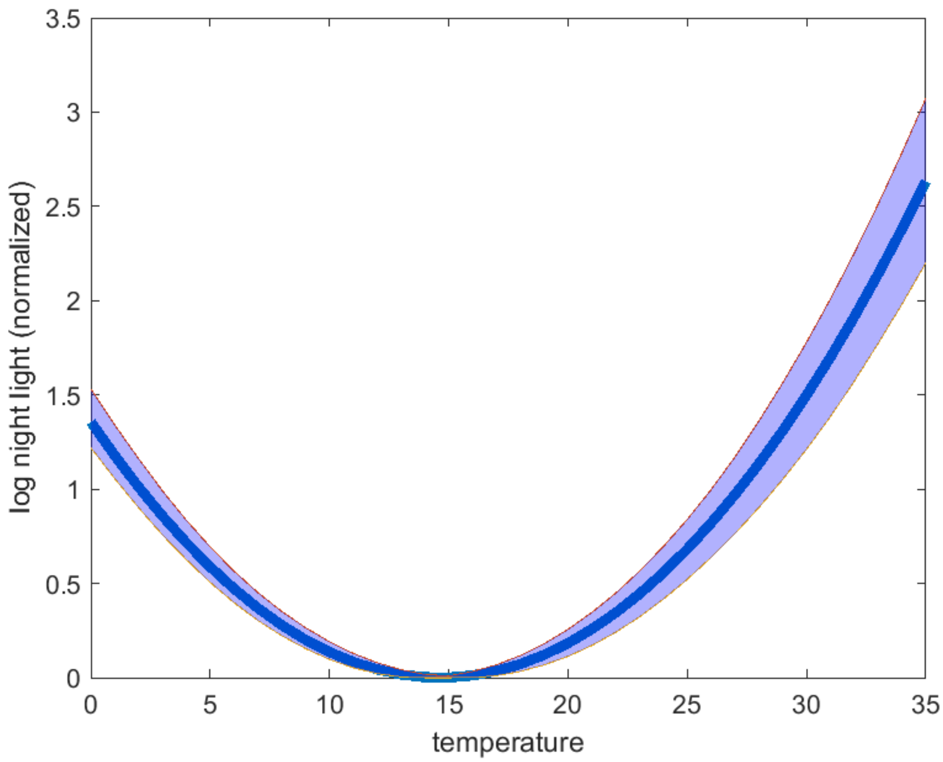
on the first-level administrative regions (states/provinces)—rather than the grid cell level—and rank them by population per square kilometers for each country. We use population in the year 2000, which is close to the middle year of our sample.

To distinguish between more and less industrial areas, we compare tropospheric nitrogen dioxide (NO_2) density across the first-level administrative regions. NO_2 is a major pollutant of industrial production and traffic from motor vehicles. While atmospheric conditions, such as wind, affect its distribution, NO_2 is a pollutant with a relatively short atmospheric lifetime and does not get transported far from its source.[14] It is therefore concentrated around cities and more industrial areas.[15] The focus on comparing the first-level administrative regions and the use of average daily data should alleviate such concerns. We sort the first administrative regions within each country by their daily average NO_2 density between 2005 and 2013.

[14]By one estimate (Shah and others, 2020), NO_2 lifetime is only several hours.

[15]For example, Filonchyk and others (2020) show that NO_2 levels reflect changes in industrial activity during the COVID-19 lockdown in China.

Figure 5. Night Light and Temperature: U-shaped Relationship



Note: This figure presents the 95% confidence interval of the relationship between night lights and temperature based on 400 bootstraps of the entire sample. For each bootstrap, the coefficients before the temperature and temperature squared terms are computed. The implied quadratic function's minimum value is normalized to be zero.

Table 7 conducts the same regression as equation (6) by quartiles of population density and by NO_2 density separately. In each case, all quartiles exhibit a U-shaped relationship between night light and temperature with a statistically significant coefficient before the quadratic term of temperature. A pattern emerges by comparing the results across quartiles: as we move to regions with higher population density or higher industrial production, the critical point of temperature T^* tends to increase. In other words, the impact of global warming on electricity demand might be felt more strongly in rural and less industrial areas, because the average temperature has already risen above their critical point or will rise above it first.

Figure 6 plots the estimated quadratic relationships by quartiles of population density and NO_2 density, with the minimum value of night light normalized to zero for comparison purposes. At low temperatures, a 1°C increase in temperature tends to reduce electricity consumption in rural and less industrial areas by less, while at high temperatures, it tends to increase their electricity consumption by more. This suggests that global warming would have a greater impact on the electricity demand of rural and less industrial areas.

