

# **Supplementary information**

# Day-to-day temperature variability reduces economic growth

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## **Supplementary Information for:**

# Day-to-day temperature variability reduces economic growth

Maximilian Kotz<sup>a, b</sup>, Leonie Wenz<sup>a, c, d, \*</sup>, Annika Stechemesser<sup>a, b</sup>, Matthias Kalkuhl<sup>c, e</sup>, Anders Levermann<sup>a, b, f</sup>.

- (a) Potsdam Institute for Climate Impact Research, Potsdam, Germany;
- (b) Institute of Physics, Potsdam University, Potsdam, Germany;
- (c) Mercator Research Institute on Global Commons and Climate Change, Berlin, Germany;
- (d) Department of Agriculture and Resource Economics, University of California, Berkeley, USA;
- (e) Faculty of Economic and Social Sciences, Potsdam University, Potsdam, Germany;
- (f) Columbia University, New York, NY, USA.

<sup>\*</sup> corresponding author: <a href="mailto:leonie.wenz@pik-potsdam.de">leonie.wenz@pik-potsdam.de</a>.

Overview: this document provides supplementary information for Kotz, Wenz,

Stechemesser, Kalkuhl and Levermann (2020). The document is structured in the following sections:

- 1. An assessment of the independence of the effect of day-to-day temperature variability of the frequency of extreme days.
- 2. An assessment of the importance of the proximity of the underlying temperature level to heat-stress thresholds for the effect of day-to-day temperature variability.
- 3. Results of sectoral level regressions.
- 4. Results of various robustness tests.
- 5. Testing and accounting for spatial dependence.
- 6. Partitioning of the data by per-capita income.
- 7. Estimating the long-term impact of the effect of day-to-day variability with distributed lag-models.
- 8. Summary statistics.

#### 1 Section 1. Robustness of results with respect to the frequency of heat-stress days.

- 2 As with any measure of variability, the measure of day-to-day temperature variability defined
- 3 in Kotz et al. 2020 reflects both the high-frequency variability of daily temperature and, to
- 4 some degree, the frequency of days with extreme temperature (heat-stress days). Therefore, we
- 5 test whether the observed effect of day-to-day temperature variability on regional growth rates
- 6 reflects that of the high-frequency variability of daily temperature, or the frequency of heat-
- 7 stress days, by explicitly controlling for the frequency of heat-stress days in our regression
- 8 models.
- 9 We calculate degree days, as defined in (1), as a measure of the frequency of heat-stress days.
- 10 The extent to which daily temperature,  $T_{x,d,y}$ , in grid cell x, on day d, crosses critical
- temperature thresholds,  $T_C$ , is summed over the year, y, to calculate the degree days,  $\breve{T}_{>T_C,r,y}$ :

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$$\check{T}_{>T_C,r,y} = \sum_d^{D_y} \frac{1}{\sum_x^{N_r} w_{x,r}} \sum_x^{N_r} w_{x,r} H(T_{x,d,y} - T_C). (T_{x,d,y} - T_C)$$
 (1)

- 15  $D_y$  is the number of days of a given year.  $N_r$  is the number of grid cells which fall at least
- partially within a given region, r, and  $w_{x,r}$  are the weightings assigned to those grid cells as
- outlined in the methods section of the main manuscript. H is the Heaviside step function.  $T_C$  is
- set at 25 and 30 degrees to reflect empirical findings of a non-linear response of productive
- elements of the economy to temperature, as shown in (2). The effect of day-to-day temperature
- variability is unaltered by the inclusion of these additional controls, as shown in Table S1. This
- suggests that day-to-day temperature variability does not predominantly reflect the frequency
- of extreme days and that variability of daily temperature is inherently damaging.

	(1)	(2)	(3)	(4)	(5)	(6)
$ ilde{T}_{r,y}$	0541***	0542***	0542***	115***	116***	116***
	(.0046)	(.0046)	(.0046)	(.015)	(.015)	(.015)
$\hat{T}_r.\tilde{T}_{r,y}$				.00192***	.00195***	.00194***
, ,				(.0005)	(.0005)	(.0005)
$\delta ar{T}_{r,y}$	.000956	.00118	.00123	.00217	.00264	.00252
	(.002)	(.002)	(.002)	(.0021)	(.0021)	(.0021)
$\bar{T}_r.\delta \bar{T}_{r,y}$	00093***	000967***	000972***	00102***	0011***	00108***
,,,	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
$\delta \bar{T}_{r,y-1}$	00137	00122	00119	000307	.0000102	0000725
,,,	(.0021)	(.0021)	(.0021)	(.0021)	(.0021)	(.0021)
$\bar{T}_r.\delta\bar{T}_{r,y-1}$	000683***	000705***	000709***	000746***	000791***	000777***
,9	(.00019)	(.00019)	(.00019)	(.0002)	(.00019)	(.0002)
$P_{r,y}$	.000264*	.000275	.00027*	.000257	.000278*	.000264*
. , 9	(.00013)	(.00014)	(.00013)	(.00013)	(.00014)	(.00013)
$\check{\mathrm{T}}_{>25,r,y}$		8.87e-06			.0000175	
> 20,1,19		(.000027)			(.000027)	
$\check{\mathrm{T}}_{>30,r,y}$			.0000629			.0000765
200,1,9			(.000079)			(.000079)
N	28872	28872	28872	28872	28872	28872
adj. $\mathbb{R}^2$	0.226	0.226	0.226	0.226	0.226	0.226
BIC	-33221	-33211	-33211	-33229	-33220	-33220

