INTERNATIONAL MONETARY FUND

Shedding Light on the Local Impact of Temperature

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WP/24/178

2024
AUG

WORKING PAPER

 WP/24/178

IMF Working Paper
African Department and Institute for Capacity Development

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Authorized for distribution by Luc Eyraud and Mercedes Garcia-Escribano
August 2024

ABSTRACT: We use a new dataset to estimate the impact of temperature on economic activity at a more geographically and temporally disaggregated level than the existing literature. Analyzing 30-kilometer grid cells at a monthly frequency, temperature has a negative, highly statistically significant, and quantitatively large effect on output: a 1 °C increase in monthly temperature is associated with a 0.77 percent reduction in nighttime lights, a proxy for local economic activity. The effects of even a temporary increase in temperature persist for almost one year after the shock. Increases in temperature have an especially large, negative impact on growth in poorer countries, indicating that they are more vulnerable to the impact of climate change.

RECOMMENDED CITATION: Hoang, Da, Duong Trung Le, Ha Nguyen, and Nikola Spatafora. 2024. "Shedding Light on the Local Impact of Temperature". IMF Working Paper No. 24/178, International Monetary Fund, Washington, DC.

JEL Classification Numbers:	Q54; O47
Keywords:	Climate change; temperature; economic growth; nighttime lights

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WORKING PAPERS

Shedding Light on the Local Impact of Temperature

Prepared by Da Hoang, Duong Trung Le, Ha Nguyen, and Nikola Spatafora[1]

[1] The author(s) would like to thank Guy Amouzou Agbe, Robert Beyer, Luc Eyraud, Vladimir Klyuev, Mercedes Garcia-Escribano, Yao Jiaxiong, Thibault Lemaire, Emanuele Massetti, Luca Ricci, Gregor Schwerhoff, Can Sever, Filippos Tagklis, and seminar participants at the IMF and World Bank for valuable comments and feedback.

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I. Introduction

Climate change is a key global challenge. Temperatures are rising. Droughts, floods, wildfires, and massive storms are occurring more frequently with devastating effects. Understanding the impact of rising temperature, the most basic manifestation of climate change, on economic activity is fundamental to adaptation and mitigation efforts.

The economic literature has generally found that higher temperature hurts economic activity, particularly for hot and poor countries. The early literature examined the relationship between average temperature and aggregate economic variables (e.g., Sachs and Warner, 1997; Gallup, Sachs, and Mellinger, 1999). It found that hotter countries tend to be poorer. However, this relationship might be driven by omitted variables, such as country institutions. The more recent literature uses fluctuations in temperature within a country to control for slow-moving country characteristics.[2] It finds that higher temperature reduces economic growth in poor countries (Dell et al., 2012; Acevedo et al., 2020) and the United States (Colacito et al., 2019). The negative effects run through reduced total factor productivity growth (Letta and Tol, 2019), reduced investment and labor productivity (Acevedo et al., 2020; Kalkuhl and Wenz, 2020) and reduced sectoral productivity (Lepore and Fernando, 2023). Burke et al. (2015) document the non-linear effect of temperature: economic growth rises with average annual temperature until approximately 13 °C, at which point the relationship reverses.

The literature typically examines the impact of average annual temperature on annual economic outcomes.[3] However, temperature at a given location may vary greatly across seasons. For instance, temperature in Washington, D.C., varies greatly within the year (Appendix Figure 1); the annual average of close to 21 °C can be misleadingly moderate because Washington D.C. has a cold winter and a hot summer. Averaging temperature over the entire year may therefore miss important fluctuations, suggesting the importance of carrying out the analysis at a frequency that is higher than annual.

Similarly, averaging temperature over a large geographic area, such as a country or even a province, may miss important details. Both temperature and its fluctuations, and the structure of economic activity and its sensitivity to temperature, may vary greatly across space. Hence, examining the impact of temperature requires analysis at a more granular spatial level.

In this paper, we explicitly acknowledge that both temperature and its effects are highly heterogeneous and localized. To that end, we analyze the link between temperature and economic activity using data finely disaggregated across both time and space. We examine the impact of monthly temperature on economic activity within 30-kilometer by 30-kilometer grid cells. Going to the grid and monthly levels allows us to estimate the effects of temperature more precisely across different climate zones. This analysis offers new insights to

[2] See, for instance, Kahn et al., 2021; Acevedo et al., 2020; Colacito et al., 2019; Letta and Tol, 2019; Cashin et al., 2017; and Dell et al., 2012. See also the surveys by Chang et al. (2023), Auffhammer (2018), and Dell et al. (2014).

[3] See, for instance, Berg et al., 2023; Newell et al.,2021; Acevedo et al., 2020; Kalkuhl and Wenz, 2020; Burke et al., 2015; Dell et al., 2012; and Deschênes and Greenstone, 2007. Akyapi et al. (2022) identify, among a large number of annual climate indicators, those most predictive of economic damage.

complement the existing literature, which focuses on annual average temperature and economic outcomes at the country level.[4]

Granular analyses come with their challenges. The first and most obvious issue is the lack of economic data at the local level.[5] In this paper, local economic activity is proxied by the intensity of nighttime lights. A large literature points to the value of nighttime lights as an indicator for economic activity (Chen and Nordhaus, 2011; Hu and Yao, 2022; Martinez, 2022; Asher et al., 2021). Related to our paper, Felbermayr et al. (2022) examine the impact of storms, excessive precipitation, droughts, and cold spells on economic activity proxied by nighttime lights.

Overall, we find a negative and highly statistically significant effect of temperature on the growth of nighttime lights. Relatedly, our heterogeneity analysis indicates that this significant effect of temperature is found also in locations with relatively lower average temperatures. This significant effect is observed in countries across the income distribution, although it is statistically larger in poorer areas.

Under our fully specified model, a 1 °C increase in monthly-average temperature reduces the contemporaneous year-over-year growth of monthly nighttime lights by 0.77 percent. Common estimates of the elasticity of nighttime lights with respect to GDP in turn suggest this would be associated with a reduction in GDP growth, relative to baseline, of between 0.5 and 0.77 percentage points. This magnitude is larger than the findings often reported in the literature that uses more aggregated data.[6] Our estimates are more in line with Acevedo et al. (2020), which report that a 1 °C increase in annual temperature reduces output growth by 0.6–1.2 percentage points for low- and middle-income countries, although the effect is largely not statistically significant for advanced economies.

A key question is how these effects change across different climate zones. So far, there is little evidence because of the lack of granular data. The literature tends to find stronger effects in poorer countries and in warmer areas (Dell et al., 2012; Burke et al., 2015, Acevedo et al., 2020). In an early and influential paper, Burke et al. (2015), using country-average and annual average temperature data, find uneven impacts of temperature on GDP growth: positive for countries with average temperature below 13 °C, and negative for countries with average temperatures above that. However, recent research suggests that this finding of uneven effects is not robust. For instance, Nath et al. (2023) show that the uneven effects disappear when controlling for lagged temperature. The fragile findings with annual- and country-average data once again indicate the need for more granular analyses.

An important and related issue is that the literature using aggregate data is often incapable of disentangling the impact of rising temperature in hot locations from that in poorer regions; that is, it is unclear if the impact reflects a hot climate or low economic development. We revisit this debate in this paper. Using very granular data, we can control for both factors. We assign any given grid cell in any given month to a specific

[4] Nguyen (2024) examines the impact of US-county level seasonal temperature on country-level job growth. The paper finds that a hotter summer hurts job growth, but a warmer winter helps.

[5] Some efforts have been made to compute cell-level cross cell product (see Geiger et al., 2017, but only for 10-year increments).

[6] For example, using country average and annual average temperature data, Dell et al. (2012) find that on average, across all countries, a 1 °C increase in temperature reduces a country's annual GDP growth by 0.3 percentage points, and the decline is not statistically significant.

temperature bin, depending on its average monthly temperature in that month.[7] We then examine the impact of temperature across different temperature bins. We find that the impact of temperature on growth in nighttime lights is negative and statistically significant, except in colder areas. In other words, our findings support the common hypothesis that temperature affects economic activity more negatively in relatively warm areas.

At the same time, we find that, when controlling for temperature, income levels also matter. Within each temperature bin, we find that temperature has more negative effects in grid cells that are part of a low- or middle-income country. Our result therefore suggests that temperature does have a relatively more severe effect on economic activity in poorer areas.

