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Abstract

Since the first concerns about potential damages from climate change impacts, their economic assessment has emerged as one of the most challenging and controversial issues. While there is evidence of non-linear impact of climate change on economic activity at the country level, we use the highest resolution economic activity data available to revisit the relationship between climatic exposure and economic performance to investigate the potential distribution of future climate impacts across space. The increased detail of the economic processes involved allows us to study the impact of climatic stressors at the local level, explicitly accounting for spatial dependence and decreasing estimation biases. We find that the global optimal temperature maximizing economic activity is 9°C. As a result, a uniform increase of 1°C in temperature above the current grid-cell specific climatic conditions would reduce mean global economic activity by 7.9%. Extreme temperature events further exacerbate these negative impacts, one standard deviation increase in the frequency of warm spells could reduce mean global economic activity by approximately an additional 1.6%. The uneven distribution of impacts across grid-cells results in a significant worsening of income inequality both across and within countries. Grid-cells with the lowest level of economic activity also experience the highest losses, while global average Gini coefficient increases from the historical value of 0.33 to 0.46 in 2100. Inequality will increase within all the major continents and regions, with the highest increases in South America and Asia.

Introduction

Climate sciences have made significant advancements in our understanding of the physics of climate and in improving our knowledge of many of the associated environmental impacts since the publication of the first IPCC report. Yet, assessments of climate change impacts on the overall economic performance seem not to have advanced at a similar pace (Schellnhuber et al. 2014; Burke et al. 2015; Stern 2016; Tol 2016; IMF 2017). Two broad methodologies have been used for the economic assessment of climate change impacts: model-based and econometric approaches. Integrated Assessment Models (IAM) explicitly describe the causal chain from climate drivers to the socioeconomic impacts by linking simplified climate and economic modules in unifying mathematical structures. The connection can be achieved either through "hard-links" (Anthoff et al. 2012; Moore and Diaz 2015; De Cian et al. 2016) or by chaining sequentially climate, process-based, and macroeconomic models as in "soft-linked" frameworks (Eboli et al. 2010; Ciscar et al. 2011; Ciscar et al. 2014; OECD 2015).

Econometric approaches analyse historical data to identify and estimate the relationship between impact endpoint indicators such as GDP and observed changes in climate or weather (Newell et al. 2021; Dell et al. 2014). Model-based studies and econometric approaches find qualitatively similar results regarding uneven distribution and non-linear pattern of economic impacts of climate change; However, quantitative estimates differ greatly between the two. Econometric studies tend to find higher damage, especially for temperature increase in the range of 1 to 2°C (Dell et al. 2014; Burke et al. 2015). Cross-sectional evidence identifies stronger negative impacts, with per capita income falling up to 8.5% with 1°C additional increase in temperature – whereas panel data studies highlight losses in the range of 1-3% (Newell et al. 2021; IMF 2017; Dell et al. 2014)[1]. Model-based approaches report losses often lower than 1% of world GDP for similar temperatures, with some studies reporting slight gains (Greenstone et al. 2013; Tol 2014; Nordhaus and Moffat 2017). There are several reasons behind these differences; economic models have built-in a significant degree of implicit and explicit adaptation and account for substitution and adjustments induced by prices that are generally not explicit in econometric studies (Sue Wing and De Cian 2014). Model-based economic assessments have been criticized for weak empirical foundation of damage functions (IPCC 2014; Diaz and Moore 2017), incomplete representation of potentially large social impacts such as conflicts and migration, and non-market impacts such as human health and biodiversity losses (Stern 2013; Burke 2015; Dietz and Stern 2015; Stern 2016). Using observed data, econometric-based estimates can capture the effect of major climate shocks and natural disasters or events (Felbermayr and Gröschl 2014) that economic models and IAMs often cannot. Another important difference between the majority of IAMs and the emerging climate econometric literature is the granularity of the analysis. While empirical impact studies are increasingly exploiting the availability of gridded biophysical data to estimate direct impacts (Oyebamiji et al. 2015; Blanc 2017), IAMs remain constrained to geopolitical boundaries and resolve the economy at the country level at best. The integration over heterogeneous geographic and socioeconomic units certainly masks areas of positive and negative impacts located within the same country or region, generally leading to smaller aggregate impacts.

We contribute to this literature by shedding light on the relationship between climatic exposure and economic performance by regressing high-resolution economic activity data on temperature and precipitation between 1980 and 2010. Our dataset eventually reports observations for more than 51,000 grid-cells. Compared to the use of country-level aggregated data, grid-cell level analysis makes it possible to increase the detail of the global processes scrutinized (Nordhaus 2006) and to investigate for the impact of climatic stressors at the local level that country-level data do not support even with population-weighted average climatic data (Burke et al. 2015; Dasgupta 2018). High-resolution data allows an improved description of processes occurring within a country by limiting the "averaging effect", making it possible to control explicitly for spatial dependence. We show that the spatial resolution of the data used is influential in determining the results and that aggregated data tend underestimate climate change damages. Given the local nature of climatic impacts and considering that most economic decisions are also made at the local-level (Donaldson and Storeygard 2016), such approach should provide more policy-relevant results.

[1] For completeness, studies based on macro data tend to show lower impacts compared to micro-oriented research Burke et al. (2015).

Data and Methodology

This analysis uses social-economic data from the Global Carbon Project's (GCP) dataset (Murakami and Yamagata 2019). The dataset provides historical global population and GDP in grids of 0.5°×0.5° for every decade between 1980 and 2010 and for Shared Socioeconomic Pathways (SSPs) 1-3 for 2020-2100. The downscaling procedure used is based on spatial and economic interaction among cities and an ensemble of learning techniques. The final gridded data are an ensemble mean of six statistical downscaling procedures, three deterministic and three stochastic, outcomes of geographically weighted regressions. GDP is downscaled using gridded population information and controlling for length and density of major roads, agricultural area, urban area density and expansion, and urban population. The authors use sixteen sub-models to downscale country-level GDP, where each sub-model distributes GDP using distribution weights. These distribution weights are computed by multiplying baseline variable with control variable. The baseline variables capture the difference in urban expansion/shrinkage while control variables capture the influence from auxiliary variables (city population, urban area, agricultural areas, total length of principal road, and distance to the nearest airport). The authors use a temporal smoothing of the downscaling results to ensure that gridded estimates evolve over time. Figure S1 in the SI shows the spatial distribution of grid-cells with baseline (2010) level of economic activity larger than the first quartile. Our regression analysis is based on the historical data for the period of 1980-2010.

The source of the climatic data is the University of Delaware reconstruction assembled by Matsuura and Willmot (2015) version 4.01, which provides 0.5°×0.5° gridded monthly average temperature and total precipitation data for all land areas over the period 1900-2014, as interpolated from station data. Table 1 below summarizes the descriptive statistics of the variables used in the empirical analysis.

Variable	Mean	Std. Dev.	Min	Max
Gridded GDP (PPP, billion US$2005)	0.42	3.80	0.00	381.17
Log of Economic Activity	-5.66	5.04	-40.30	5.94
Decadal Temperature (°C)	8.24	14.91	-33.65	37.42
Decadal Precipitation (mm/year)	63.80	61.46	0.02	863.64
Gridded Population (million)	0.06	0.36	0.00	34.27

Table 1: Descriptive statistics

By combining the high-resolution economic activity data with gridded climate data, we revisit the relationship between climatic exposure and economic performance to investigate the potential distribution of future climate impacts across space. The high-resolution data reduces the averaging effect, where negative and positive performances compensate each other. Accordingly, we expect to detect possibly higher losses than previous studies. Specifically, following the recent climate econometric literature (Nordhaus 2006; Dell et al. 2012; Dell et al. 2014; Burke et al. 2015; IMF 2017), we estimate a reduced-form relationship (see SI) between mean surface temperature and economic activity with a granularity of 0.5°×0.5° between 1980 and 2010. The panel regression is specified in Eq. (1):

$$ln(y_{it}) = \alpha_i + \gamma_t + \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_3 P_{it} + \beta_4 P_{it}^2 + \varepsilon_{it} \quad (1)$$

where grids-cells are indexed by *i* and decades by *t*. y_{ij} is the economic activity at each grid measured by the spatially downscaled GDP data by Murakami and Yamagata (2016) (see SI for further details), (T) and $(T)^2$ are the decadal average surface temperature and temperature squared at each grid. Newell et al. (2021), albeit using country-level data, find that level effects models, similar to the one we are using, provide more robust estimates. They also find that predictive accuracy does not depend on the functional form of temperature which can give some flexibility in the choice of specification. Anyway, in the appendix we provide a set of robustness tests among which a cubic temperature function We also control for decadal mean precipitation (P) and its second-degree polynomial $(P)^2$. α_i is the grid cell fixed-effects, controlling for time invariant factors that differ across grid-cells such as institutions, elevation, soil characteristics, and geographic position (land locked or coastal area). γ_t is the decadal time fixed-effects capturing trends common to all grid-cells including technological change and global prices changes.