Standard errors clustered at the regional level

**Table S1.** Regression results for climate variables on regional growth rates including measures of degree days to control for the frequency of heat-stress days. Degree days above  $25\,^\circ\text{C}$  and  $30\,^\circ\text{C}$  are shown in the final two rows of the table. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ - seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta\bar{T}$  - first difference of annual mean temperature; P - total annual precipitation;  $\tilde{T}_{>T_C}$  - degree days above critical temperature threshold  $T_C$ .

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

35 Section 2. The importance of the proximity of the underlying temperature level to heat-

stress thresholds for the effect of day-to-day temperature variability.

37 If the effect of day-to-day temperature variability were to predominantly reflect the frequency

of heat-stress days, its strength would depend on the proximity of the underlying temperature

level to heat-stress thresholds. Therefore, in addition to the tests outlined in the previous

section, an assessment of the importance of the underlying temperature level was undertaken.

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Firstly, an interaction of day-to-day temperature variability with the mean annual temperature

level was assessed and no significant interaction was found. However, due to the seasonal cycle

of temperature the annual mean temperature is unlikely to accurately reflect the underlying

temperature level on top of which day-to-day temperature variability (defined as the standard

deviation of daily temperature within each month, see main manuscript) is realised. Therefore,

we re-define separate measures of day-to-day temperature variability for each season

(accounting for hemispheric differences such that boreal JJA is aggregated with austral DJF

and vice versa) and assess the effect of season-specific temperature variability. This utilises the

regular within-region changes of the seasonal cycle to proxy the temperature level on top of

which day-to-day temperature variability is realised. Moreover, by construction it accounts for

inter-regional heterogeneity in the definition of high-temperatures and heat-stress days.

Regions with a seasonal cycle of less than 20, 15, 10, 5 and 0 degrees are separately excluded

from this analysis to allow us to separately consider all regions of our panel, and only regions

in which a considerable seasonal cycle is present.

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The regression models are shown below:

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$$g_{r,y} = \sum_{s=1}^{4} \alpha_s \, \tilde{T}_{s,r,y} + \beta \, \overline{T}_{r,y} + \gamma \, \overline{T}_r \cdot \overline{T}_{r,y} + \rho P_{r,y} + \mu_r + \eta_y + \varepsilon_{r,y}.$$
 (2)

 $g_{r,y}$  are the regional growth rates of region r and year y.  $\tilde{T}_{s,r,y}$  is the season-specific measure of day-to-day temperature variability for season s. The further variables and controls are those of mean temperature, precipitation and regional and year fixed effects as described in the main manuscript (Methods, Equation 4). The estimates of  $\alpha_s$  are shown in Table S2.

We find that day-to-day temperature variability in spring, summer and autumn have significant effects of equivalent magnitudes. This suggests that the effect of day-to-day temperature variability is not dependent on the proximity of the underlying temperature level to heat-stress thresholds, thereby providing further evidence that greater variability is inherently damaging. An insignificant effect of negligible magnitude is noted in winter. A possible explanation for the absence of an effect in winter is that economic agents are already sheltered from the effects of weather and its variability by adapting their activity to avoid particularly harsh winter conditions.

Including regions with a					
Seasonal temperature difference:	>20℃	> 15℃	>10°C	>5°C	>0℃
$ ilde{T}_{Sum.,r,y}$	0235*** (.0034)	0204*** (.0033)	0204*** (.0032)	0241*** (.0032)	-0.0257*** (0.0032)
$ ilde{T}_{Wint.,r,y}$	.00402* (.0017)	.00323 (.0017)	.00355* (.0016)	.00313 (.0016)	0.00225 (0.0016)
$ ilde{T}_{Aut.,r,y}$	0259*** (.0024)	0265*** (.0023)	0254*** (.0023)	0218*** (.0023)	-0.198*** (0.0023)
$ ilde{T}_{Spr.,r,y}$	0306*** (.0023)	0303*** (.0022)	0309*** (.0022)	0306*** (.0022)	-0.0307*** (0.0022)
N	17565	19992	22358	26274	29603
adj. $\mathbb{R}^2$	0.342	0.326	0.309	0.247	0.227
BIC	-24500	-28003	-31059	-31561	-33717

Standard errors in parentheses

Standard errors clustered at the regional level

**Table S2.** The effects of season specific day-to-day temperature variability measures on regional growth rates are assessed. Climate variables are denoted as follows:  $\tilde{T}_s$ - season-specific day-to-day temperature variability.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

