Temperature variability and long-run economic development

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Abstract

This study estimates causal effects of temperature variability on long-run economic development, which are not accounted for in most estimates of the costs of future climate change. For identification I use a novel research design based on spatial first-differences. Economic activity is proxied by nightlights. Informed by the underlying physical mechanisms, I distinguish between day-to-day, seasonal, and interannual variability. The results suggest an economically large and statistically significant negative effect of day-to-day variability on economic activity. Regarding seasonal variability, I find a smaller but also negative effect. The estimated effect of interannual variability is positive at low and negative at high temperatures. These effects are robust, they can be identified in urban and rural areas, and they cannot be explained with the spatial distribution of agriculture. The results suggest that temperature variability will add to the costs of anthropogenic climate change, especially in relatively warm and currently relatively poor regions.

Keywords: climate, temperature, nightlights, day-to-day variability, seasonal variability, interannual variability

JEL Codes: Q54, Q56, R11, R12, R14, O13, O44

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1 Introduction

The debate about how climate and climate change influence economic development has a long history, but with few exceptions it has been all about annual mean climate. Fluctuations of temperature around its annual mean have thus been mostly neglected, although temperature variability is generally very common. For example, in many countries temperature frequently changes by several degrees Celsius from one day to the next. Furthermore, in many places temperature differs by more than 10 degrees Celsius between summer and winter. Differences between years are generally smaller, but annual mean temperature can still change by about 1-2 degrees Celsius from one year to the next, comparable in magnitude to global warming over the last 100 years. The current lack of evidence on the effects of this variability at the time scale of days, months, and years means that possible costs of larger variability are not included in most estimates of the costs of future climate change.

Advancing our understanding of the consequences of temperature variability has possibly been hindered by the challenge of identifying its causal effects. In recent years, the marginal effect of climate on economic activity has primarily been estimated with panel regression models using annual observations and unit and year fixed effects (Dell et al., 2012; Burke et al., 2015a). While this approach has generally been regarded as more credibly identifying causal effects than cross-sectional regressions, it cannot be used for variables that need to be measured over periods longer than a year and that change relatively slowly, such as seasonal and interannual temperature variability.

In this paper I estimate the causal effect of temperature variability at different time scales on long-run economic development. For identification I use a novel econometric framework based on differences between geographically proximate observations (Druckenmiller and Hsiang, 2018). This spatial first-differences research design allows me to identify the effect of slow-changing climatic variables under weaker assumptions than a regression on a cross-section of levels. The identification strategy can be interpreted as matching based on geographical proximity with a continuous treatment variable. I apply this method to a global dataset consisting of grid cells with a size of approximately 25 km x 25 km that contain information on economic activity, measured by satellites as the intensity of light at night, and temperature and its variability from climate reanalysis, as well as several climatic and geographic controls.

Temperature variability at different time scales has different underlying physical mechanisms, predictability, and projected changes under future climate change. I therefore distinguish between temperature variability at the time scales of days, months, and years: *day-to-day*, *seasonal*, and *interannual* variability. To measure these variables, I calculate the intra-monthly standard deviation of daily temperature levels, the intra-annual range of monthly mean temperatures, and the inter-annual standard deviation of annual mean temperatures respectively.

My empirical results suggest economically large and statistically significant negative effects of *day-to-day* and *seasonal* temperature variability on long-run economic development. On average, one sample standard deviation of variability reduces nightlights by 16 and 7 percent, respectively the sample standard deviations are 1.44 for day-to-day variability and 14.71 for seasonal variability). If these effects are benchmarked with the estimated effect of annual mean temperature, they correspond to increases of annual mean temperature from 25 degree Celsius to approximately 30 and 28 degrees Celsius, respectively. Regarding *interannual* variability, I find a positive effect on economic activity below and a negative effect above an annual mean temperature of 20 degrees Celsius.

I discuss several theories about why and how temperature variability can affect economic activity, including non-linear effects of daily temperature levels (ex post effects) and greater uncertainty (ex ante effects). Because I use cross-sectional variation of long-term averages for identification, my estimates capture both ex post and ex ante effects. This contrasts most previous work that used time-series variation with annual frequency and thus captured primarily ex post effects (Pretis et al., 2018; Kotz et al., 2021b; Rudik et al., 2021). In line with the empirical effects that I find, previous micro-econometric evidence suggests overall negative effects of temperature variability on economic activity. The fact that day-to-day variability is less predictable than seasonal temperature variability and hence introduces larger uncertainty could explain its more negative effect. Regarding interannual variability, I note that the pattern of estimated coefficients is consistent with an asymmetry whereby the benefits/costs of colder-than-average years are smaller than the benefits/costs of warmer-than-average years, possibly due to heating being less costly and generally more widespread than cooling (Rode et al., 2021).

Previous research suggests that nightlights are a better proxy for GDP per capita in urban areas than in rural areas and that the spatial distribution of nightlights also reflects the local sectoral composition of the economy (Chen and Nordhaus, 2019; Gibson, 2020). I therefore also examine whether my results are primarily driven by urban areas and whether they can be explained by the spatial distribution of agricultural activity. I find that the estimated coefficients are indeed largest in urban areas, but I also find significant effects with the same sign for less densely populated regions, including the least densely populated areas within countries. Furthermore, the main results are unaffected by controlling for the spatial distribution of agricultural activity.

This is to my knowledge the first study to examine the long-run effect of temperature variability accounting for both ex ante and ex post effects and examining variability at multiple time scales. The results generally agree with previous studies finding negative effects of day-to-day variability on regional GDP (Kotz et al., 2021b), negative effects of daily and seasonal temperature variability on regional GDP in the US (Rudik et al., 2021), and negative effects of seasonal temperature variability on specific economic outcomes such as in agriculture (Mendelsohn et al., 2007a) and health (Hovdahl, 2020). Furthermore, I find positive marginal effects of annual mean temperature at relatively low temperature levels and negative effects at relatively high temperatures, consistent with previous findings of a negative quadratic relationship between annual mean temperature and economic growth (Burke et al., 2015b; Kalkuhl and Wenz, 2020).

The results also contribute to the debate about the the future costs of anthropogenic climate change. With few exceptions (Calel et al., 2020; Kikstra et al., 2021; Rudik et al., 2021), temperature variability is not accounted for in estimated costs of climate change. My results suggest that the costs of temperature variability should be included in assessments of future costs and deserve a closer look at their geographical distribution. Climate models project that seasonal variability will tend to decrease in cold and increase in relatively warm countries (Dwyer et al., 2012). These projections, together with my results, suggest that accounting for seasonal variability decreases the costs of climate change in relatively cold countries and increases its costs in relatively warm (and currently poor) countries. The results on interannual temperature variability are generally less robust, but suggest that the benefits or costs of projected changes to interannual variability depend on current annual mean temperature levels. Together with projections of climate models (Bathiany et al., 2018), the results suggest that future changes to interannual temperature variability also tend to increase the costs of climate change in relatively warm (and currently poor) countries. Also observed trends of day-to-day variability over the last decades suggest additional economic costs of climate change in relatively warm countries (Kotz et al., 2021a).

The use of spatial first-differences reduces omitted variable biases (Druckenmiller and Hsiang, 2018). However, because identification still relies on cross-sectional variation, I conduct a formal sensitivity analysis and several robustness tests. Specifically, I show that any omitted variable would need to be more strongly associated with both temperature variability and nightlights than any of the climatic control variables (annual mean temperature, precipitation, precipitation variability, relative humidity, solar radiation) or geographic control variables (elevation, terrain ruggedness, distance from coast, distance from inland water body) such that controlling for this confounder could make the estimates insignificant. I also compare estimates obtained from spatial differences in only either the North-South or the West-East direction and with different functional forms for my control variables.

Another concern regarding the identification strategy is reverse causality: climate can have an effect on local economic development, but local economic development can also influence the local climate. To address this concern I use an alternative source of nightlights data which allows me to examine changes of nightlights over time. This enables me to regress changes of nightlights over time on temperature variability observed over an earlier period. By doing so, any feedbacks from local economic development on local climate are excluded by design, but the main results can still be recovered.

The paper is structured as follows. In the next Section, I briefly explain why temperature variability might matter for economic activity (Section 2.1), introduce the three measures of climate variability and explain their geographical distribution (Section 2.2). I then describe the data in Section 3. In Section 4, I present the research design and identification strategy. All results are presented in Section 5: I first present the main results (Section 5.1) and then conduct several robustness tests (Section 5.2 and 5.3). In Section 6 I discuss several mechanisms that could explain the results. Finally, I discuss results in light of previous findings and point out implications for future research in Section 7.

2 Climate variability

2.1 How temperature variability can affect economic activity

Annual mean temperature affects economic production in both developing and developed countries (Dell et al., 2012; Burke et al., 2015b; Kalkuhl and Wenz, 2020). This effect appears to be non-linear, with possibly positive marginal effects at low and increasingly negative marginal effects at high temperature levels (Burke et al., 2015b; Kalkuhl and Wenz, 2020). These empirical results have been explained with alternative mechanisms, including effects of daily temperature levels on human cognitive processes (Almås et al., 2019) and effects of daily temperature levels on production unrelated to labour, such as crop failures in agriculture.

Temperature variability can add to the costs of annual mean temperature if the relationship between daily temperature levels and economic production is non-linear. In that case, the net costs of variability in any given location depend on the relative frequencies of different levels. This effect of temperature variability is explored for example by Rudik et al. (2021) and by Calel et al. (2020) and Kikstra et al. (2021) using integrated assessment models with non-linear damage functions, which yield an overall negative effect of larger variability. Such effects are also a possible explanation of the negative effect of diurnal temperature ranges reported in prior work (Mitton, 2016). Alternatively, temperature variability introduces costs if there are heterogeneous locally optimal temperature levels. Such locally optimal temperature levels have been documented for example for the choice of crops in South America (Seo and Mendelsohn, 2008) and can be observed for human physiology (Hanna and Tait, 2015). In both areas, detrimental effects of temperature variability have been reported on respectively crop yields (Wheeler et al., 2000) and temperature-related mortality (Hovdahl, 2020).