Since we detect evidence of spatial dependence across the grids (SI: Figure S2) and using Moran's *I* test for spatial autocorrelation, we reject the null hypothesis of spatial independence. Thus, not controlling for spatial dependence would result in biased estimates of the impact climate change. Furthermore, information criterion tests and Root Mean Square Error (RMSE) suggests that the spatial lag specifications are more robust (SI: Table S1). We introduce spatial-weight matrices (*W*) measuring the potential climatic *spillover* effect across neighbouring grids based on distance decay parameters in Eq. (1). This method assumes that the variable of interest decreases in influence with distance from its sampled grid (Baltagi et al. 2003). Previous studies (e.g. Nordhaus 2006) that have used data at the grid cell level but did not control for spatial dependence, thus producing biased results.

We use three different spatial weights matrices; 1) negative exponential spatial weights with the decay parameter set to 0.75, 2) inverse power function with the distance decay parameter set to four, and 3) a binary spatial weight with the distance threshold set to 400 km based on the greatest Euclidean distance measured between two places on a Cartesian plane. In all these cases, the spatial dependence between grid-cells decays as distance between two grid cells increases. By incorporating the spatial weights, we also include the spatial lag of temperature and run a spatial cross-regressive model (SLX model) of the form:

$$ln(y_{ij}) = \alpha_i + \gamma_t + X\beta_{it} + \rho W X_{it} + \varepsilon_{ij} \quad (2)$$

where, ρ is a spatial autoregressive coefficient, $X\beta_{it}$ encompasses temperature and precipitation in eq. (1) and W is the spatial weight matrix. The term $\rho W X_{it}$ measures the potential spillover effects that occurs in temperature across grids cells (Baltagi et al. 2003). In this specification, temperature changes in both own- and neighbouring cells affect economic output[2].

To estimate the burden of future climate change on economic activity, we apply the delta change method (Hay et al. 2000; Diaz-Nieto and Wilby 2005; Dasgupta 2018) by combining our non-linear estimations of (2) with future warming scenarios produced by a multi-model ensemble of nineteen GCMs that contributed to phase 5 of the Coupled Model Intercomparison Project (CMIP5)[3]. The delta method consists in comparing each GCM's projections (2080-2100) against its own simulation of the historical period (1965 – 2005) and computing the change in economic activity according to eq. (3):

$$Percentage\ change\ in\ economic\ activity = \left[\left(\frac{exp(\hat{\beta}_1 T^{future} + \hat{\beta}_2 T^{future^2})}{exp(\hat{\beta}_1 T^{historical} + \hat{\beta}_2 T^{historical^2})}\right) - 1\right] * 100 \quad (3)$$

Given the bias of Earth System Model-simulated climate compared to the historical distribution, we compute differences in temperature between ESM-simulated current and future climate. Climate scenarios used are the Representative Concentration Pathways (RCPs) 4.5, 6.0, and 8.5 (van Vuuren D.P. et al. 2011). Compared to the reference period (1986-2005), surface temperature in the 20-year period 2081-2100 is expected to increase by approximate 1.8°C (range 1.1°C to 2.6°C) under RCP4.5, 2.2°C (range 1.4°C to 3.1°C) under RCP6, and 3.7°C (range 2.6°C to 4.8°C) under RCP8.5.

Results

Historical responsiveness of economic activity to temperature changes. In line with prior studies (Nordhaus 2006; Burke et al. 2015), we find that economic activity is smooth, non-linear, and concave in temperature (Figure 1). However, the optimal temperature maximizing economic activity is found to be 9°C,

[2] Additionally, we ran a number of robustness tests such as controlling for; country-year fixed-effects, temperature and precipitation interaction-term, cubic terms for temperature and precipitation and also run our base specification without correcting for spatial dependence. All these robustness tests provide consistent results (SI: Section 4).

[3] We use the multi-model mean temperature from RCP 8.5 ensemble of ACCESS1-0, ACCESS1-3, bcc-csm1-1, BNU-ESM, CanESM2, CCSM4, CESM1-BGC, CESM1-CAM5, CMCC-CM, CMCC-CMS, CNRM-CM5, CSIRO-Mk3-6-0, EC-EARTH, FGOALS-g2, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, and GISS-E2. Data have been downloaded from https://climexp.knmi.nl/start.cgi.

lower than the 12°C and 13°C estimated by Nordhaus (2006) and Burke et al. (2015), respectively. As evident from the estimated optimal temperatures using the coarser resolution data (1°×1°: Table 2 and country-level: Figure 2), this is partially driven by the higher spatial resolution economic data used in this paper. As temperature increases beyond this threshold, there is a negative impact on economic activity.

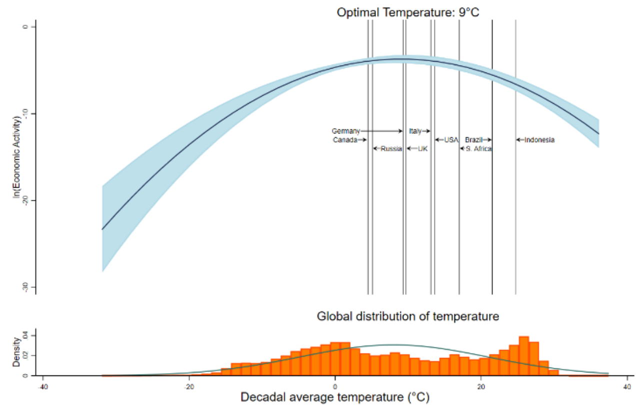

Figure 1: Impact of temperature on economic activity (Spatial lag of temperature and FE): Global non-linear relationship between decadal average temperature and log of economic activity (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, N=134,201). Specification includes precipitation controls, and grid-cell and decadal fixed-effects. For illustrative purposes, vertical lines indicate population weighted average temperature for selected countries in 2010. Histogram shows global distribution of temperature exposure. Figure adapted from Burke et al. (2015) based on authors' estimations.

We summarise the econometric estimations from the different specifications and the optimal temperature in Table 2 below. The linear terms for both temperature and precipitation are positive while the second-degree polynomials are negative, pointing to a concave relation between economic activity and the climate stressors. We also add country-decade fixed-effects to control for regional shocks such as country-level policies changing over time (SI: Figure S7; right-panel). In this case, optimal temperature is estimated to be slightly lower at 8.6°C. We also run the base specification without controlling for spatial dependence and estimate a slightly lower optimal temperature of 8.6°C (SI: Figure S8; right-panel).

