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The effects of weather conditions on economic growth: Evidence from global subnational economic output and income

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Abstract: The effects of weather on economic growth continue to be debated. Previous studies economic output, but income better reflects living standards; income and output are the same at the national level, but differ at a finer spatial scale. This study assembles a unique database comprising global subnational GDP and GDI per capita data from over 1600 regions across more than 180 countries and analyzes the effects of weather conditions on economic growth. There is a significant negative effect of annual mean temperature on income, while weather conditions do not significantly affect output per capita growth. We also find significant interaction effects between weather and weather variability, as well as different adaptations between rich and poor regions. The omission of data from a large number of poor and hot countries in previous subnational research has led to an underestimation of the economic impact of weather shocks. Focusing on output rather than income, previous studies also appear to have underestimated the impact of climate change.

JEL codes: O44, Q54

Key words: climate change, climate damages, gross domestic product, gross domestic income, panel regression

The effects of weather conditions on economic growth: Evidence from global subnational economic output and income

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Significance Statement

Previous papers studied the impact of weather on economic output. Living standards, however, depend on income rather than output. A substantial share of economic output is generated in inhospitable places far from where people live. Using a new, global income database at the subnational level, we show that weather has a larger effect on income than on output. The impact of climate change is thus larger than previously thought.

Main Text

Introduction

Estimates of the effects of weather conditions on economic growth are important for the social cost of carbon (1-3), the inequitable impact of climate change (4-6), and the physical risks to financial institutions (7-9). Early estimates focused on national impacts and thus had difficulty disentangling the effect of climate from the effects on institutions (10-12). Later studies used subnational records (states, provinces, etc.) to partially overcome this and, as nationally averaged rainfall is a relatively meaningless concept, to document the impact of precipitation on economic growth (13, 14). One limitation of such studies is that they focus on economic output to measure economic activity, rather than income.

At the national level, ignoring statistical differences, economic output, Gross Domestic Product (GDP), and economic income, Gross Domestic Income (GDI), are the same as the value of goods and services produced equals the income earned from producing those goods and services. However, this is not true at the subnational levels. The greatest discrepancies are in business districts in inner cities (high output, low income), in retirement enclaves (high income, low output) and in mines, and oil and gas fields (high output, low income). Output is recorded at the location of the economic activity, income at the place of residence. The difference between output and income is correlated with climate. For instance, the exploitation of oil and gas in the harsh climates of Siberia and the Arabian desert yields high output, but hardly anyone lives there and certainly not the owners (*SI appendix*, Fig. S3c). Growth rates also differ (Fig. 1).

[Figure 1 about here]

However, because output data is easier to collect for subnational regions, previous studies use output as the measure of economic activity (15-17), resulting in a potentially biased estimation of the impact of weather on people's living standards (18). In addition, previous subnational studies (13-14) have a large number of missing observations in Africa, which may bias the results. To address these issues, this study established a unique database comprising global subnational GDP per capita and GDI per capita data from over 1600 regions across more than 180 countries combined with temperature and precipitation data. We estimate the effects of weather conditions on both output and income growth. Weather is measured by the annual mean temperature, total precipitation, the change in temperature and precipitation, and the month-to-month variability of temperature and precipitation. We also study the interactions between weather conditions and heterogeneity between different regions.

Main findings

Weather, weather change, and weather variability have no significant effect on output per capita growth (*SI Appendix*, Table S4, column 6), consistent with some prior research (12, 13).

However, we find significant effects of temperature and precipitation on income per capita growth, with optimum temperatures and precipitation levels of 10°C and 250 cm, respectively (Figure 2, *SI Appendix*, Table S4, column 3)¹. The current average regional mean temperature (19°C) exceeds the optimum temperature. If the annual mean temperature further increases by 1°C, income per capita growth is expected to decrease by 1.4%. In contrast, the current average regional total precipitation (120 cm) is well below the optimum precipitation, with a 1 cm increase in precipitation resulting in an increase of 2.1% in GDI per capita growth. However, the projected change in precipitation is highly heterogeneous across the world. While some regions may experience a substantial increase in precipitation, others may experience a decrease. Therefore, the results of our analysis regarding the averaged regional total precipitation should be interpreted with caution.

[Figure 2 about here]

Interaction effects

The interactions between temperature and temperature variability, as well as precipitation and precipitation variability have a statistically significant effect on income per capita growth, but cross-variabilities do not (*SI Appendix*, Table S5). Specifically, the effect of temperature on income per capita growth remains unchanged with changes in temperature variability (Figure 3b), but the temperature variability is expected to reduce its negative effect on income per capita growth with increasing temperature (Figure 3c). Particularly in hot regions (30°C), the rise of temperature variability leads to an increase in income per capita growth rather than a reduction. Precipitation and precipitation variability show a positive synergistic effect on income per capita growth, which becomes more pronounced with an increase in precipitation and precipitation variability (Figure 3e-f). These findings suggest that the effective adaptation that large weather variability in harsh climates does not exacerbate the negative effects on the economy. The interaction effects of weather conditions on output are almost the same as those on income but with wider confidence intervals (*SI Appendix*, Figure S4).

[Figure 3 about here]

Heterogeneity analysis

Economic income in Poor regions is more sensitive to the annual mean temperature than rich regions (Figure 4a; *SI Appendix*, Table S6, columns 1 and 2). Specifically, a 1°C increase in temperature leads to an additional reduction of 0.09% in income per capita growth in poor

¹ Post-estimation tests reveal the presence of first-order serial correlation within our fixed-effects panel model (*SI Appendix*, Table S10). Nevertheless, the autoregressive coefficient of our regression model is 0.19, indicating a minimal effect of serial correlation. We also try to include the lagged dependent variable in the model, but the results suggest that this approach fails to eliminate serial correlation and instead further produces second-order correlation. Therefore, we still rely on the results of our main regression model. Although it may produce an unreliable standard error, the estimation coefficient is consistent, thus, our main findings that the weather has a more significant effect on income than output remains robust.

regions compared to 0.07% in rich regions. However, the income per capita growth in the poor regions shows lower sensitivity to temperature change and variability, as well as all precipitation conditions (Figure 4a-b). These results suggest the different adaptations of rich and poor regions to different weather conditions. In particular, the effect of temperature variability in poor regions reverses from negative to positive with the temperature increase, while it remains negative in rich regions (Figure 4c-b). The effect of precipitation variability shows a similar trend that the positive effect of precipitation variability in poor regions is more pronounced with the increase of precipitation compared to the rich regions (Figure 4e-f).

In terms of economic output, we find that poor regions are more sensitive to all effects of temperature conditions and the effect of precipitation (*SI Appendix*, Figure S5a-b). In addition, although the increase in temperature mitigates the negative effect of temperature variability in rich and poor regions, this effect is more pronounced in rich regions than in poor regions (*SI Appendix*, Figure S5c-f). These results suggest that the economic output in poor regions is more sensitive to weather conditions than their economic income. Studies based on economic output advocate that poor regions are expected to have higher economic damage with the increase of climate change. However, when considering the economic income, the effects of weather conditions on poor regions may not be as bad as people expected.

[Figure 4 about here]

Robustness Checks

We compared our main findings with those derived from two widely used output databases: the World Bank database (11) and the Kalkuhl database (13). Since the World Bank data is at the country-level, we aggregated the subnational data to the country-level and focused on shared countries with the same time series to ensure the comparability of results. We find that our results are similar to those based on the World Bank database (*SI Appendix*, Table S15, columns 1 and 2), suggesting the reliability of our GDP per capita data. However, when we use the Kalkuhl database, the statistical significance of annual mean temperature and annual total precipitation is substantially lower than the results based on the other two databases (*SI Appendix*, Table S15, columns 3). In addition, when we subset our database with the same countries as the Kalkuhl database (subnational level), the coefficients of annual mean temperature and annual total precipitation are also lower than those based on whole observations (*SI Appendix*, Table S16, columns 1 and 3). This may be because the Kalkuhl database only covers 77 countries and omits vast majority of countries in Africa, Southeast Asia and Central America, which are regions that experience higher temperature, precipitation and poverty. Our research shows that these regions' economic output is more sensitive to the weather. Omitting these regions, therefore, may underestimate the effects of temperature and precipitation on economic output growth. We also replaced our weather database from CRU to

ERA5 and used the weighted anomaly standardized precipitation. All of these results are consistent with our main results.

Discussion

The effect of weather conditions on the economy provides valuable insight into the damage caused by climate change. However, empirical findings in the literature are often contradictory. In addition, previous literature uses economic output as the measure of economic activity, even though income better reflects living standards.

Using a global subnational economic database comprising over 1600 regions across more than 180 countries, our study finds that weather conditions have no growth effects on economic output per capita. However, we find strong evidence that the changes in annual mean temperature and annual total precipitation affect income per capita growth. This finding suggests that using the output to measure economic activity will underestimate the damage of weather conditions.

There are significant interactions between temperature and temperature variability, and between precipitation and precipitation variability. The increase of temperature and precipitation is expected to have a positive effect on the relationship between weather variability and economic growth. The negative effects of adverse weather conditions on poor regions may not be as high as in some previous studies. Although the change in annual mean temperature has more negative effects on poor regions, they are less sensitive to the annual change and monthly variability of temperature. In addition, the annual changes and monthly variability of precipitation are expected to have positive effects on poor regions.

Overall, there are three contributions of this study. Despite this progress, further analysis is required to reveal the mechanisms behind these effects. For instance, more research is needed to explain why annual changes and monthly variability in precipitation have positive effects on poor regions. As a first contribution, this study fills the research gap on the effects of weather conditions on income growth, highlighting the negative effects of weather conditions on people's living standards. Second, using global economic subnational data, this study provides a complete picture of the effects of weather conditions on economic growth. Studies that omitted tropical counties may underestimate the effects of weather conditions on economic growth. Third, this study provides more evidence of different adaptations of regions to different weather conditions

Materials and Methods

Data Source

The temperature and precipitation data used in this study were derived from the CRU database, which provides a high-resolution ($0.5^{\circ}\times 0.5^{\circ}$ resolution), monthly grid of land-based observations going back to 1901. The CRU database has implemented a degree of

homogenization and revealed no substantial discrepancies with other climate databases. It has been widely used throughout the literature, allowing us to compare our results with other research findings (13, 19, 20). We also conducted a robustness check by using the reanalysis data from the ERA5 dataset.

The gross domestic income per capita (2011 PPP) used in this study is obtained from the Global Data Lab (<https://globaldatalab.org/shdi/table/lgnic/>). For high-income countries and some middle-income countries, subnational GDI per capita was obtained based on data derived from national statistical offices and Eurostat. For most low- and middle-income countries, subnational GDI per capita data were obtained based on the International Wealth Index (IWI). The IWI is a comparable asset-based wealth index constructed on data from 165 surveys held over a period of 15 years and over 2.1 million households in 97 low- and middle-income countries. It measures household wealth on the basis of information from asset ownership, housing quality, and access to public services. Based on the IWI score, the subnational GDI per capita data were estimated using a regression model between national GDI per capita and national IWI score and further improved by scaling them based on national GDI per capita values (*SI Appendix*, Table S1).

The gross domestic product per capita (2011 PPP) is obtained from Kummu, Taka and Guillaume (21). The database was initially collected by Gennaioli, La Porta, Lopez-de-Silanes and Shleifer (15) based on various government statistical agencies. It includes GDP data from 1569 subnational regions across 110 countries between 1990 and 2010 and covers most countries in Central and South Africa, which is generally omitted by other GDP databases. Kummu, Taka and Guillaume (21) extended the time series of this database from 2010 to 2015 and filled in the missing countries based on national GDP data. Overall, the database extended by Kummu, Taka and Guillaume (21) covers the global subnational GDP data with no missing data areas and converts the data to constant international US dollars from 2005 to 2011, which is consistent with the gross domestic income data used in this study (*SI Appendix*, Table S1).