These possible costs of temperature variability are associated with realised temperature levels (ex post effects of variability). In addition, temperature variability can affect economic activity through expectations (ex ante effects of variability). To the extent that larger variability implies greater uncertainty about future temperature levels, and assuming there are effects of realised temperature levels on production, larger temperature variability means larger uncertainty of income and returns to investments. This uncertainty can have a negative effect on economic activity by discouraging investment. Such effects of variability have been documented e.g. for exchange rate fluctuations (Aghion et al., 2009) and volatility of government spending (Ramey and Ramey, 1994). Regarding climate, the effect of rainfall variability on output volatility was examined e.g. by Malik and Temple (2009). Economic agents can be expected to respond to greater climate uncertainty through risk diversification (Bellemare et al., 2013; Bezabih and Di Falco, 2012; Ashraf and Michalopoulos, 2015; Colmer, 2021; Buggle and Durante, 2021), but such diversification might not always be possible, be limited in its effectiveness, and come at a cost.

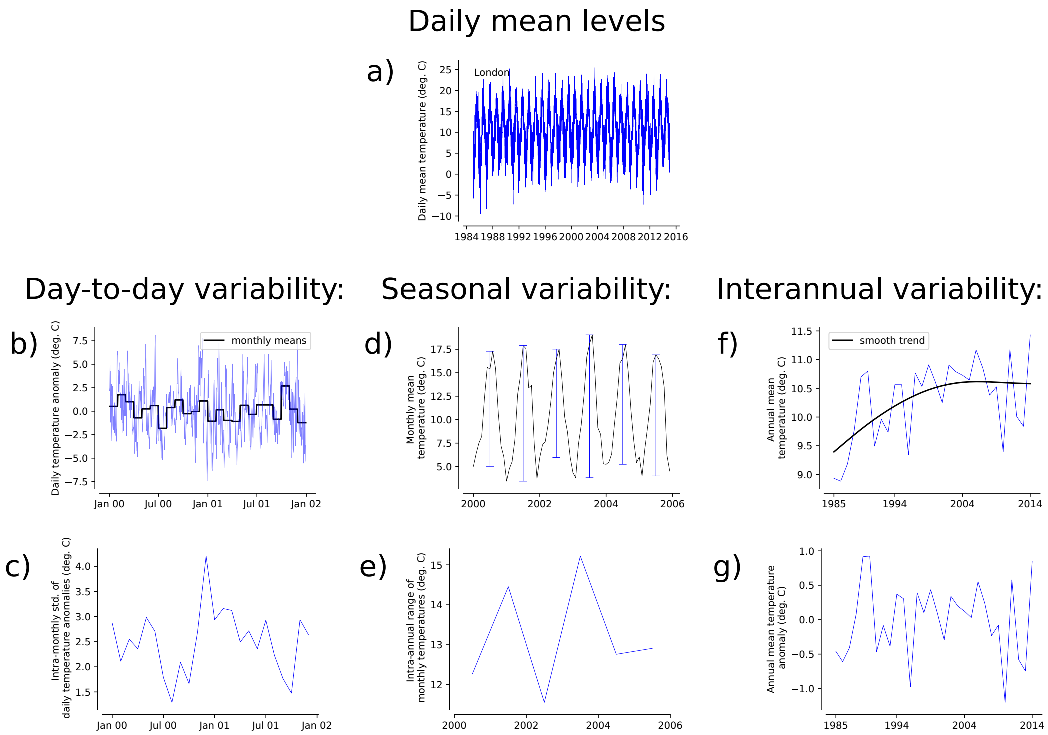
Overall, it can therefore be expected that ceteris paribus temperature variability has a negative effect on economic activity, either due to more frequently observed detrimental temperature levels, more frequent deviations from locally optimal temperature levels, or larger uncertainty. Only in situations in which greater variability means more frequent beneficial temperature levels and this positive ex post effect is larger than possible negative ex ante effects, will variability have a net positive effect. Because of non-linear effect of temperature levels, the effects of variability are expected to depend on the average temperature level. Furthermore, the effect of variability is expected to depend on the time scale of variability because more frequent fluctuations can be learned about more easily while they allow for less time for adjustments, as well as on its predictability.

2.2 Temperature variability: day-to-day, seasonal, and interannual

Due to human activity, mainly the burning of fossil fuels and the associated emission of greenhouse gases into the atmosphere, temperatures have been increasing since at least the second half of the 20th century. This slow trend has been overlaid by fluctuations on a range of time scales. In this paper I examine variability at the time scale of days, months, and years, that is day-to-day, seasonal, and interannual variability, respectively. In this Section, I first describe how I isolate varibility at different time scales and then explain the global distribution of temperature variability at different time scales with the underlying physical processes of weather and climate.

I define day-to-day temperature variability as fluctuations of temperature within the same month after subtraction of a smooth average annual cycle (Figure 1b,c). To estimate a smooth average annual cycle, I follow (Moberg et al., 2000) and fit a smooth curve into the multi-year average daily mean temperatures (daily mean temperatures averaged over my reference period 1985-2014). I use a Hodrick-Prescott filter with a smoothing parameter $\lambda = 10,000$ which subtracts trends extending over multiple years but not fluctuations from one year to the next. I subtract the average cycle because in countries with large annual cycles (large differences of temperature between summer and winter), this cycle means relatively steep trends in spring and fall, which lead to variation of temperature within months. Its subtraction prior to the calculation of intra-monthly standard deviations of daily temperature levels thus ensures that day-to-day variability is isolated from any influence of seasonal variability (Moberg et al., 2000).

Figure 1. Calculation of my three measures of temperature variability: day-to-day, seasonal, and interannual variability.



Notes: The top figure shows daily temperature levels for London from 1985 to 2014 using ERA5 reanalysis (see Section 3). The first column (Figures b, c) show two steps to calculate the day-to-day variability: after subtraction of a smooth average annual cycle, I calculate the intra-monthly standard deviation of daily temperature anomalies (Figure b), which I then average 1985-2014 (Figure c). The second column (Figures d,e) show two steps to calculate seasonal variability: I first calculate the intra-annual range of monthly mean temperatures (Figure d), which I then average 1985-2014 (Figure e). The third column (Figures f, g) show two steps to calculate inter-annual variability: I first subtract a smooth trend from annual mean temperatures (Figure f) and then calculate the inter-annual standard deviation of annual temperature anomalies 1985-2014 (Figure g). Figures b, c, d, e do not show the full time period 1985-2014 for readability.

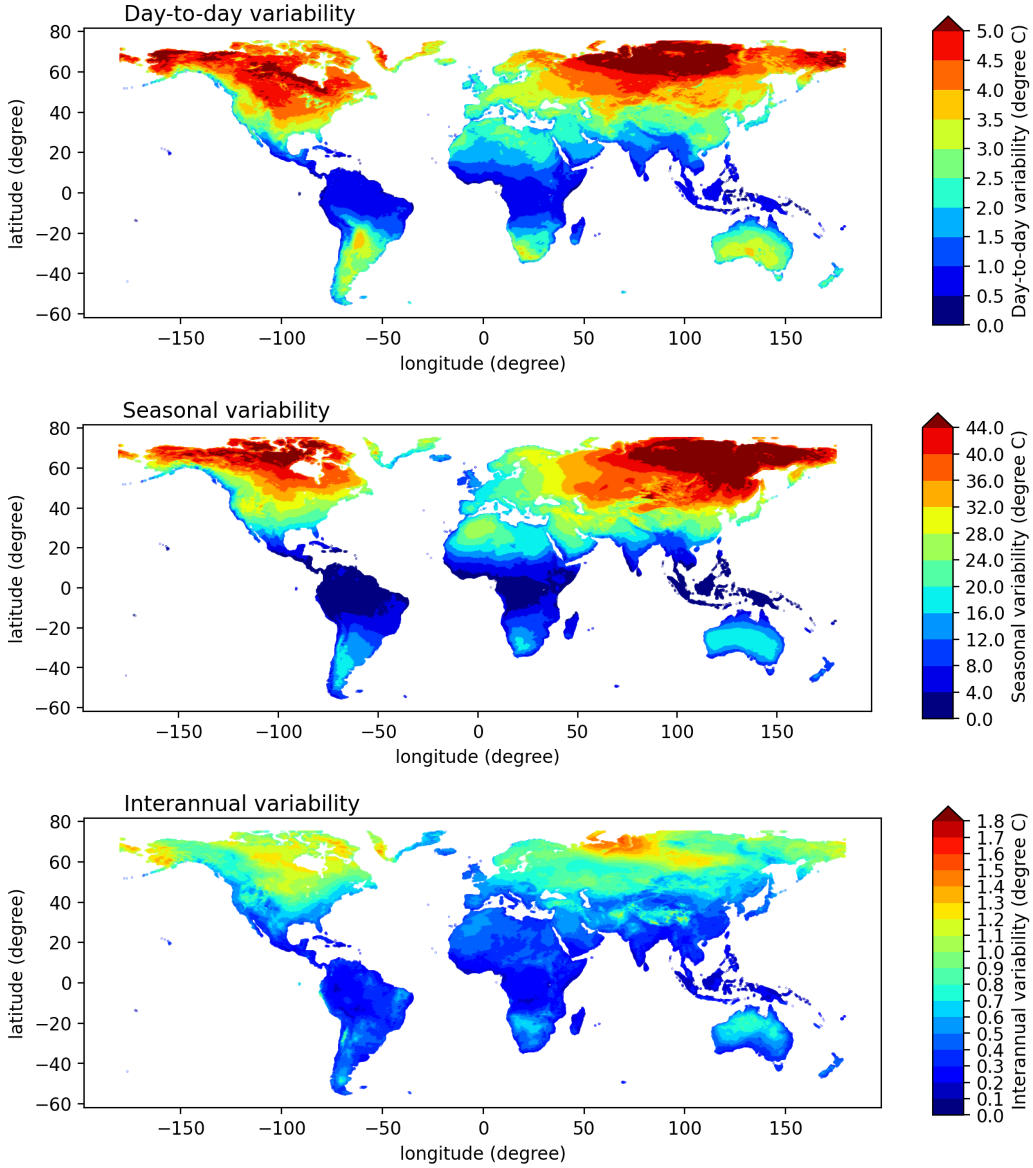
Seasonal temperature variability is quantified using the intra-annual range of monthly mean temperatures (Figure 1d,e). I choose monthly means instead of daily means to reduce the influence of potentially rare and extreme days. Furthermore, I use the range of monthly means instead of the standard deviation of monthly means in order to exclude any conflation with day-to-day variability. The main results are however very similar if I measure seasonal variability using the inter-monthly standard deviation of monthly mean temperatures, with a slightly higher significance of the effect of seasonal variability (Appendix D). For both day-to-day and seasonal temperature variability, I average the monthly values of intra-monthly standard deviations and the annual values of intra-annual ranges respectively over the period 1985-2014, which is the 30 years period preceding the year of the nightlights data.