#### Section 3. Sectoral level regression results.

Sector:	Agri.	Agri.	Man.	Man.	Serv.	Serv.
$\tilde{T}_{r,y}$	0333***	128***	0333***	13***	0335***	0793***
	(.0077)	(.024)	(.0058)	(.019)	(.0041)	(.014)
$\hat{T}_r. ilde{T}_{r,y}$		.00311***		.00315***		.0015***
		(8000.)		(.00062)		(.00043)
$\delta ar{T}_{r,y}$	0167***	0133**	.0134***	.0168***	.014***	.0156***
	(.0042)	(.0042)	(.0034)	(.0035)	(.0018)	(.0019)
$\bar{T}_r.\delta \bar{T}_{r,y}$	000222	000438	00179***	00201***	00106***	00117***
	(.00035)	(.00035)	(.00028)	(.00029)	(.00015)	(.00016)
$\delta \bar{T}_{r,y-1}$	.00285	.00509	.00752**	.00979***	.00625***	.00733***
70	(.0041)	(.0041)	(.0028)	(.0028)	(.0018)	(.0019)
$\bar{T}_r.\delta\bar{T}_{r,y-1}$	000216	000349	00117***	00131***	000582***	000646***
, ,	(.00034)	(.00034)	(.00026)	(.00026)	(.00016)	(.00016)
$P_{r,y}$	00021	00022	0000285	0000383	.000217	.000213
. , ,	(.0002)	(.0002)	(.00018)	(.00018)	(.00013)	(.00013)
N	20119	20119	20143	20143	20143	20143
adj. $R^2$	0.149	0.150	0.239	0.240	0.253	0.253
BIC	-12758	-12767	-20007	-20025	-31498	-31499

Standard errors in parentheses

Standard errors clustered at the regional level

Table S3. Sectoral level regression results. The impacts of day-to-day temperature variability on regional growth rates of the agricultural, manufacturing and services sectors are approximately equal. This implies that a broad range of economic sectors are sensitive to changes in day-to-day temperature variability. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ - seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta \bar{T}$  - first difference of annual mean temperature; P - total annual precipitation.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

#### Section 4. Additional robustness tests.

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Climate data set:	EWEMBI	EWEMBI	Climate data set:	WATCH	WATCH
$ ilde{T}_{r,y}$	0471*** (.0058)	217*** (.019)	$ ilde{T}_{r,y}$	05*** (.0062)	23*** (.02)
$\hat{T}_r. ilde{T}_{r,y}$		.00596*** (.00067)	$\hat{T}_r.\tilde{T}_{r,y}$		.0063*** (.00072)
$\delta ar{T}_{r,y}$	.00659* (.0026)	.00962*** (.0026)	$\delta ar{T}_{r,y}$	.00445 (.0029)	.00767** (.0029)
$ar{T}_r.\deltaar{T}_{r,y}$	000797** (.00024)	000963*** (.00024)	$\bar{T}_r.\delta \bar{T}_{r,y}$	00057* (.00026)	000745** (.00026)
$\delta ar{T}_{r,y-1}$	.00164 (.0025)	.00376 (.0025)	$\delta ar{T}_{r,y-1}$	000933 (.0026)	.0012 (.0026)
$ar{T}_r.\deltaar{T}_{r,y-1}$	000468* (.00023)	000565* (.00023)	$\bar{T}_r.\delta\bar{T}_{r,y-1}$	000226 (.00024)	000321 (.00024)
$P_{r,y}$	.000391** (.00013)	.000312* (.00013)	$P_{r,y}$	.000507*** (.00014)	.000426** (.00014)
N	28872	28872	N	26712	26712
adj. $R^2$	0.222	0.225	adj. $R^2$	0.225	0.228
BIC	-33095	-33196	BIC	-30560	-30664

Standard errors in parentheses

Standard errors clustered at the regional level

Standard errors in parentheses

Standard errors clustered at the regional level

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$$p < 0.05$$
, \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ 

Table S4. Robustness check of the main regression results using the EWEMBI and WATCH climate data sets as alternatives. Results are consistent with those obtained using ERA5 data. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ -seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta \bar{T}$  - first difference of