Another important point relates to the long-term effects of temperature on economic activity. Could a temporary temperature shock induce long-lasting growth effects? To answer this question, we rely on local projection models to analyze the impulse response of economic activity, proxied by nighttime lights, following an increase in temperature. We find that even a temporary shock to monthly temperatures has a relatively persistent effect on economic activity, which remains statistically significant for almost a year, although the effect wanes as the time horizon expands.

II. Data and Empirical Specification

II.1 Data

Data for the main analysis variables—temperature and nighttime lights—are collected from two main sources. The temperature and precipitation data are collected from the ERA5 Monthly Aggregates dataset (C3S, 2017; Gorelick et al., 2017). ERA5 is the fifth-generation global climate reanalysis produced by European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 Monthly provides aggregated values for each month for seven ERA5 climate reanalysis parameters: 2m air temperature (in Kelvin, converted to Celsius), 2m dewpoint temperature, total precipitation (in meters), mean sea level pressure, surface pressure, 10m u-component of wind and 10m v-component of wind. The dataset is available from January 1979 to June 2020 and covers the entire globe with a grid cell resolution of about 30 kilometers (that is, with data on 30-kilometer wide square areas). We collect monthly maximum air temperature at 2m and monthly total precipitation.

We collect nighttime lights data as monthly average radiance composite images from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) (Elvidge et al., 2013). This version is an alternative configuration of the VIIRS DNB, which corrects for stray light (data near the edges of the swath are excluded). Data impacted by cloud cover is also excluded. And, since the usefulness of nighttime lights to proxy economic activity can be affected by snow, we exclude observations where snow cover (collected from ERA5 dataset) exceeds 50 percent in a month.[8] The dataset is available from January 2014 to June 2022 with a grid cell

[7] Specifically, each grid cell in any given calendar month is assigned to one of six possible temperature bins (less than 0 °C, 0 °C–10 °C, 10 °C–20 °C, 20 °C–30 °C, 30 °C–35 °C, and greater than 35 °C), depending on its average temperature in that month. For example, the grid cells covering Washington D.C. have an average January temperature between 0 °C and 10 °C, and an average June temperature between 20 °C and 30 °C.

[8] Snow cover in the presence of moonlight can make an area appear very bright (Zhang et al, 2023). The results are also robust to excluding observations where snow cover exceeds 40 percent or 60 percent.

resolution of about 500 meters. To merge temperature and precipitation data with nighttime light data, we collect the monthly data for the overlapping period from January 2014 to June 2020 (78 months) using grid cells of 30 kilometers by 30 kilometers, which are available for both datasets. Finally, we collect grid-cell level data on population (CIESIN and SEDAC, 2018). All data are collected via Google Earth Engine.

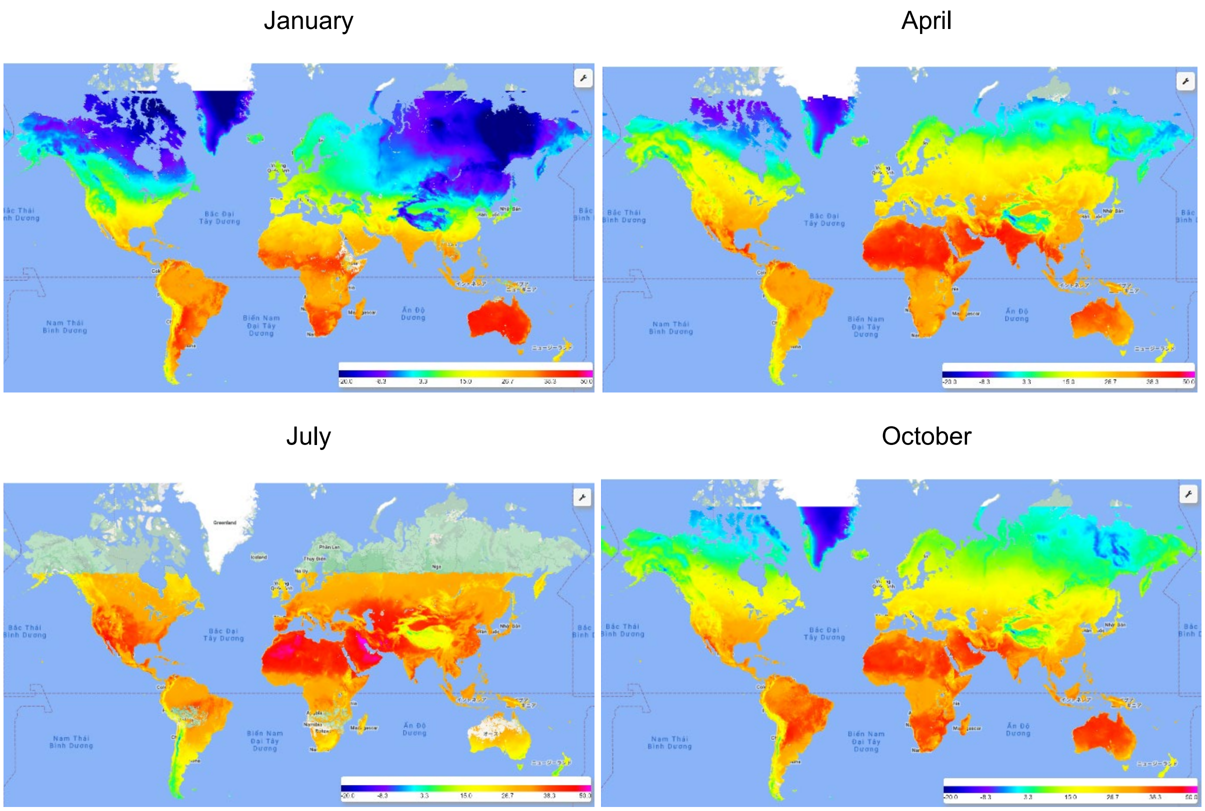
Table 1 presents summary statistics of nighttime lights and temperature. Across all cell-month observations, the median year-on-year (YoY) growth rate of nighttime light is approximately 4 percent, with significant variation (94 percentage points). The average temperature is 28.5 °C. Temperature has increased by 0.10°C (or 0.46 percent) annually for the typical (median) cell. Figure 1 illustrates the spatial and seasonal variations in temperature across the globe; blue tones denote lower temperatures, red tones higher temperatures.

Table 1: Summary Statistics.

	YoY Growth in Nighttime Lights	Temperature (°C)	YoY Change in Temperature (°C)	Total monthly precipitation (meter)
Observations (cell X month)	8,438,699	12,517,650	10,585,842	12,517,650
Number of cells	197,166	200,648	200,648	200,648
Mean	0.1167	28.5310	0.1293	0.0758
Std	0.9360	9.3457	3.0510	0.1017
Min	-24.2884	-9.9429	-22.2279	0.0000
P1	-2.5226	4.8381	-8.1817	0.0000
P5	-1.1159	10.6698	-4.7809	0.0000
P25	-0.2597	22.7557	-1.4121	0.0089
Median	0.0405	30.3510	0.0980	0.0434
P75	0.4174	34.8485	1.6333	0.1001
P95	1.6501	42.0870	5.2489	0.2760
P99	3.1880	45.4611	8.6147	0.4515
Max	14.4289	53.7555	20.9840	4.0605

Note: Summary statistics of nighttime light (YoY growth) and temperature (in level and YoY change). Units are percentage points, except for the rows “Observations (cell X month)” and “Number of cells”. Each grid cell is a 30-kilometer by 30-kilometer square. Monthly observations from January 2014 to June 2020 (78 months).

Figure 1: Average temperature by selected calendar month, across the world.



Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; and IMF staff calculations.
Note: The maps exclude cells with zero or missing nighttime lights.