Table 7. Night Light and Temperature by Population and NO_2 Quartile

by population density quartile

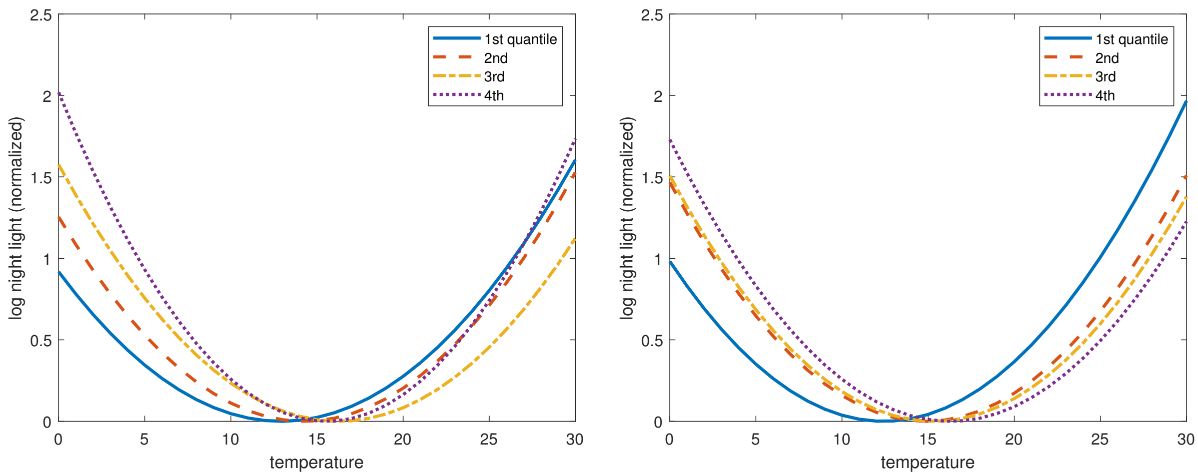
	(log) night light			
	1st	2nd	3rd	4th
temperature	-0.142***	-0.176***	-0.194***	-0.259***
	(0.0246)	(0.0340)	(0.0271)	(0.0239)
temperature squared	0.00550***	0.00617***	0.00596***	0.00833***
	(0.000890)	(0.00108)	(0.000905)	(0.000755)
Obs	186838	162287	171222	166312
Adjusted R^2	0.920	0.942	0.946	0.952
Critical point T^*(℃)	12.9	14.3	16.3	15.6

by NO_2 density quartile

	(log) night light			
	1st	2nd	3rd	4th
temperature	-0.158***	-0.197***	-0.197***	-0.212***
	(0.0281)	(0.0209)	(0.0293)	(0.0387)
temperature squared	0.00637***	0.00661***	0.00641***	0.00652***
	(0.00102)	(0.000733)	(0.000968)	(0.00105)
Obs	189752	169437	169227	162497
Adjusted R^2	0.931	0.939	0.943	0.950
Critical point T^*(℃)	12.4	14.9	15.3	16.3

Note: This table presents results of ordinary least squares regressions of night lights on temperature at the grid level by population and NO_2 density quartiles. All regressions contain year and grid-cell fixed effects. The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered at the first administrative (state/province) level. Stars indicate significance levels: $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$. Throughout, the first quartile represents the lowest value and the fourth quartile represents the highest value.

Figure 6. Night Light and Temperature by Population and NO_2 Quartile



(a) **by Population Density Quartile** **(b)** **by NO_2 Density Quartile**

Note: Panel (a) presents the estimated quadratic relationship between night lights and temperature by quartiles of population density at the first administrative level. Panel (b) presents the estimated quadratic relationship between night lights and temperature by quartiles of nitrogen dioxide density at the first administrative level. Each quadratic function's minimum value is normalized to zero. Throughout, the first quartile represents the lowest value and the fourth quartile represents the highest value.

C. Level and Growth Effects

Up to now we have only focused on the level effect of temperature on electricity consumption. A natural question is whether this effect will last and for how long. In other words, it remains unclear whether temperature fluctuations would have a growth impact on electricity consumption.