annual mean temperature; P - total annual precipitation.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(1)	(2)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ ilde{T}_{r,y}$		<u> </u>
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	,,,	(.0046)	(.015)
$\delta \bar{T}_{r,y}$ .00179 .00333 (.0024) $\bar{T}_{r}.\delta \bar{T}_{r,y}$ 000978***00109*** (.00022) (.00023) $\delta \bar{T}_{r,y-1}$ 00300166 (.0023) (.0024) $\bar{T}_{r}.\delta \bar{T}_{r,y-1}$ 000555**000635**	$\hat{T}_r.\tilde{T}_{r,y}$		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(.0005)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\delta ar{T}_{r,u}$	.00179	.00333
$\delta \bar{T}_{r,y-1} = \begin{array}{ccc} (.00022) & (.00023) \\ &00166 \\ (.0023) & (.0024) \\ & \bar{T}_r.\delta \bar{T}_{r,y-1} &000555^{**} &000635^{**} \end{array}$	. , 9	(.0023)	(.0024)
$\delta \bar{T}_{r,y-1} = \begin{array}{ccc} (.00022) & (.00023) \\ &00166 \\ (.0023) & (.0024) \\ & \bar{T}_r.\delta \bar{T}_{r,y-1} &000555^{**} &000635^{**} \end{array}$	$\bar{T}_r.\delta\bar{T}_{r,y}$	000978***	00109***
(.0023) (.0024) $\bar{T}_r.\delta\bar{T}_{r,y-1}  \text{000555**}  \text{000635**}$	, g	(.00022)	(.00023)
$\bar{T}_r.\delta\bar{T}_{r,y-1}$ 000555**000635**	$\delta \bar{T}_{r,y-1}$	003	00166
		(.0023)	(.0024)
(00004) (00004)	$\bar{T}_r.\delta\bar{T}_{r,y-1}$	000555**	000635**
(.00021) (.00021)		(.00021)	(.00021)
$P_{r,y}$ .000239 .000231	$P_{r,y}$	.000239	.000231
(.00013) (.00013)		(.00013)	(.00013)
N 28829 28829	N	28829	28829
adj. $R^2$ 0.225 0.226	adj. $R^2$	0.225	0.226
BIC -33151 -33161	BIC	-33151	-33161

Standard errors clustered at the regional level

Table S5. Robustness check of the main regression results having weighted ERA5 climate data by population rather than by area. Results are consistent with those based on area weighting. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ - seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta \bar{T}$  - first difference of annual mean temperature; P - total annual precipitation.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

Functional form of				
Region-specific time trends:	Linear	Quadratic	Linear	Quadratic
$\widetilde{T}_{r,y}$	0572***	0473***	12***	145***
	(.0046)	(.0045)	(.015)	(.015)
$\hat{T}_r. ilde{T}_{r,y}$			.00197***	.00309***
			(.00052)	(.00053)
$\delta ar{T}_{r,y}$	.00161	.0045*	.00292	.00674**
-	(.0021)	(.0022)	(.0021)	(.0022)
$ar{T}_r.\deltaar{T}_{r,y}$	000926***	000999***	00103***	00116***
	(.00021)	(.00022)	(.00021)	(.00022)
$\delta \bar{T}_{r,y-1}$	.0000768	.00344	.00124	.00545*
	(.0021)	(.0022)	(.0021)	(.0022)
$ar{T}_r.\deltaar{T}_{r,y-1}$	000828***	000987***	000896***	0011***
	(.0002)	(.00021)	(.0002)	(.00021)
$P_{r,y}$	.000543***	.000434**	.000534***	.000421**
	(.00014)	(.00014)	(.00014)	(.00014)
N	28874	28874	28874	28874
adj. $\mathbb{R}^2$	0.228	0.235	0.229	0.236
BIC	-34907	-37102	-34916	-37140

Standard errors clustered at the regional level

Table S6. Robustness check of the main regression results including region-specific time trends to account for possible trends in economic and climate variables. The effects of day-to-day temperature variability and its interaction with the seasonal temperature difference are consistent and significant under the inclusion of both linear and quadratic region-specific time trends. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ - seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta \bar{T}$  - first difference of annual mean temperature; P - total annual precipitation.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

Excluding:	USA	USA	China	China	Maj. Oil Prod.	Maj. Oil Prod.
$\tilde{T}_{r,y}$	0607***	136***	0572***	114***	0472***	184***
	(.005)	(.015)	(.0047)	(.015)	(.0056)	(.018)
$\hat{T}_r.\tilde{T}_{r,y}$		.00238***		.0018***		.00473***
		(.00051)		(.00051)		(.00065)
$\delta ar{T}_{r,y}$	.0012	.00265	.000859	.00203	.00647*	.00896**
	(.0021)	(.0022)	(.0021)	(.0021)	(.0028)	(.0029)
$ar{T}_r.\deltaar{T}_{r,y}$	000994***	00111***	000893***	000983***	00114***	0013***
	(.00021)	(.00021)	(.0002)	(.00021)	(.00026)	(.00027)
$\delta \bar{T}_{r,y-1}$	000929	.000412	00165	000628	.00412	.00612*
	(.0022)	(.0022)	(.0021)	(.0022)	(.0029)	(.0029)
$\bar{T}_r.\delta \bar{T}_{r,y-1}$	000769***	000848***	00066***	00072***	00121***	00132***
	(.0002)	(.0002)	(.0002)	(.0002)	(.00025)	(.00025)
$P_{r,y}$	.000257	.000247	.000403**	.000394**	.000274	.000258
, ,	(.00014)	(.00014)	(.00013)	(.00013)	(.00014)	(.00014)
N	27206	27206	27818	27818	23989	23989
adj. $R^2$	0.235	0.235	0.228	0.228	0.220	0.222
BIC	-30138	-30154	-31641	-31646	-26341	-26399