	0.5°×0.5° Data	1°×1° Data	
Spatial lag of mean temperature	0.211***	0.231***	0.230***
	(0.000)	(0.000)	(0.000)
Spatial lag of mean temperature^2	-0.012***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.000)
Mean Temperature	0.035***	0.231***	0.230***
	(0.000)	(0.000)	(0.000)
Mean Temperature^2	-0.003***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.000)
Mean Precipitation	0.009***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Mean Precipitation^2	-0.003***	-0.000**	-0.000**
	(0.000)	(0.014)	(0.017)
Warm Spell Duration Index			-0.017***
			(0.000)
Constant	-5.784***	-2.519***	-2.563***
	(0.000)	(0.000)	(0.000)
Location fixed-effect	Yes	Yes	Yes
Time fixed-effect	Yes	Yes	Yes
Observations	134,201	44,696	44,348
R-squared	0.765	0.813	0.815
Number of grid-cells	45,725	11,174	11,087
p-values in parentheses *** p<0.01, ** p<0.05, * p<0.10, + p<0.15 All regressions include grid cell and decadal fixed-effects			
Optimal temperature (°C)	9.0	11.8	11.8
Projected impacts due to temperature change (RCP 8.5): Median [min, max, 25th, and 75th percentiles]	-56.0% [-92.7%, 6,000.3%, -77.3%, 30.5%]	-37.8% [-85.1%, 4,045.7%, -63.4%, 69.5%]	-37.3% [-84.7%, 3,924.1%, -62.9%, 69.6%]

Table 2. Regressions Results by Specification

In our dataset, 49.8% of the grid cells had an average annual temperature above 9°C in 2010. Furthermore, countries with population-weighted average temperature close to the optimal level, e.g. Italy, Germany, USA, and UK, have significant shares of their grid cells (91%, 51%, 47%, and 55%, respectively) with temperature levels above the optimal. Future warming will push more grid-cells above the threshold temperature and is likely to result in significant losses not only in today's hot and poor countries but also in many areas of temperate rich regions. Furthermore, we find that a uniform increase in mean temperature of 1°C would induce a change in economic activity between a maximum decline of 32% in tropical regions and maximum gain of 73% in cold regions with low baseline temperature such as Denmark and Russia, with a global mean loss of 7.9%. These estimates are closer in magnitude to the existing cross-sectional studies.

The role of high-resolution data

As mentioned previously, our optimal temperature is lower than what found in the existing literature. We argue that this is the result of the higher resolution of our dataset and as a simple robustness test, we repeat the same analysis on aggregate gridded GDP data at the country-level using population weights. The temperature-economic activity response-function is similar (∩-shaped) to that estimated using the gridded data. However, the optimal temperature maximizing economic activity is significantly higher at 17.3°C.

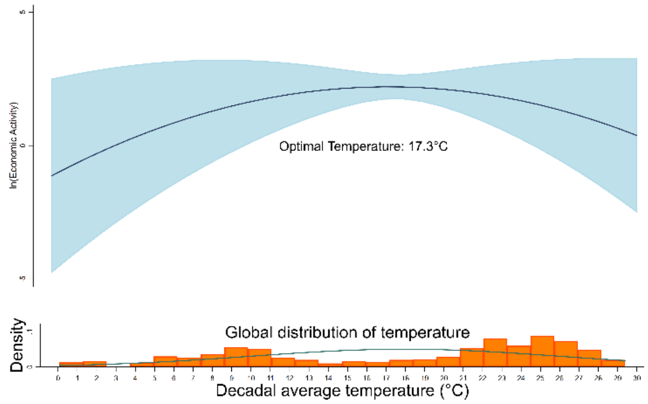

Figure 2: Impact of temperature on economic activity at the country-level: Global non-linear relationship between decadal average temperature and log of economic activity aggregated to the country-level (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, *N*=590). Specification includes precipitation controls, and country and decadal fixed-effects.

Impact of Extreme Events

We also control for extreme events (SI, Table S1) to investigate whether there are additional impacts on economic activity not captured by gradual temperature changes (Felbermayr and Gröschl 2014). To investigate their impact, we include selected Climate Extreme Indices (CEI, see SI, Table S1), as defined and developed by the Expert Team on Climate Change Detection and Indices (ETCCDI), the Expert Team on Sector-specific Climate Indices (ET-SCI) and adopted by the World Meteorological Organization (WMO). The calculation of CEI requires daily measure of (i) maximum near-surface air temperature, (ii) minimum near-surface air temperature, and (iii) near-surface precipitation. However, Matsuura and Willmot (2015) - our main source of climate data, do not provide daily observations. Accordingly, for this specific analysis, we use the Global Land Data Assimilation System (GLDAS) version 2 (Rodell et al. 2004; Kumar et al. 2006). This dataset, however, is at a coarser resolution compared to Matsuura and Willmot (2015), therefore this particular analysis had to be performed with a 1°x1° scale. Among the extreme events indicators, we find that warm spell duration (measuring the decadal count of events with at least six consecutive days with maximum surface temperature exceeding the 90^{th} percentile, see SI, Table S1) to be statistically significant. At the same time, controlling for extreme events does not influence the optimal climatic conditions. In other words, increases in warm spell events would further reduce economic activity but without substantively changing the optimal temperature (see SI, Table S6). Our results suggest that one standard deviation increase in the frequency of warm spells could reduce mean global economic activity by approximately 1.6%. Even though less informative, also the optimal temperature produced by this coarser data set, can give an indication of the role of data resolution. At the 1°x1° scale the optimal temperature is 11.8°C, closer to previous studies. For a complete set of results, see the SI.

Economic activity under future warming

To project the impact of future climate change on economic activity, we assume that the estimated relationship during 1980-2010 (main specification; SI Table S4, column 1) is representative and holds in the future. We focus on the grid cells with a baseline economic activity larger than the first quartile in 2010, see SI, Figure S1. Future warming could result in a 56% median decline in global economic activity (interquartile range: -77.3% and 30.5%) in 2090 relative to the historical reference period 1986-2005, (Figure 3) with reductions in 69% of the grid cells. Moderate temperature increases RCPs 4.5 and RCP 6 would limit economic losses to between 33% and 39%, respectively (SI, Figures S3, S4, and S6).

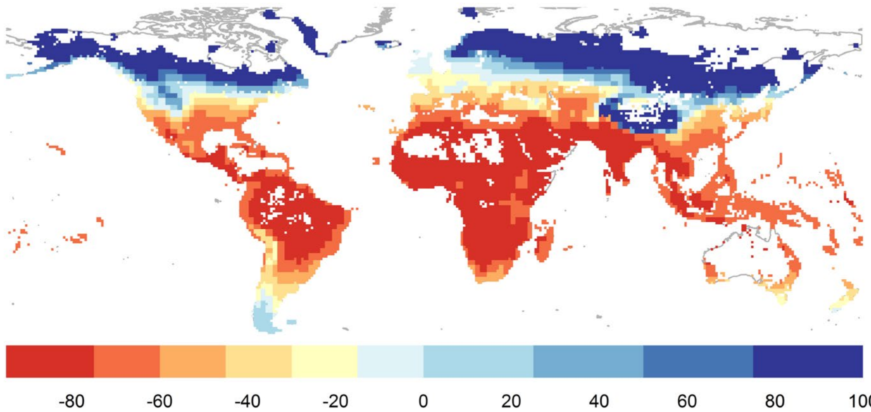

Figure 3: Projected impact of climate change on economic activity (Spatial FE): Grid cell level percentage change in economic activity due to temperature change (RCP 8.5: 2080 - 2100; ensemble of multi-model mean) using spatial regression. The median decline in economic activity is projected to be 56% (25th percentile: -77.3%; 75th percentile: 30.5%). 69% of the grid cells are expected to suffer a decline in economic activity due to climate change.

The highest adverse effects of climate change are projected in the tropical regions, resulting in a 77% median decline in economic activity. Potential gains are concentrated at high latitudes in the colder areas with low level of current economic activity, (see SI, Figure S5). Temperate regions could experience improvements in economic activity by 1% on average. Examining the distribution of impacts by baseline level of economic activity, we find that 88.2% of economic activity in 2010 will be exposed to negative impacts (35.5% of economic activity will be exposed to losses greater than 50%), whereas only 11.8% will be exposed to improvements. The distribution of impacts is “skewed to the right” as relatively large increases occur in low-economic activity grid cells. Impacts are uniformly negative in tropical areas while in temperate regions, climate-driven gains will affect only 14% of current economic activity, while the rest will be losing.

At the continental level, significant reductions are expected in Africa, South America, Asia, and Oceania (Figure 4; left-panel), whereas Europe and North America will experience lower and more dispersed impacts (inter-quintile ranges varying between -14.8% and 239.4%, and -27.5% and 134.6% respectively) due to more heterogeneous climatic conditions. Regardless, approximately 75% of their baseline GDP will still be exposed to the risk of negative impacts.