To investigate the growth impact of temperature, we augment the relationship between electricity consumption and temperature in a similar way to Dell, Jones, and Olken (2012). Previously, we have $\log E = g(T)$, or $E = e^{g(T)}$. Now we add a potential electricity consumption term $\bar{E}$ such that $E = e^{g(T)}\bar{E}$ and we allow temperature to have an impact on its growth rate:

$$\frac{d\bar{E}}{\bar{E}} = d\log\bar{E} = g_E + \gamma_E T, \tag{8}$$

where the parameter γ_E captures the growth impact of temperature on electricity consumption. Assuming night light and electricity consumption follow a linear relationship as before, we can replace E with L:

$$\log L \propto f_X(T) + \log\bar{L}, \tag{9}$$
$$d\log\bar{L} = g + \gamma T, \tag{10}$$

where the parameter γ captures the growth impact of temperature on night light. We have shown before that a quadratic function can broadly capture the relationship between night light and temperature in levels:

$$f_X(L) = \beta_2 \left(T + \frac{\beta_1}{2\beta_2}\right)^2 + C, \tag{11}$$

where C is a constant. Taking first difference of equation (9) with respect to time, we have

$$\log L_t - \log L_{t-1} = (\beta_1 + \gamma)T_t - \beta_1 T_{t-1} + \beta_2 (T_t^2 - T_{t-1}^2). \tag{12}$$

In regression equation (12), if the coefficients before T_t and T_{t-1} are statistically different, then it is evidence that γ is not zero and the growth effect exists.

Table 8 presents the regression results of equation (12), allowing the lags of temperature to have an impact on electricity consumption growth. All specifications control for year and grid-cell fixed effects. The sum of the coefficients before T_t and T_{t-1}, γ, is positive and statistically significant for all four columns, indicating that the growth effect exists throughout the medium term. Put differently, even if temperature rises temporarily in a given year and reserves in subsequent years, the increase in electricity consumption persists. Specifically, a 1°increase in temperature is estimated to increase electricity consumption growth by at least 1 percentage point.

The presence of the growth effect highlights that the impact of temperature on electricity consumption is persistent throughout the medium term. Therefore, measures that provide a temporary respite, such as bringing power ships to provide electricity, will not be enough; long-term solutions to tackle the electricity challenges posed by climate change will be needed.

D. Challenging Future for Sub-Saharan Africa

Sub-Saharan Africa (SSA) is one of the hottest regions in the world and it is most vulnerable to climate change. In section IV.A, we showed that electricity consumption and temperature follows a U-shaped relationship. To get an idea of how much 1°C increase in temperature increases electricity consumption, we focus on equation (4), the derivative of electricity consumption with respect to temperature through the chain rule, which is repeated here for convenience:

$$\frac{d\log E}{dT} = \frac{d\log E}{d\log L}\frac{d\log L}{dT} = \frac{d\log E}{d\log L} f_X'(T).$$

Table 8. Growth Effect of Temperature on Night Light

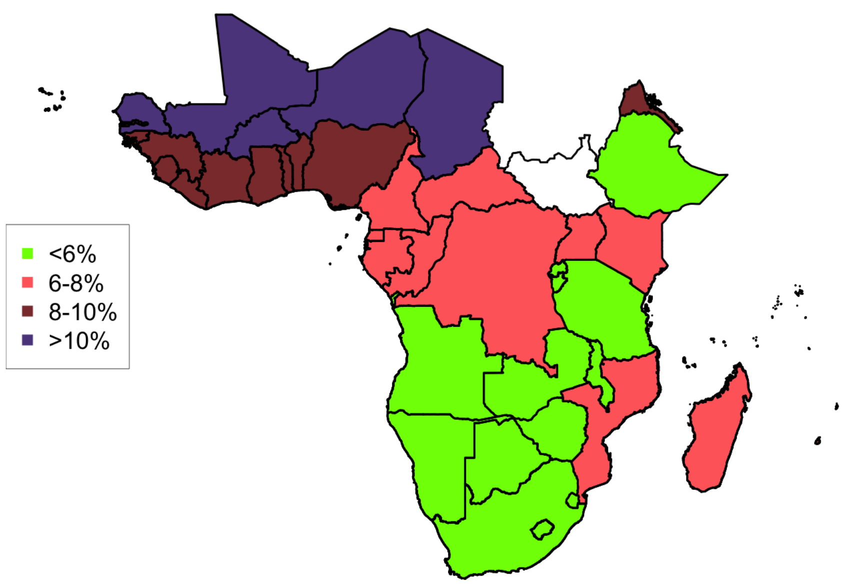
	d(log) night light			
	(1)	(2)	(3)	(4)
temperature	-0.0691***	-0.0800***	-0.0814***	-0.0686***
	(0.00734)	(0.00702)	(0.00695)	(0.00705)
temperature (1st lag)	0.0811***	0.0894***	0.0929***	0.0840***
	(0.00714)	(0.00717)	(0.00728)	(0.00725)
temperature (2nd lag)		0.00180	-0.00332	-0.0133***
		(0.00256)	(0.00277)	(0.00287)
temperature (3rd lag)			0.0191***	0.0222***
			(0.00380)	(0.00415)
temperature (4th lag)				-0.00824*
				(0.00356)
temperature squared diff	0.00205***	0.00228***	0.00229***	0.00196***
	(0.000194)	(0.000188)	(0.000188)	(0.000187)
Obs	638239	606460	574956	544299
Adjusted R^2	0.0818	0.0804	0.0833	0.0814
sum of all temp. coeff. (γ)	.012	0.011	.027	0.016
F test p-value	0.0001	0.0045	0.0000	0.0001