Two other socioeconomic variables, mean years of schooling, and population, are included in our regression model as control variables since they are also regarded to significantly impact economic growth. These data are also collected from the Global Data Lab (Access data: 22 November 2022).

Weather variability

Extreme weather events have been found to have a negative impact on human psychology, water supply, and agricultural production that further systematically increase the risk of conflict, violence, or political instability (22-27). However, most recent macroeconomic studies have focused on the level effects of weather conditions on economic growth while neglecting to identify the effects of extreme weather events, which have been found to have pronounced effects on economic activity as well (14, 28). This study therefore uses the Anomaly Standardized Precipitation (ASP) and Anomaly Standardized Temperature (AST) index as measures to identify the effects of weather variability. The ASP and AST are defined by an

annual sum of monthly precipitation or temperature anomalies from their climatological means:

$$S_{r,y} = \sum_{m=1}^{12} \frac{T_{r,m,y} - \bar{T}_{r,m}}{\sigma_{r,m}} \quad (1)$$

Where $S_{r,y}$ is the anomaly standardized precipitation/temperature in region r and year y . $T_{r,m,y}$ is the monthly total precipitation or monthly mean temperature. $\sigma_{r,m}$ is the historical standard deviation, for 25 years, of monthly total precipitation or monthly mean temperature in that region. The annual $S_{r,y}$ is further standardized by its standard deviation over 25 years to obtain a measure of the relative severity of annual precipitation/temperature variability (see *SI Appendix* for the origins of the method):

$$AST_{r,y} = S_{r,y} / \sigma_{S_r} \quad (2)$$

Empirical model

We use the fixed-effects regression model to identify the effects of weather conditions on economic growth since this model can strengthen the causal effects identification by controlling for both unobserved time-invariant and time-varying influences, such as the influences from geographical location and institutional differences (10-14). Apart from the effects of weather variability, we also consider the effects of weather and weather change in our regression model. In particular, the effect of weather is measured by $\beta T + \beta T^2$. It captures the nonlinear effect of the prevailing weather conditions on transitory and long-run economic growth. The difference between transitory and long-run growth effects is that the transitory effects imply economic growth can eventually reverse itself as the weather conditions return to their prior state. However, the long-run growth effects are not reversed, and a failure to innovate in one period leaves the country permanently further behind (10). (We additionally conducted a long-difference regression to clarify the specific effects revealed by the quadratic function of temperature and precipitation. See *SI Appendix*, Table S8). The effect of weather change is measured by $\beta \Delta T + \beta \Delta T \cdot T$ and captures a sudden change in weather conditions on contemporaneous growth rates. If there is no change between the two years, this effect disappears. The interaction term $\beta \Delta T \cdot T$ is to capture the moderating effects of the prevailing weather conditions T on ΔT . The regression model is thus defined as follows:

$$g_{i,t} = \beta_1 \Delta T_{i,t} + \beta_2 \Delta T_{i,t} \cdot T_{i,t} + \beta_3 T_{i,t} + \beta_4 T_{i,t}^2 + \beta_5 AST_{i,t} + \beta_6 AST_{i,t}^2 + X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

where $g_{i,t}$ is the GDP per capita or GDP per capita growth rate within year t in region i . $T_{i,t}$ is a vector of annual mean temperature levels (T , in °C) and annual mean precipitation values (P , in m). Coefficients β_1 and β_2 capture the effect of weather change on economic growth. Coefficients β_3 and β_4 represent the effect of weather on economic growth. β_5 and β_6 capture the effect of weather variability on economic growth. α_i and δ_t are region and year dummies to consider region and year fixed effects, respectively. $X_{i,t}$ are control variables, including the mean year of schooling and population. $\varepsilon_{i,t}$ is the error term.

In addition, a gross of the literature shows that the increase in global temperature results in an observable increase in both the intensity and frequency of anomalous events (29-31). In addition, the effect of the global mean temperature on such events is nonlinear, with a minor increase in mean temperature leading to a substantial escalation in the frequency and

intensity of anomalous events (32-34). In this case, the increase in temperature and precipitation (weather effect) is expected to intensify the effects of change in anomalous events (variability effect) on economic growth and vice versa. To assess the interaction effects between the level and variability of weather conditions, we further included the interaction term of them in equation (3) as follows:

$$g_{i,t} = \beta_1 \Delta T_{i,t} + \beta_2 \Delta T_{i,t} \cdot T_{i,t} + \beta_3 T_{i,t} + \beta_4 T_{i,t}^2 + \beta_5 AST_{i,t} + \beta_6 AST_{i,t}^2 + \gamma_1 L_{i,t} \cdot V_{i,t} + \gamma_2 L_{i,t}^2 \cdot V_{i,t} + \gamma_3 L \cdot V_{i,t}^2 + \gamma_4 L_{i,t}^2 \cdot V_{i,t}^2 + X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (4)$$

Where $L_{i,t}$ is the annual mean temperature level or annual mean precipitation value within year t in region i . $V_{i,t}$ is the AST or ASP.

Given the limited adaptive capacity and a higher share of agriculture in economic activity, poor regions are regarded to be more vulnerable to climate change than rich regions (35). To assess the heterogeneity of the level and variability effects, as well as the interaction effects of climate conditions on economic growth, we reassess our results separately for subnations with above- and below- median subnational GDI per capita or GDP per capita. The regression model for heterogeneity of level and variability effects reads:

$$g_{i,t} = \beta_1 D \cdot \Delta T_{i,t} + \beta_2 D \cdot \Delta T_{i,t} \cdot T_{i,t} + \beta_3 D \cdot T_{i,t} + \beta_4 D \cdot T_{i,t}^2 + \beta_5 D \cdot AST_{i,t} + \beta_6 D \cdot AST_{i,t}^2 + X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (5)$$

The regression model for heterogeneity of interaction effects reads:

$$g_{i,t} = \beta_1 \Delta T_{i,t} + \beta_2 \Delta T_{i,t} \cdot T_{i,t} + \beta_3 T_{i,t} + \beta_4 T_{i,t}^2 + \beta_5 AST_{i,t} + \beta_6 AST_{i,t}^2 + \gamma_1 D \cdot L_{i,t} \cdot V_{i,t} + \gamma_2 D \cdot L_{i,t}^2 \cdot V_{i,t} + \gamma_3 D \cdot L \cdot V_{i,t}^2 + \gamma_4 D \cdot L_{i,t}^2 \cdot V_{i,t}^2 + X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (6)$$

Where D is a binary variable that equals 1 when GDI per capita or GDP per capita is below the median and 0 otherwise.

Considering that the regions' adaptation to climate change may not change rapidly over a short period, we took the five-year average of GDI per capita and GDP per capita for each region and determined their median values separately. The regions with averaged GDI per capita or GDP per capita above the median are considered to be rich, while those below the median are considered to be poor.

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Figures and Tables

Diference Between Average GDIpc and GDPpc Growth Rates from 1990 to 2015

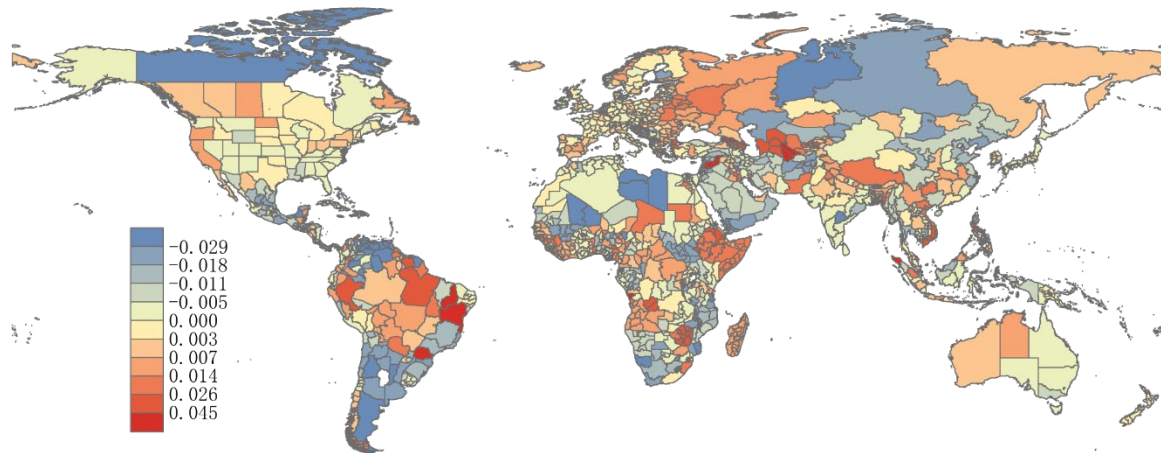


Figure 1. The difference between average GDI and GDP per capita growth rates from 1990 to 2015.

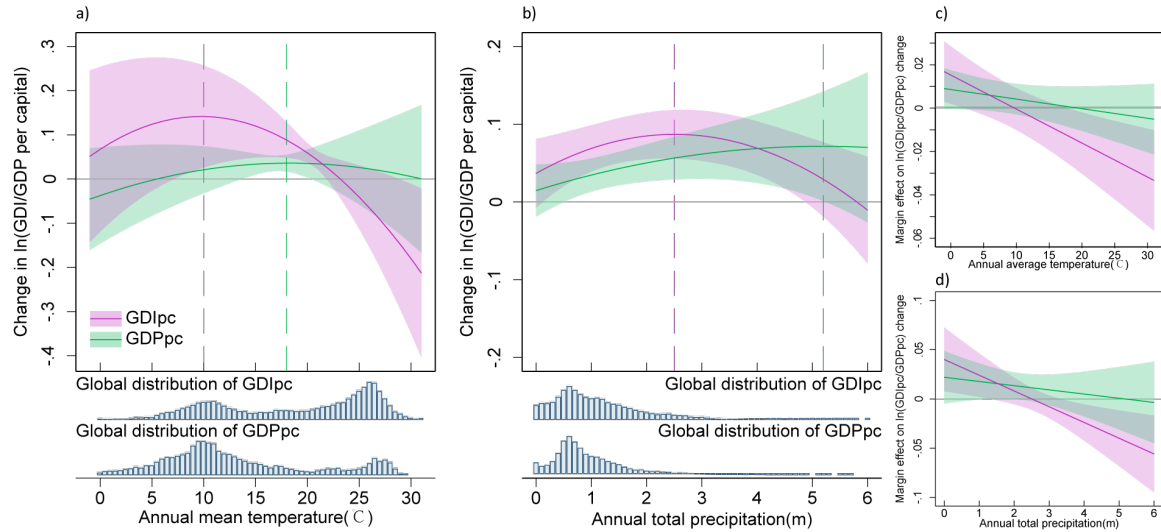


Figure 2. The level effects of annual mean temperature and total precipitation on economic income and output. a, The effect of annual mean temperature on the growth of GDI per capita (purple) and GDP per capita (green) with a 90% confidence interval when AST and ASP equal 0 and other control variables at mean values. b, The effect of annual total precipitation on the growth of GDI per capita (purple) and GDP per capita (green) with a 90% confidence interval when AST and ASP equal 0 and other control variables at mean values. c, The marginal effects of a 1°C temperature increase on the growth of GDI per capita (purple) and GDP per capita (green) with 90% confidence intervals when AST and ASP equal 0 and other control variables at mean values. d, The marginal effects of 1 precipitation increase on the growth of GDI per capita (purple) and GDP per capita (green) with a 90% confidence interval when AST and ASP equal 0 and other control variables at mean values.