II.2 Theoretical Motivation

To study the relationship between temperature and economic growth, we first present a theoretical motivation, based on Dell et al. (2012). This will inform our subsequent empirical specification. Let economic activity change according to

$$Y_t = e^{\beta T_t} A_t^{\alpha} \tag{1}$$

where *Y* denotes economic activity, *T* denotes temperature, *A* is a productivity term, and *t* denotes the month. Here, temperature has a direct level effect on economic activity, represented by β. In addition, productivity affects economic activity, as represented by α. And temperature may also affect annual productivity growth:

$$\log(A_t) - \log(A_{t-12}) = g + \lambda T_t + \sigma T_{t-12} \tag{2}$$

where λ denotes the short-run effect of temperature on productivity growth, and (λ + σ) the long-run effect. The specification allows for either positive or negative effects of temperature on productivity growth. Taking logs and year-over-year first differences of (1), and combining with (2), yields

$$\log(Y_t) - \log(Y_{t-12}) = \beta(T_t - T_{12}) + \alpha(g + \lambda T_t + \sigma T_{t-12})$$

$$\Rightarrow \qquad \log(Y_t) - \log(Y_{t-12}) = \alpha g + (\beta + \alpha\lambda)T_t + (\alpha\sigma - \beta)T_{t-12} \tag{3}$$

So, temperature affects the growth rate of output; the short-run growth effect is given by $(\beta + \alpha\lambda)$, and the long-run effect by $[\alpha\ (\lambda + \sigma)]$. Equation (3) forms the basis for the empirical specification.

II.3 Empirical Specification

Contemporaneous Effects of Temperature

In line with the theoretical motivation, the main empirical regression takes the form

$$\log(L_{c,t}) - \log(L_{c,t-12}) = \beta_0 + \beta_1 T_{c,t} + \beta_2 T_{c,t-12} + \sigma_1 P_{c,t} + FE_t + FE_{c,m} + \epsilon_{c,t} \tag{4}$$

where *L* denotes nighttime lights, *T* denotes the average temperature of the month, *c* indexes the (30-kilometer by 30-kilometer) grid cells, and *t* denotes the month. Changes in nighttime lights proxy for changes in economic activity. FE_t are month-specific fixed effects that capture global factors affecting the growth of nighttime lights across all cells in a particular month. $FE_{c,m}$ are cell–by–calendar-month fixed effects, which controls for the calendar-month-specific growth of nighttime lights for each grid cell.[9] They address different seasonality for different cells. For instance, they handle the fact that the northern and southern hemispheres have opposite seasons, or that nighttime lights may grow especially fast during summer months for cells located in cold climate zones. Our preferred specification further controls for precipitation as a contemporaneous covariate climate factor, where $P_{c,t}$ denotes a vector comprising two dummies indicating whether a grid cell experienced abnormally high (one standard deviation above the long-term average precipitation in a particular calendar month) or low (one standard deviation below) in month t.[10]

We use equation (4) to analyze the contemporaneous effect of temperature on the year-over-year growth of nighttime lights. T_t is the main explanatory variable, capturing month *t*'s temperature. The key coefficient of interest is β_1.[11] We view the estimated effect of local temperature on local economic activity as causal, since local temperature is best viewed as exogenous with respect to local economic activity. In particular, there is little risk of reverse causality from local economic activity to local temperature.[12] The control variable T_{t-12} captures the

[9] Essentially, $FE_{c,m}$ includes12 fixed effects per grid cell, each corresponding to a calendar month in a year.

[10] More specifically, the precipitation dummies are defined as follow:

High_P$_{c,t}$ = 1 if $P_{c,t} > average(P_{c,t}) + std(P_{c,t})$, and = 0 otherwise; and

Low_P$_{c,t}$ = 1 if $P_{c,t} < average(P_{c,t}) - std(P_{c,t})$, and = 0 otherwise;

where $P_{c,t}$ denotes the total precipitation level of the month, and both averages and standard deviations are cell–calendar-month specific.

[11] Which corresponds to the parameters $(\beta + \alpha\lambda)$ in equation (3).

[12] In principle, some omitted, climate-related variable might both be systematically correlated with local temperature, *and* affect local economic activity. The most obvious such variable is precipitation; as discussed, we therefore control for this.

impact of temperature in the same month of the previous year. Standard errors are clustered at the province (specifically, first-tier administrative) level in each country where data are available.

We then extend the analysis, investigating separately the impact of positive and negative changes in temperature:

$$\log(L_{c,t}) - \log(L_{c,t-12}) = \beta_0 + \beta_1 T_{c,t} + \beta_2 T_{c,t-12} + \gamma_1 Positive_{c,t} + \gamma_2 T_{c,t} \times Positive_{c,t} + \sigma_1 P_{c,t} + FE_t + FE_{c,m} + \epsilon_{c,t} \quad (5)$$

where the indicator $Positive_{c,t}$ = 1 if $(T_{c,t} - T_{c,t-12}) \geq 0$, and = 0 otherwise. Here, the contemporaneous effect of temperature on the year-over-year growth of nighttime lights is given by β_1 for negative temperature shocks, and $(\beta_1 + \gamma_2)$ for positive temperature shocks.

In an analogous manner, we also investigate separately the impact of large positive and large negative changes in temperature, defined as those changes that are more than one standard deviation away from the average temperature change:

$$\log(L_{c,t}) - \log(L_{c,t-12}) = \beta_0 + \beta_1 T_{c,t} + \beta_2 T_{c,t-12} + \delta_1 T_{c,t} \times High\ Positive_{c,t} + \delta_2 T_{c,t} \times High\ Negative_{c,t} + \mu_1 High\ Positive_{c,t} + \mu_2 High\ Negative_{c,t} + \sigma_1 P_{c,t} + FE_t + FE_{c,m} + \epsilon_{c,t} \quad (6)$$

where the indicators

High Positive$_{c,t}$ = 1 if $(T_{c,t} - T_{c,t-12}) > average(T_{c,t} - T_{c,t-12}) + std(T_{c,t} - T_{c,t-12})$, and = 0 otherwise; and

High Negative$_{c,t}$ = 1 if $(T_{c,t} - T_{c,t-12}) < average(T_{c,t} - T_{c,t-12}) - std(T_{c,t} - T_{c,t-12})$, and = 0 otherwise;

and both averages and standard deviations are cell-specific.

Dynamic Effects of Temperature

We also want to examine the dynamic impact of temperature on nighttime lights, including the long-run effect. To this end, we employ a flexible empirical specification, adopting the local linear projections methodology (Jordà, 2005). Impulse response analysis using local projections has become a popular alternative to the traditional structural vector autoregressive (SVAR) models. In particular, local projections offer the following benefits over the traditional approach: (i) they are more robust to misspecification, since they do not constrain the shape of impulse response functions; (ii) they can accommodate nonlinear and more flexible specifications; and (iii) they are easier to implement, because they only require standard linear regressions (Jordà, 2005).

Our specification takes the form:

$$\log(L_{c,t+h}) - \log(L_{c,t-1}) = \alpha_{c,h} + \beta_h T_{c,t} + X_{c,t} + \sigma_1 P_{c,t} + FE_t + FE_{c,m} + \epsilon_{c,t} \quad (7)$$

where h denotes the projection horizon, and $\log(L_{c,t+h}) - \log(L_{c,t-1})$ captures the growth rate of nighttime lights between $t-1$ and $t+h$. $T_{c,t}$ is the temperature in month t; $X_{c,t}$ are other time-varying cell-specific controls; FE_t are the global month fixed effects; $FE_{c,m}$ are the cell–calendar-month fixed effects. In the baseline regression, the controls $X_{c,t}$ take the form

$$X_{c,t} = \left\{ \left\{ \lambda_\tau T_{c,t-\tau} \right\}_{\tau=1}^{11}, \left\{ \delta_\tau T_{c,t+\tau} \right\}_{\tau=1}^{h}, \left\{ \theta_\tau \log\left(L_{c,t-\tau} \right) \right\}_{\tau=1}^{11} \right\}$$

That is, we control for temperature and nighttime lights in the previous eleven months. As proposed by Teulings and Zubanov (2014), we also control for forward values of temperature. We estimate and plot the coefficients β_h to form an impulse response of (log) nighttime lights to temperature at time t over the projection horizon (constrained here to 24 months given sample size limitations). Again, standard errors are clustered at the province level.

We use an analogous specification to investigate the dynamic properties of temperature itself:

$$T_{c,t+h} = \alpha_{c,h} + \beta_h T_{c,t} + \lambda_h X_{c,t} + FE_t + FE_{c,m} + \epsilon_{c,t} \quad (8)$$

where $X_{c,t} = \left[T_{c,t-\tau} |_{\tau=1}^{11} \right]$.