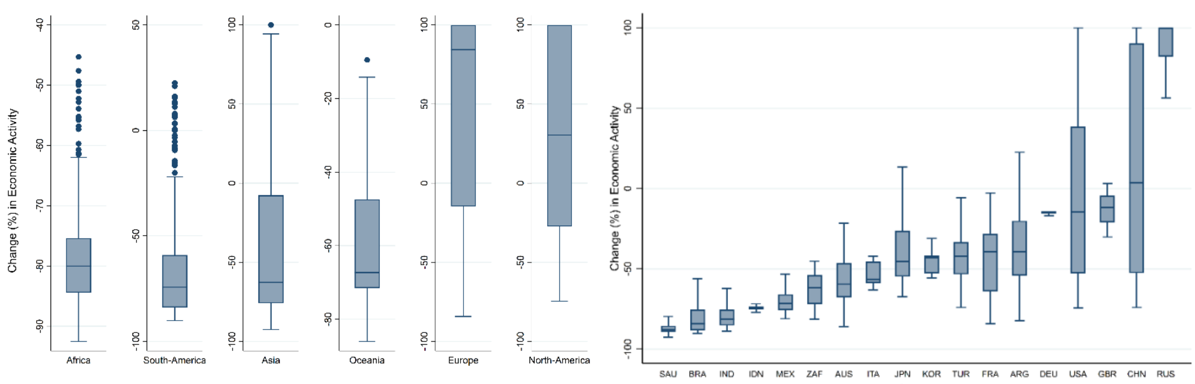

Figure 4 (Left-panel): Projected regional impact of climate change on economic activity: impact on economic activity due to temperature change (RCP 8.5: 2080 - 2100; ensemble of multi-model mean), grid cells grouped by continents. Africa, Asia, Oceania, and South America are projected to experience high decline in economic activity, while the impact will be positive in North America and Europe. Boxplots show the spatial distribution within continents.

Figure 4 (Right-panel): Projected impact of climate change on economic activity in G-20 countries: impact on economic activity due to temperature change (RCP 8.5: 2080-2100; ensemble of multi-model mean), grid-cells grouped by G-20 countries. The median change in economic activity is negative in all countries except China and Russia. Maximum values for USA, China, and Russia are 3,247%, 896%, and 2,718 %, respectively. The large percentage increases (>500%) are concentrated in a small fraction of grid cells (6%, 2.3%, and 12.2%, respectively) characterized by a rather low baseline economic activity (mean GDP values of $2.66 million, $5.24 million, and $6.25 million, global mean GDP is $420 million, see Table S1).

At the country level, all the G-20 countries except China and Russia will experience median declines in economic activity (Figure 4; right-panel), ranging between -11.9% and -87.9%. Russia's median gain of 178.3% is driven by the relatively cold current climate and the relatively low levels of economic activity in many of its grid cells. China, similar to the US and Europe, covers multiple climatic zones and features a wide distribution of impacts with the inter-quantile range spanning between -52.7% and 90.3%. In Europe, France will face substantial impacts, with all the grid-cells suffering a decline in economic activity by the end of the century. The largest declines in economic activity (above 80%) are expected to occur in Mali, United Arab Emirates, Niger, and Burkina Faso. Losses between -69% and -84% will be suffered by emerging economies such as Indonesia, India, Brazil, and Mexico located in the tropics.

Future warming and growing inequality

Assuming that economic activity is a proxy for income level, its substantial redistribution across climatic zones also results in a substantial change in income distribution. Results suggest that climate change exacerbates income inequality not only across but also within countries. Grid-cells with the lowest level of economic activity also experience the highest losses and global Gini coefficient increases from the historical value of 0.33 to 0.46 in 2100 (Figure 5; left-panel) due to warming.

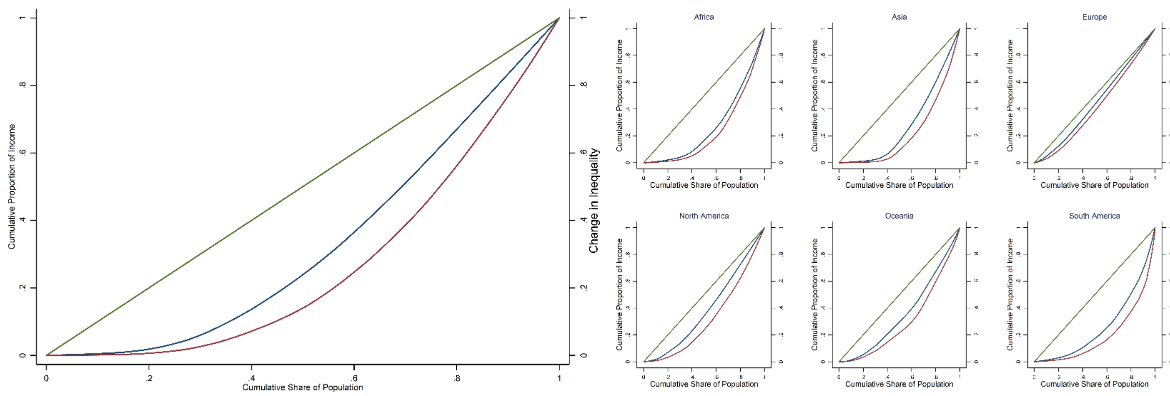

Figure 5 (Left-panel): Impact of climate change on inequality: Lorenz curve comparison shows that inequality will increase substantially. Lorenz curve under future climate change (red line) is further away from the line of perfect equality (green line) than the under current climate (blue line). Gini coefficients have been estimated using RCP 8.5: 2080 - 2100; ensemble of multi-model mean.

Figure 5 (Right-panel): Impact of climate change on regional inequality: Lorenz curve comparison shows that inequality will increase substantially across regions. Lorenz curve under future climate change (red line) is further away from the line of perfect equality (green line) than the under current climate (blue line). Gini coefficients have been estimated using RCP 8.5: 2080 - 2100; ensemble of multi-model mean.

Inequality will also increase within all the major continents and regions, with the highest increases in South America and Asia (Figure 5; right-panel). Among the G-20 countries, the most significant inequality increases are projected to occur in India, Italy, and Argentina. Inequality reduction could potentially occur in a few 'cold' countries such as Canada and Russia (SI, Table S5 and Figure S6). Thus, our spatial analysis, as previously highlighted by Hsiang et al. (2017) in the context of US, suggests that equity adverse impacts of climate change are likely to be widespread and affect also developed countries with "advanced" social structures and temperate climate. It is worth mentioning that these impacts on economic activity and equity are entirely "climate-change driven" and abstract from the actual implementation of policies that could redistribute gains and losses.

Conclusion

We revisit the relationship between climatic exposure and economic performance using the highest resolution economic activity data available (0.5°×0.5°). Decadal panel data and spatial econometrics enables more robust coefficient identification while reducing the risks of aggregation bias and endogeneity. While there is evidence of non-linear impact of climate change on economic activity at the country-level (Burke et al. 2015; IMF 2017), using gridded data provides increased detail of the global process enabling us to study the impact of climatic stressors at the local level. Furthermore, explicitly controlling for spatial dependence reduce estimation bias.

Our results confirm that the non-linear relationship between climatic exposure and economic activity already detected using country-level data, holds even with high-resolution data. Using climatic data with a resolution of 0.5°×0.5° we estimate an optimal temperature of 9°C, lower than the 12°C and 13°C estimated by Nordhaus (2006) and Burke et al. (2015), respectively. This is partly driven by the higher spatial resolution economic data that we use in this paper. Using aggregated gridded GDP data to the country-level we estimate a significantly higher temperature at 17.3°C, while using GLDAS at a 1°×1° specification and including extreme events we estimate an optimal temperature of 11.8°C, closer to previous studies. Both tests point to the role of spatial scale, indicating that optimal temperature is higher when using lower granularity data, leading to smaller impacts.

Future warming under RCP 8.5 scenario is likely to result in a 56% median decline in global economic activity in 2090 relative to the reference period. Moderate temperature increases under RCPs 4.5 and RCP 6.0 scenarios would limit economic median losses to between 33% and 39%, respectively. Our results are larger than the 23% estimated by Burke et al. (2015), with high-resolution data and lower optimal temperatures being the main drivers of these estimates. We also show that extreme hot climate events (warm-spells) exert statistically significant and negative influence on economic activity in addition to the gradual temperature effect but do not influence the optimal temperature. The higher resolution of our results highlights another important implication, that there are widespread adverse distributional consequences not only *between* but also *within* countries. Negative implications on equity are found not only in poor hot countries but also in many of the developed countries.