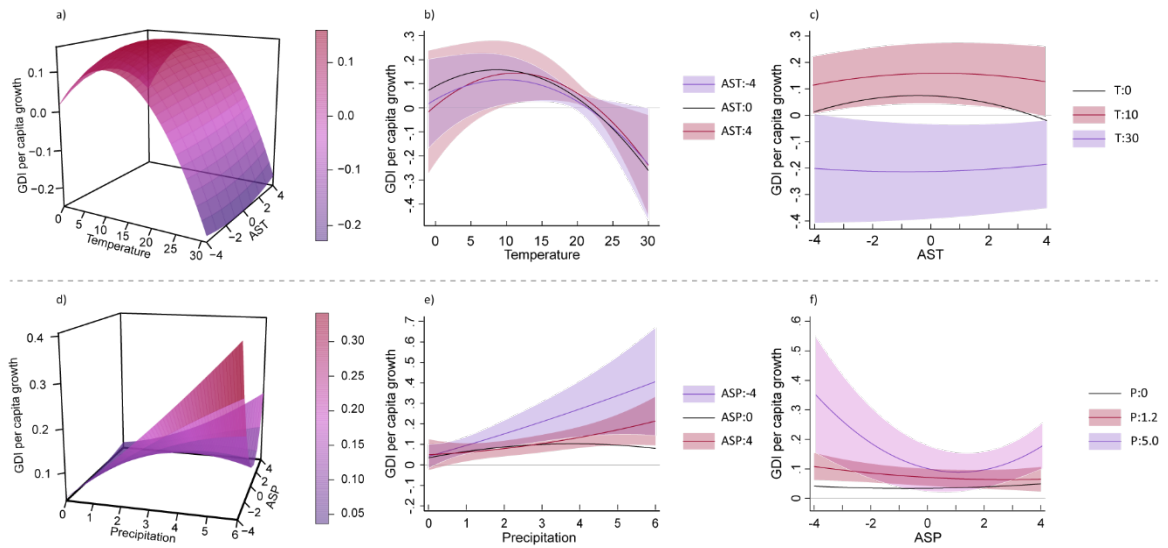


Figure 3. The interaction effects of weather and weather variability on GDI per capita growth. a-c, The combined effects of temperature ($^{\circ}\text{C}$) and AST on GDI per capita growth with a 90% confidence interval when ASP equals 0 and other control variables at mean values. d-f, The combined effects of precipitation (m) and ASP on GDI per capita growth with a 90% confidence interval when AST equals 0 and other control variables at mean values.

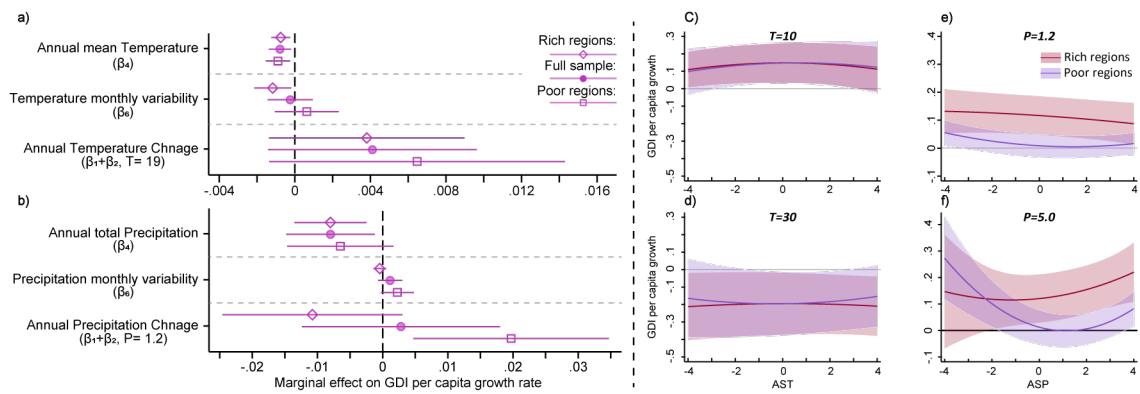


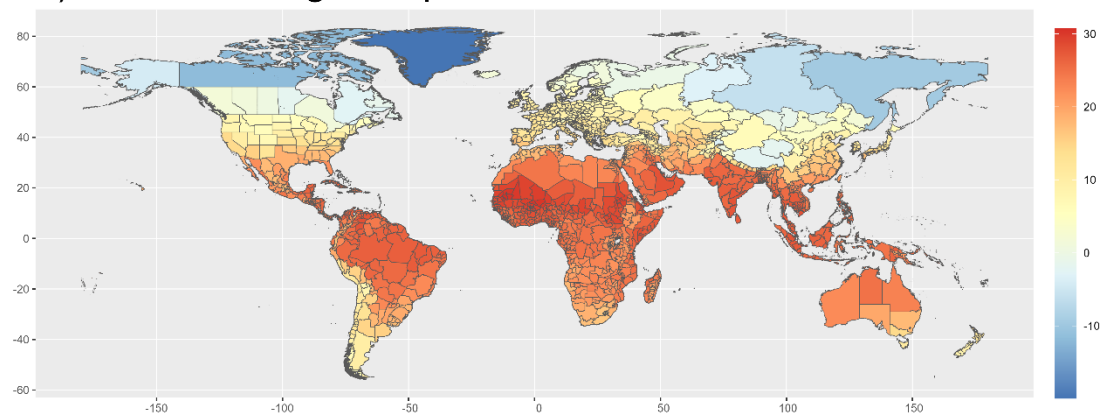
Figure 4. The heterogeneity analysis for effects of weather conditions on economic income growth by poor and rich regions. a, The marginal effects of temperature, temperature change and temperature variability on GDI per capita with a 90% confidence interval. b, The marginal effects of precipitation, precipitation change, and precipitation variability on GDI per capita with a 90% confidence interval. c-d, The effects of variability in temperature on the GDI per capita when the temperature is equal to 10 or 30 with a 90% confidence interval. e-f, The effects of variability in precipitation on the GDI per capita when the temperature was equal to 1.2 and 5.0 with a 90% confidence interval.

Supporting Information

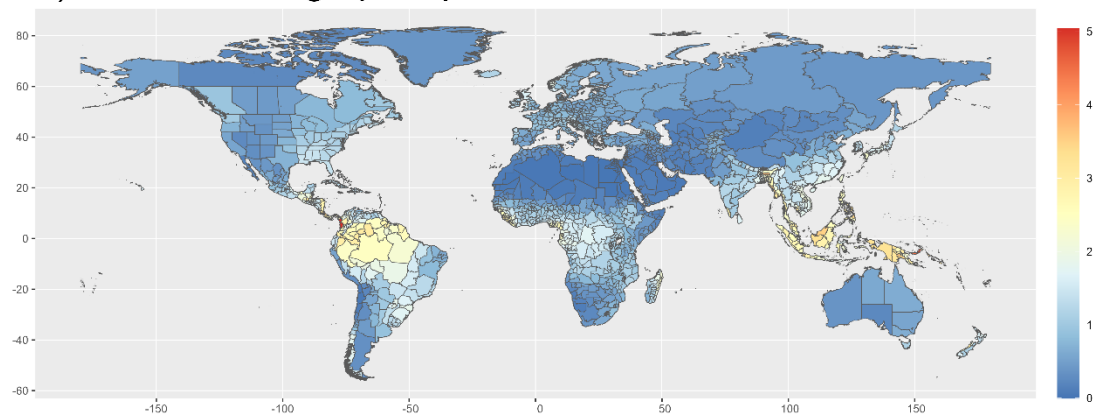
SI 1 – Descriptive statistics

Figure S1 shows the weather and weather changes from 1990 to 2015. The distribution of regions with high temperatures and high precipitation remains broadly consistent. Over the past decades, most regions have experienced a temperature increase, except for regions such as the eastern United States, Northern Europe, and Bangladesh. In contrast, precipitation remained almost unchanged over most regions, with only a few regions around the equator experiencing precipitation change. However, the change in these regions exhibits substantial heterogeneity. For instance, Ecuador is experiencing a significant precipitation increase, but neighboring Colombia is experiencing a considerable precipitation decrease.

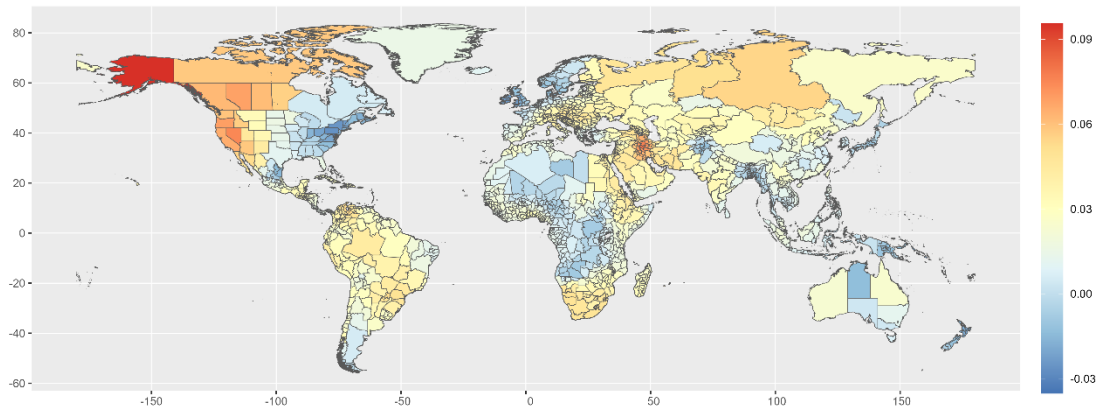
a) Annual average temperature from 1990 to 2015



b) Annual average precipitation from 1990 to 2015



c) Annual average temperature change from 1990 to 2015



d) Annual average precipitation change from 1990 to 2015

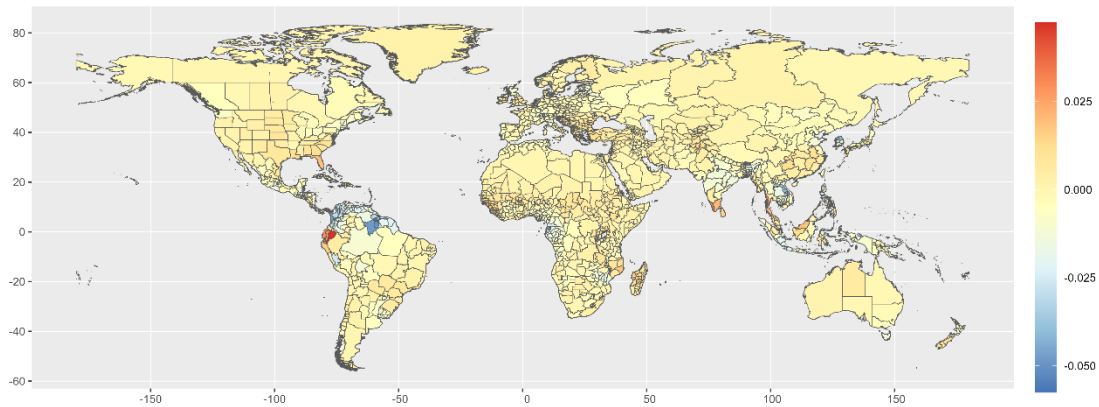
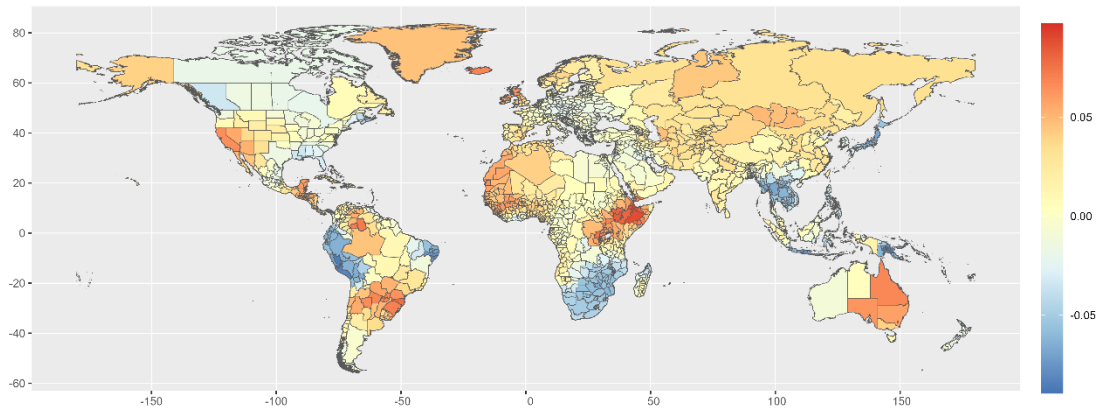