III. Findings

III.1 Contemporaneous Effects

Table 2 presents the estimated aggregate contemporaneous effect of temperature on the growth of nighttime lights, using fixed-effect estimation (Eq. 4). Our estimates indicate a statistically significant and negative effect of temperature on the growth of nighttime lights. This is statistically significant at the 1 percent confidence level and is robust to different specification forms. Under our fully specified model that controls for month-specific fixed effects, cell by calendar-month fixed effects, and contemporaneous indicators of precipitation anomalies, a 1 °C increase in temperature causes a contemporaneous 0.77 percent contraction in nighttime light intensity. Common estimates of the elasticity of nighttime lights with respect to GDP in turn suggest this would be associated with a reduction in GDP growth of between 0.50 and 0.77 percentage points.[13] As discussed, this estimate is larger than the findings often reported in the literature that uses more aggregated data. Our estimates also suggest that higher-than-normal precipitation (that is, excessive rainfall) is associated with a reduction in growth in nighttime lights. Our main temperature estimates, however, are not sensitive to controlling for precipitation (see Section IV).

[13] The baseline elasticity of nighttime lights with respect to GDP is estimated at 1 in Henderson et al. (2012), 1.3 in Hu and Yao (2022), and 1.55 in Beyer et al. (2022). These are estimates at the annual and quarterly frequency; no estimates are available at the monthly frequency.

Table 2: Aggregate contemporaneous effect of temperature

	(1)	(2)
Temperature (t)	-0.0046*** (0.0015)	-0.0077*** (0.0022)
Temperature (t-12)	0.0060*** (0.0015)	0.0026 (0.0026)
High precipitation	-0.0156** (0.0064)	-0.0202*** (0.0069)
Low precipitation	0.0006 (0.0066)	0.0031 (0.0083)
Month-specific fixed effects	Yes	Yes
Cell-specific fixed effects	Yes	No
Cell × calendar-month fixed effects	No	Yes
Number of observations	8,438,699	8,438,699
Number of cells	197,166	197,166

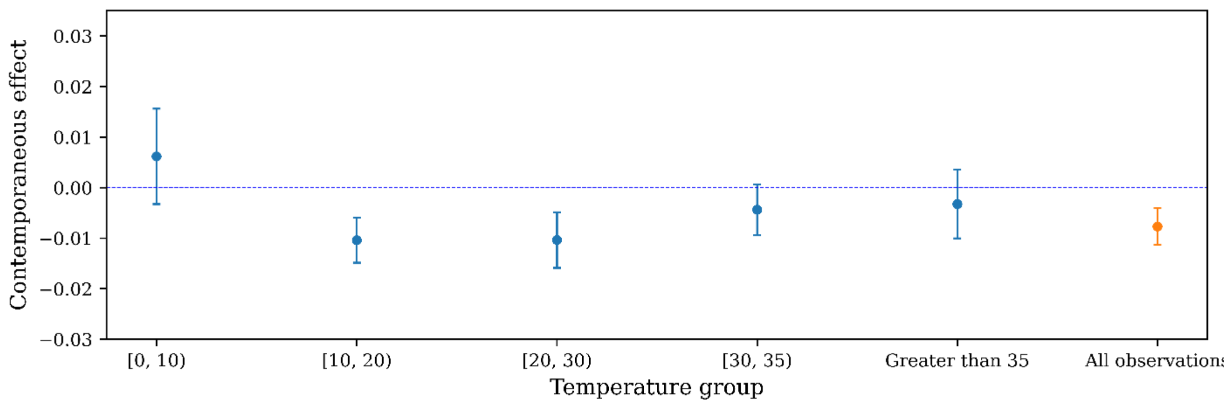
Note: Standard errors in parentheses are clustered at the province level; ***: p < 0.01, **: p < 0.05, *: p < 0.1. High/low levels of precipitation are defined as those that are more than one standard deviation higher/lower than the cell-calendar month average precipitation.

Next, we address the important question of how the effect of higher temperature varies across climate zones. The literature typically examines this question parametrically, for instance, adding quadratic terms in temperature (e.g., Burke et al., 2015). Our rich data allow us to answer the question non-parametrically: we can estimate the impacts of higher temperature by temperature bins. To proceed, we calculate the long-term average monthly temperature over 2014–2022 for each cell and calendar month. This monthly average temperature can then be used to allocate the observations into 6 temperature bins: (<0 °C), [0 °C, 10 °C), [10 °C, 20 °C), [20 °C, 30 °C), [30 °C, 35 °C), or [> 35 °C), based on the observation's cell and calendar month. A cell can belong to different temperature bins depending on its long-term average monthly temperature for each of the calendar months. For example, the cell's winter months might belong to the [0 °C, 10 °C) bin while the cell's summer months might belong to the [20 °C, 30 °C) bin. As mentioned, to eliminate the effect of snow cover on nighttime lights, we remove observations of cells where snow cover exceeds 50 percent in a given month. Correspondingly, cells in temperature group (<0 °C) are dropped from the analysis since they are mostly covered by snow (see Appendix Table 1 for the number of observations and number of countries by temperature group, and Appendix Table 2 for the 20 countries with the greatest number of grid cells in each temperature group). We then run regression models for each temperature group controlling for month fixed effects and for the cell–by–calendar-month fixed effects of each group (i.e., corresponding to column (2) in Table 2).

The contemporaneous effect of a 1 °C increase in temperature is estimated at approximately a 1 percent reduction in the growth of nighttime lights for the temperature groups [10 °C, 20 °C) and [20 °C, 30 °C), and about a 0.3–0.45 percent reduction for the temperature groups [30 °C, 35 °C) and [>=35 °C) (Figure 2; see

Appendix Table 3 for the corresponding detailed estimation results).[14] In relatively warm climate zones, an increase in temperature makes economic activity, and especially outdoor work, more difficult. On the other hand, for the low temperature group [0 °C, 10 °C), an increase in temperature has a positive impact on the growth of nighttime lights (albeit not significantly different from zero at the 10 percent level). This is consistent with the literature; for example, using annual-average and country-average data, Burke et al. (2015) document that rising temperature boosts growth in colder countries.

Figure 2: Contemporaneous effect by temperature group.

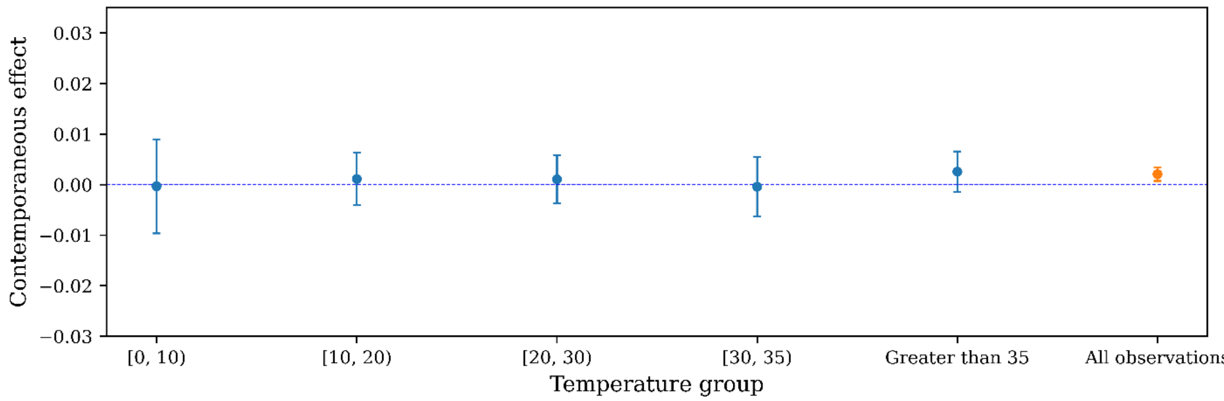


Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; and IMF staff calculations.
Note: Coefficient plots illustrate contemporaneous effects of temperature on the growth of nighttime lights across temperature bins (Eq. 4). Whiskers represent 90% confidence interval.

The estimated effect of a given change in temperature on economic activity is in general not significantly influenced by considering separately in the estimation the effect of positive and negative changes in temperature (Figure 3), or of large positive and large negative changes in temperature (Appendix Figure 2 and Appendix Figure 3).

[14] As Appendix Table 3 indicates, the four temperature groups have similar sample sizes.