Interannual variability is calculated as the between-year standard deviation of annual mean temperatures over the same 30 year period (Figure 1c,f). Before I calculate the standard deviation, I remove a slow trend in order to isolate interannual variability from any warming (or cooling) trends due to decadal climate variability or anthropogenic climate change.

The global maps of temperature variability reflect the influence of astronomy, geography, and climate dynamics (Figure 2). While the maps of day-to-day, seasonal, and interannual variability resemble each other and suggest positive correlations between the variables, I explain in the following how the relative importance of several physical processes differs. I look into the econometric implications of the high degree of spatial correlation in Section 4.

Day-to-day variability is generally larger at higher latitudes. This is primarily due to the influence of high and low pressure systems travelling eastwards at these latitudes, which cause frequent changes between local advection of cold (polar) and warm (tropical) air. Furthermore, day-to-day variability is larger further away from the coastline as land responds faster than water to changes in air temperature between days.

Figure 2. Geographical distribution of temperature and its variability: day-to-day, seasonal, and interannual variability (top to bottom).



Source: ERA-5 reanalysis (see Section 3.2).

Seasonal variability of temperature is generally larger at high latitudes than at low latitudes due to the tilt of Earth's axis (Figure 2b). Furthermore, because land responds faster to changes in solar radiation than oceans and the land areas are larger in the Northern hemisphere than in the Southern hemisphere, seasonal variability is generally larger in the Northern hemisphere and smaller closer to the coast and large inland water bodies (Legates and Willmott, 1990). Because at mid and high latitudes the wind tends to flow from West to East and the temperature of a parcel of air is influenced by the temperature of the surface over which it has been transported (McKinnon et al., 2013; Stine and Huybers, 2012), seasonal variability also tends to be larger on the Eastern parts of large continents (America, Eurasia).

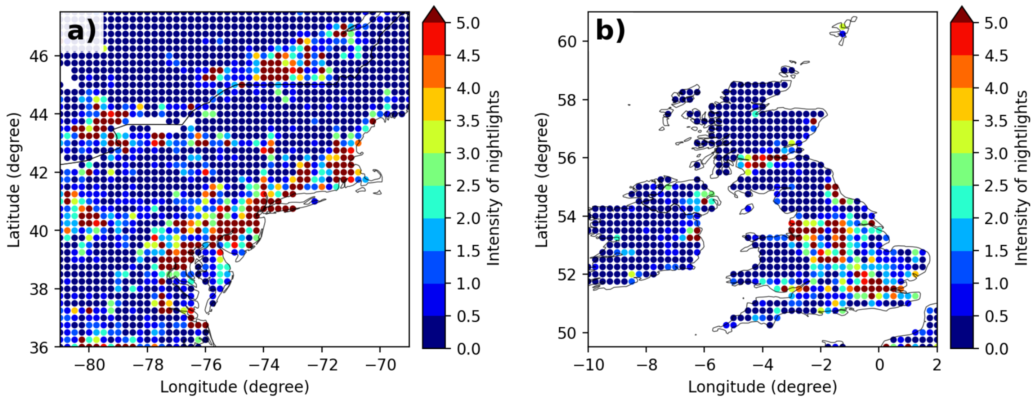
Interannual temperature variability is partly driven by external astronomical influences, such as solar cycles of about 11 years, but primarily due to internal climate variability (Mann and Park, 1994). Internal climate variability results from oscillations in the climate system, which are often related to interactions between different components of the climate system, such as the atmosphere and the ocean. Examples are the El-Nino Southern Oscillation (ENSO) and the North-Atlantic Oscillation (NAO) (IPCC, 2013). Interannual variability is generally larger further away from the coasts because the oceans have a larger heat storage capacity and thus a larger year-to-year inertia than land (Figure 2c). Interannual variability is largest in high Northern latitudes and at high altitude due to its amplification by the snow/ice-albedo feedback.

3 Data and descriptive statistics

3.1 Economic variables

I proxy economic activity by the intensity of lights at night (Chen and Nordhaus, 2011; Henderson et al., 2012; Nordhaus and Chen, 2015). Nightlights are measured by satellites and come with a resolution that outcompetes census-based measures of economic activity. This granularity of the data is particularly important in my research design, as identification rests on the comparability of neighbouring observations. Another advantage of using nightlights instead of population or GDP is that nightlights are consistently measured with the same quality and the same resolution worldwide. I take data on the intensity of lights at night from the satellites of the Visible Infrared Imaging Radiometer Suite (VIIRS) (Elvidge et al., 2017). The VIIRS is a relatively new satellite product which can be regarded as a successor of the popular DMSP data. As compared to the DMSP data, the VIIRS data suffers less from blurring, a lack of sensor calibration, and a limited range of sensitivity (Chen and Nordhaus, 2019; Gibson et al., 2021).

Figure 3. Geographical distribution of VIIRS nightlights: a) North-Eastern coast of the USA and b) the British Isles.



Source: VIIRS nightlights.

I use annual average radiance values which have undergone some post-processing to remove the effect of clouds and to filter out fires and other ephemeral lights. I use nightlights for the year 2015 with a resolution of 15 arc-seconds, which I aggregate to a resolution of 0.25 degrees. The year 2015 is the earliest year for which VIIRS nightlights were available at the time of the analysis. Because interest is in the effect of climate, typically defined over 30 years, on the level of economic development, climatic averages of 1985-2014 are combined with nightlights for 2015. Robustness tests with an average of nightlights 2015-2019 and with a very recent version of the VIIRS nightlights data yield the same results (Appendix G).

As most economic activity occurs on land rather than on water, the average radiance tends to be larger in grid cells with a higher share of land area. This could bias my results if the share of land area correlates with my climatic variables. I address this concern by multiplying the average radiance of a grid cell by the total area of the grid cell and dividing it by its total land area. All grid cells without land area are dropped from the data. Because the distribution of normalised nightlights is highly skewed, I log-transform the data.

At a global scale, the spatial distribution of VIIRS nightlights primarily shows the location of large metropolitan areas. At the regional scale, the spatial distribution of nightlights also shows variation outside metropolitan areas (Figure 3).

Although I prefer the VIIRS data to the DMSP data due to technological improvements (Gibson et al., 2021), I also download DMSP data for an additional robustness check for the years 1992 and 2012. The data are processed with the same steps as the VIIRS data. Furthermore, I use population data from the Gridded Population of the World (GPW) dataset version 4.0 (Center For International Earth Science Information Network-CIESIN-Columbia University, 2018). I choose this dataset as it is based on official censuses only and thus independent of my nightlights data. I also use data on the global distribution of cropland and pasture lands (Ramankutty et al., 2008) provided by NASA (Ramankutty et al., 2010), which I aggregate from its native resolution to a resolution of 0.25 degrees.

3.2 Climate variables

I use climate data from the global reanalysis ERA-5. Reanalysis data are produced by feeding an adjusted weather forecast model with the full global record of observational data, including weather station records and satellite data (Parker, 2016). ERA-5 belongs to the newest generation of reanalysis datasets and is provided with a resolution of 0.25 degrees. I choose reanalysis data instead of station-based weather data because of the physical consistency of reanalysis data. Furthermore, meteorological measurements are globally unevenly distributed and I expect that processing with a dynamic model evens out some of the heterogeneity in data quality.

The reanalysis data also has the advantage that they include climate variables in addition to temperature and precipitation. I include several additional variables in my model to reduce potential biases due to omitted climate variables. These biases could lead to a misattribution of empirically observed causal effects, but are not necessarily problematic as long as the physical relationships between the variables can be expected to be constant over time or if the estimated relationships are not used for future projections. To avoid misattribution, I also include relative humidity and solar radiation in my regressions. I use daily mean values of all climate variables for the period 1985 to 2014, which is the 30 years period prior to the VIIRS nightlights data, and for the period 1982-1991 (the period before the DMSP nightlights data). In another robustness check, I find that the results are qualitatively very similar if I use an earlier period for the climate data (1955-1984) (Appendix F).

3.3 Geographical covariates

The use of the spatial-first differences research design reduces omitted variable biases from all variables whose spatial gradients do not systematically correlate with the gradients of temperature variability at the spatial scale of my observations (about 25 km). For example, I expect that any differences in institutions between countries cannot bias my results. Furthermore, in order to reduce biases from specific variables, I also include several geographic controls.

Table 1. Descriptive statistics. Number of observations: 233,362.