Our work opens various lines of new research opportunities. First, high-resolution data have a significant potential for the subnational characterization of future climate change on economic risk and its distributional implications. Exploiting this potential can produce relevant information for national and local planners in the implementation of effective and anticipatory adaptation strategies and plans. Second, our empirical results provide evidence of the role of weather extreme events as additional drivers of losses in economic activity. This avenue of research deserves more investigation, to better assess the role of historical extreme events and in terms of future implications due to changes in their frequency and intensity.

Finally, the relationship between warming and economic performance identified in this paper can guide a re-calibration of the damage functions currently used in IAMs. This can help to address the weak empirical foundation of these damage functions, perceived as the major shortcoming of these models that remain useful tools to explore cost-effective and cost-efficient climate change policies. Accordingly, once updated with the new information, IAMs can be used to produce a more robust wave of impact and policy assessments.

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Supplementary Information for Global Temperature Effects on Economic Activity and Equity: A Spatial Analysis

1. Data and Methodology

This analysis uses social-economic data from the Global Carbon Project's (GCP) dataset (Murakami and Yamagata 2019). The dataset provides decadal global population and GDP scenarios in grids of 0.5°×0.5° by country between 1980 and 2100. Our regression analysis is based on the historical data for the period of 1980-2010. Murakami and Yamagata (2016) incorporate spatial and economic interaction among cities and an ensemble of learning techniques to downscale both population and GDP. GDP is downscaled using the downscaled population information and controlling for length and density of major roads, agricultural area, urban area and density, and urban population. Eventually, the gridded data are an ensemble mean of six statistical downscaling procedures, three deterministic, and three stochastic, outcomes of geographically weighted regressions. For the detailed description of the downscaling procedure, please refer to Murakami and Yamagata (2016).

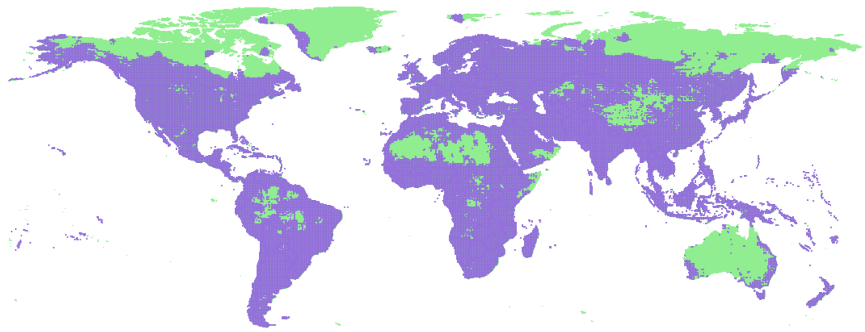

Figure S1| Map of grid cells with economic production: Purple areas represent grid cells with the top 75% of economic activity in 2010.

Our main source for climatic data is the University of Delaware reconstruction assembled by Matsuura and Willmot (2015) version 4.01, which contains 0.5°×0.5° gridded monthly average temperature and total precipitation data for all land areas over the period 1900-2014, as interpolated from station data.

2. Econometric Frameworks

2.1. Spatial Econometrics Framework: Main specification

It is reasonable to presume that the economic activity in a grid is spatially dependent on economic activity in the neighbouring grids. This is known as the "first law of geography": "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970). Indeed, using Moran's *I* test for spatial autocorrelation, we reject the null hypothesis of spatial independence. Specifically, the Moran's Scatterplot in Figure S2 (left-panel) shows the high spatial dependence among the grid-cells, reporting a very high value of Moran's *I* (0.93), while the Local Indicators of Spatial Association (LISA) in Figure S2 (right-panel) shows significant levels of clustering among grid cells, also indication of spatial dependence.

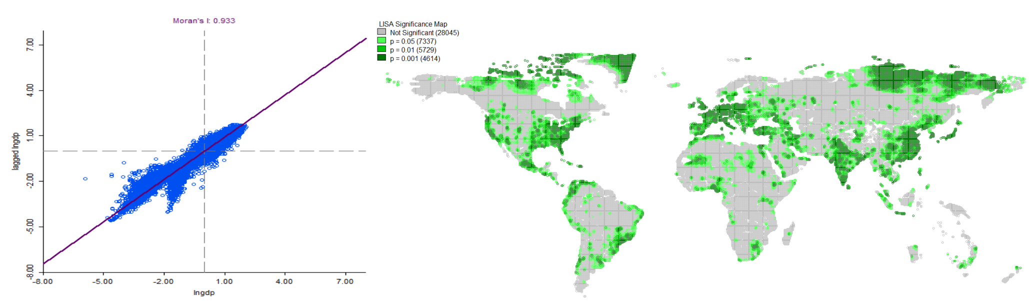

Figure S2| Left-panel: Moran's scatter plot: Moran's *I* is estimated at 0.93 - high autocorrelation among grid cells, $p = 0.001$.
Right-panel: LISA Significance Map: shows significance of clustering among grid cells.

	AIC	BIC	RMSE
Spatial FE	142,376	142,425.1	0.4113
OLS	142,648.3	142,697.3	0.4117

Table S1. Tests for choosing base specification

Thus, we implement spatial regressions with different spatial weight matrices to control for spatial dependence and get robust estimates of optimal climatic conditions maximizing economic activity. We use three different spatial weights matrices, 1) negative exponential spatial weights, with the decay parameter set to 0.75, 2) inverse power function, with the distance decay parameter set to four, and 3) a binary spatial weight with the distance threshold set to 385 km based on the greatest Euclidean distance measured between two places on a Cartesian plane. In all these cases, the spatial dependence between grid cells decays as distance between two grid cells increases. By incorporating the spatial weights, the spatial regression reads as equation (1):

$$\ln(y_{ij}) = \alpha_i + \gamma_t + \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_3 P_{it} + \beta_4 P_{it}^2 + \varepsilon_{ij} \quad (1)$$

We include the spatial lag of temperature and run a spatial cross-regressive model (SLX). Eventually, the SLX model with spatial weight matrix can be written as;

$$ln(y_{ij}) = \alpha_i + \gamma_t + X\beta_{it} + \rho W X_{it} + \varepsilon_{ij} \quad (2)$$

where, ρ is a spatial autoregressive coefficient and *W* is the spatial weight matrix. The term $\rho W y_{it}$ measures the potential spillover effect that occurs in temperature across grids cells (Baltagi 2003). One particular reason for the choice of the SLX specification is the fact that this specification is completely specified. Furthermore, in this specification, temperature changes in both own- and neighbouring cells affect economic output in a way that is causally identified.

2.2. Extreme Events Specification

Extreme events can also exert an impact on economic activity and on the estimation of optimal climatic conditions maximizing it. To investigate their impact, we include selected climate extreme indices (CEI, see Table S2), as defined and developed by the Expert Team on Climate Change Detection and Indices (ETCCDI), the Expert Team on Sector-specific Climate Indices (ET-SCI) and adopted by the World Meteorological Organization (WMO). The calculation of CEI requires daily measure of (i) maximum near-surface air temperature (TX), (ii) minimum near-surface air temperature (TN), and (iii) near-surface precipitation (PR). However, Matsuura and Willmot (2015) - our main source of climate data, do not provide daily observations. Thus, we use the Global Land Data Assimilation System (GLDAS) version 2 (Rodell et al. 2004 and Kumar et al. 2006), available at the coarser spatial resolution of 1°×1° but providing the required time resolution (in fact 3-hourly data are available).

Extreme Events' Indicator	Description	Units	Mean	Std. Dev.	Min	Max
Cold Spell Duration Index (CSDI)	Annual count of events with at least six consecutive days when TN < 10th percentile[4]	Days	-0.09	1.07	-6.62	11.52
Warm Spell Duration Index (WSDI)	Annual count of events with at least six consecutive days when TX > 90th percentile	Days	-0.30	0.71	-1.54	11.00
Consecutive Dry Days (CDD)	Maximum number of consecutive dry days (annual) when PR < 1.0 mm (longest dry spell)	Days	0.24	1.37	-1.61	24.33
Consecutive Wet Days (CWD)	Maximum number of consecutive wet days (annual) when PR > 1.0 mm (longest wet spell)	Days	-0.07	1.03	-6.25	10.33

Table S2. Description of climate extreme indices used in the study

[4] Percentiles are grid-cell specific, computed over a baseline threshold period of 1961-1990.