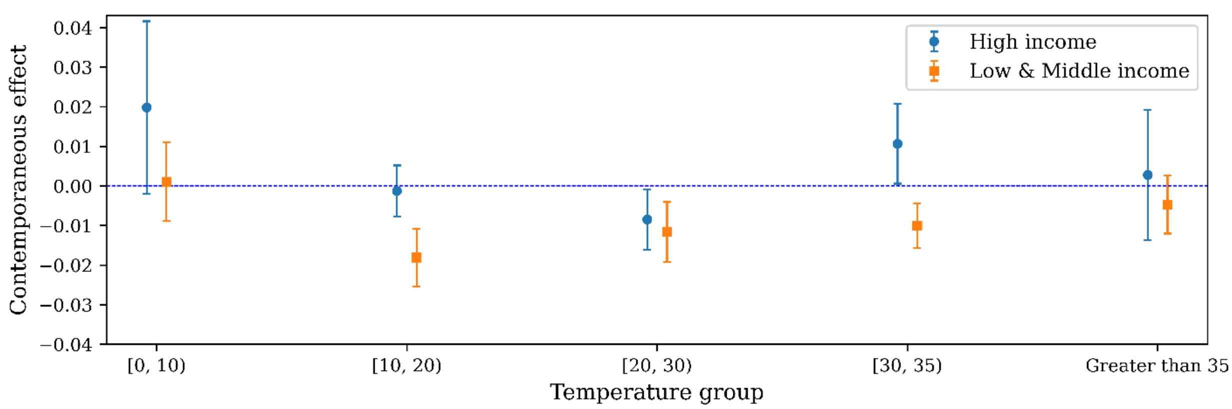
Figure 3: Contemporaneous effect by temperature group: Difference in coefficients between positive and negative temperature changes.



Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; and IMF staff calculations.
Note: Plots illustrate, for the contemporaneous effects of temperature on the growth of nighttime lights across temperature bins, the difference γ_2 in coefficients between positive and negative temperature changes (Eq. 5). Whiskers represent 90% confidence interval.

Our data granularity allows for a further disaggregation of effects by both temperature bin and countries' level of economic development. Across all temperature bins, the impact of temperature on economic activity is consistently more negative in low- and middle-income countries than in high-income countries (Figure 4; see Appendix Table 4 for the corresponding detailed estimation results). The difference is particularly large when focusing on areas that lie in the [30 °C, 35 °C) temperature zone.

Figure 4: Contemporaneous effect by temperature and income group.

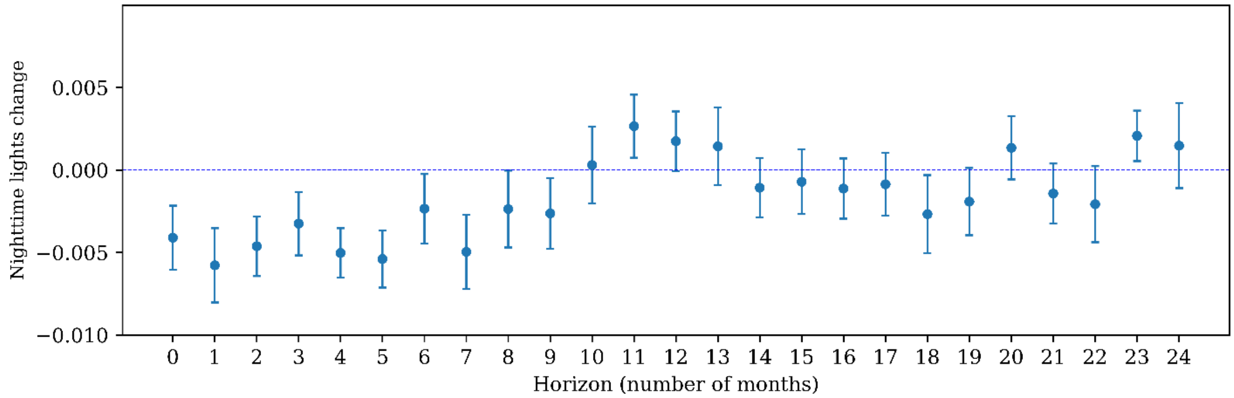


Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; and IMF staff calculations.
Note: Coefficient plots illustrate contemporaneous effects of temperature on the growth of nighttime lights across temperature bins and income groups (Eq. 4). Whiskers represent 90% confidence interval.

III.2 Dynamic Effects

In addition to estimating the contemporaneous effect of temperature, we rely on local projection models to analyze the impulse response of nighttime lights at the monthly frequency following a 1 °C increase in temperature. After a temperature shock, we observe a statistically significant reduction in nighttime lights, which persists for three quarters (Figure 5). During the first quarter after the shock, nighttime lights decrease by on average 0.5 percent. As the time horizon expands, the effect gradually wanes in terms of magnitude and statistical significance. The effect only becomes statistically insignificant in the fourth quarter after the shock.

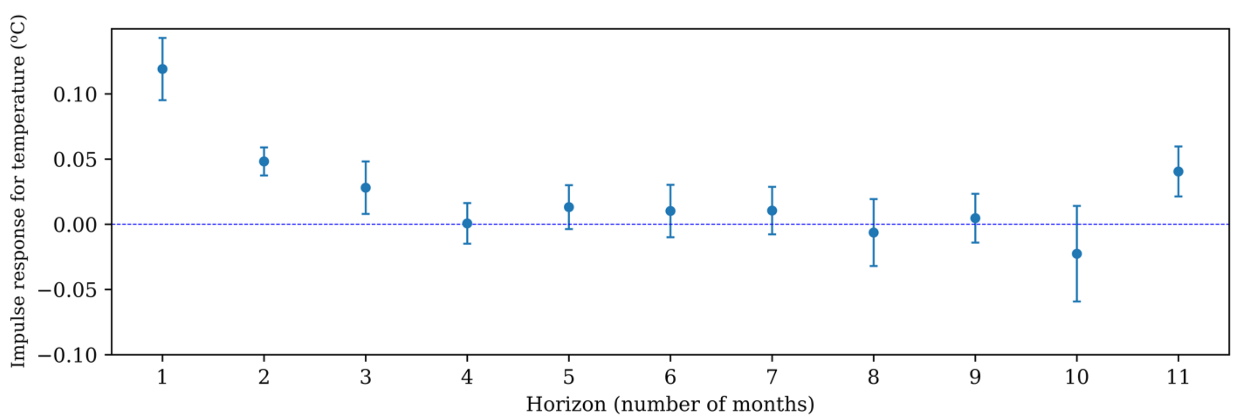
Figure 5: Dynamic response of nighttime lights to a temperature shock.



Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; and IMF staff calculations.
Note: Estimated impulse responses using local projections model (Eq. 7). Whiskers represent 90% confidence interval.

This relatively persistent response of economic activity to a temperature shock occurs even though temperature itself is far less persistent. In particular, following a temperature shock at the monthly level, temperatures remain only elevated for 3 months (Figure 6). This finding suggests that the persistence in temperature changes is not the main cause of the persistence in the effects on the growth of nighttime lights.

Figure 6: Dynamic response of temperature to a temperature shock.



Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; and IMF staff calculations.
Note: Estimated impulse responses using local projections model (Eq. 8). Whiskers represent 90% confidence interval.

IV. Robustness Checks

We also perform a series of exercises to investigate the robustness of our contemporaneous and dynamic-effect estimations. Table 3 show robustness checks for five additional specifications, focusing on potential data irregularities which might affect the estimation results from our baseline model. Model 1.1 in Table 3 corresponds to a specification that omits observations in 2017, a satellite re-configuration period.[15] Model 1.2 omits the 1% lowest and 1% highest growth in nighttime lights; this helps address the concern that some extreme growth in nighttime lights could reflect non-climate factors (for instance, rural electrification). Model 1.3 omits both the 1% lowest and 1% highest growth in nighttime lights, and the 1% lowest and 1% highest nighttime lights. Model 1.4 omits the 30-km grid cells with populations of less than 100, essentially removing unpopulated areas. Model 1.5 corresponds to a specification which does not control for precipitation. The estimated relationships between nighttime lights and temperature are robust to all these checks.[16]

Similarly, Figure 7 shows the dynamic responses of growth in nighttime lights to a 1 °C increase in temperature for each of the five robustness checks discussed above. The estimated dynamic relationship between nighttime lights and temperature is also robust to all these checks.

Table 3: Contemporaneous effect by temperature group: Robustness checks.