Variable	Unit	Mean	Std.	Min.	Max.
log Nightlight intensity VIIRS		0.11	0.35	0.00	7.19
log Nightlight intensity DMSP		0.46	0.87	0.00	13.72
Elevation	km	0.62	0.80	-0.24	6.31
Terrain ruggedness	-	102.42	146.06	0.00	1355.07
Distance from nearest coast	1000 km	0.55	0.52	0.00	2.50
Distance from nearest lake/river	1000 km	0.28	0.50	0.00	6.33
Annual mean temperature	deg C	25.29	13.39	-5.94	48.82
Day-to-day var. of temperature	deg C	2.96	1.44	0.31	6.07
Seasonal var. of temperature	deg C	24.37	14.71	0.74	65.08
Interannual var. of temperature	deg C	0.64	0.30	0.10	1.56
Annual total precipitation	mm	69.50	67.73	0.05	2499.60
Seasonal var. of precipitation	mm	49.79	42.37	0.16	1037.65
Interannual var. of precipitation	mm	0.01	0.01	0.00	0.38
Annual mean rel. humidity	%	89.34	7.03	64.94	98.62
Annual mean solar radiation	W m-2	179.87	57.63	76.34	309.41
Share of cropland	%	10.66	19.64	0.00	100.00
Share of pasture land	%	18.47	27.06	0.00	100.00

Notes: Climate variables computed over period 1985-2014. VIIRS nightlights annual composite for 2015. DMSP nightlights annual composite 2012.

Elevation increases transport costs and is hence a major geographic factor for economic development. Furthermore, elevation is one of them main determinants of local climate. I take data on elevation from the Global Land One-kilometer Base Elevation (GLOBE) dataset in version 1 provided by the National Oceanic and Atmospheric Administration (NOAA) (Hastings et al., 1999). The data has global coverage with a horizontal resolution of 0.0083°. I download the data as tiles, merge them, and then aggregate it to 0.25° by averaging.

Previous research has revealed a statistically significant association between terrain ruggedness and economic development in Africa (Nunn and Puga, 2012). Furthermore, terrain ruggedness influences the horizontal and vertical exchange of air, which in turn affect the local climate at the surface. I therefore also include terrain ruggedness as a control variable. Data on terrain ruggedness is taken from a global dataset with a resolution of 1 km (Shaver et al., 2018), which I aggregate to 0.25 degrees.

Economic activity tends to be clustered at the coasts in many countries (Henderson et al., 2018). Furthermore, seasonal variability of temperature tends to be smaller closer to the coast (Section 3.2). I therefore also include distances from the nearest coast and distance from inland water bodies as control variables. Distances from the nearest coast are taken from a dataset provided by the NASA. The dataset covers the whole globe with a uniform horizontal resolution of 0.04°. I also use data on distance from inland water bodies (GloboLakes dataset provided by the CEDA archive) (Carrea et al., 2015). The data were created from ENVISAT satellite images. The data are provided with a 300 m resolution. I aggregate both datasets to a resolution of 0.25 degrees using mean values.

3.4 Descriptive statistics

The final dataset consists of 233,362 complete observations (Table 1). Each observation corresponds to a grid cell of 0.25 degrees width in both latitudinal and longitudinal direction, which corresponds to about 28 km at the equator, about 23 km at 45 degrees latitude, and about 20 km at 60 degrees latitude. The final data excludes grid cells that are not located on land and grid cells on land that are covered by water or ice. Furthermore, due to the spatial coverage of the nightlights data, the dataset is bounded by the latitudes 75 N and 60 S. For the main analysis, nightlights in the year 2015 are combined with time-invariant geographical covariates and climate variables averaged over the period 1985-2014. The exclusion of the year 2015 in the climate data and the averaging over multiple years reduces the influence of (contemporaneous) extreme events, and a 30-years period corresponds to the conventional definition of climate.

4 Econometric strategy

I estimate the model using a spatial first-differences research design. The spatial first-differences (SFD) estimator has recently been proposed as an econometric estimation method that can reduce omitted variable bias for cross-sectional data (Druckenmiller and Hsiang, 2018). The SFD estimator uses only variation between spatially adjacent units of observations. Identification hence relies on the local conditional independence assumption

$$E\left[Y_i|(D_{i-1}, X_{i-1})\right] = E\left[Y_{i-1}|(D_{i-1}, X_{i-1})\right] \forall i \tag{1}$$

whereby observations are indexed with i along a spatial dimension, Y is the outcome variable (log nightlights in the main model of this paper), D is the treatment variable (temperature variability), and X are control variables (climatic and geographic covariates). Equation 1 means that the SFD estimator requires that, conditional on all covariates, *spatially adjacent units of observation* with the same treatment have the same expected outcome. This is a weaker assumption than the assumption underlying a conventional cross-sectional regression of levels, for which conditional on all covariates *all units of observation* with the same treatment need to have the same expected outcome.

The OLS estimator of the SFD design can then be written as

$$\hat{\beta}_{SFD} = (\Delta X' \Delta X)^{-1}(\Delta X' \Delta Y) \tag{2}$$

where Δ refers to the first difference between adjacent units of observations. If the local conditional independence assumption (Equation 1) is satisfied, it implies that

$$E\left[\Delta X' \Delta C\right] = 0. \tag{3}$$

for any potentially omitted variable C. The SFD estimator thus eliminates biases due to omitted variables if the spatial differences of the treatment variable and the spatial differences of a potential confounder are not systematically correlated (Druckenmiller and Hsiang, 2018). Another strength of the SFD research design is a unique robustness test. This robustness test exploits the fact that the estimator can be used with spatial differences in any direction, including North to South (NS) and West to East (WE). If the identifying assumption of SFD is satisfied, the regression coefficients obtained from differences in different directions should be statistically the same (Druckenmiller and Hsiang, 2018). I conduct this robustness test in Section 5.

The SFD framework can also be compared with a spatial regression-discontinuity (RD) research design. In contrast to an estimation with RD, the SFD estimator does not require a discontinuity of the treatment variable. Instead, the marginal effect is recovered from all changes in the outcome (nightlights) and treatment variable (temperature variability) along the North-South or East-West direction. This reduces the risk that estimates primarily reflect correlations of gradients in temperature variability and nightlights in places with sharp gradients of temperature variability because of extraordinary geographical features, where the identifying assumption for a model with polynomial terms of all control variables might be violated. This concern is addressed with a robustness check in which the top 5% and bottom 5% of observations in terms of temperature variability are excluded and which yields very similar results as the main estimation (Appendix E).

Grid cells at a distance of about 20-30 km can generally be expected to have relatively similar climates. This might raise the question whether differences in temperature variability as observed over 30 years are due to systematic differences in climate or instead due to singular events in this time period that affected one location more than the other. If the latter concern was correct, the SFD estimator would identify a short-term effect of weather rather than a long-term effect of climate (Hsiang, 2016). To address this concern, I vary the time periods over which temperature variability (1955-1984 and 1985-2014) and nightlights (2015 and 2015-2019) are observed and find similar results (Appendices F and G). This suggests that my estimates can be interpreted as the marginal effects of climate rather than weather.

To illustrate the strengths of the SFD framework, I estimate a simple model in which I explain variation of nightlights by day-to-day temperature variability (and annual mean temperature). The exercise focuses on day-to-day variability as I can use recent estimates of its effect on regional GDP per capita using variation across time for identification as a benchmark (Kotz et al., 2021b). Using the sign of this previously reported effect as a reference, the results suggest that the SFD estimator reduces omitted variable biases as compared to a regression with levels. While this first evidence is reassuring, possible omitted variable biases are in more depth discussed in the next Section. Furthermore, what has not been reported before but is important for this paper, the SFD estimator also reduces multicollinearity in the model (Appendix B). The reason for the latter insight is that annual mean temperature and temperature variability at different time scales are influenced by latitude and thus strongly correlated with each other (and with other climate variables such as solar radiation). These correlations are substantially reduced when one uses spatial first differences instead of levels as the influence of latitude is smaller (relative to other variables) if one compares only neighbouring observations (Appendix B). Taken together, the SFD estimator thus seems to be a promising tool for navigating concerns of omitted variable biases on the one hand and multicollinearity on the other hand, which have been identified as key challenges of empirical work on the effect of weather and climate on socioeconomic outcomes (Auffhammer et al., 2013).

5 Results

5.1 Main results

Previous authors have found non-linear relationships between annual mean temperature and GDP per capita (Burke et al., 2015a). Similarly, non-linear associations have been reported between daily temperature levels and many different socio-economic outcomes including labour productivity and health (Carleton and Hsiang, 2016). This suggests that the effect of temperature variability on long-run economic outcomes might be moderated by the effect of annual mean temperature (Section 2.1). I explore this hypothesis by estimating a flexible model in which I interact temperature variability with dummy variables for bins of annual mean temperature that are 4 degrees Celsius wide:

$$\begin{aligned} \Delta \log n_i = & \sum_k \delta_i^k \left(1 + \beta_1^k \Delta\sigma_i^d + \beta_2^k \Delta\sigma_i^m + \beta_3^k \Delta\sigma_i^y + \beta_4^k \Delta\overline{T}_i\right) \\ & + \lambda\Delta\tilde{\mathbf{C}}_i + \gamma\Delta\mathbf{G}_i + \epsilon_i \end{aligned} \tag{4}$$

where observations are indexed by i and Δ is the spatial first difference operator. Units of observations are grid cells with 0.25 degrees width, corresponding to about 25 km at the Equator. The vector n_i contains annual mean nightlight intensity per land area. Day-to-day, seasonal variability and inter-annual variability of temperature are denoted by σ^d, σ^m, and σ^y, respectively. δ_i^k is an indicator variable for temperature bin k that takes on values 0 and 1, $\overline{T}$ is annual mean temperature, and $\tilde{\mathbf{C}}$ is a matrix of climate controls including terms for annual total precipitation, relative humidity, solar radiation, and the same three measures of variability of precipitation. The matrix of geographic controls $\mathbf{G}$ includes grid cell averages of the distance to the nearest coast, the distance to the nearest water body, elevation, and terrain ruggedness. I estimate models with quadratic polynomials for all control variables. Standard errors are clustered at the country level to account for heteroskedasticity and spatial autocorrelation. I also estimate models with standard errors clustered at the level of subnational administrative units, which yields smaller standard errors. This suggests that unexplained factors that determine the intensity of lights at night tend to be correlated within countries (e.g. electrification).

The results suggest that day-to-day variability and seasonal variability tend to reduce economic activity at most levels of annual mean temperature (Appendix C). Regarding annual mean temperature, I find a positive marginal effect at annual mean temperatures between 4-16 degrees Celsius and a negative effect at all other temperature levels. This pattern of marginal effects is consistent with results of previous findings indicating a negative quadratic relationship between annual mean temperature and economic growth (Burke et al., 2015b), except the negative marginal effect at very low temperature levels.