Note: All regressions control for year and grid-cell fixed effects. Standard errors are in parentheses and clustered at the first administrative level. Stars indicate significance levels: $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Section III.C shows that $d\log E/d\log L = 0.583$. The point estimates of regression (6) for the entire sample implies that $f'_X(T) = -0.186 + 2 \times 0.00634T$. For SSA countries in our sample, the average temperature of all year-cell observations is 23.7°C. This implies that $d\log E/dT = 6.7\%$: a 1°C increase in temperature increases electricity consumption of all SSA countries by 6.7%, which is about adding the electricity consumption of Nigeria, the second largest electricity consumption country in sub-Saharan Africa in 2014. Accounting for the uncertainty in the slope estimates of the U-shaped relationship Figure 5, the 95% confidence interval for $d\log E/dT$ ranges from 6.0% to 7.5%.

Figure 7 presents the percent increase in electricity consumption in response to a 1°C increase in annual average temperature for SSA countries. Notably, West Africa, particularly the Sahel region, with average temperature already high, is more sensitive to climate change and could experience more than 10% increase in electricity demand for a 1°C increase in temperature. Recent study by Nordhaus (2018) shows that the global mean temperature could increase by about 1°C from the 2010s to the 2050s and by about 3°C to 2100 without substantial mitigation of greenhouse gas emissions. Such speed of global warming will add to the challenge for SSA countries to meet their electricity demand. Considering that many still lack adequate electricity access, they will struggle to reach the Sustainable Development Goals. Investment in basic infrastructure, such as the electricity power grid, would therefore be essential not only to expand electricity access but to increase energy efficiency and reduce carbon footprint. Geospatial electrification, which uses data such as night light to determine the most cost-effective conventional and renewable energy technologies for bringing electricity to specific localities, is among the quantitative tools to assess sustainable development policy options (Mentis and others, 2017).[16]

Figure 7. Impact of a 1℃ Increase in Temperature on Electricity Consumption in Sub-Saharan African Countries



Note: This figure presents the percent increase in electricity consumption in response to 1℃ increase in annual average temperature.

Great uncertainties still exist around our estimates of the response of electricity consumption to temperature increase. First, while the relationship between night light and temperature is

[16]See, for example, UN modeling tools for sustainable development: https://un-modelling.github.io/modelling-tools/.

estimated on grid-level data, our estimate of the elasticity of electricity consumption to night light is based on country-level data. Whether the relationship between electricity consumption and night light is similar at different levels of spatial disaggregation remains to be verified by more granular electricity data. Second, the interactions between electricity consumption, economic growth, and climate change can be complex. On the one hand, solving electricity capacity constraints could spur more economic growth, which increases electricity demand further; on the other, a warming climate might negatively impact economic growth, which reduces electricity demand. Furthermore, economic growth, depending on how green it will be, has implications on the speed of climate change. A general equilibrium model that takes care of the endogeneity of those variables would be needed for forecasting electricity demand more precisely. We leave that for future research.

V. Conclusion

This paper investigates the relationship between electricity consumption and temperature using panel data on a global scale. To overcome the data constraint on electricity consumption, we use satellite-recorded night light as its proxy. We first establish a linear relationship between electricity consumption and night light at the country level. We show that night light reflects both the extensive and intensive margins of electricity at annual frequency. We then uncover a U-shaped relationship between night light and temperature using grid-level data. We find that the critical point of temperature for minimum electricity consumption is about 14.6°C for the world, which the average temperature of the world has already surpassed; the critical point is higher for urban and more industrial areas. We also find that the impact of temperature on electricity consumption is persistent, lasting through out the medium term. We highlight that sub-Saharan Africa is the most vulnerable to climate change: a 1°C increase in temperature could increase the region's electricity consumption by about 6.7%, adding to the challenge of lack of electricity access already facing the region.