Figure S1 Global weather and weather changes from 1990 to 2015. a, Global annual average temperature ($^{\circ}\text{C}$) from 1990 to 2015. **b,** Global annual total precipitation (m) from 1990 to 2015 **c,** Global average temperature change ($^{\circ}\text{C}$) from 1990 to 2015. **d,** Global average precipitation change (m) from 1990 to 2015. The data come from the CRU database.

Figure S2 shows the weather variability from 1990 to 2015. It is evident that the distribution of weather variability differs from the distribution of weather change (Figure S1c,d). Some regions, such as West Africa, Southeast Asia, and Oceania, are experiencing less weather change but observable weather variability. These disparities encouraged us to further consider the effects of weather variability on economic growth.

a) Annual average temperature variability from 1990 to 2015



b) Annual average precipitation variability from 1990 to 2015

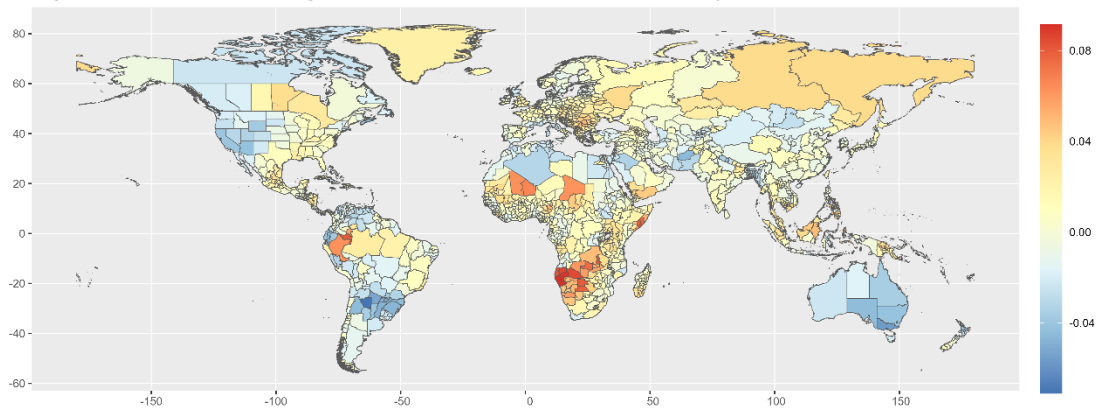
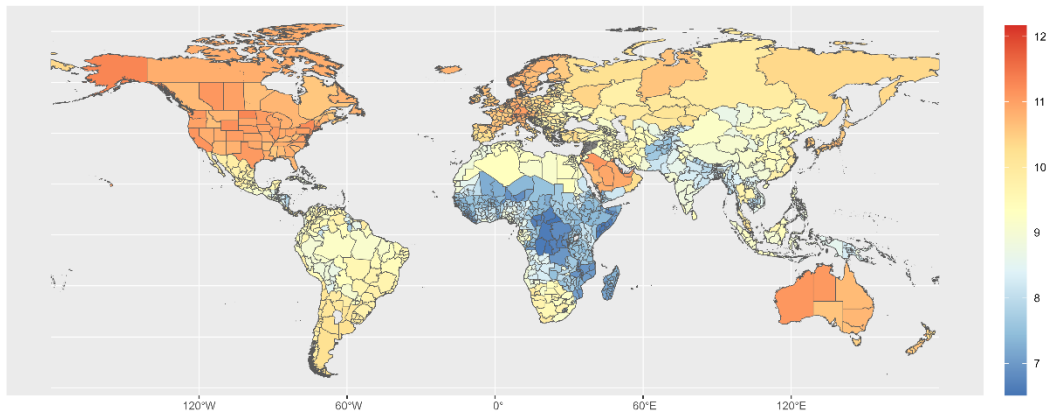


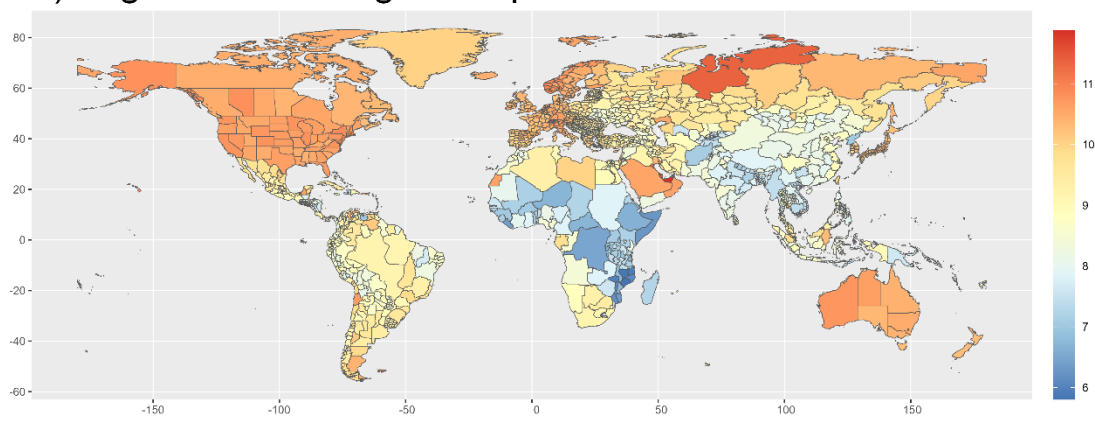
Figure S2 Global weather variability from 1990 to 2015. a, Global annual average temperature variability from 1990 to 2015. **b,** Global annual average precipitation variability from 1990 to 2015.

Figure S3 shows the subnational GDI and GDP per capita from 1990 to 2015. As depicted in Figure S3c, the distribution of GDI per capita differs from the distribution of GDP per capita due to the fact that output is recorded at the location of the economic activity, while income is recorded at the place of residence.

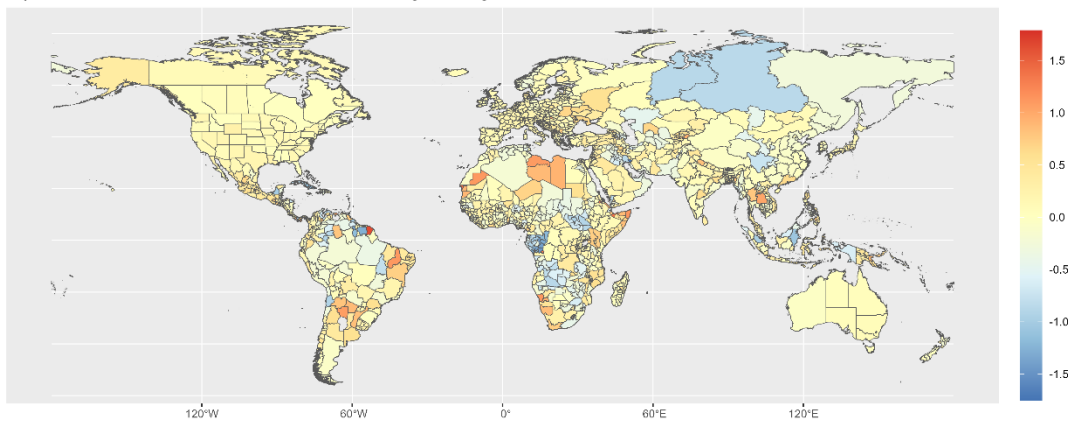
a) Log annual average GDPpc from 1990 to 2015



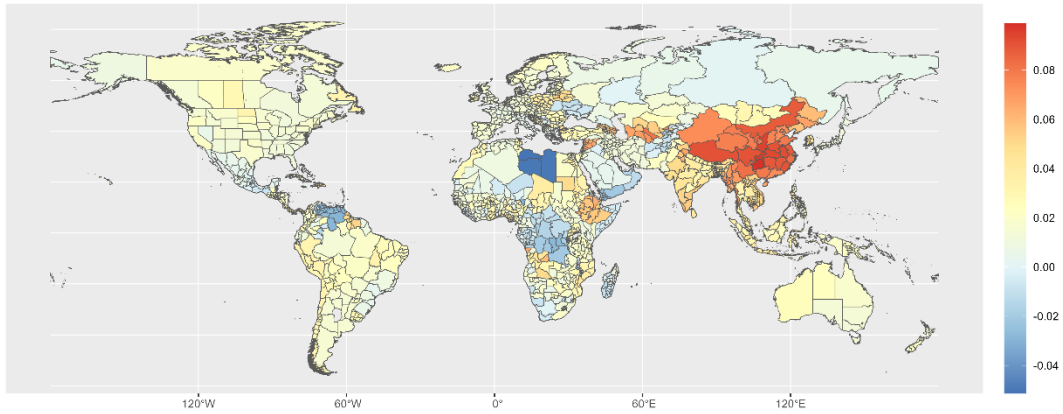
b) Log annual average GDPpc from 1990 to 2015



c) Difference between average log GDPpc and GDPpc from 1990 to 2015



d) Annual average GDPpc growth rate from 1990 to 2015



e) Annual average GDPpc growth rate from 1990 to 2015

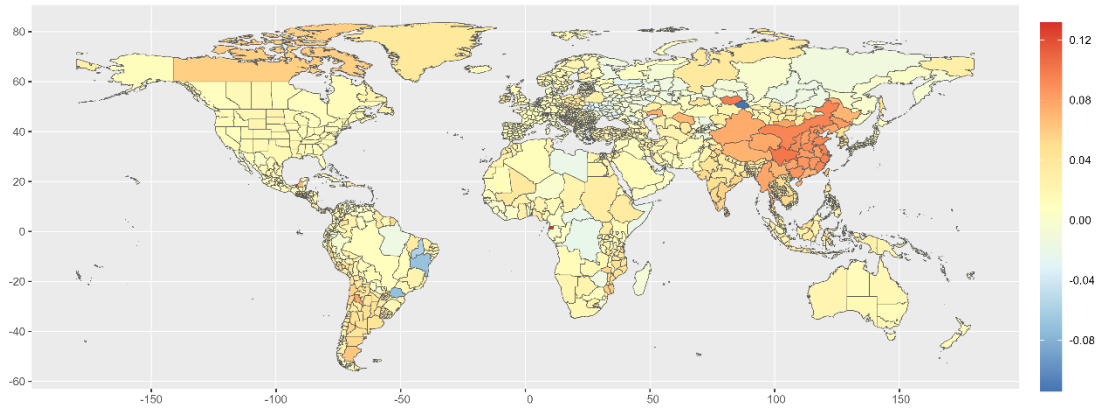


Figure S3 Global GDP and GDI per capita. **a**, Global annual average GDI per capita (2011 PPP) from 1990 to 2015 in logarithm. **b**, Global annual average GDP per capita (2011 PPP) from 1990 to 2015 in logarithm **c**, The difference between average GDI and GDP per capita from 1990 to 2015. **d**, Global annual average GDI per capita growth rate from 1990 to 2015. **e**, Global annual average GDP per capita growth rate from 1990 to 2015.