Standard errors clustered at the regional level

Table S7. Robustness check of the main regression results under the exclusion of the U.S., China, or the top ten oil producing countries (as documented by the U.S. Energy Information Administration, (3)). The results of the main specification are consistent with those in which these countries are removed, precluding the possibility that the observed effect is driven by the response of a particularly dominant country or industry. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ - seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta \bar{T}$  - first difference of annual mean temperature; P - total annual precipitation.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

#### Section 5. Testing and accounting for spatial dependence.

The intuition of Tobler's first law of Geography (that "everything is related to everything else, but nearer things are more related than distant things") suggests that the climate and economic variables considered here are likely to exhibit correlation across both space and time. Such correlations would limit the independence of our observations, leading to both underestimation of standard errors and over-confidence in significance tests. Here, we provide two separate tests for the spatial dependence of both our climate and economic variables, before explaining how we account for such dependence through the error clustering specifications of our statistical tests.

*Tests for spatial dependence: inter-regional pair-wise correlations.* 

First, we calculate pair-wise correlations between regional time-series of climate and economic variables as a function of inter-regional distance. We consider time-series of day-to-day temperature variability, detrended annual mean temperature, and regional growth rates. Climate variables are highly correlated over short distances, and these correlations exhibit near-linear decays to zero with inter-regional distance (Fig. S2 a-b, d-e). The decay-length of approximately 2,500km is in good agreement with previous assessments of the extent of regional weather systems as inferred from the decay of synchronization in extreme rainfall events (4).

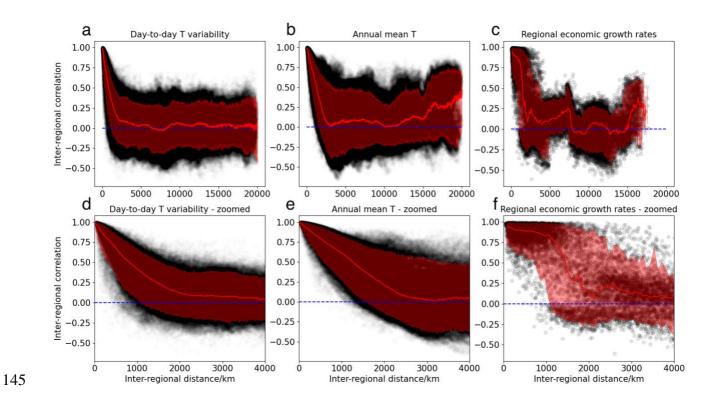


Fig S1. Inter-regional pair-wise correlation coefficients of day-to-day temperature

variability (a, d), detrended annual mean temperature (b, e) and regional economic growth rates (c, f) as a function of inter-regional distance. Individual data points are shown scattered (black, with alpha=0.01 for a, b, d & e and alpha=0.1 for c & f). The median and 5th and 95th percentiles shown for each 20km (100km for c & f) bin are shown in red. Panels a-c are equivalent to d-f, but the horizontal scale is exaggerated in d-f to emphasise the distance at which correlations decay to zero.

Economic growth rates exhibit similar spatial behaviour, Fig. S2 c & f. High correlations at short-distances decay to zero by an inter-regional distance of approximately 2,000km. Fewer data are available for economic growth than for climate variables and the data availability is limited further in this case by the constraint of constructing a balanced panel from our original un-balanced economic dataset. The balanced dataset contains data for only 275 regions across 8 countries, each with 29 years. This leads to greater noise and clear discontinuities (such as at

7,500km) due to the lack of certain global regions. However, the decay of inter-regional correlations of growth rates with inter-regional distance is still clear.

163 Tests for spatial dependence: spatial-lag models.

As a second test of the spatial-autocorrelation of climate and economic variables, we run spatial-lag models. Day-to-day temperature variability,  $\tilde{T}_{i,y}$ , detrended annual mean temperature,  $\bar{T}_{i,y}$ , and growth rates,  $g_{i,y}$ , are assessed using the following regression models:

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$$\tilde{T}_{i,y} = \alpha \sum_{j=1}^{N} W_{i,j} \, \tilde{T}_{i,j} + \mu_r + \epsilon_{i,y}$$
 (2)

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$$\overline{T}_{i,y} = \alpha \sum_{j=1}^{N} W_{i,j} \overline{T}_{j,y} + \mu_r + \epsilon_{i,y}$$
 (3)

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$$g_{i,y} = \alpha \sum_{j=1}^{N} W_{i,j} g_{j,y} + \mu_r + \epsilon_{i,y}$$
 (4)

in which  $W_{i,j}$  is the element of the spatial-weighting matrix relating the  $i^{th}$  region to the  $j^{th}$ . N is the total number of regions and  $\mu_r$  is a regional fixed effect. We use spatial-weighting matrices which assign equal weight to all regions j to which the distance from region i falls within a certain range. We fit separate models in which these ranges increase successively so as to assess the extent of spatial autocorrelation at different inter-regional distances (these ranges are shown by the horizontal extent of the blue bars in Fig. S3). Smaller ranges are considered in the case of economic growth because the lesser amount of economic data requires a sparser spatial-weighting matrix for the model to converge. The magnitude and standard error of  $\alpha$  (as defined in the above equations) is used to infer the extent of spatial autocorrelation at a given inter-regional distance. These values are shown in Fig. S3.