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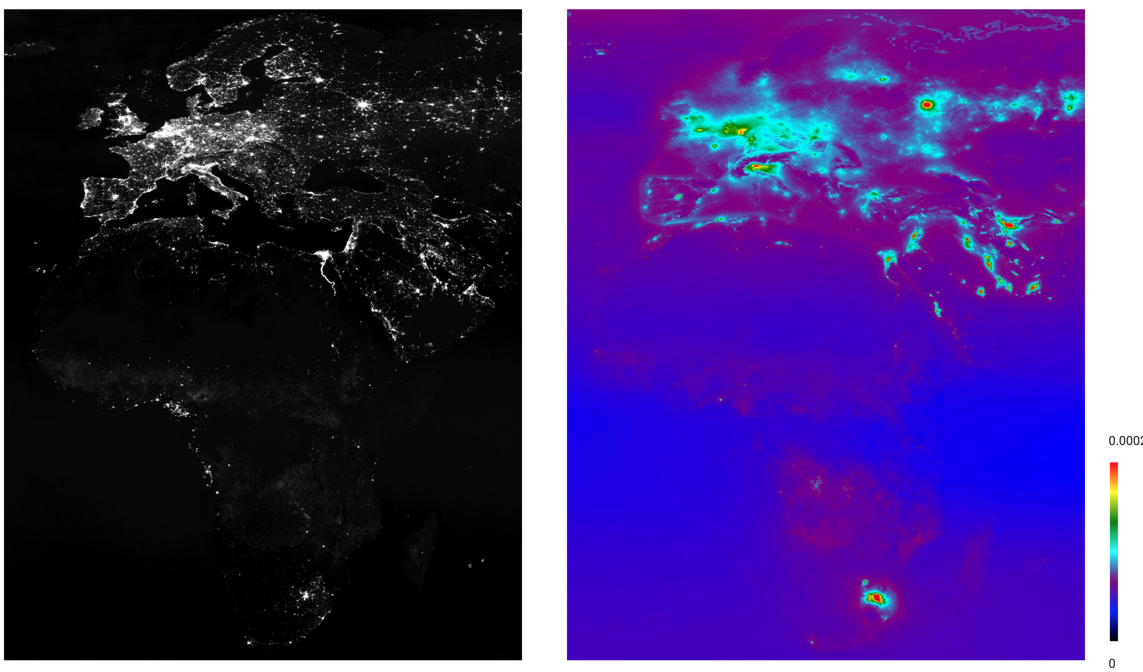
Appendix A. Illustrations of Satellite Data

This paper uses satellite recorded night light data as a proxy for electricity consumption. Panel (a) of Figure 8 presents an example of the satellite image of night lights in 2010 covering Europe and Africa. Bright areas indicate lights at night. One can see the contours of most Western European countries such as the United Kingdom, Spain, France, Germany, and Italy. For North Africa, the Nile river is visible. For sub-Saharan Africa, only major cities can be seen at the picture's resolution.

Figure 8. Night Lights and Nitrogen Dioxide: Europe vs. Africa



(a) **DMSP/OLS Night Lights** **(b)** NO_2 **density**

Note: Panel (a) presents DMSP/OLS night lights in 2010 for Europe and Africa. Panel (b) presents daily average of total vertical column of NO_2 between 2018 and 2019 from Sentinel-5 Precursor satellite Near Real-Time datasets by the European Space Agency. The unit of NO_2 is mol/m^2.

Nitrogen dioxide (NO_2) is a major pollutant of industrial production and burning fossil fuels. Tropospheric nitrogen dioxide (NO_2) is used in this paper to group regions into more or less industrial ones. Panel (b) of Figure 8 shows an example of the average NO_2 density based on Sentinel-5 Precursor satellite Near Real-Time datasets by the European Space Agency (ESA). It covers the same region as that of Panel (a). Red colors indicate high levels of NO_2 density. One can see that Southern United Kingdom, Northern France, and Northern Italy are among regions with high NO_2 density in Europe. Cairo (Egypt) and Johannesburg (South Africa) are regions with highest NO_2 density in Africa.