Table S3 below summarizes the specifications utilized in this paper.

Specification	Climate drivers	Spatial resolution	Climate data source
FE + spatial correlation (main specification)	T, P	0.5°×0.5°	Matsuura and Willmot (2015)
FE + spatial correlation	T, P	1°×1°	GLDAS
FE + spatial correlation	T, P, extreme events	1°×1°	GLDAS

Table S3. Summary of regression features

3. Results

3.1. Summary of Results from the Different Specifications

Econometric estimations from the different specifications and the optimal temperature and GDP loss in the RCP 8.5 scenario are reported in Table S4 below. The linear term for both temperature and precipitation are positive while the second-degree polynomial terms are negative, pointing to a bell-shaped relation between economic activity and the two climate variables. The optimal temperature estimated using the 0.5° data are lower than that estimated from the 1° data. As a result, the damages due to climate change are higher under the former specification.

	0.5°×0.5° Data	1°×1° Data (GLDAS)	
Spatial lag of mean temperature	0.211***	0.231***	0.230***
	(0.000)	(0.000)	(0.000)
Spatial lag of mean temperature^2	-0.012***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.000)
Mean Temperature	0.035***	0.231***	0.230***
	(0.000)	(0.000)	(0.000)
Mean Temperature^2	-0.003***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.000)
Mean Precipitation	0.009***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Mean Precipitation^2	-0.003***	-0.000**	-0.000**
	(0.000)	(0.014)	(0.017)
Warm Spell Duration Index			-0.017***
			(0.000)
Constant	-5.784***	-2.519***	-2.563***
	(0.000)	(0.000)	(0.000)
Location fixed-effect	Yes	Yes	Yes
Time fixed-effect	Yes	Yes	Yes
Observations	134,201	44,696	44,348
R-squared	0.765	0.813	0.815
Number of grid-cells	45,725	11,174	11,087
p-values in parentheses *** p<0.01, ** p<0.05, * p<0.10, + p<0.15 All regressions include grid cell and decadal fixed-effects			
Optimal temperature (°C)	9.0	11.8	11.8
Projected impacts due to temperature change (RCP 8.5): Median [min, max, 25th, and 75th percentiles]	-56.0% [-92.7%, 6,000.3%, -77.3%, 30.5%]	-37.8% [-85.1%, 4,045.7%, -63.4%, 69.5%]	-37.3% [-84.7%, 3,924.1%, -62.9%, 69.6%]

Table S4. Regressions Results by Specification

For the sake of completeness, Figures S3 and S4 provide maps of gridded GDP losses under RCP4.5 and RCP6, respectively. The pattern of distribution of damages are very similar to that under RCP 8.5.

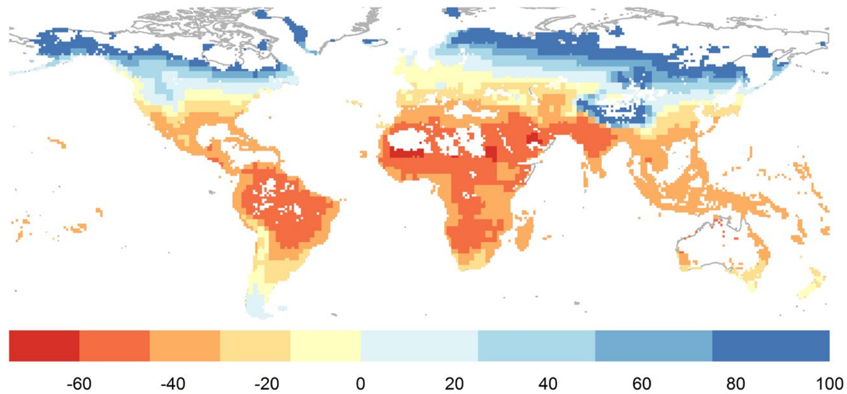

Figure S3| Projected impact of climate change on economic activity: Grid cell level percentage change in economic activity due to temperature change (RCP 4.5: 2080 - 2100; ensemble of multi-model mean) using spatial regression with fixed-effects. Grid cell level estimates using delta method. The median decline in economic activity is projected to be -33.2% (25th percentile: -53.4%; 75th percentile: 26.4%). 66% of the grid cells are expected to suffer a decline in economic activity due to climate change.

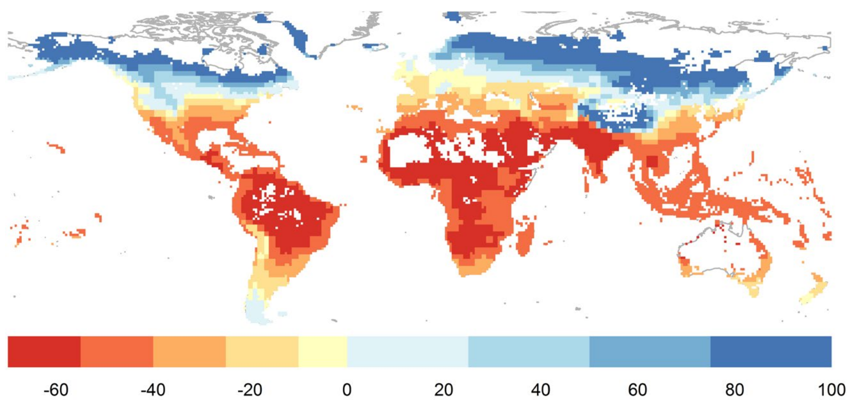

Figure S4| Projected impact of climate change on economic activity: Grid cell level percentage change in economic activity due to temperature change (RCP 6: 2080 - 2100; ensemble of multi-model mean) using spatial regression with fixed-effects. Grid cell level estimates using delta method. The median decline in economic activity is projected to be -38.8% (25th percentile: -43.2%; 75th percentile: 19.5%). 67% of the grid cells are expected to suffer a decline in economic activity due to climate change.

3.2. Distribution of Grid cells with High Gain due to Climate Change

Figure S5 below maps the concentration of grid cells with high gains due to climate change; most of these grid-cells are located in areas with low levels of temperature.

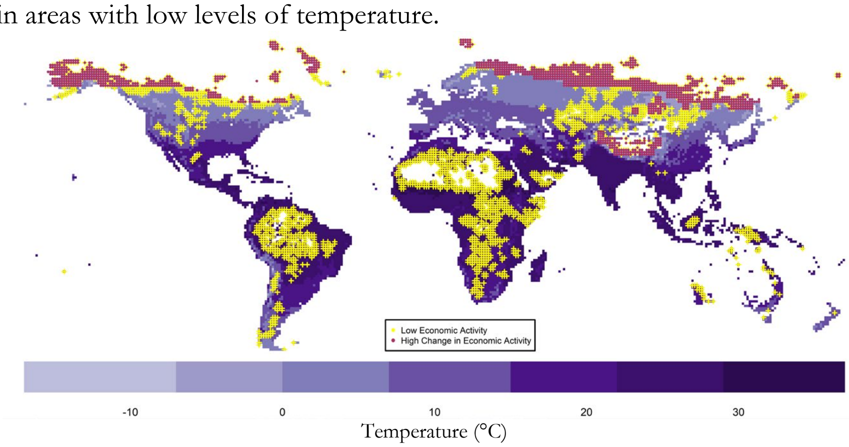

Figure S5| Average decadal temperature (°C) with bottom 10th percentile of economic activity grids and high increase due to climate change: Gridded decadal temperature (2010) mapped (purple) with first-quartile of economic activity grids (yellow) and high change in economic activity (maroon, greater than 200%) due to temperature change (RCP 8.5: 2080 - 2100; ensemble of multi-model mean) superimposed. Grid cells in very low temperature regions are likely to benefit from warming by the end of the 21st century but very high increases in economic activity will also occur in grids with very low levels.

3.3. Regional Impacts

Gridded data allows the computation of impacts of climate change by region under the different RCPs. As shown in Figure S6, Africa, Asia, Oceania, and South America will experience significant median declines in economic activity, while Europe and North America will gain.