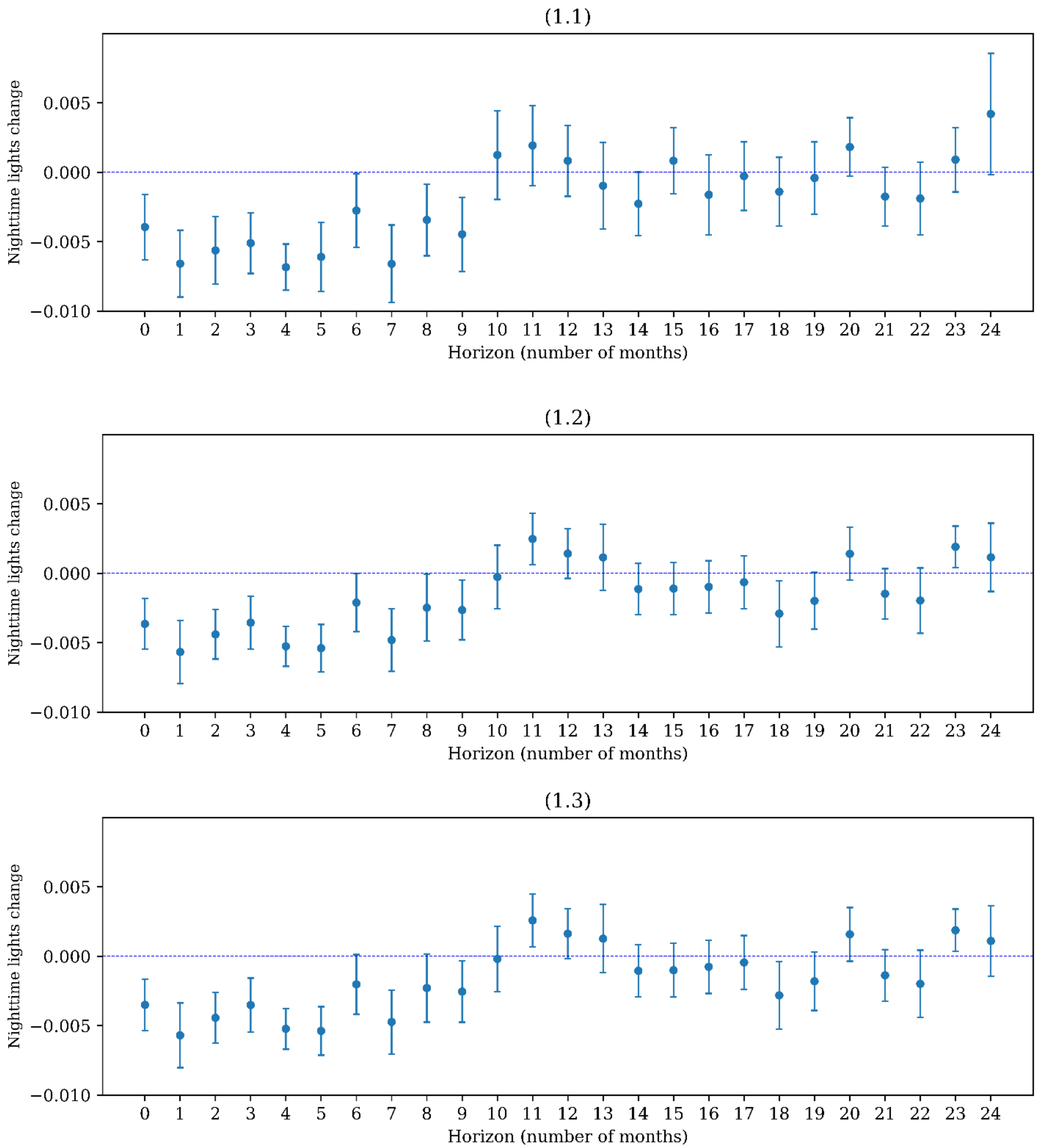
	Model 1.1	**Model 1.2**	**Model 1.3**	**Model 1.4**	**Model 1.5**
Temperature - lag0	-0.0073** (0.0029)	-0.0042** (0.0019)	-0.0043** (0.0019)	-0.0066*** (0.0022)	-0.0071*** (0.0022)
Temperature - lag12	0.0068*** (0.0022)	0.0054*** (0.002)	0.0055*** (0.002)	0.0082*** (0.0019)	0.0026 (0.0026)
High precipitation	-0.0281*** (0.0072)	-0.0129** (0.0057)	-0.0131** (0.0057)	-0.0282*** (0.0062)	N/A
Low precipitation	0.0196** (0.0098)	0.0031 (0.007)	0.0031 (0.007)	0.0141* (0.0074)	N/A
Month-specific FE	Yes	Yes	Yes	Yes	Yes
Cell × calendar month FE	Yes	Yes	Yes	Yes	Yes
Number of observations	7,039,914	8,269,925	8,157,719	7,127,418	8,438,699
Number of cells	197,103	197,157	196,502	145,627	197,166

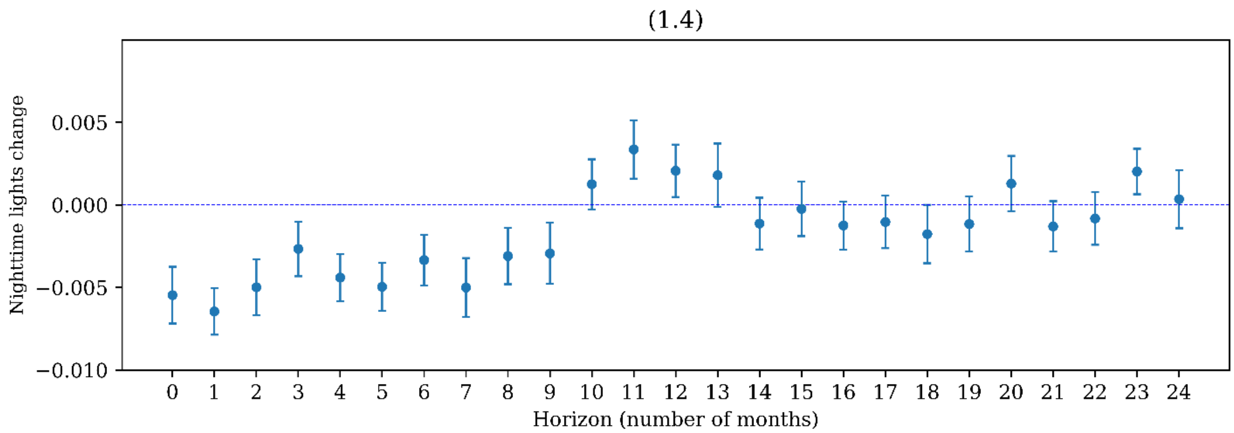
Note: Model 1.1 corresponds to a specification omitting observations in 2017, a satellite re-configuration period. Model 1.2 omits the 1% lowest and 1% highest growth in nighttime lights. Model 1.3 omits both the 1% lowest and 1% highest growth in nighttime lights, and the 1% lowest and 1% highest nighttime lights. Model 1.4 omits the 30km grid cells with populations of less than 100. Model 1.5 corresponds to a specification which does not control for total precipitation.

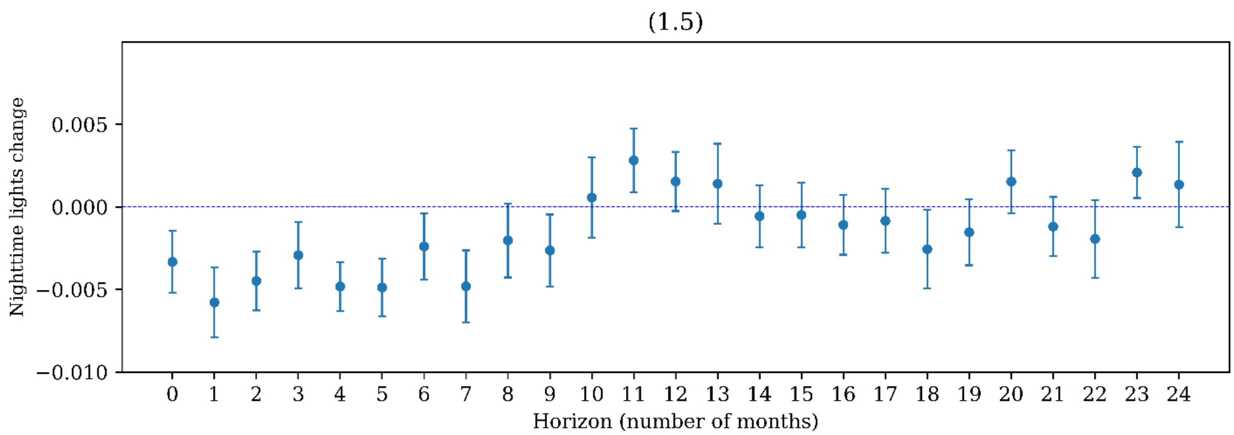
[15] Starting on January 12, 2017, the VIIRS was produced using new calibration parameters which result in better radiometric quality especially for low radiances. Since we use year-on-year (12-month) growth in nighttime lights as the dependent variable, we remove observations for the year 2017 as a robustness check to ensure consistent nighttime lights measurement.