While the ESA NO_2 has a relatively high resolution, it only dates back to 2018. To correspond well to the time period of night light data (1992-2013), this paper uses NO_2 data of Level-3 daily global gridded (0.25x0.25 degree) Nitrogen Dioxide Product (OMNO2d) from the National Aeronautics and Space Administration (NASA), which have a lower resolution but start from October 2004. For the purpose of sorting first administrative regions by NO_2 density, we use the 2005-2013 daily average within each administrative region as the measure of NO_2 density .

APPENDIX B. ADDITIONAL ROBUSTNESS CHECKS

Standard errors

In the main text of the paper, we cluster standard errors by first administrative regions. This is because we have 2478 states and provinces but only 22 years (1992-2013). The limited number of clusters by year may cause the standard error to be biased. Table 9 presents results with standard errors clustered by both year and state. Compared to Table 6, the coefficient before the second order term of temperature remains statistically significant for the whole sample and for most subsamples that use continent-level data.

Region-specific time trend

In Table 6, we only control for year and grid-cell fixed effects. No region-specific time trend is added. Now we consider a few region-specific time trends, including continent-specific, country-specific, and state/province-specific time trends. Note that adding region-specific time trends increases the number of parameters substantially. For example, to control for state/province-specific time trends, we are effectively estimating 54516 parameters (2478 states/provinces $\times$ 22 years).

Table 10 presents the results when controlling for region-specific time trends. The coefficients before the second order term of temperature remain statistically significant. As we add more local time trend, the t-statistic declines. The estimated critical point in each specification is below the average temperature, supporting the finding that the world has exceeded the critical point of electricity consumption. The relationship between night light and temperature conditional on region-specific trends, however, is likely to omit important channels through

Table 9. Night Light and Temperature: Two-way Clustering

	(log) night lights						
	World		Asia	Americas	Africa	Europe	Oceania
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
temperature	-0.186***	-0.185***	-0.185*	-0.156*	-0.247	-0.0963**	-0.0211
	(0.0416)	(0.0414)	(0.0721)	(0.0565)	(0.145)	(0.0325)	(0.0609)
temperature squared	0.00634***	0.00639***	0.00553**	0.00514**	0.00697*	0.00208	0.000508
	(0.00118)	(0.00119)	(0.00179)	(0.00139)	(0.00332)	(0.00220)	(0.00155)
precipitation		0.00470					
		(0.00492)					
precipitation squared		-0.0000636					
		(0.000118)					
Obs	691660	691660	207379	215931	121433	124266	22651
Adjusted R^2	0.943	0.943	0.923	0.956	0.904	0.957	0.928
Critical point T^*(℃)	14.6	14.5	16.7	15.2	17.7	23.1	20.8
Average T(℃)	16.8	16.8	15.8	16.8	24.4	6.0	18.9

Note: This table presents results of ordinary least squares regressions of night lights on temperature at the grid level. All regressions contain year and grid-cell fixed effects. The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered by both year and the first administrative region (state/province). Stars indicate significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

which temperature affects night lights, such as local economic growth. As such we use year and grid-cell fixed effects in the main text.

The nonparametric estimates in Figure 3 show that when temperature is below 0°C or above 26°C, the impact of temperature on night lights cannot be estimated precisely and is not statistically different from zero. Focusing on the temperature range between 0 and 26°C, which is roughly 80% of the whole sample, columns (2), (4), and (6) show that the coefficients before the quadratic term is statistically significant and the U-shaped relationship reappears. The implied critical points of temperature are higher than that of column (1) in Table 6. However, columns (2), (4), and (6) estimate the relationship between night lights and temperature conditional on region-specific trends and likely omit important channels through which temperature affects night lights, such as local economic growth.

Table 10. Night Light and Temperature

	(log) night light		
	(1)	(2)	(3)
temperature	-0.151***	-0.0676***	-0.0569**
	(0.0383)	(0.0126)	(0.0195)
temperature squared	0.00483***	0.00242***	0.00169**
	(0.000991)	(0.000359)	(0.000507)
UN region×year fixed effects	Yes	-	-
country×year fixed effects	-	Yes	-
state×year fixed effects	-	-	Yes
Obs	691660	691544	680209
Adjusted R^2	0.945	0.952	0.956
Critical point T^*(℃)	15.6	13.9	16.8
Average T(℃)	16.8	16.8	16.8

Note: This table presents results of ordinary least squares regressions of night lights on temperature at the grid level. All regressions contain year and grid-cell fixed effects. The coefficients on the constant term are omitted in the table. Standard errors are in parentheses and clustered by the first administrative region (state/province). Stars indicate significance levels: $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.