...

Table S1 presents the descriptive statistics of the data used in this study. Due to the different definitions of subnational regions, the database for GDP per capita(Panel B) has more countries but fewer regions than the database for GDI per capita(Panel A). To ensure comparability between GDI and GDP per capita results, we harmonized the two datasets by matching the shared countries between Panel A and Panel B. As a result, we created the Panel A-C and Panel B-C databases (Table S2), which cover over 1600 regions across more than 180 countries.

Table S1 Descriptive statistics for original data.

Database	Variable		Mean	SD	Min	Max	Obs.	Regions	Countries	Time
Panel A: GDI per capita	GDI per capita growth rate	$g_{i,t}$	0.020	0.070	-1.14	0.78	47875	1784	183	1991-2019
	Annual mean temperature(°C)	$T_{i,t}$	19.18	7.74	-13.02	31.36				
	Annual mean precipitation(m)	$P_{i,t}$	1.20	0.83	0.00063	6.43				
	Anomaly standardized temperature	$AST_{i,t}$	0.038	1.28	-4.19	4.60				
	Anomaly standardized precipitation	$ASP_{i,t}$	0.018	1.01	-5.72	5.06				
Panel B: GDP per capita	GDP per capita growth rate	$g_{i,t}$	0.020	0.078	-2.65	2.31	41713	1669	195	1991-2015
	Annual mean temperature(°C)	$T_{i,t}$	15.55	8.32	-20.72	29.72				
	Annual mean precipitation(m)	$P_{i,t}$	1.07	0.71	0.00027	6.30				
	Anomaly standardized temperature	$AST_{i,t}$	-0.23	1.22	-4.55	5.11				
	Anomaly standardized precipitation	$ASP_{i,t}$	-0.0097	1.02	-5.39	6.09				
Panel C: Control variables	Mean years of schooling (year)	$Edu_{i,t}$	7.03	3.40	0.17	15	50020	1805	186	1990-2019
	Population (million)	$Pop_{i,t}$	5.03	18.39	0.0008	464				

Table S2 Descriptive statistics for the panel analysis.

Database	Variable		Mean	SD	Min	Max	Obs.	Regions	Countries	Time
Panel A-C: GDI per capita	GDI per capita growth rate	$g_{i,t}$	0.021	0.072	-1.14	0.78	40711	1784	183	1991-2015
	Annual daily mean temperature(°C)	$T_{i,t}$	19.07	7.76	-13.02	31.36				
	Annual daily mean precipitation(m)	$P_{i,t}$	1.20	0.83	0.00063	6.43				
	Anomaly standardized temperature	$AST_{i,t}$	-0.16	1.22	-4.19	4.50				
	Anomaly standardized precipitation	$ASP_{i,t}$	0.0049	1.02	-5.72	5.06				
	Mean years of schooling (year)	$Edu_{i,t}$	6.92	3.38	0.23	14.71				
	Population (million)	$Pop_{i,t}$	5.02	18.09	0.00082	431				
Panel B-C: GDP per capita	GDP per capita growth rate	$g_{i,t}$	0.020	0.077	-2.65	2.31	39881	1623	181	1991-2015
	Annual daily mean temperature(°C)	$T_{i,t}$	15.48	8.26	-13.31	29.72				
	Annual daily mean precipitation(cm)	$P_{i,t}$	1.07	0.71	0.00027	6.30				
	Anomaly standardized temperature	$AST_{i,t}$	-0.22	1.22	-4.55	5.03				
	Anomaly standardized precipitation	$ASP_{i,t}$	-0.0082	1.02	-5.39	6.09				
	Mean years of schooling (year)	$Edu_{i,t}$	8.31	2.93	0.40	14.71				
	Population (million)	$Pop_{i,t}$	7.71	48.94	0.021	2315				

Note: Kosovo and South Sudan in Panel A-C are merged into the regions of Serbia and Sudan in Panel B-C; therefore, there are two more countries in Panel A-C than in Panel B-C.

SI 2 – Pre-estimation Tests

Unit Root Test

We conduct unit root tests to determine if the variable in the regression model changes with time (stationary or nonstationary). To mitigate the impact of cross-sectional dependence, we subtracted cross-sectional means during the unit root tests. The results in Table S3 indicated that all variables in this study's regression models are stationary. Our regression results are therefore not spurious.

Table S3. Unit root test results

Variables	Panel A-C (Income)			Panel B-C (Output)		
	LLC ¹	IPS ²	HT ³	LLC ¹	IPS ²	HT ³
$g_{i,t}$	-38.56***	-79.21***	0.033***	-50.46***	-76.68***	0.11***
$T_{i,t}$	-44.57***	-86.67***	0.023***	-53.37***	-95.28***	-0.011***
$P_{i,t}$	-49.40***	-91.52***	0.021***	-56.50***	-98.91***	-0.0073***
$AST_{i,t}$	-40.57***	-86.21***	0.13***	-58.37***	-94.96***	0.065***
$ASP_{i,t}$	-53.65***	-94.96***	0.021***	-59.53***	-100***	-0.016***
$\Delta T_{i,t}$	-99.56***	-130***	-0.48***	-93.15***	-130***	-0.48***
$\Delta P_{i,t}$	-110***	-130***	-0.46***	-120***	-130***	-0.47***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The null hypothesis of these tests is that all panels contains unit roots.

1. LLC denotes Levin-Lin-Chu test with time trend and subtracts cross-sectional means
2. IPS denotes Im-Pesaran-Shin test with time trend and subtracts cross-sectional means
HT denotes the Harris-Tzavalis test with a time trend and subtracts cross-sectional means

SI 3 – Methods

Weighted Anomaly Standardized Precipitation

The WASP was first proposed by Lyon and Barnston (4) and has been widely used to explain the temporal variability of precipitation in each region(5-7). It is measured by an annual sum of monthly rainfall anomalies from their climatological means and weighted by the climatological contribution of monthly precipitation to the annual precipitation:

$$WS_{r,y} = \sum_{m=1}^{12} \frac{P_{r,m,y} - \bar{P}_{r,m}}{\sigma_{r,m}} \cdot \frac{\bar{P}_{r,m}}{\bar{P}A_r} \quad (S1)$$

Where $WS_{r,y}$ is the weighted anomaly standardized precipitation in region r and year y . $P_{r,m,y}$ is the monthly total precipitation. $\bar{P}_{r,m}$ is the historical mean of monthly total precipitation over the study year, $\sigma_{r,m}$ is the historical standard deviation of monthly total precipitation in that region, and $\bar{P}A_r$ is the historical mean of annual total precipitation in that region. The annual $WS_{r,y}$ is further standardized by the standard deviation of $WS_{r,y}$ at a given region over time to obtain a measure of the relative severity of annual precipitation surpluses or deficits:

$$WASP_{r,y} = WS_{r,y} / \sigma_{S_r} \quad (S2)$$

Although the WASP index is designed for precipitation, it can also be defined for temperature, the Weighted Anomaly Standardized Temperature (WAST)(5). In addition, the WASP was initially designed for tropical regions where the climate can be clearly divided into rainy and dry seasons. The weighting factor $\frac{\bar{P}_{r,m}}{PA_r}$ is used to dampen large standardized anomalies that result from small precipitation amounts occurring near the start or end of dry seasons and to emphasize anomalies during the core rainy seasons. Since the climate situation across most of the world cannot be simplified into rainy and dry seasons, the weighting factor may introduce problematic effects by emphasizing deviations occurring in months with higher precipitation totals(5). Therefore, we did not use the weighting factor for analysis in this study. However, we also conduct a robustness check with the weighting factor for anomaly standardized precipitation in the regression models; see the robustness checks section below for details.

SI 4 – Supplementary Results

Results of the main regression model

Table S4 shows the regression results with different specifications. Columns (1) and (4) are based on the specification developed by Burke, Hsiang and Miguel (8) (BHM model), which considers the nonlinear effects of weather conditions by including the quadratic function of temperature and precipitation. Columns (2) and (5) are based on the specification developed by Kalkuhl and Wenz (9) (KW model), which further considers the effects of temperature and precipitation changes. Columns (3) and (6) are based on the specification developed by this study that considers the effects of weather, weather change, and weather variability on economic growth. All these models use year and region fixed effects regression models clustered by country levels.

Across all model variations, the effects of temperature on economic income are consistently statistically significant. Although the effect of precipitation is not statistically significant in Column (2), it is statistically significant at high precipitation levels. In contrast, the effects of precipitation on economic output are not statistically significant in any model variation. While the effect of temperature on economic output are significant under the BHM and KW models, these effects lose their statistical significance when considering the effect of weather variability. These findings suggest that failure to consider the variability effects could lead to an overestimation of the impact of weather conditions on economic growth.

Table S4. Fixed-effects regression models for the effects of weather conditions on economic output and income

Dep var.	(1)	(2)	(3)	(4)	(5)	(6)
		GDI per capita growth			GDP per capita growth	
ΔT		-0.00385 (0.0047)	-0.00415 (0.0047)		-0.00109 (0.0031)	-0.000717 (0.0032)
ΔT^*T		0.000395 (0.0003)	0.000433 (0.0003)		0.000236 (0.0002)	0.000210 (0.0002)
ΔP		0.00325 (0.0126)	0.00504 (0.0127)		-0.00357 (0.0109)	-0.00294 (0.0109)
ΔP^*P		-0.000758 (0.0048)	-0.00186 (0.0047)		-0.00248 (0.0047)	-0.00254 (0.0047)
T	0.0131** (0.0056)	0.0166** (0.0078)	0.0153* (0.0081)	0.00559* (0.0029)	0.00640 (0.0049)	0.00800 (0.0054)
T ²	-0.000430** (0.0002)	-0.000612** (0.0003)	-0.000784*** (0.0003)	-0.000255** (0.0001)	-0.000356* (0.0002)	-0.000219 (0.0002)
P	0.0140 (0.0095)	0.0112 (0.0164)	0.0401** (0.0197)	0.0127 (0.0095)	0.0174 (0.0165)	0.0220 (0.0162)
P ²	-0.00525*** (0.0018)	-0.00489 (0.0031)	-0.00800** (0.0034)	-0.00250 (0.0023)	-0.00141 (0.0034)	-0.00213 (0.0032)
AST			0.00252 (0.0030)			-0.00274 (0.0017)
AST ²			-0.000244 (0.0006)			-0.000347 (0.0006)
ASP			-0.00381* (0.0019)			-0.000786 (0.0012)
ASP ²			0.00114 (0.0009)			0.0000783 (0.0005)
Edu	0.00140 (0.0050)	0.00134 (0.0050)	0.00139 (0.0050)	0.00568 (0.0085)	0.00553 (0.0086)	0.00559 (0.0085)
Pop	-0.000426 (0.0003)	-0.000410 (0.0003)	-0.000455* (0.0003)	-0.00113 (0.0012)	-0.00113 (0.0012)	-0.00115 (0.0012)
Obs.	40711	40711	40711	39881	39881	39881
Adj. R ²	0.12	0.13	0.13	0.13	0.13	0.13
Year	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015
Fixed effects	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year
Cluster (SE)	Country	Country	Country	Country	Country	Country
ME at 19°C	-0.0033	-0.0067	-0.014*	-0.0041	-0.0071	-0.00032
..SE	0.0035	0.0049	0.0082	0.0037	0.0046	0.0059
ME at 30°C	-0.0084*	-0.014*	-0.024**	-0.0097*	-0.015*	-0.0051
..SE	0.0052	0.0074	0.011	0.0059	0.0082	0.0095
ME at 1.2 m	0.0014	-0.00048	0.021*	0.0067	0.014	0.017
..SE	0.0059	0.10	0.012	0.0050	0.0093	0.010
ME at 5.0 m	-0.028***	-0.028**	-0.024**	-0.012	0.0032	0.0071
..SE	0.0076	0.012	0.011	0.015	0.020	0.019

Note: *p < 0.10, **p < 0.05, ***p < 0.01. ME stands for marginal level effects of weather shocks on economic growth. Clustered standard errors at country level in parentheses.