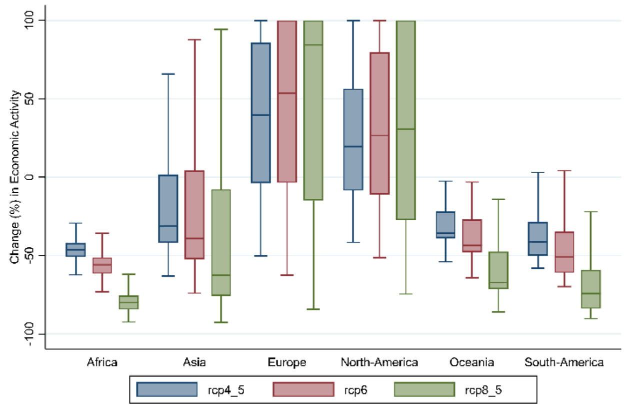

Figure S6| Projected regional impact of climate change on regional economic activity: impact on regional economic activity due to temperature change (RCP 4.5, RCP 6; and RCP 8.5: 2080 - 2100; ensemble of multi-model mean), grid cells grouped by continents.

3.4. Impact of Future Climate Change on Inequality

Tables S4 and S5 provide the change in Gini coefficients due to climate change across regions and G-20 countries.

Region	Gini - Historical	Gini - Future	Change
Africa	0.45	0.52	0.08
Asia	0.43	0.55	0.12
Europe	0.10	0.17	0.04
North-America	0.21	0.35	0.11
Oceania	0.28	0.39	0.10
South-America	0.47	0.60	0.12

Table S4. Macro-Regional Gini-coefficients

Country	Gini - Historical	Gini - Future	Change
ARG	0.28	0.42	0.14
AUS	0.26	0.36	0.11
BRA	0.30	0.39	0.08
CAN	0.11	0.05	-0.06
CHN	0.26	0.43	0.17
DEU	0.00	0.02	0.02
FRA	0.04	0.10	0.06
GBR	0.02	0.06	0.04
IDN	0.14	0.13	0.00
IND	0.61	0.83	0.22
ITA	0.14	0.32	0.18
JPN	0.13	0.25	0.12
KOR	0.04	0.10	0.06
MEX	0.27	0.33	0.06
RUS	0.18	0.11	-0.06
SAU	0.36	0.40	0.05
TUR	0.12	0.24	0.12
USA	0.22	0.36	0.13
ZAF	0.14	0.16	0.02

Table S5. G-20 Countries Gini-coefficients

4. Robustness Checks

4.1. Optimal temperature estimated from different specifications, spatial resolution, and climatic data.

Table S6 below summarizes the results in term of optimal temperature and GDP loss in the RCP 8.5 for different specifications, models, spatial resolutions and climatic database. Murakami and Yamagata (2016) is the source of the socioeconomic data.

Specification	Optimal temperature (°C)	Climate drivers	Spatial resolution	Climate data source	Projected impacts due to change in T Median [min, max, 25th and 75th percentiles]
FE + spatial correlation (main specification)	9.0	T, P	0.5°×0.5°	MW	-56.0% [-92.7%, 6000.3%, -77.3%, 30.5%]
FE	8.6	T, P	0.5°×0.5°	MW	-64.5% [-96.1%, 13,322.6%, -84.1%, 31%]
FE + spatial correlation	11.8	T, P	1°×1°	GLDAS	-37.8% [-85.1%, 4,045.7%, -63.4%, 69.5%]
FE	8.5	T, P	1°×1°	GLDAS	-70.9% [-97.5%, 18,192.8%, -87.1%, 34.6%]
FE + spatial correlation	11.8	T, P, extreme events	1°×1°	GLDAS	-37.3% [-84.7%, 3,924.1%, -62.9%, 69.6%]
FE	8.6	T, P, extreme events	1°×1°	GLDAS	-69.7% [-97.3%, 16,631.9%, -86.4%, 35.6%]

Table S6. Summary of regression features and results in RCP 8.5

The apparent direct correlation between granularity of the investigation and damage estimation is confirmed. On the contrary, controlling for spatial correlation tends to increase the optimal temperature, i.e. to decrease damage estimates. This leads us to speculate that spatial analyses not considering this are biased upward. Extreme events (warm spells) are statistically significant but do not affect the optimal temperature.

4.2. Including country-year fixed-effects

To control for regional shocks such as country-level policies that changes over time, we include country-decade fixed-effects to our base specification. The optimal temperature estimated in this case is 8.6°C (Figure S7), slightly lower than the 9°C estimated in the base specification.

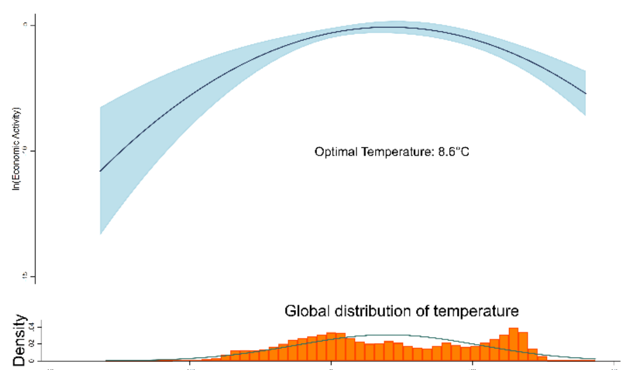

Figure S7: Impact of temperature on economic activity (Spatial lag of temperature and FE): Global non-linear relationship between decadal average temperature and log of economic activity (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, N=134,201). Specification includes precipitation controls, country-decade, grid cell, and decadal fixed-effects.

4.3. Specification without controlling for spatial dependence and adding cubic terms

As further robustness tests, we control for cubic precipitation (top-right panel) and temperature terms (bottom-right panel) and run our base specification without correcting for spatial correlation. The results show that the gridded economic and temperature response-functions are non-linear and concave in nature. The optimal temperatures maximizing economic activity are also within 0.5°C of each other except the specification controlling for cubic temperature. However, the cubic term for temperature is negative, suggesting that that relationship with gridded economic activity do not follow a cubic pattern.

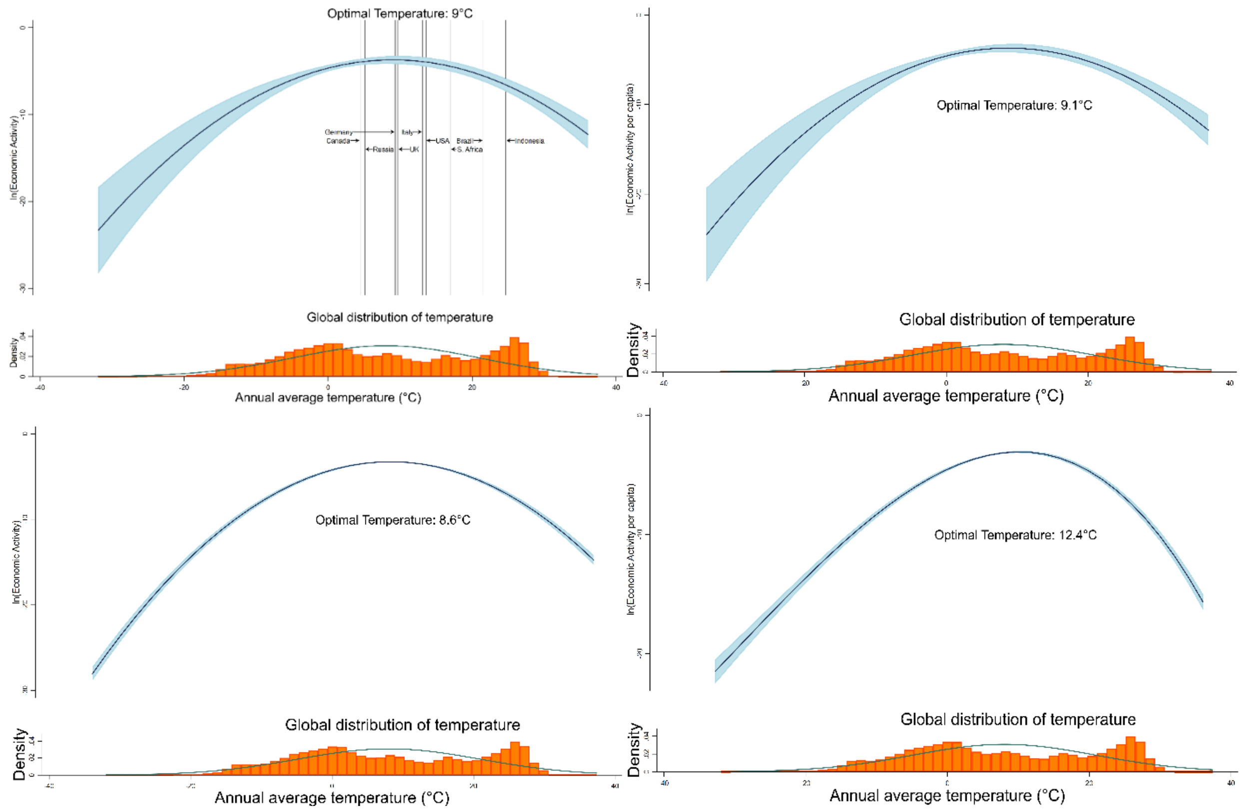

Figure S8: Impact of temperature on economic activity: Top left-panel shows the global non-linear relationship between decadal average temperature and log of economic activity controlling for spatial dependence (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, N=134,201). Specification includes precipitation controls, and grid cell and decadal fixed-effects. Top right-panel specification includes cubic-precipitation. Bottom left-panel provides results from specification without correcting for spatial correlation while bottom right-panel is again non-spatial but with cubic-temperature.