Furthermore, the analysis with the binned-model yields negative coefficients of day-to-day and seasonal variability across most levels of annual mean temperature, but an coefficients of interannual variability whose sign is positive at low and negative at high levels of annual mean temperature. For parsimony I thus also estimate a model that is as simple as possible but still able to produce these main findings. The model includes linear terms for day-to-day seasonal variability and an interaction between a linear term for interannual variability and a dummy variable for annual mean temperature:

$$\begin{aligned}\Delta \log n_i = {} & \beta_1 \Delta\sigma_i^d + \beta_2 \Delta\sigma_i^m \\ & + \delta(\overline{T_i} < 20)\left(1 + \beta_3^A \Delta\sigma_i^y\right) \\ & + \delta(\overline{T_i} \geq 20)\left(1 + \beta_3^B \Delta\sigma_i^y\right) \\ & + \lambda \Delta \mathbf{C}_i + \gamma \Delta \mathbf{G}_i + \epsilon_i \end{aligned} \tag{5}$$

where $\delta(\overline{T_i} \geq 20)$ and $\delta(\overline{T_i} < 20)$ are indicator variables that take on the value 1 if annual mean temperature $\overline{T}_i$ is larger or equal/smaller than 20 degrees Celsius and 0 otherwise. As expected from the patterns in Figure 5, the estimation yields negative coefficients of day-to-day and seasonal temperature variability (Column 1 in Table 2). For interannual variability, I find a positive coefficient below 20 degree Celsius and a negative coefficient above this temperature level.

Table 2. Results of a linear model estimated with SFD.

Dependent variable:	*log Nightlight density*		
Spatial first differences:	Pooled	WE	NS
Column:	1	2	3
Day-to-day variab. of T	-0.50448***	-0.69073***	-0.41483***
	(0.12930)	(0.15170)	(0.11675)
Seasonal variab. of T	-0.28016	-0.14383	-0.32325*
	(0.17127)	(0.17498)	(0.17247)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.17134***	0.16404***
	(0.04441)	(0.05661)	(0.04454)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.23005**	-0.25865**
	(0.10077)	(0.09922)	(0.11796)
Effect of increase by 1 deg. C on log nightlights			
Day-to-day variab. of T	-0.11631	-0.15926	-0.09564
Seasonal variab. of T	-0.00632	-0.00325	-0.00729
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19185	0.18926	0.18119
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27857	-0.25410	-0.28569
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0249	0.0250	0.0254
df	448877	224426	224425

Notes: The table shows the results of a linear model (Equation 5) estimated with spatial first-differences. Standard errors in parentheses. WE = West-East, NS = North-South. Pooled = pooling differences in WE and NS.

The magnitude of the estimated coefficients is substantial. An increase of day-to-day and seasonal variability by one standard deviation (1.44 and 14.71 degrees Celsius, respectively) is associated with a reduction of nightlights by about 17 percent and 9 percent respectively (Column 1 in Table 2). For interannual variability, the magnitude is about 6 percent below and 8 percent above 20 degree Celsius of annual mean temperature.

As a first robustness test, I compare the results obtained by estimating the model with spatial first-differences in the West-East (WE) direction (Column 2) with the results obtained from North-South (NS) differences (Column 3), as well as with differences in these two directions pooled (Column 1). If my estimated coefficients of temperature variability could be explained with an omitted variable whose association with temperature variability or nightlights were not similar in both directions, I would expect to obtain different estimates. However, for both directions I find that all coefficients have the same sign, similar magnitude, and similar significance.

As another robustness test I change the model specification for all control variables. I test models with linear terms, linear and quadratic terms, and linear terms interacted with bins of annual mean temperature. The results are presented in Table 12 in Appendix I. Overall, the estimated coefficients of temperature variability are similar across specifications (Columns 4, 5, 6).

In the next paragraphs I conduct two additional robustness tests using this model, before turning to a discussion of mechanisms in Section 6.

5.2 Sensitivity analysis

In order to quantify the robustness of my key results to omitted variable bias I also conduct a formal sensitivity analysis. Specifically, I calculate how much of the residual variation of temperature variability and the residual variation of nightlights of the model in Equation 5 an omitted variable would need to explain such that including this additional variable could make the estimated coefficients of temperature variability insignificant or even reduce them to zero. Following Cinelli and Hazlett (2020), I quantify the robustness using partial R^2, which means that my results on robustness are not specific to any assumed functional form of the omitted variable in the model, but instead provide an upper bound on the sensitivity to any set of omitted variables including non-linear terms and interactions. The full results are presented in Table 11 in Appendix H.

To make the estimated coefficients insignificant at $\alpha = 0.05$, I find that an omitted variable would need to explain at least 2.71, 0.74, 0.92, and 0.45 percent of the residual variation of nightlights and of the residual variation of day-to-day, seasonal, and interannual variability below and above an annual mean temperature of 20 degrees Celsius, respectively. To reduce the estimates to zero, these robustness values are respectively 2.99, 1.03, 1.28, and 0.94 percent. These values can be put into perspective by comparing them with the partial R^2 of variables included in the model. This benchmarking shows that none of the included climatic and geographic control variables are comparably strongly associated with both nightlights and temperature variability. While a few variables are sufficiently strongly associated with temperature variability, none of these explains enough of the residual variation of nightlights. This means that no potentially omitted variable that is similarly strongly associated with temperature variability and nightlights as any of the included control variables could make my results insignificant if it were additionally included in the model.

5.3 Reverse causality

It is well established that air temperature tends to be higher in the center of a city than in its surroundings due to what is referred to as the urban heat island. If the spatial distribution of economic activity affected also the variability of temperature, for example through human land use that changes the heat capacity of the surface, the statistically significant association between temperature variability and nightlights could generally also be explained with reverse causality. I address this concern by regressing changes of nightlights over time (between 1992 and 2012) on temperature variability measured over an earlier period (1982 to 1991). This means that any effects of nightlights on temperature variability are intentionally excluded by the design of the regression. For this analysis I use the older DMSP nightlights data, as the VIIRS data is only available since 2015.

I first regress DMSP nightlights in 2012 on climate over the period 1982-2011 (Table 3, Column 1), similar to my main regression with VIIRS data. I find the same key results as for the VIIRS data: a (significantly) negative coefficient of day-to-day and seasonal variability and a negative and positive coefficient of interannual variability of temperature respectively below and above an annual mean temperature of 20 degrees Celsius. The size of the coefficients is more difficult to compare as the two datasets measure the intensity of nightlights with different technological devices and on different scales.

To address the concern of reverse causality, I regress the growth of nightlights between 1992 and 2012 on the mean climate of the period 1982 to 1991 (Column 2). Reassuringly, I find the same sign and significance of the coefficients as in Column 1. I take this as evidence that my results are robust to possible confounding effects due to reverse causality. This result holds true also if I include nightlight density in 1992, which is likely associated with temperature variability from 1982-1991 and, as the results confirm (Column 3), also with subsequent changes in nightlights.

Table 3. Results of regressions addressing concerns of reverse causality using the DMSP nightlights data.

Dependent variable:	*log NL (2012)*	*Δ log NL (1992 vs. 2012)*	
Time period for climate variables:	1982 - 2011	1982 - 1991	1982 - 1991
Column:	1	2	3
Day-to-day variab. of T	-0.31131***	-0.04719*	-0.07712***
	(0.08156)	(0.02665)	(0.02819)
Seasonal variab. of T	-0.19933	-0.06371**	-0.07539**
	(0.12123)	(0.02934)	(0.03635)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.12011***	0.02603*	0.02898*
	(0.02794)	(0.01419)	(0.01541)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.11410	-0.01148	-0.01724
	(0.07603)	(0.02808)	(0.02979)
Nightlights in 1992			-0.12585***
			(0.01775)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0473	0.0102	0.0374
df	448877	448877	448876

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 5) estimated with spatial first-differences. Standard errors in parentheses. NL = nightlights taken from the DMSP data.

6 Mechanisms

6.1 Urban areas

It is well known that nightlights are a better proxy for GDP per capita in urban areas than in rural areas (Chen and Nordhaus, 2019; Gibson et al., 2021). I therefore examine whether my results are primarily driven by urban areas. To do so, I first categorise all grid cells based on their population density relative to all other grid cells of the same country and then estimate my model on subsets of the data. I find that the magnitude of my estimated effects is largest in urban areas defined as the 5 percent most densely populated grid cells of every country (Appendix J). At the same time I find significant effects of the same sign also in less densely populated areas, including the 50 percent least densely populated areas. The effect of temperature variability thus seems to be geographically widespread and not limited to urban areas.

6.2 Agriculture

A possible explanation for my empirical effects is that temperature variability affects the local sectoral composition of economic activity. For instance, regions with higher seasonal variability could be relatively more or less suitable for agriculture than regions with lower variability. Because agricultural activity tends to be associated with lower levels of nightlights than other economic activity for a similar total economic output (Chen and Nordhaus, 2019; Gibson et al., 2021), these climatically induced relative advantages could be reflected in the spatial distribution of nightlights and thus explain the estimated coefficients.

I thus use satellite data on agricultural land use to examine heterogeneity of the estimated effects across regions with different types of economic activity. I include both cropland and land used for pasture in my model. I find that land used for pasture has indeed a significant effect on nightlights, but my estimates of temperature variability remain unaffected by including either one or both of these variables (Table 14 in Appendix K). These results suggest that the estimated effect of temperature variability on nightlights cannot be explained with the spatial distribution of agricultural activity.