Results of Interaction Effects

Table S5 shows the combined effects of weather conditions on economic growth. Given the significant multicollinearity between the interaction terms and with other variables, we utilized the joint hypotheses test (F test) to assess the statistical significance of these effects. Our findings indicate that only the interaction effects between T and AST, as well as P and ASP, significantly affect economic income. Although the interaction effects between T and AST, as well as P and ASP, shared the same trend on economic output, they retained wide confidence intervals, especially for the interaction effects between T and AST (Figure S4).

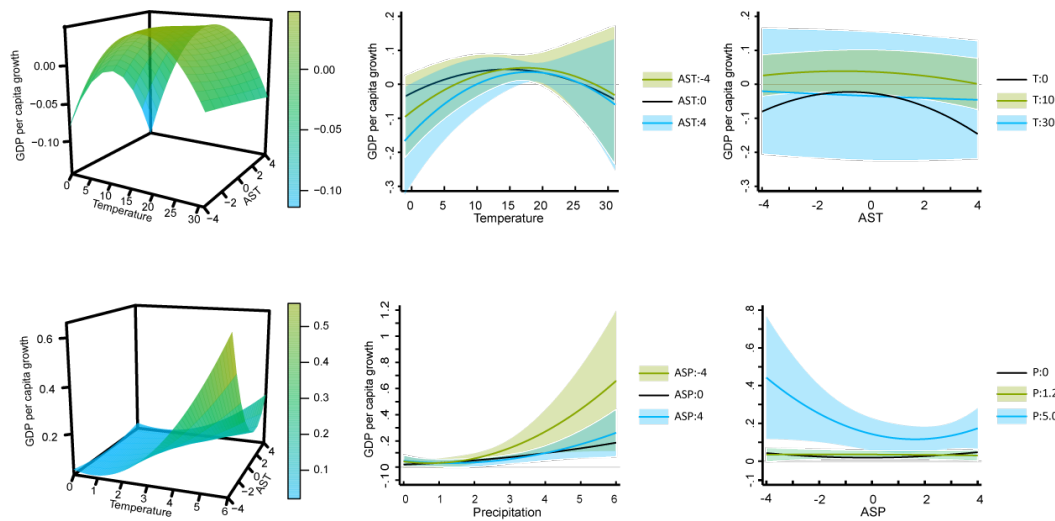


Figure S4. The interaction effects of weather and weather variability on GDP per capita growth. a-c, The combined effects of temperature ($^{\circ}\text{C}$) and AST on GDP per capita growth with a 90% confidence interval when ASP equals 0 and other control variables at mean values. **d-f,** The combined effects of precipitation (m) and ASP on GDP per capita growth with a 90% confidence interval when AST equals 0 and other control variables at mean values.

Table S5. Effects of weather conditions on economic income and output with interactions

Dep var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GDI per capita growth				GDP per capita growth			
ΔT	-0.00390 (0.0047)	-0.00429 (0.0048)	-0.00413 (0.0047)	-0.00410 (0.0047)	-0.000657 (0.0032)	-0.000942 (0.0033)	-0.000691 (0.0032)	-0.000682 (0.0032)
ΔT^*T	0.000425 (0.0003)	0.000441 (0.0003)	0.000422 (0.0003)	0.000433 (0.0003)	0.000218 (0.0002)	0.000228 (0.0002)	0.000224 (0.0002)	0.000208 (0.0002)
ΔP	0.00463 (0.0126)	0.00492 (0.0127)	0.00623 (0.0131)	0.00638 (0.0127)	-0.00314 (0.0109)	-0.00327 (0.0109)	-0.00150 (0.0105)	-0.00283 (0.0109)
ΔP^*P	-0.00182 (0.0047)	-0.00184 (0.0047)	-0.00245 (0.0048)	-0.00253 (0.0048)	-0.00262 (0.0047)	-0.00243 (0.0047)	-0.00339 (0.0044)	-0.00265 (0.0047)
T	0.0174 (0.0113)	0.0153* (0.0082)	0.0136* (0.0080)	0.0156* (0.0080)	0.00954 (0.0078)	0.00851* (0.0051)	0.00953* (0.0056)	0.00820 (0.0054)
T^2	-0.000902** (0.0004)	-0.000786*** (0.0003)	-0.000795*** (0.0003)	-0.000771*** (0.0003)	-0.000328 (0.0003)	-0.000234 (0.0002)	-0.000239 (0.0002)	-0.000218 (0.0002)
P	0.0404** (0.0197)	0.0418** (0.0207)	0.0344* (0.0204)	0.0358** (0.0170)	0.0224 (0.0163)	0.0260* (0.0154)	0.0189 (0.0173)	0.00988 (0.0213)
P^2	-0.00796** (0.0034)	-0.00846** (0.0037)	-0.00672* (0.0036)	-0.00470 (0.0036)	-0.00202 (0.0032)	-0.00287 (0.0031)	-0.00140 (0.0035)	0.00299 (0.0049)
AST	-0.00408 (0.0062)	0.00252 (0.0030)	0.00650 (0.0045)	0.00223 (0.0029)	-0.00822* (0.0043)	-0.00272 (0.0016)	-0.00449 (0.0035)	-0.00285* (0.0016)
AST^2	-0.00477** (0.0024)	-0.000237 (0.0006)	-0.000325 (0.0015)	-0.000252 (0.0006)	-0.00546* (0.0032)	-0.000325 (0.0006)	-0.000713 (0.0018)	-0.000354 (0.0006)
ASP	-0.00382** (0.0019)	-0.00453* (0.0023)	-0.00356* (0.0019)	0.000973 (0.0026)	-0.000892 (0.0012)	0.00102 (0.0019)	-0.000765 (0.0012)	0.000552 (0.0024)
ASP^2	0.00116 (0.0009)	0.00103 (0.0017)	0.00114 (0.0010)	0.000697 (0.0014)	0.0000525 (0.0005)	0.00404 (0.0029)	0.0000812 (0.0005)	0.00164 (0.0015)
T^*AST	0.000762 (0.0006)				0.000684 (0.0004)			
T^2*AST	-0.0000187 (0.0000)				-0.0000172 (0.0000)			
T^*AST^2	0.000262 (0.0003)				0.000502 (0.0004)			
T^2*AST^2	-0.00000208 (0.0000)				-0.0000106 (0.0000)			
T^*ASP		-0.00000553 (0.0003)				-0.000376 (0.0003)		
T^2*ASP		0.00000190 (0.0000)				0.0000125 (0.0000)		
T^*ASP^2		-0.0000513 (0.0002)				-0.000570 (0.0003)		
T^2*ASP^2		0.00000247				0.0000162*		

			(0.0000)			(0.0000)		
P*AST			-0.00454				0.000719	
			(0.0033)				(0.0032)	
P ² *AST			0.00108				0.000185	
			(0.0009)				(0.0008)	
P*AST ²			0.000292				0.000193	
			(0.0015)				(0.0019)	
P ² *AST ²			-0.000125				0.0000537	
			(0.0003)				(0.0004)	
P*ASP						-0.00535*		0.000937
						(0.0028)		(0.0041)
P ² *ASP						0.000196		-0.00155
						(0.0007)		(0.0014)
P*ASP ²						-0.000341		-0.00253
						(0.0018)		(0.0020)
P ² *ASP ²						0.000436		0.000852
						(0.0003)		(0.0006)
Edu	0.00109	0.00144	0.00137	0.00149	0.00525	0.00568	0.00558	0.00557
	(0.0049)	(0.0050)	(0.0050)	(0.0049)	(0.0085)	(0.0085)	(0.0085)	(0.0085)
Pop	-0.000457*	-0.000454*	-0.000471*	-0.000435	-0.00124	-0.00119	-0.00116	-0.00114
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Obs.	40711	40711	40711	40711	39881	39881	39881	39881
Adj. R ²	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Year	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015
Fixed effects	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year
Cluster (SE)	Country	Country	Country	Country	Country	Country	Country	Country
F test:	2.29*	0.41	0.78	4.71***	1.03	1.68	1.26	1.67
$\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4$								

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Clustered standard errors at country level in parentheses.

Results of Heterogeneity Analysis

Table S6. Heterogeneity analysis for the effects of weather conditions on economic output and income between rich and poor regions

Dep var.	(1) GDI per capita growth		(3) GDP per capita growth	
	Rich	Poor	Rich	Poor
ΔT	-0.00536 (0.0046)	0.00320 (0.0130)	0.000159 (0.0037)	-0.00435 (0.0045)
ΔT^*T	0.000485 (0.0003)	0.000153 (0.0006)	0.000326 (0.0003)	0.000254 (0.0003)
ΔP	-0.0190 (0.0139)	0.0322** (0.0154)	-0.0101 (0.0120)	0.00427 (0.0127)
ΔP^*P	0.00663 (0.0050)	-0.0112* (0.0062)	-0.00242 (0.0049)	-0.00469 (0.0055)
T	0.0161** (0.0079)	0.0201** (0.0091)	0.0104* (0.0061)	0.0115* (0.0065)
T ²	-0.000748** (0.0003)	-0.000896*** (0.0003)	-0.000247 (0.0002)	-0.000296 (0.0002)
P	0.0380** (0.0180)	0.0317 (0.0237)	0.0172 (0.0189)	0.0239 (0.0177)
P ²	-0.00730** (0.0033)	-0.00712* (0.0041)	-0.000107 (0.0038)	-0.00274 (0.0034)
AST	0.000135 (0.0028)	0.00377 (0.0034)	-0.00560*** (0.0019)	-0.00148 (0.0019)
AST ²	-0.00120** (0.0006)	0.000620 (0.0009)	0.0000163 (0.0007)	-0.000504 (0.0008)
ASP	-0.00278 (0.0017)	-0.00389 (0.0029)	-0.000156 (0.0017)	-0.00113 (0.0012)
ASP ²	-0.000496 (0.0006)	0.00222* (0.0013)	-0.000908** (0.0004)	0.000827 (0.0008)
Edu		0.00184 (0.0050)		0.00591 (0.0084)
Pop		-0.000501* (0.0003)		-0.00122 (0.0012)
Obs.	40711		39881	
Adj. R ²	0.13		0.13	
Year	1991-2015		1991-2015	
Fixed effects	Region, Year		Region, Year	
Cluster (SE)	Country		Country	
ME at 19°C	-0.012	-0.014*	0.00099	0.00021
..SE	0.0084	0.0078	0.0058	0.0058
ME at 30°C	-0.021*	-0.025**	-0.0044	-0.0063
..SE	0.011	0.011	0.0095	0.0096
ME at 1.2 m	0.020*	0.015	0.017	0.017
..SE	0.011	0.015	0.011	0.011
ME at 5.0 cm	-0.020*	-0.022*	0.016	-0.0034
..SE	0.013	0.012	0.023	0.020

Note: *p < 0.10, **p < 0.05, ***p < 0.01. ME stands for marginal level effects of weather shocks on economic growth. Clustered standard errors at country level in parentheses.