4.4. Including spatial lag of precipitation

While our base specification controls for spatial lag of temperature, as a robustness test we control for spatial lag of precipitation in the specification below. The results show that the optimal temperature (9°C) is unchanged from our base specification.

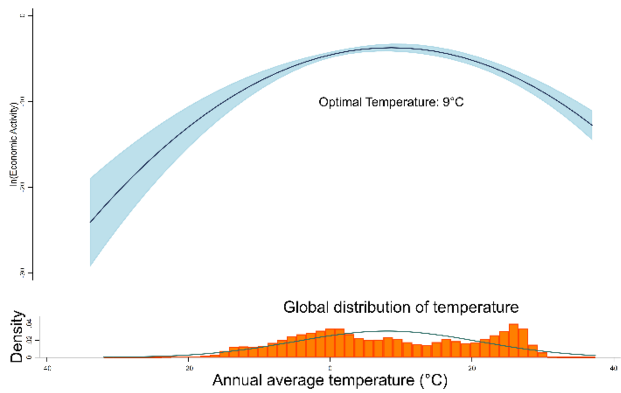

Figure S9: Impact of temperature on economic activity: Global non-linear relationship between decadal average temperature and log of economic activity controlling for spatial dependence (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, N=134,201). Specification includes spatial lag of precipitation, and grid cell and decadal fixed-effects.

4.5. Country-level analysis

In this section, we aggregate the gridded GDP data to the country-level using population weights as a robustness test. The temperature-economic activity response-function estimated using the country-level data is similar (∩-shaped) to those estimated using the gridded data. However, the optimal temperature maximizing economic activity is significantly higher at 17.3°C. This higher optimal temperature can be explained by the coarser spatial resolution of the country-level data.

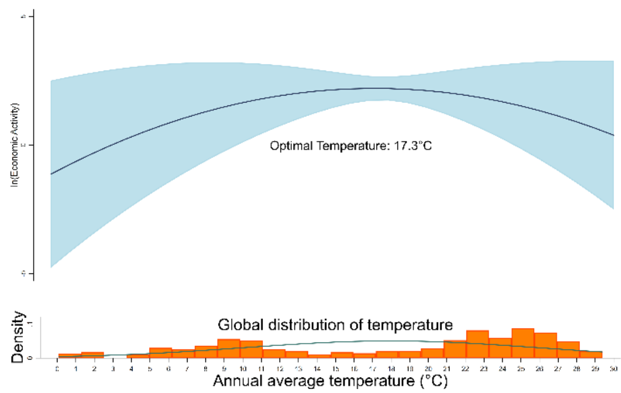

Figure S10: Impact of temperature on economic activity at the country-level: Global non-linear relationship between decadal average temperature and log of economic activity aggregated to the country-level (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, N=590). Specification includes precipitation controls, and country and decadal fixed-effects.

4.6. Impact on economic activity per capita

We use log of economic activity as the dependent variable in our base specification, as a robustness test we provide results for log of economic activity per capita in this section. The response-function is similar to our base specification while the optimal temperature is higher at 10.1°C. One reason we use choose not to use per capita as our base specification is the added uncertainty associated with downscaled population data.

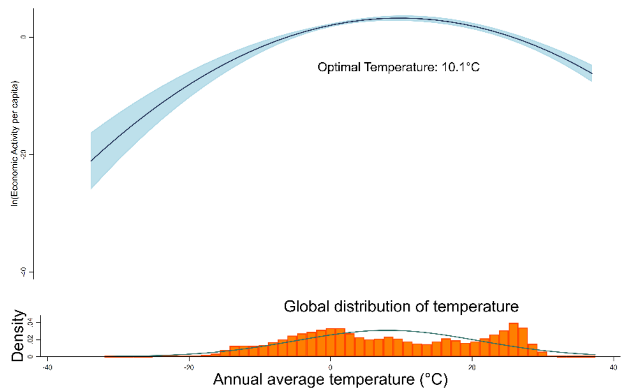

Figure S11: Impact of temperature on economic activity per capita (Spatial lag of temperature and FE): Global non-linear relationship between decadal average temperature and log of economic activity per capita (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, *N*=134,201). Specification includes precipitation controls, and grid cell and decadal fixed-effects. For illustrative purposes, vertical lines indicate population weighted average temperature for selected countries in 2010. Histogram shows global distribution of temperature exposure.

4.7. Alternative climate data – ERA5

As an additional robustness test to the Matsuura and Willmot (2015) climate data used in the main analysis of our paper, we use the ERA5 reanalysed data from ECMWF. The results suggest the optimal temperature maximizing economic activity is lower at 8.4°C compared to 9°C estimated from the main specification.

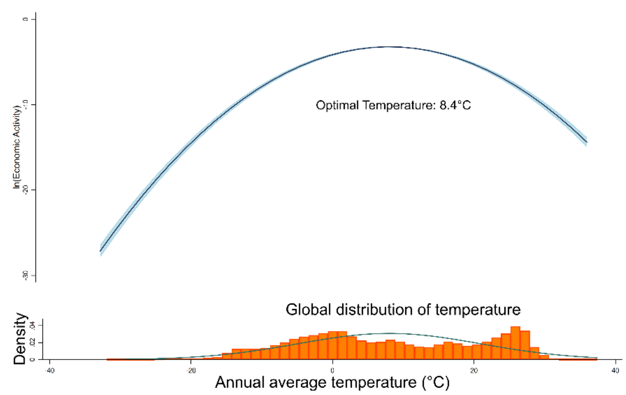

Figure S12: Impact of temperature on economic activity: Global non-linear relationship between decadal average temperature from ERA5 dataset and log of economic activity controlling for spatial dependence (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, *N*=134,201). Specification includes precipitation controls, and grid cell and decadal fixed-effects.

4.8. Temperature – precipitation interaction

In this section, we control for a precipitation-temperature interaction-term. This coefficient is negative and statistically significant, while the optimal temperature is estimated to be 9.8°C.

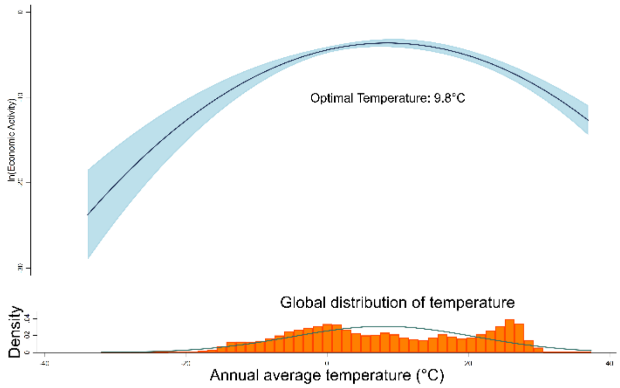

Figure S13: Impact of temperature on economic activity: Global non-linear relationship between decadal average temperature and log of economic activity controlling for spatial dependence (dark navy line, relative to the optimum condition) during 1980-2010 with 95% confidence interval (blue, with robust standard errors, N=134,201). Specification includes precipitation controls, precipitation-temperature interaction-term, and grid cell and decadal fixed-effects.

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