7 Conclusion

In this paper I combine a global high-resolution satellite-derived dataset on nightlights with climate reanalysis data and additional geographical datasets to examine how day-to-day, seasonal, and interannual temperature variability affect economic activity. I use a spatial first-differences research design (Druckenmiller and Hsiang, 2018), which reduces potential omitted variable biases and multicollinearity of climate and geographical variables. This allows me to study how temperature variability at different time scales influences aggregate economic activity. Furthermore, compared to previous work on the short-run effect of annual weather fluctuations (Burke et al., 2015a; Dell et al., 2012), I focus on the long-run effects of climate including the potential effect of adaptation (Waldinger, 2022). Compared to previous work on the long-run effect of climate (Nordhaus, 2006; Mendelsohn and Massetti, 2017), I use a recently developed econometric framework which allows for a more plausible identification of causal effects.

This approach allows me to identify the total effect of temperature variability including possibly non-linear effects of daily temperature levels (ex post effects) and larger uncertainty (ex ante effects). Evidence from microeconometric studies suggest this total effect to be predominantly negative. Furthermore, I expect these effects to be more negative for variability at larger time scale due to more difficult learning about variability and to be more negative for variability that is less predictable. Because of the underlying physical processes of climate day-to-day and interannual variability are less predictable than seasonal variability.

I find a statistically significantly negative effect of day-to-day variability on economic activity across the range of observed annual mean temperatures. On average, one additional degree Celsius of the average within-month standard deviation of daily temperature levels reduces economic activity by about 11 log points (approximately 11 percent). Regarding seasonal variability, I also find a negative but smaller and less significant effect on economic activity. On average, one degree Celsius of the average within-year range of monthly mean temperatures reduces nightlights by about 0.6 percent. My results on interannual variability suggest that it has a positive effect at low temperature levels (about 19 percent per degree Celsius of the between-year standard deviation of annual mean temperatures) and a negative effect at high temperature levels (about 28 percent per degree Celsius).

While I am to my knowledge the first to empirically analyse the effect of seasonal and interannual variability on aggregate economic activity, the results align with previous work finding a negative short-term effect of day-to-day variability on regional GDP (Kotz et al., 2021b) and existing literature reporting negative effects of temperature variability on agriculture (Wheeler et al., 2000; Mendelsohn et al., 2007b) and health (Hovdahl, 2020). Furthermore, consistent with previous findings (Burke et al., 2015b; Kalkuhl and Wenz, 2020), I find a positive marginal effect of annual mean temperature at relatively low temperatures and a negative marginal effect at high temperatures, with a globally optimum annual mean temperature of about 20 degrees Celsius.

My methodology allows me to compare the estimated coefficients of annual mean temperature with the estimated effects of temperature variability. On average, one sample standard deviation of seasonal and day-to-day variability reduces nightlights by 9 and 17 percent, respectively. If these effects are benchmarked with the estimated effect of annual mean temperature, they correspond to increases of annual mean temperature from 25 degree Celsius to approximately 28 and 30 degrees Celsius, respectively.

I explore several explanations for my findings. Regarding my estimated effect of interannual variability I find one possible explanation consistent with my results: Below the optimal temperature, the positive effect of unexpectedly warmer-than-average temperatures could be larger than the negative effect of colder-than-average temperatures, whereas above the optimal temperature, the negative effect of unexpectedly warmer-than-average temperatures could be relatively larger. This could be the case, for example, if responding to a colder-than-average year wa generally easier or less costly than responding to a warmer-than-average year.

It is well known that nightlights are a better proxy for GDP per capita in urban areas than in rural areas and to some extent also reflect the local sectoral composition of the economy (Chen and Nordhaus, 2019; Gibson et al., 2021). I therefore examine whether my results are primarily driven by urban areas and whether my results can be explained by the spatial distribution of agricultural activity. I find that the estimated effects of temperature variability are indeed strongest in urban areas, but can also be recovered from less densely populated regions, including the least densely populated areas within countries. Furthermore, my results are unaffected by controlling for the spatial distribution of agricultural activity.

My results are robust to a variety of robustness tests. I also recover my main results also for models that include no control variables and for models for which all control variables are included with flexible functional forms. Furthermore, my results pass a robustness test unique to the spatial first-differences research design, namely comparing estimates obtained by using spatial differences in orthogonal geographical directions. Furthermore, I conduct a sensitivity analysis which indicates that an omitted variable would need to be more strongly associated with nightlights and temperature variability as any of my geographic and climate control variables to render the estimated coefficients of temperature variability insignificant. In an additional robustness test, I show that my results cannot be explained by reverse causality.

My results suggest that more research should be devoted to temperature variability. Several avenues could be pursued. For example, temperature variability might have influenced the initial spatial allocation of economic activity but could also have shaped subsequent local economic development including sectoral specialisation (Emerick, 2018; Henderson et al., 2017) and migration (Cattaneo and Peri, 2016). My methodology does not allow me to separate these two effects as nightlights are available only for recent decades. Furthermore, research is needed to investigate how the influence of temperature variability changes as economies develop, and to examine specific mechanisms in more detail.

Further research seems especially important given that climate models project changes to the seasonal cycle (Dwyer et al., 2012) and interannual temperature variability (Bathiany et al., 2018). Also day-to-day temperature variability seems to be influenced by anthropogenic climate change (Kotz et al., 2021a; Wan et al., 2021). Given the geographical patterns of these trends and projections, my results suggest that future increases of day-to-day, seasonal, and interannual temperature variability might add to the economic costs of climate change especially in currently relatively warm regions. I thus conclude that temperature variability at different time scales deserves more attention in economics research to improve our understanding of its influence on human societies and to get better estimates of the expected costs of future climate change and their geographical distribution.

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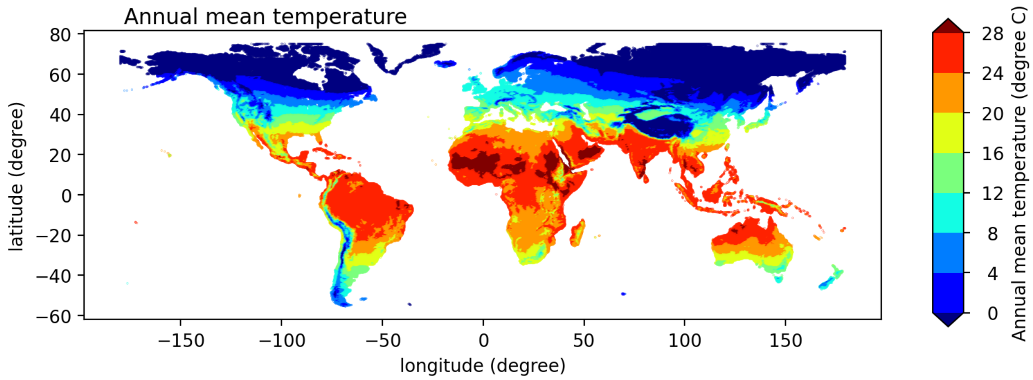
A Map of annual mean temperature

Figure 4. Global map of annual mean temperature.



Notes: The figures shows the global distribution of annual mean temperature using the same bins as in Section 5.2. Source is ERA-5 reanalysis for 1985-2014 (see Section 3.2).

B Omitted variable biases and multicollinearity

To illustrate the strengths of the SFD framework, I estimate a simple model in which I explain variation of nightlights by day-to-day temperature variability. The exercise focuses on day-to-day variability as I can use recent estimates of its effect on regional GDP per capita using variation across time for identification as benchmark (Kotz et al., 2021b). I use two models, one without any other explanatory variables and one that also includes annual mean temperature. I first estimate the two models using levels of all variables and then with the SFD estimator.

I first focus on the model with only day-to-day variability (Columns 1 and 2 in Table 4). I find that using levels yields a significantly positive coefficient, contrary to the result by Kotz et al. (2021b). Visual inspection of Figure 2 shows that levels of day-to-day variability are relatively low in the tropics and tend to increase with latitude. Estimates using levels could thus be confounded by any other variable correlated with latitude, such as institutions/colonial legacies. By contrast, the SFD estimator yields a significantly negative coefficient, consistent with the previously reported result.

Because I use different data and focus on long-term rather than short-term effects of day-to-day variability, the comparability of these estimates with previous results is limited. Given that the assumptions that need to be satisfied for an unbiased estimate from levels are stronger than those of the SFD estimator, I expect that the estimates obtained from levels are more prone to omitted variable biases. The results presented in Table 4 include some evidence for it: including annual mean temperature in the model changes the

Table 4. Results of a model estimated with levels and SFD.

Dependent variable:	*log Nightlight density*			
Estimator:	levels		SFD	
Column	1	2	3	4
Day-to-day variab. of T	0.11857***	0.04641**	-0.76479***	-0.68200***
	(0.03601)	(0.02297)	(0.19528)	(0.18304)
Annual mean temperature		0.12265***		0.89835***
		(0.02853)		(0.11474)
R2	0.0673	0.1055	0.0041	0.0082
df	224454	224453	448909	448908

Notes: The table shows the results of a linear model similar to Equation 4 but without interaction terms estimated with spatial first-differences. Differences in West-East and North-South are pooled. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

estimated coefficient of day-to-day variability obtained from levels by about 60 percent, while its inclusion changes the SFD estimate by much smaller 10 percent.

This latter result points to another advantage of the SFD estimator as compared to the levels-estimator. Because temperature variability at all frequencies (day-to-day, seasonal, interannual) and annual mean temperature are all influenced by latitude (Section 2.2), levels of these variables tend to be highly correlated. This raises concerns about multicollinearity, which has been recognised as a major challenge of empirically disentangling the effect of multiple climate variables (Auffhammer et al., 2013).

A common indicator of multicollinearity in a model is the Variance Inflation Factor (VIF) which is a measure of how much variation of one explanatory variable in a model is explained by all the other explanatory variables. I calculate the VIF for a model in which I include the annual mean of temperature

Table 5. Variance inflation factors for a model including all geographic and climatic controls in addition to day-to-day, seasonal, and interannual temperature variability.