Table S6 shows the regression results for heterogeneity analysis between rich and poor regions. We find that the effects of weather conditions on poor and rich regions are quite different. Regarding the effects on economic income, although the difference is not statistically significant, we find that poor regions are more sensitive to the effect of temperature. In contrast, the increases of weather change and weather variability have higher negative effects on rich regions. These results suggest the different adaptations of rich and poor regions to different weather conditions.

Different with economic income, we find that the economic output of poor regions is more sensitive to all effects of temperature conditions and the effect of precipitation, while the economic output of rich regions is more sensitive to the effects of precipitation variability and precipitation change (Figure S5a-b). The heterogeneity of interaction effects of weather conditions on economic output is consistent with economic income: The positive effects of weather variability on poor regions' GDP per capita growth are more significant with increasing temperature and precipitation.

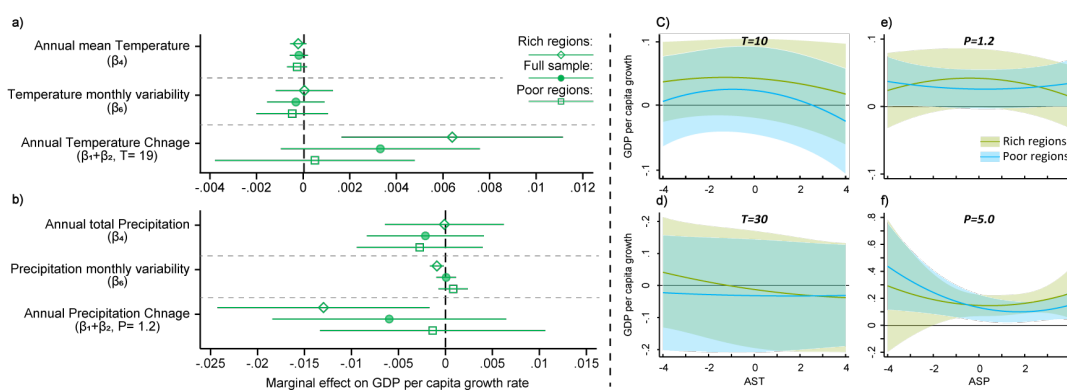


Figure S5. The heterogeneity analysis for effects of weather conditions on economic output growth by poor and rich regions. **a**, The marginal effects of temperature, temperature change, and temperature variability on GDP per capita with a 90% confidence interval. **b**, The marginal effects of precipitation, precipitation change, and precipitation variability on GDP per capita with a 90% confidence interval. **c-d**, The effects of variability in temperature on the GDP per capita when the temperature is equal to 10°C or 30°C with a 90% confidence interval. **e-f**, The effects of variability in precipitation on the GDP per capita when the temperature was equal to 1.2 and 5.0 with a 90% confidence interval.

Table S7 Heterogeneity analysis for the interaction effects of weather conditions on economic output and income between rich and poor regions

Dep var.	(1)	(2)		(3)	(4)	(5)	(6)		(7)	(8)
	Rich	GDI per capita growth		Rich	Poor	Rich	GDP per capita growth		Rich	Poor
		Poor					Poor			
ΔT	-0.00363 (0.0048)			-0.00352 (0.0042)			-0.000715 (0.0032)			-0.000804 (0.0032)
ΔT^*T	0.000414 (0.0003)			0.000339 (0.0003)			0.000218 (0.0002)			0.000209 (0.0002)
ΔP	0.00572 (0.0121)			0.00466 (0.0132)			-0.00302 (0.0108)			-0.00332 (0.0109)
ΔP^*P	-0.00196 (0.0046)			-0.00155 (0.0047)			-0.00268 (0.0047)			-0.00248 (0.0047)
T	0.0177 (0.0114)			0.0142* (0.0072)			0.00858 (0.0077)			0.00817 (0.0053)
T^2	-0.000872** (0.0004)			-0.000652** (0.0003)			-0.000284 (0.0003)			-0.000219 (0.0002)
P	0.0382** (0.0192)			0.0300 (0.0200)			0.0230 (0.0160)			0.0128 (0.0209)
P^2	-0.00778** (0.0034)			-0.00465 (0.0037)			-0.00220 (0.0031)			0.00241 (0.0048)
AST	-0.00407 (0.0063)			0.00185 (0.0025)			-0.00745* (0.0042)			-0.00274* (0.0016)
AST^2	-0.00475* (0.0025)			-0.000276 (0.0004)			-0.00555* (0.0033)			-0.000361 (0.0006)
ASP	-0.00373* (0.0019)			0.000564 (0.0022)			-0.000943 (0.0012)			0.00140 (0.0025)
ASP^2	0.00118 (0.0009)			0.000120 (0.0010)			0.0000593 (0.0005)			0.00221 (0.0016)
T^*AST	0.000588 (0.0006)	0.000984 (0.0007)					0.000793 (0.0005)	0.000419 (0.0004)		
T^2*AST	-0.0000147 (0.0000)	-0.0000268 (0.0000)					-0.0000292* (0.0000)	-0.00000687 (0.0000)		
T^*AST^2	0.000299 (0.0003)	0.000254 (0.0003)					0.000580 (0.0004)	0.000422 (0.0004)		
T^2*AST^2	-0.00000579 (0.0000)	- (0.0000)					-0.0000122 (0.0000)	-0.00000755 (0.0000)		
P^*ASP				-0.00567 (0.0035)	-0.00403 (0.0026)				-0.00228 (0.0047)	0.000441 (0.0042)
P^2*ASP				0.00137 (0.0010)	-0.000182 (0.0006)				0.000121 (0.0019)	-0.00158 (0.0014)

P*ASP ²		0.000233 (0.0014)	0.00100 (0.0014)	-0.00430* (0.0026)	-0.00224 (0.0020)
P ² *ASP ²		-0.00000765 (0.0004)	0.000153 (0.0003)	0.00106 (0.0009)	0.000767 (0.0006)
Edu	0.00131 (0.0050)	-0.000156 (0.0040)	0.00533 (0.0085)	0.00565 (0.0085)	
Pop	-0.000475* (0.0003)	-0.000672*** (0.0002)	-0.00124 (0.0012)	-0.00113 (0.0012)	
Obs.	40711	40711	39881	39881	
Adj. R ²	0.13	0.13	0.13	0.13	
Year	1991-2015	1991-2015	1991-2015	1991-2015	
Fixed effects	Region, Year	Region, Year	Region, Year	Region, Year	
Cluster (SE)	Country	Country	Country	Country	

Note: *p < 0.10, **p < 0.05, ***p < 0.01. ME stands for marginal level effects of weather shocks on economic growth. Clustered standard errors at country level in parentheses.

Long-difference Model

The models above capture the impacts of weather on economic growth. The effects of climate are absorbed in the fixed effects. While climate change is an accumulation of changes in the weather, adaptation to weather and climate is different. One way to overcome these limitations is to use cross-sectional regressions in growth rates over longer time intervals (long-difference model):

$$g_{i,p} = \beta_1 \Delta T_{i,p} + \beta_2 \Delta T_{i,p} \cdot T_{i,p-1} + \beta_3 T_{i,p-1} + \beta_4 T_{i,p-1}^2 + \beta_5 AST_{i,p-1} + \beta_6 AST_{i,p-1}^2 + X_{i,p} + \alpha_i + \delta_p + \varepsilon_{i,p}$$

where $g_{i,p}$ is the logarithmic change in average GDP per capita or GDP per capita over a longer period p . We determined the average temperature and precipitation as well as GDP per capita and GDP per capita at 5-year intervals. Contrary to the annual panel model, transitory effects in the long-difference model can be expected to be rather small because of the longer time periods considered. The quadratic term coefficients, therefore, capture the long-run growth rates of the economy affected by weather conditions. α_i are country dummies to consider country fixed effects. $X_{i,p}$ is another control variable that might influence the growth of the economy, including the mean years of schooling, and population. $\varepsilon_{i,p}$ is the error term.

Table S8. Long-differences: The effects of weather on economic output and income

Dep var.	(1)	(2)	(3)	(4)
	GDI per capita growth		GDP per capita growth	
ΔT	-0.0150 (0.0254)	-0.00359 (0.0268)	0.0637 (0.0625)	0.0590 (0.0590)
$\Delta T \cdot L.T$	-0.00147 (0.0012)	-0.00172 (0.0014)	-0.00700* (0.0039)	-0.00685* (0.0038)
ΔP	-0.00881 (0.0553)	-0.0278 (0.0587)	-0.0110 (0.0870)	-0.0530 (0.1129)
$\Delta P \cdot L.P$	-0.000391 (0.0194)	0.00681 (0.0166)	-0.0426** (0.0193)	-0.0227 (0.0247)
L.T	-0.00223 (0.0015)	-0.00204 (0.0015)	0.000221 (0.0017)	-0.000123 (0.0015)
L.T ²	0.0000499 (0.0001)	0.0000498 (0.0001)	0.0000164 (0.0000)	0.0000271 (0.0000)
L.P	0.0221 (0.0150)	0.0185 (0.0162)	0.0143 (0.0182)	0.00488 (0.0127)
L.P ²	-0.00491 (0.0047)	-0.00398 (0.0047)	-0.00361 (0.0038)	-0.000594 (0.0028)
AST	0.00403 (0.0105)	0.00399 (0.0105)	-0.0150 (0.0296)	-0.0144 (0.0295)
AST ²	0.00816 (0.0096)	0.00799 (0.0104)	0.0228 (0.0183)	0.0223 (0.0182)
ASP	-0.0263** (0.0114)	-0.0237* (0.0139)	0.00617 (0.0137)	0.00788 (0.0149)
ASP ²	0.00560 (0.0120)	0.00917 (0.0149)	-0.0529 (0.0425)	-0.0522 (0.0419)
Edu	-0.00499* (0.0026)	-0.00594* (0.0032)	0.000788 (0.0050)	0.000853 (0.0051)
Pop	-0.000271 (0.0002)	-0.000240 (0.0002)	-0.000553 (0.0005)	-0.000533 (0.0005)
Obs.	1726	1500	1524	1524
Adj. R ²	0.81	0.80	0.45	0.45
Periods	2010-2015 vs. 2005-2009	2010-2015 vs. 1995-1999	2010-2015 vs. 2005-2009	2010-2015 vs. 1995-1999
Lag(periods)	1	3	1	3
Fixed effects	Region, Year	Region, Year	Region, Year	Region, Year
Cluster (SE)	Country	Country	Country	Country

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at country level in parentheses.

The results of the long-difference regressions are presented in Table S8. Our findings indicate that the long-term effects of weather conditions on GDI and GDP per capita growth are not statistically significant.

SI 5 – Post-estimation Tests

Cross-Sectional Dependency Test

We use the method described by Pesaran (1) to conduct the cross-section dependency tests. Our results indicate the presence of the cross-section dependency within our fixed effects regression model. To address this concern, we implemented clustered standard errors in our regression analysis, clustering the observations by country, as recommended by MacKinnon, Nielsen and Webb (2).