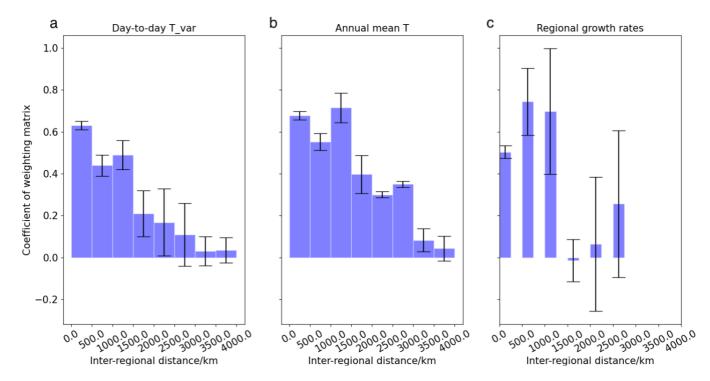


Fig. S2. The magnitude of the coefficient of the spatial-weighting matrix (α in equations 2-4) defined over different inter-regional distances is used to assess the spatial autocorrelation of climate variables (a-b) and regional growth rates (c). The horizontal extent of the bars indicates the range of inter-regional distances which are considered in each spatial-weighting matrix. The error-bars indicate the uncertainty in the estimated magnitude of spatial-autocorrelation.

This analysis suggests that the spatial autocorrelation of climate variables decays to zero between 2,000-3,000km and that the spatial autocorrelation of economic growth decays to zero by 1,500km. This is in good agreement with the conclusions obtained using pair-wise correlations of regional climate and economic variables.

Accounting for spatial dependence

To account for the observed spatial dependence of both climate and economic variables one should cluster standard errors into groups within which these variables are highly correlated. The climate and economic variables no longer exhibit correlation at distances greater than 2,500km. This distance is greater than the extent of the smallest countries (e.g. Belgium: ~250km), but smaller than the maximum extent of the largest countries (Russia ~9,000km, USA ~4,500km, China ~ 4,800km), and is even comparable to the extent of some of the largest sub-national regions (Sakha Republic, Russia ~2,500km). Clustering errors at the regional level may therefore lead to under-conservative estimations, whereas clustering at the national level may lead to over-conservative estimates. As such, we present standard errors clustered at the sub-national level in the main manuscript (in keeping with previous studies of the effect of climate variables on sub-national growth rates (2, 5)) and provide additional tests in which errors are clustered at the national level, Table S8. The effect of day-to-day temperature variability remains statistically significant when errors are clustered at either level. The effect also remains significant when clustering errors by both region and year, or country and year simultaneously.

Standard errors clustered by:	Country	Country	Region-year	Region-year	Country-year	Country-year
$ ilde{ ilde{T}}_{r,y}$	0541**	115**	0541*	115	0541*	115*
	(.018)	(.042)	(.025)	(.063)	(.021)	(.056)
$\hat{T}_r.\tilde{T}_{r,y}$		.00192		.00192		.00192
		(.0016)		(.0022)		(.0019)
$\delta ar{T}_{r,y}$	.000956	.00217	.000956	.00217	.000956	.00217
	(.0053)	(.0057)	(.013)	(.013)	(.0099)	(.01)
$\bar{T}_r.\delta \bar{T}_{r,y}$	00093	00102	00093	00102	00093	00102
	(.00055)	(.00056)	(.00093)	(.00091)	(.00081)	(.00081)
$\delta \bar{T}_{r,y-1}$	00137	000307	00137	000307	00137	000307
	(.0062)	(.0066)	(.0095)	(.0094)	(.0079)	(.0082)
$\bar{T}_r.\delta \bar{T}_{r,y-1}$	000683	000746	000683	000746	000683	000746
	(.00057)	(.00059)	(.0009)	(.00088)	(.00084)	(.00084)
$P_{r,y}$	.000264	.000257	.000264	.000257	.000264	.000257
. , ,	(.00049)	(.0005)	(.00058)	(.00058)	(.00057)	(.00057)
N	28872	28872	28872	28872	28872	28872
adj. $R^2$	0.226	0.226	0.226	0.226	0.226	0.226
BIC	-33221	-33229	-33221	-33229	-33221	-33229

Table S8. Robustness check of the main regression results under different error clustering schemes to account for different spatial and temporal correlation of climate and economic variables. Standard errors are clustered at the country, region-year and country-year level. Under even the most conservative error clustering scheme, the effects of day-to-day temperature variability remain significant. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ - seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta \bar{T}$  - first difference of annual mean temperature; P - total annual precipitation.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