	Levels	Spatial first-differences		
Variable		Pooled	NS	WE
Day-to-day var. of temperature	59.11	1.87	1.94	1.81
Seasonal var. of temperature	58.94	1.91	2.00	1.81
Interannual var. of temperature	35.02	1.47	1.50	1.42
Annual mean temperature	141.12	3.83	4.13	3.48

Notes: The table shows the VIF of linear models including annual mean temperature, its day-to-day, seasonal, and interannual variability, as well as all climatic and geographic control variables shown in Table 1. Estimates obtained from spatial first-differences are shown for differences in West-East (WE) and North-South (NS) direction and for differences in the two directions pooled.

and its day-to-day, seasonal, and interannual variability as well as linear terms of all climatic and geographic control variables (Table 1). Typical critical thresholds for multicollinearity are 5 and 10, corresponding to 80 and 90 percent of all variation being explained by other explanatory variables. I find that multicollinearity is indeed a major concern for the levels-estimator, but is mitigated by using spatial first-differences (Table 5). This analysis of the VIF simultaneously accounts for the correlation of temperature variability at different time scales and its correlation with any of the climatic and geographic control variables. Focusing only on the correlation of temperature variability across time scales, I find that spatial first-differencing also substantially reduces their cross-correlations (Table 6).

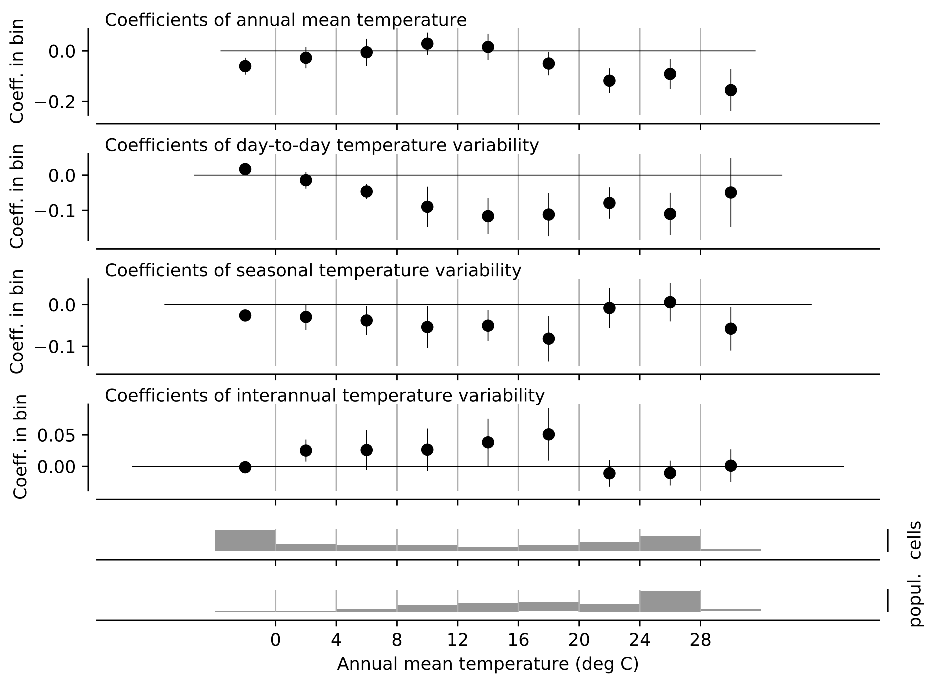
Table 6. Pearson correlation coefficients between different temperature variables.

Variable	(0)	(1)	(2)	(3)
Pearson correlation of levels				
(0) Annual mean temperature		-0.83	-0.86	-0.81
(1) Day-to-day var. of temperature	-0.83		0.90	0.89
(2) Seasonal var. of temperature	-0.86	0.90		0.83
(3) Interannual var. of temperature	-0.81	0.89	0.83	
Pearson correlation of spatial first-differences				
(0) Day-to-day var. of temperature		0.60	0.48	-0.11
(1) Seasonal var. of temperature	0.60		0.50	0.09
(2) Interannual var. of temperature	0.48	0.50		0.02
(3) Annual mean temperature	-0.11	0.09	0.02	

Notes: n/a.

C Estimated coefficients across bins of annual mean temperature

Figure 5. Estimated marginal effects of annual mean temperature and day-to-day, seasonal, and interannual temperature variability at different levels of annual mean temperature.



Notes: The figure shows the estimated coefficients of a model with linear terms for annual mean temperature, day-to-day, seasonal, and interannual temperature variability in bins of annual mean temperature (Equation 4). The coefficients can be interpreted as marginal effects. Error bars show 95 percent confidence intervals. The bottom two rows show histograms of grid cells and population within the same temperature bins. The geographic distribution of these bins is shown in Figure 4 in Appendix A.

D Alternative measures for seasonal variability

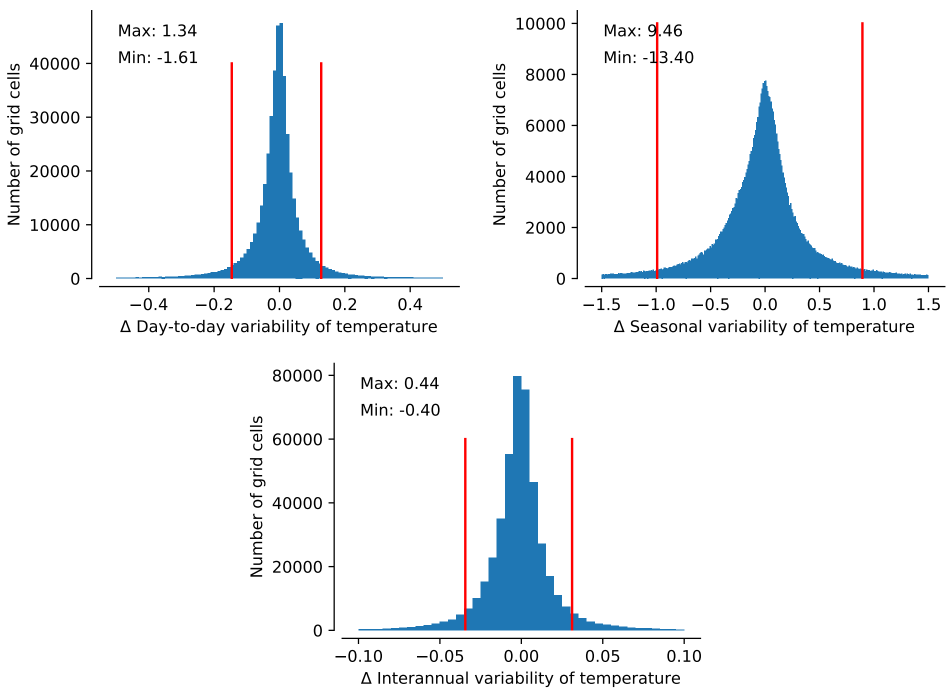
Table 7. Results of a model estimated with SFD with two alternative measures for seasonal variability of temperature.

Dependent variable:	*log Nightlight density*	
Seasonal variability:	range	std
Column	1	2
Day-to-day variab. of T	-0.50448***	-0.50031***
	(0.12930)	(0.13259)
Seasonal variab. of T (std)		-0.30724*
		(0.16225)
Seasonal variab. of T (range)	-0.28016	
	(0.17127)	
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.16939***
	(0.04441)	(0.04337)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.25686**
	(0.10077)	(0.10038)
Day-to-day variab. of T	-0.11631	-0.11535
Seasonal variab. of T (std)		-0.01906
Seasonal variab. of T (range)	-0.00632	
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19185	0.18710
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27857	-0.28372
Climate controls (linear)	x	x
Climate controls (quadratic)	x	x
Geographic controls (linear)	x	x
Geographic controls (quadratic)	x	x
R2	0.0249	0.0250
df	448877	448877

Notes: The table shows the results of a model as shown in Equation 5 estimated with spatial first-differences, pooling differences in WE and NS. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E Discontinuities of treatment

Figure 6. Histograms of first-differences in temperature variability.



Notes: The figure shows histograms of observations in terms of spatial first-differences in temperature variability pooling differences in WE and NS. Red lines indicate 5% and 95% percentile.

Table 8. Results of a model estimated with SFD with subsamples, excluding the bottom 5% and top 5% of observations in terms of the first-difference in temperature variability.

Dependent variable:	*log Nightlight density*		
Spatial first differences:	Pooled	Pooled	Pooled
Sampling based on:	Day-to-day	Season.	Inter-ann.
Day-to-day variab. of T	-0.79884***	-0.76855***	-0.61238***
	(0.14882)	(0.15450)	(0.16967)
Seasonal variab. of T	-0.41895***	-0.08313	-0.31921**
	(0.13591)	(0.16946)	(0.14780)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.16195***	0.11883***	0.16700*
	(0.03496)	(0.04223)	(0.08586)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.13970	-0.20035**	-0.07319
	(0.08815)	(0.09252)	(0.09005)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0183	0.0217	0.0212
df	403988	403988	403985

Notes: The table shows the results of a model as shown in Equation 5 estimated with spatial first-differences, pooling differences in WE and NS. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F Climate data for 1955-1984

Table 9. Results of a model estimated with SFD for different climate periods..

Dependent variable:	*log Nightlight density*	
Time period (climate):	1985-2014	1955-1984
Column	1	2
Day-to-day variab. of T	-0.50448***	-0.47408***
	(0.12930)	(0.13475)
Seasonal variab. of T	-0.28016	-0.27510
	(0.17127)	(0.19847)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.08998
	(0.04441)	(0.07277)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.19300***
	(0.10077)	(0.07264)
Effect of increase by 1 deg. C on log nightlights		
Day-to-day variab. of T	-0.11209	-0.10534
Seasonal variab. of T	-0.00623	-0.00612
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19115	0.09902
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27755	-0.21240
Climate controls (linear)	x	x
Climate controls (quadratic)	x	x
Geographic controls (linear)	x	x
Geographic controls (quadratic)	x	x
R2	0.0249	0.0247
df	448877	448877

Notes: The table shows the results of a model as shown in Equation 5 estimated with spatial first-differences, pooling differences in WE and NS. Standard errors in parentheses. Nightlights are for the year 2015. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G Nightlights for 2015-2019

Table 10. Results of a model estimated with SFD using different versions and time periods of the nightlights data.