[16] Additional results, available upon request, also confirm that the results are robust to using monthly average rather than monthly maximum temperatures.

Figure 7: Dynamic response of nighttime lights to a temperature shock: Robustness checks.







Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; CIESIN and SEDAC, 2018; and IMF staff calculations.
Note: Model 1.1 corresponds to a specification omitting observations in 2017, a satellite re-configuration period. Model 1.2 omits the 1% lowest and 1% highest growth in nighttime lights. Model 1.3 omits both the 1% lowest and 1% highest growth in nighttime lights, and the 1% lowest and 1% highest nighttime lights. Model 1.4 omits the 30km grid cells with populations of less than 100. Model 1.5 corresponds to a specification which does not control for total precipitation.

V. Conclusions

We use a new dataset and methodology, which allows us to estimate the impact of temperature on economic activity, proxied by nighttime lights, at a more geographically and temporally disaggregated level than the existing literature. Overall, we find a negative and highly statistically significant effect of temperature on economic activity. Our more granular approach results in finding a larger effect than is often reported. In particular, our preferred specification finds that a 1 °C increase in temperature reduces the contemporaneous growth of nighttime lights by 0.77 percent. And the effects of even temporary increases in temperature on growth in nighttime lights are persistent, lasting almost a year.

We also find that the impact of temperature on growth in nighttime lights is negative and statistically significant except in colder areas. In other words, our findings support the common hypothesis that temperature affects economic activity more negatively in relatively warm areas. At the same time, even when controlling for temperature, income levels also matter. Within each temperature bin, temperature has more negative effects in grid cells that are part of a low- or middle-income country. Our results therefore suggest that temperature has a relatively more severe effect on economic activity in poorer areas. Finally, all these results survive an exhaustive battery of robustness checks aimed at controlling for outliers and various types of measurement error.

Finally, it is important to note that the historical short-run responses to a given change in temperature may well differ from the future long-run impact of climate change, in either direction. For instance, the magnitude of future climate change may lie well beyond recently observed temperature fluctuations, and may involve severe non-linear impacts ("tipping points"). Again, the impact of climate change will depend on the extent of adaptation. Stronger adaptation efforts, such as more widespread uses of drought-resistant seeds, as well as diversification into more resilient sectors, may soften the impact of rising temperatures. On the other hand, there may be limits to how much ecosystems can adapt. And, as climate change becomes more pronounced, human behavior and economic activity may change unpredictably—for instance, through large-scale migration out of severely affected areas.

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Appendix

A. Supplementary Results

Appendix Table 1: Number of observations, number of cells and number of countries by temperature group.

Temperature group	Number of observations	Number of cells	Number of countries
[0 °C, 10 °C)	322,271	64,396	72
[10 °C, 20 °C)	1,337,642	110,371	95
[20 °C, 30 °C)	2,327,248	143,240	180
[30 °C, 35 °C)	2,332,987	125,112	166
>35 °C	2,118,551	85,935	136

Appendix Table 2: Top 20 countries with the largest number of observations for each temperature group.

No.	[0 °C, 10 °C)	[10 °C, 20 °C)	[20 °C, 30 °C)	[30 °C, 35 °C)	>35 °C
1	China	Russia	Russia	Brazil	Australia
2	Russia	China	United States	United States	Brazil
3	Canada	Canada	Canada	China	India
4	United States	United States	China	Dem Rep of the Congo	Algeria
5	Kazakhstan	Kazakhstan	Australia	Australia	Saudi Arabia
6	Mongolia	Argentina	Argentina	India	United States
7	Ukraine	Mongolia	Kazakhstan	Russia	Sudan
8	Sweden	Chile	Algeria	Indonesia	Mali
9	Finland	France	Mexico	Mexico	Libya
10	Poland	Iran	Iran	Kazakhstan	Niger
11	Belarus	Turkey	Mongolia	Argentina	China
12	Norway	Peru	India	Angola	Chad
13	Argentina	United Kingdom	Brazil	Colombia	Mauritania
14	Uzbekistan	Sweden	Libya	Venezuela	Iran
15	Chile	Germany	Turkey	Algeria	Argentina
16	Greenland	Ukraine	South Africa	South Africa	Kazakhstan
17	India	Spain	Indonesia	Tanzania	Egypt
18	Lithuania	Poland	Chile	Canada	Mexico
19	Latvia	Italy	France	Peru	Pakistan
20	Afghanistan	Norway	Saudi Arabia	Saudi Arabia	Nigeria

Appendix Table 3: Contemporaneous effect by temperature group (corresponding to Figure 2).

Variable	Temperature group				
	[0.0, 10.0)	[10.0, 20.0)	[20.0, 30.0)	[30.0, 35.0)	>35.0
temp(month, cell) - lag0	0.0062	-0.0104***	-0.0104***	-0.0044	-0.0032
temp(month, cell) - lag12	0.0101	0.0065**	0.0023	0.0036	-0.0065
Precipitation control	Yes	Yes	Yes	Yes	Yes
Month-specific FE	Yes	Yes	Yes	Yes	Yes
Cell × calendar month FE	Yes	Yes	Yes	Yes	Yes
Number of observations	322,271	1,337,642	2,327,248	2,332,987	2,118,551
Number of cells	64,396	110,371	143,240	125,112	85,935

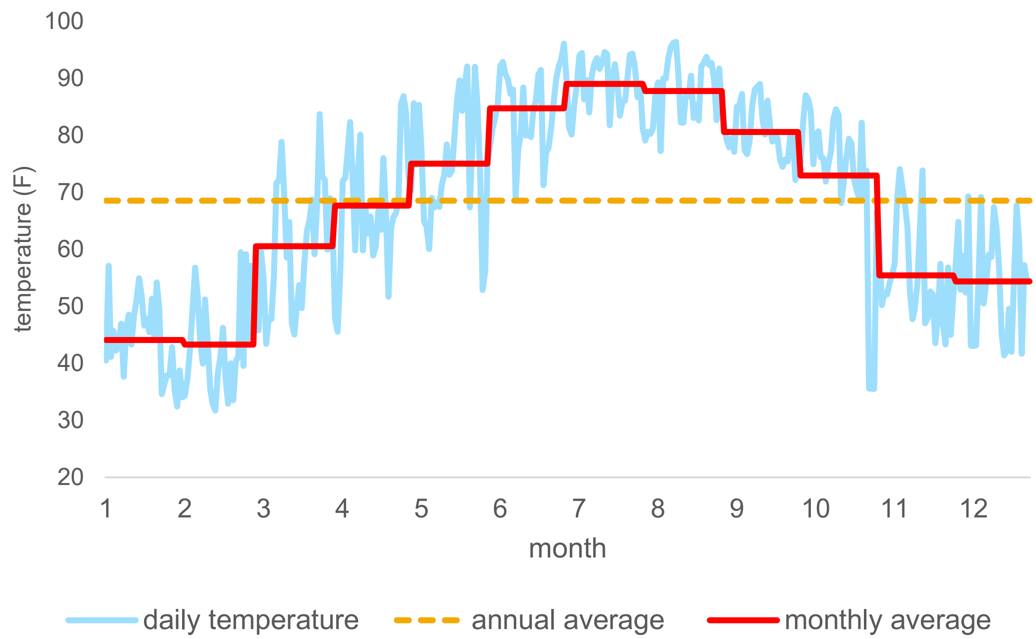
Note: Estimates corresponding to Figure 2. Standard errors in parentheses are clustered at the province level; ***: p < 0.01, **: p < 0.05, *: p < 0.1

Appendix Table 4: Contemporaneous effect by temperature group and income group (corresponds to Figure 4)