#### Section 6. Partitioning of the data by per-capita income.

Partitioned by:	Above median national income	Below median national income	Above median regional income	Below median regional income
$\tilde{T}_{r,y}$	137***	113***	0897***	139***
	(.019)	(.022)	(.017)	(.025)
$\hat{T}_r.\tilde{T}_{r,y}$	.0036***	.000959	.00121*	.00203*
	(.00061)	(.00068)	(.00057)	(.00081)
$\delta ar{T}_{r,y}$	.0111***	00495	.00762**	0108**
	(.0028)	(.0032)	(.0026)	(.0042)
$ar{T}_r.\deltaar{T}_{r,y}$	00168***	00101**	00155***	000445
070	(.0003)	(.00031)	(.00026)	(.00036)
$\delta \bar{T}_{r,y-1}$	.0107***	0083*	.00832**	0153***
	(.003)	(.0036)	(.0027)	(.0042)
$\bar{T}_r.\delta \bar{T}_{r,y-1}$	00137***	.0000173	0015***	.00028
	(.00032)	(.00028)	(.00027)	(.00032)
$P_{r,y}$	000476**	.000629***	000662***	.000705***
1.5.	(.00018)	(.00019)	(.00017)	(.0002)
N	12803	16069	15995	12876
adj. $\mathbb{R}^2$	0.323	0.239	0.301	0.213
BIC	-21689	-15004	-23932	-11586

Standard errors in parentheses

Standard errors clustered at the regional level

\* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

**Table S9.** Regression results having partitioned data based on above- and below-median regional and national income per capita, as defined in ED Fig 2. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability;  $\hat{T}$ - seasonal temperature difference;  $\bar{T}$  - annual mean temperature;  $\delta \bar{T}$  - first difference of annual mean temperature;

*P - total annual precipitation.* 

- Section 7. Estimating the long-term impact of the effect of day-to-day temperature
- variability with distributed lag-models.

248

- 249 A distributed lag model is used to investigate the long run economic impact of day-to-day
- 250 temperature variability:

251

252 
$$g_{r,v} = \alpha_0 \tilde{T}_{r,v} + \sum_{i=1}^{L} \alpha_i \tilde{T}_{r,v-i} + \mu_r + \eta_v + \epsilon_{r,v}$$
 (5)

253

- 254  $g_{r,y}$  is the first difference in the logarithm of gross regional product and  $\tilde{T}_{r,y}$  the day-to-day
- temperature variability. L is the number of lags included in the model,  $\mu_r$  and  $\eta_y$  the regional
- and yearly fixed effects, and  $\varepsilon_{r,y}$  is the region-year error.

257

- 258 The long run propensity is used to estimate the net effect of all the years of lagged data,
- 259 following Chapter 10 of Econ 311: Examining Economic Data and Models from the
- University of Miami Department of Economics (6). Let, the long run propensity,  $\theta$ , be
- defined as the sum of the impacts of each lagged temperature variability variable:

262

$$263 \theta = \sum_{i=0}^{L} \alpha_i. (6)$$

264

265 Substituting into equation 5, one can write;

266

267 
$$g_{r,y} = (\theta - \sum_{i=1}^{L} \alpha_i) \tilde{T}_{r,y} + \sum_{i=1}^{L} \alpha_i \tilde{T}_{r,y-i} + \mu_r + \eta_y + \epsilon_{r,y}$$
 (7)

- The long run propensity,  $\theta$ , may then be estimated from a regression based on the following
- 270 equation:

272 
$$g_{r,y} = \theta \tilde{T}_{r,y} + \sum_{i=1}^{L} \alpha_i (\tilde{T}_{r,y-i} - \tilde{T}_{r,y}) + \mu_r + \eta_y + \epsilon_{r,y}$$
 (8)

in which transformed variables  $(\tilde{T}_{r,y-i} - \tilde{T}_{r,y})$  are used in addition to  $\tilde{T}_{r,y}$  as the independent variables. This allows estimates of the error and significance of the long run propensity,  $\theta$ , to be made (5). Estimates of  $\alpha_i$  are shown below in Table S10 and estimates of  $\theta$  in Fig. S6.

No. lagged variables included:	0	1	2	3	4	5
$ ilde{T}_{r,y}$	0582***	0584**	0574**	054**	0541**	0552***
	(.017)	(.017)	(.017)	(.017)	(.016)	(.016)
$ ilde{T}_{r,y-1}$		.00408	.00357	.00236	.00222	.00597
		(.0095)	(.0091)	(.0092)	(.0093)	(.0099)
$\tilde{T}_{r,y-2}$			00754	00804	00879	00844
			(.019)	(.018)	(.018)	(.018)
$ ilde{T}_{r,y-3}$				.0354*	.0343*	.0324*
				(.014)	(.014)	(.012)
$ ilde{T}_{r,y-4}$					.00134	.000623
					(.012)	(.012)
$ ilde{T}_{r,y-5}$						.00667
						(.022)
N	27567	27567	27567	27567	27567	27567
adj. $R^2$	0.219	0.220	0.220	0.222	0.223	0.226
BIC	-31917	-31893	-31887	-31930	-31946	-32022

Standard errors in parentheses.