Dependent variable:	*log Nightlight density*		
Spatial first differences:	Pooled	Pooled	Pooled
VIIRS version	v1	v2	v2
Nightlights time period	2015	2015	2015-2019
Day-to-day variab. of T	-0.50448***	-0.49211***	-0.48630***
	(0.12930)	(0.13332)	(0.13045)
Seasonal variab. of T	-0.28016	-0.26720	-0.26709
	(0.17127)	(0.16633)	(0.16823)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.16691***	0.16386***
	(0.04441)	(0.04755)	(0.04906)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.25554**	-0.27256***
	(0.10077)	(0.10221)	(0.10035)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0249	0.0255	0.0274
df	448877	448877	448877

Notes: The table shows the results of a model as shown in Equation 5 estimated with spatial first-differences, pooling differences in WE and NS. Standard errors in parentheses. Main estimates are obtained with nightlights in version 1 for the year 2015. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

H Sensitivity analysis

The sensitivity of my estimated coefficients of temperature variability to the inclusion of omitted variables in the model is quantified using the robustness value (Cinelli and Hazlett, 2020). The robustness value is the partial R^2 that an omitted variable would need to have with both temperature variability and nightlights to reduce the estimated coefficient of temperature variability to zero. I also quantify the robustness value that would make the estimated coefficients insignificant (at $\alpha = 0.05$). The robustness values of day-to-day, seasonal, and interannual variability are shown in Table 11. Furthermore, the table shows the partial R^2 of the control variables of my model as benchmarks and the critical values for those variables for which the robustness value is exceeded by one of the two partial R^2.

For example, to make my estimated coefficient of day-to-day variability insignificant, a variable that was added to the model would need to have a partial R^2 of at least 2.71 (robustness value) with both out dependent variable (nightlights) and my treatment variable (day-to-day temperature variability). To reduce the estimated coefficient to zero, the robustness value is 2.99. To interpet these values, I can use my climatic and geographic variables that are already included in the model as benchmarks. The first section of the table shows that there are only three variables (annual mean temperature, annual mean relative humidity, and annual mean solar radiation) that have a partial $R^2 \geq 2.71$ (robustness value for significance) for day-to-day variability (Column 2). For these three variables the partial R^2 with day-to-day variability exceeds the robustness value, which means that even a partial R^2 with nightlights smaller than the robustness value could make my estimated coefficients zero/insignificant (if these variables were an omitted confounder). I therefore quantify the critical value for the partial R^2 of these variables with nightlights, which are shown in the bottom section of the table. The critical values are 0.77, 0.80, and 1.76 respectively. I can see in the top part of the table (Column 1) that these critical values are not exceeded by the corresponding partial R^2.

Also the results for seasonal and interannual variability are reassuring. I find that four and one of my control variables respectively explain enough of the variation of temperature variability to be able to render the estimated coefficient insignificant (Columns 4, 6, and 8) but for none of these variables my model has a strong enough association with both nightlights and my temperature variability variables to make my estimated coefficients of temperature variability insignificant (Columns 3, 5, and 7).

The benchmarking of this sensitivity analysis can also be interpreted as a balancing test. Specifically, Columns 2 and 4 in Table 11 show the partial R^2 of all covariates for regressions on my treatment variables, day-to-day (Column 2), seasonal variability (Column 4) and interannual variability (Columns 6 and 8). The results suggest that no single covariate can explain more than 10 percent of the residual variation of day-to-day variability, 4 percent for seasonal variability, or 6 percent of the residual variation of interannual variability.

Table 11. Results of a sensitivity analysis as proposed by Cinelli and Hazlett (2020).

Variable	Day-to-day variability		Seasonal variability		Interann. var. ($\overline{T} < 20$)		Interann. var. ($\overline{T} \geq 20$)	
	$R^2_{Y\sim X_j\mid\sigma^d,X_{-j}}$	$R^2_{\sigma^d\sim X_j\mid X_{-j}}$	$R^2_{Y\sim X_j\mid\sigma^m,X_{-j}}$	$R^2_{\sigma^m\sim X_j\mid X_{-j}}$	$R^2_{Y\sim X_j\mid\sigma^y_A,X_{-j}}$	$R^2_{\sigma^y_A\sim X_j\mid X_{-j}}$	$R^2_{Y\sim X_j\mid\sigma^y_B,X_{-j}}$	$R^2_{\sigma^y_B\sim X_j\mid X_{-j}}$
Annual mean temperature	0.04115	9.52375	0.04115	1.19277	0.04915	0.97199	0.03630	0.11316
Annual total precipitation	0.00305	0.23419	0.00305	0.09516	0.00411	0.37066	0.00175	0.14781
Annual mean rel. hum.	0.00614	9.25113	0.00614	3.33312	0.01823	1.73334	0.01449	5.28454
Solar rad. annual mean	0.06589	4.59948	0.06589	0.67956	0.06872	0.21369	0.10980	0.68666
Elevation	0.41257	2.64177	0.41257	3.18982	0.55558	0.06992	0.21424	0.17217
Ruggedness	0.27404	0.09342	0.27404	0.19660	0.27126	0.16736	0.29237	0.03908
Distance from nearest coast	0.02488	0.06632	0.02488	2.02610	0.02687	0.43462	0.03704	0.35219
Distance from nearest lake/river	0.24401	0.29917	0.24401	0.20186	0.43069	0.02648	0.17840	0.01711
Robustness values	2.99583		1.03060		1.27824		0.94189	
Critical values								
Annual mean temperature	0.87896		0.88902					
Annual mean rel. hum.	0.90759		0.31125		0.93829		0.16052	
Solar rad. annual mean	1.91905							
Elevation			0.32571					
Distance from nearest coast			0.51895					
Robustness values (significance)	2.71166		0.74064		0.91828		0.45353	
Critical values (significance)								
Annual mean temperature	0.76793		0.77734					
Annual mean rel. hum.	0.79475		0.24619		0.82353		0.11478	
Solar rad. annual mean	1.75567							
Elevation			0.25908					
Distance from nearest coast			0.43408					

Notes: The table shows the results of a sensitivity analysis using a model with spatial first differences pooled in North-South and West-East directions. Standard errors in parentheses. See text for explanation and an example of how to read the table. All values are shown in percent.

I Control variables

Table 12. Results of models estimated with different control variables.

Dependent variable:	*log Nightlight density*					
Spatial first differences:	Pooled	WE	NS	Pooled	Pooled	Pooled
Column	1	2	3	4	5	6
Day-to-day variab. of T	-0.50448***	-0.69073***	-0.41483***	-0.60062***	-0.55172***	-1.03221***
	(0.12930)	(0.15170)	(0.11675)	(0.15917)	(0.13816)	(0.20010)
Seasonal variab. of T	-0.28016	-0.14383	-0.32325*	-0.22194	-0.23241*	0.44984***
	(0.17127)	(0.17498)	(0.17247)	(0.15297)	(0.13572)	(0.08412)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.17134***	0.16404***	0.19419***	0.24093***	0.24093***
	(0.04441)	(0.05661)	(0.04454)	(0.04814)	(0.03951)	(0.05338)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.23005**	-0.25865**	-0.19005**	-0.18553**	-0.10075
	(0.10077)	(0.09922)	(0.11796)	(0.08443)	(0.09012)	(0.09327)
Climate controls (linear)	x	x	x	x		
Climate controls (quadratic)	x	x	x			
Climate controls (linear in bins)					x	
Geographic controls (linear)	x	x	x	x		
Geographic controls (quadratic)	x	x	x			
Geographic controls (linear in bins)					x	
R2	0.0249	0.0250	0.0254	0.0208	0.0312	0.0051
df	448877	224426	224425	448887	448800	448904

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 5) estimated with spatial first-differences. Standard errors in parentheses. WE = West-East, NS = North-South. Pooled = pooling differences in WE and NS.

J Urban versus rural areas

Table 13. Results of regressions with subsampling observations based on population density.

Dependent variable:	*log Nightlight density*		
Population density (percentiles):	> 95	80-95	< 50
Spatial first differences:	Pooled	Pooled	Pooled
Column:	1	2	3
Day-to-day variab. of T	-0.91061	-0.20431	-0.24728***
	(0.76166)	(0.21245)	(0.08610)
Seasonal variab. of T	-2.77649*	-0.95826***	-0.16781*
	(1.46725)	(0.33788)	(0.10051)
Interann. variab. of $T * \delta(\overline{T} < 20)$	1.25644	0.23916*	0.05253**
	(0.91921)	(0.13205)	(0.02431)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.24114	-0.02971	-0.17792**
	(0.86465)	(0.18254)	(0.08717)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0926	0.0181	0.0228
df	6220	23428	293981

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 5) estimated with spatial first-differences. Grid cells are sampled based on their ranking (percentile) in terms of population density of the within-country distribution of grid cells. For example, Column 1 shows results for a model which includes only grid cells that are among the 5 percent most densely populated grid cells of the corresponding country. Because I use spatial first-differences, I require that grid cells and their neighbours to the West and North must fulfill this requirements.

K Agricultural land use

Table 14. Results of regressions to examine the role of agriculture.

Dependent variable:	*log Nightlight density*		
Spatial first differences:	Pooled	Pooled	Pooled
Column:	1	2	3
Day-to-day variab. of T	-0.50895***	-0.51023***	-0.50749***
	(0.12933)	(0.12783)	(0.12773)
Seasonal variab. of T	-0.30296*	-0.31293*	-0.31289*
	(0.18080)	(0.18653)	(0.18356)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17643***	0.19750***	0.19352***
	(0.04819)	(0.05019)	(0.05023)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.24130**	-0.23328**	-0.23376**
	(0.10101)	(0.10163)	(0.10149)
Share of cropland	0.06278*		0.05787
	(0.03758)		(0.03868)
Share of pasture		-0.07376***	-0.06962***
		(0.02069)	(0.02169)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0260	0.0263	0.0268
df	445969	445969	445968

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 5) estimated with spatial first-differences. Standard errors in parentheses.