Variable	Temperature group									
	[0 °C, 10 °C)		[10 °C, 20 °C)		[20 °C, 30 °C)		[30 °C, 35 °C)		>35 °C	
	High income	Low & Middle income	High income	Low & Middle income	High income	Low & Middle income	High income	Low & Middle income	High income	Low & Middle income
temp(month, cell) - lag0	1.98%	0.11%	-0.13%	-1.81%***	-0.85%*	-1.16%**	1.06%*	-1.00%***	0.28%	-0.47%
temp(month, cell) - lag12	0.99%	0.99%	0.64%**	0.64%**	0.23%	0.23%	0.40%	0.40%	-0.66%	-0.66%
temp(month, cell) - lag0 x I(Low & Middle Income)	-1.84%		-1.69%**		-0.32%		-2.07%***		-0.82%	
temp(month, cell) - lag0 x I(High Income)		1.98%		1.68%**		0.32%		2.12%***		0.57%
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-specific FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell × calendar month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	322,271	322,271	1,337,642	1,337,642	2,327,248	2,327,248	2,332,987	2,332,987	2,118,551	2,118,551
Number of cells	64,396	64,396	110,371	110,371	143,240	143,240	125,112	125,112	85,935	85,935

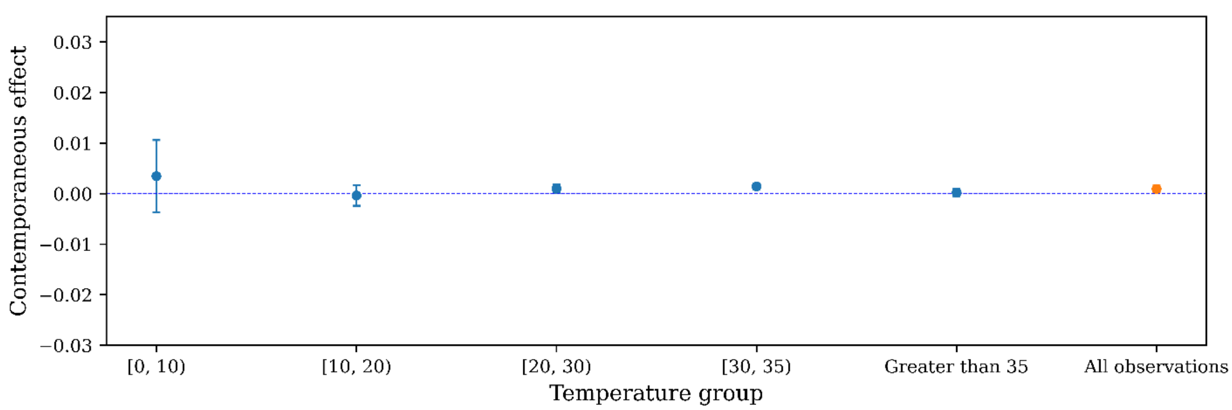
Note: Estimates corresponding to Figure 4 using estimates in the first row (corresponding to temperature at lag0). Standard errors in parentheses are clustered at the province level; ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Appendix Figure 1: Temperature in Washington D.C. in 2021



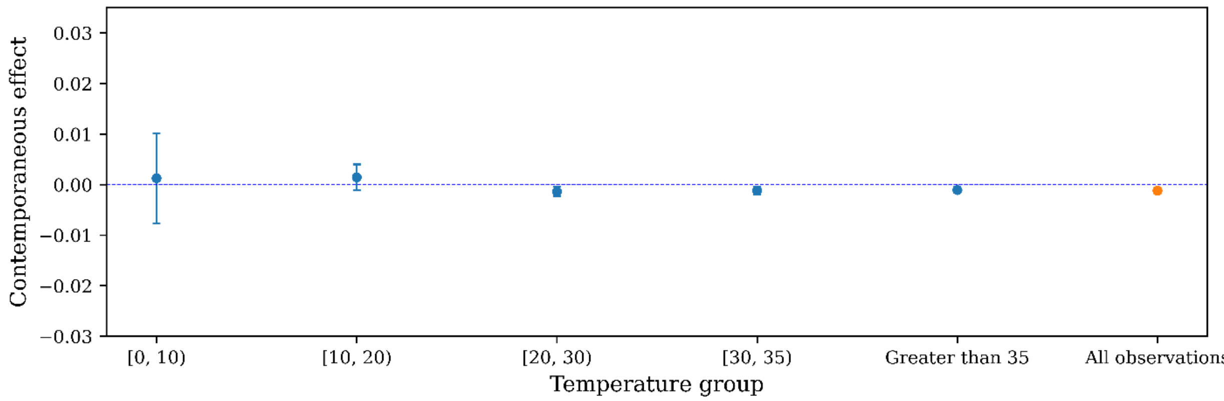
Source: C3S, 2017; Gorelick et al., 2017; and IMF staff calculations.

Appendix Figure 2: Contemporaneous effect by temperature group: Additional impact of large positive temperature changes.



Source: C3S, 2017; Gorelick et al., 2017; Elvidge et al., 2013; CIESIN and SEDAC, 2018; and IMF staff calculations.
Note: Plots illustrate, for the contemporaneous effects of temperature on the growth of nighttime lights across temperature bins, the additional coefficient δ_1 on large positive temperature changes (Eq. 6). Whiskers represent 90% confidence interval.

Appendix Figure 3: Contemporaneous effect by temperature group: Additional impact of large negative temperature changes.



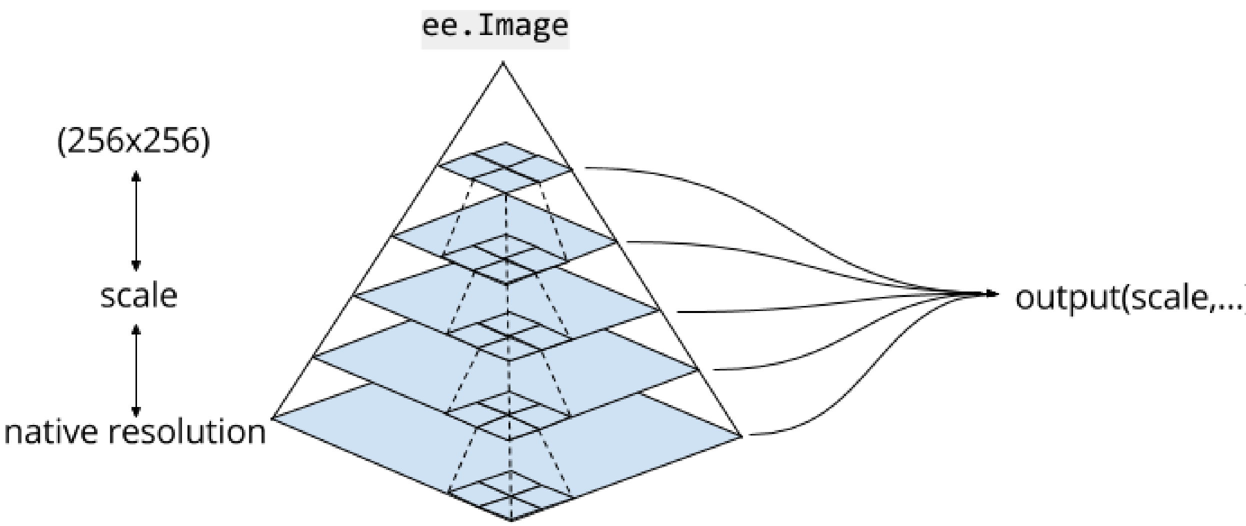
Source: C3S, 2017; Gorelick et al., 2017; and IMF staff calculations.
Note: Plots illustrate, for the contemporaneous effects of temperature on the growth of nighttime lights across temperature bins, the additional coefficient δ_2 on large negative temperature changes (Eq. 6). Whiskers represent 90% confidence interval.

B. Data Description: the Google Earth Engine

In the Google Earth Engine, the pixel resolution of an image is handled through the scale parameter. Image assets in Google Earth Engine exist at multiple scales, in Image pyramids (Appendix Figure 4). Each pixel at a given level of the pyramid is calculated from a 2x2 block of pixels at the lower level (shown by dashed lines). For continuous valued images, the pixel values are aggregated as the average of pixel values from lower levels. For discrete valued images, upper-level pixel values are a sample (usually the top left pixel) of pixels from lower levels.

When an image is requested at a specific scale, Google Earth Engine chooses a level of the pyramid with the closest scale less than or equal to the scale specified by the analysis and resamples (using nearest neighbor by default) as necessary.

Appendix Figure 4: A graphic representation of an image dataset in Earth Engine.



Source: Google Earth Engine, 2024.

PUBLICATIONS

Shedding Light on the Local Impact of Temperature
Working Paper No. WP/2024/178