Standard errors clustered at the national level.

Lagged estimates of other climate variables are included, but not shown.

**Table S10.** Point estimates of the delayed effect of day-to-day temperature variability on regional growth rates from distributed lag models including up to 5 lagged variables, as described in equation 5 of the supplementary methods. Evidence of a partial-recovery in the third year is observed in the growth dynamics. Further lagged variables are not considered since no significant effect is noted in the fourth or fifth year. Climate variables are denoted as follows:  $\tilde{T}$  - day-to-day temperature variability.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

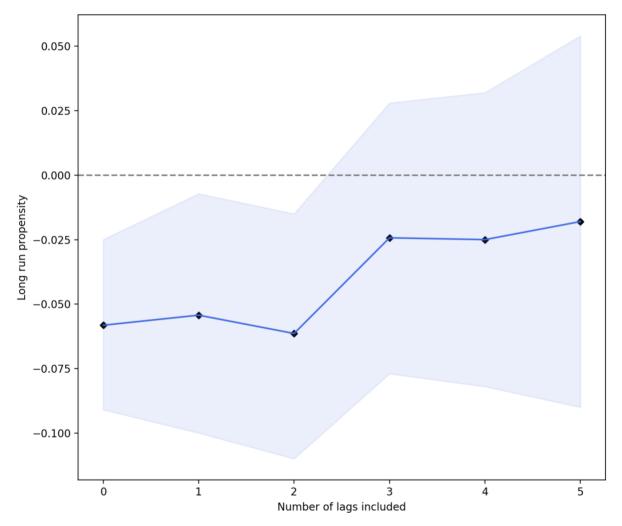


Fig S3. Investigating the persistence of the impact of an increase in day-to-day temperature variability on regional growth rates with distributed lag models, including up to 5 years of lags. The long run propensity, θ, as defined in equation 6 is shown with 95% confidence intervals. These long term impacts are negative and significant up to and including two years of lagged data. A partial recovery is noted in the third year, consistent with the point estimates of the effects of the lagged variables in Table S10, beyond which estimates of the long run propensity are still negative, but statistically less significant.

## Section 8. Summary statistics of regression variables.

	Symbol	Mean	SD	Min.	Max.	$SD_b$	$SD_w$
Per-capita growth rate	$g_{r,y}$	0.0684	0.161	-2.44	2.30	0.0623	0.156
Day-to-day temperature variability (°C)	$ ilde{T}_{r,y}$	2.39	1.19	0.312	6.39	1.16	0.206
Historical-average seasonal temperature difference (℃)	$\hat{T}_r$	21.7	12.26	2.41	54.8	12.15	0
Annual-average temperature (°C)	$\bar{T}_{r,y}$	14.6	7.91	-13.6	29.8	7.81	0.661
First difference of annual-average temperature (°C)	$\delta ar{T}_{r,y}$	0.0378	0.725	-4.13	3.80	0.0227	0.725
Degree days > 25 ℃	$\check{T}_{>25,r,y}$	167	291	0	1972	285	54
Degree days > 30 ℃	$\check{T}_{>30,r,y}$	13.1	58.0	0	901	58.1	13.2
Annual total precipitation (mm)	$P_{r,y}$	40.5	30.57	0.00248	607	29.2	7.15

 $SD_{b/w}$  denotes the between and within region standard deviation. Within region changes are exploited in panel regression models.

**Table S11.** Summary statistics of the variables used in the regression models. Cross-sectional ('between') standard deviations are shown in the column ' $SD_b$ ' and within-region standard deviations are shown in the column ' $SD_w$ '.

#### 318 **References**

- 319 1. Schlenker, W. & Roberts, M.J. Nonlinear temperature effects indicate severe damages to
- 320 U.S. crop yields under climate change. *Proc. Nat. Acad. Sci.* **106** (2009).
- 321 2. Burke, M., Hsiang, S. & Miguel, E. Global non-linear effect of temperature on economic
- 322 production. *Nature* **527**, 235–239 (2015).
- 323 3. Wikipedia, List of countries by oil production
- 324 (https://en.wikipedia.org/wiki/List\_of\_countries\_by\_oil\_production) (2020). Accessed
- 325 01.02.2020.
- 4. Boers, N., Goswami, B., Rheinwalt, A. et al. Complex networks reveal global pattern of
- extreme-rainfall teleconnections. *Nature* **566**, 373–377 (2019).
- 328 5. Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production:
- 329 Evidence from a global panel of regions. Journal of Environmental Economics and
- 330 *Management.* 102360, ISSN 0095-0696, (2020).
- 6. J Li, Econ 311: Examining Economic Data and Models
- 332 (http://www.fsb.miamioh.edu/lij14/311\_2014f\_note\_ch1011.pdf) Chapters 10 and 11. (2020).