Table S9. Cross-section dependence tests results

Tests	Models	Methods	Results
GDI panel data	Without fixed effects	Pesaran test	444.98***
	With fixed effects	Pesaran test	95.59***
GDP panel data	Without fixed effects	Pesaran test	599.06***
	With fixed effects	Pesaran test	101.65***

*Note: *p < 0.10, **p < 0.05, ***p < 0.01. We use the “xtcdf” command in Stata to conduct these tests. The null hypothesis for this approach is that the cross-section is independent.*

Serial Correlation Test

We use the Lagrange Multiplier (LM) statistic, as described by Born and Breitung (3), to conduct the serial correlation test. The results indicate a first-order serial correlation in our fixed effects regression models. While the inclusion of the first-order lagged dependent variable helps mitigate the impact of serial correlation, it also produces the second-order serial correlation for GDI panel data. Therefore, we still rely on the results based on the fixed effects regression model.

Table S10. Serial correlation test results

Tests	Models	Methods	Results
GDI panel data	Without fixed effects	LM test (first order)	9.95***
	With fixed effects	LM test (first order)	3.59***
	With fixed effects and first-order lagged dependent variable	LM test (first order)	3.58***
	Without fixed effects	LM test (second order)	4.71***
	With fixed effects	LM test (second order)	0.62
	With fixed effects and first-order lagged dependent variable	LM test (second order)	2.17**
GDP panel data	Without fixed effects	LM test (first order)	12.01***
	With fixed effects	LM test (first order)	7.30***
	With fixed effects and first-order lagged dependent variable	LM test (first order)	1.65*
	Without fixed effects	LM test (second order)	6.16***
	With fixed effects	LM test (second order)	1.10
	With fixed effects and first-order lagged dependent variable	LM test (second order)	0.90

*Note: *p < 0.10, **p < 0.05, ***p < 0.01. We use the “xtqptest” command in Stata to conduct these tests. The null hypothesis for this approach is that there is no serial correlation.*

Table S11. Serial correlation analysis under different regression models for the effects of weather conditions on economic output and income

Dep var.	(1)	(2)	(3)	(4)	(5)	(6)
		GDI per capita growth			GDP per capita growth	
L.Dep var.			-0.000719 (0.0502)			0.112** (0.0437)
ΔT	0.00642* (0.0033)	-0.00415 (0.0047)	-0.00804 (0.0053)	0.00734*** (0.0018)	-0.000718 (0.0032)	-0.00160 (0.0033)
ΔT^*T	-0.000529** (0.0002)	0.000433 (0.0003)	0.000724 (0.0004)	-0.000573*** (0.0001)	0.000210 (0.0002)	0.000208 (0.0002)
ΔP	0.0114 (0.0094)	0.00504 (0.0127)	0.0130 (0.0124)	-0.00680 (0.0090)	-0.00293 (0.0109)	0.00468 (0.0114)
ΔP^*P	-0.00550 (0.0034)	-0.00186 (0.0047)	-0.00479 (0.0047)	-0.000181 (0.0038)	-0.00254 (0.0047)	-0.00555 (0.0049)
T	0.00000852 (0.0006)	0.0153* (0.0081)	0.0173** (0.0081)	0.000614 (0.0007)	0.00800 (0.0054)	0.00607 (0.0051)
T ²	-0.00000819 (0.0000)	-0.000784*** (0.0003)	-0.000931*** (0.0003)	-0.0000105 (0.0000)	-0.000219 (0.0002)	-0.000207 (0.0002)
P	0.00704* (0.0042)	0.0401** (0.0197)	0.0394* (0.0202)	0.00593 (0.0046)	0.0220 (0.0162)	0.0152 (0.0159)
P ²	-0.000586 (0.0011)	-0.00800** (0.0034)	-0.00715* (0.0037)	-0.000910 (0.0013)	-0.00213 (0.0032)	-0.000692 (0.0031)
AST	0.00236* (0.0014)	0.00252 (0.0030)	0.00351 (0.0024)	0.000263 (0.0013)	-0.00274 (0.0017)	-0.00209 (0.0017)
AST ²	-0.000928 (0.0006)	-0.000244 (0.0006)	-0.000141 (0.0006)	-0.000974* (0.0006)	-0.000347 (0.0006)	-0.000128 (0.0006)
ASP	-0.00101 (0.0014)	-0.00381* (0.0019)	-0.00427** (0.0018)	0.00192 (0.0012)	-0.000787 (0.0012)	-0.000583 (0.0012)
ASP ²	0.000652 (0.0009)	0.00114 (0.0009)	0.00120 (0.0010)	-0.000241 (0.0006)	0.0000784 (0.0005)	-0.0000574 (0.0005)
Edu	-0.000261 (0.0006)	0.00139 (0.0050)	-0.00174 (0.0046)	-0.000740 (0.0008)	0.00558 (0.0085)	0.00506 (0.0083)
Pop	0.000215 (0.0002)	-0.000455* (0.0003)	-0.000398 (0.0003)	0.0000136 (0.0000)	-0.00115 (0.0012)	-0.00145 (0.0010)
Obs.	40711	40711	38931	39881	39881	38326
Adj. R ²	0.008	0.127	0.168	0.007	0.131	0.139
Year	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015	1991-2015
Fixed effects	None	Region, Year	Region, Year	None	Region, Year	Region, Year
Cluster (SE)	Country	Country	Country	Country	Country	Country

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Clustered standard errors at country level in parentheses.

SI 6 – Robustness Checks

Data Comparison

We compared the database used by this study (hereinafter referred to as the Kummu database) with two other widely used output databases – Kalkuhl and World Bank databases – and discussed their differences.

The Kalkuhl database is obtained by Kalkuhl and Wenz (9). It is a subnational-level database that contains over 1500 regions in 77 countries. The time series of the database is from 1900 to 2014. But it is a highly unbalanced panel database, with over 60% of regions' duration less than 25 years. The data stem from various statistical agencies of central or federal governments. 44 out of 77 countries used GDP data, while the others used other data to measure GDP such as Gross Value Added (GVA) or income to measure GDP (including countries that used these output data in certain years). The values of the data are converted to USD using *market* exchange rates from the FRED database of the Federal Reserve Bank of St. Louis.

World Bank database used by Burke, Hsiang and Miguel (8), Dell, Jones and Olken (10) and many other studies. It is obtained from the World Bank World Development Indicators database (<https://databank.worldbank.org/reports.aspx?source=World-Development-Indicators>). It is a country-level database that contains 266 countries from 1960 to 2021. The values of the data are converted to the 2017 constant international US dollars (2017 PPP).

Table S12 shows the descriptive statistics of Kummu, Kalkuhl and the World Bank database. To ensure comparability among these three databases, we aggregated the Kummu and Kalkuhl data from the subnational to the country level and focused on the shared countries and years. We find that Kummu and World Bank databases share the similar statistical results. The differences between the means of GDP per capita growth rates in the Kummu and World Bank databases are also statistically insignificant. However, due to the inconsistent data source and the different currency conversion methods, the GDP per capita data in the Kalkuhl database shows a significant difference from the data in the Kummu and World Bank databases.

Table S12. Descriptive statistics of three output databases

Database		(1) Kummu	(2) Kalkuhl	(3) World Bank
	Mean	0.025	0.065	0.027
	S.D.	0.042	0.132	0.039
	Min	-0.232	-0.846	-0.171
	Max	0.336	1.134	0.236
	Obs.		1173	
	Countries		77	
	Years		1991-2014	
t-test	Kummu		-9.89***	-1.07
	Kalkuhl			9.50***
	World Bank			

Notes: the alternative hypothesis of t-test is $H_a: \mu \neq \mu_0$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The difference is consistent when we conducted regression and correlational analyses. We used the fixed-effects regression and Pearson, Spearman tests to reveal the relations between these three databases. As shown in Table S13 and Table S14, although all results are statistically

significant, the GDP per capita growth rates in Kummu and World Bank database has higher R² value and correlation coefficient, while they are lower between the Kalkuhl database and the other two databases. The results suggest a higher relation between Kummu and World Bank database and a weaker one between the Kalkuhl and the other two databases.

Table S13. Fixed-effects regression results between three output databases

Dep var.	(1) World Bank	(2) World Bank	(3) Kalkuhl
Kummu	0.677*** (0.017)		0.833*** (0.097)
Kalkuhl		0.094*** (0.008)	
Obs.	1172	1172	1172
R ²	0.78	0.54	0.41
Fixed effect	Country, Year	Country, Year	Country, Year

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Clustered standard errors at country level in parentheses.

Table S14. Correlation analysis results between three output databases

	Pearson Correlation			Spearman Correlation		
	Kummu	Kalkuhl	WorldBank	Kummu	Kalkuhl	WorldBank
Kummu	1.00	0.48***	0.85***	1.00	0.52***	0.89***
Kalkuhl		1.00	0.41***		1.00	0.49***
WorldBank			1.00			1.00

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

Compared with the above two output per capita databases, the database used in our study has three advantages: First, Given the high heterogeneity of climate and economic activities, data aggregated at the country level tends to dilute or completely mask some useful information(11). The subnational database provided by Kummu allows for a more detailed spatial description of climate and economic variables. Second, the Kummu database covers almost all countries worldwide, while Kalkuhl omitted the vast majority of countries in Africa, Southeast Asia and Central America. These omitted regions happen to be hot, wet, and less developed. Omitting these regions may cause biased estimates. Third, the Kummu database uses GDP data for all years. This homogeneous data allows for more accurate estimates.

Results Comparison

We also compared our estimates with the results obtained from Kalkuhl and World Bank databases. To ensure the comparability of results, we aggregated the subnational data to the country level and restricted the time series to 1991-2010 (using shorter years to consistent with the study conducted by Burke, Hsiang and Miguel (8)). Table S15 shows the results based on Burk's specification. Columns (1), (2), and (5) share the same countries (170 countries), while Columns (3) and (4) only include the 77 countries in the Kalkuhl database. The results suggest similar effects of temperature and precipitation based on the World Bank database and Kummu database (Table S15, columns (1), (2), and (5)).

Table S15 Country-level Regression results based on three output databases

Data source	(1) World Bank	(2) Kummu	(3) Kalkuhl	(4) Kummu	(5) This study
Dep var.	GDP per capita growth				GDI per capita growth
T	0.0143** (0.0065)	0.0176*** (0.0067)	0.0184 (0.0130)	0.000977 (0.0054)	0.00218* (0.0011)
T ²	-0.000451** (0.0002)	-0.000582** (0.0002)	-0.000778 (0.0006)	-0.000146 (0.0003)	-0.0000503* (0.0000)
P	0.0229* (0.0123)	0.0226* (0.0117)	-0.0785 (0.0566)	0.00698 (0.0156)	0.00609 (0.0040)
P ²	-0.00759*** (0.0029)	-0.00671** (0.0026)	0.0242* (0.0137)	-0.00173 (0.0049)	-0.00156* (0.0008)
Pop	-0.000258 (0.0002)	-0.000262 (0.0002)	0.000105 (0.0005)	-0.000095 (0.00016)	-0.0000475 (0.0000)
Edu	0.000652 (0.0047)	-0.00145 (0.0049)	0.00853 (0.0140)	-0.00285 (0.00466)	0.0000849 (0.0008)
Obs.	3419	3419	1090	1090	3419
Adj. R ²	0.207	0.226	0.307	0.448	0.119
Fixed effects	Country, Year	Region, Year	Region, Year	Region, Year	Region, Year
Cluster (SE)	Country	Country	Country	Country	Country

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Clustered standard errors at country level in parentheses.

Table S16 Subnational-level Regression results based on Kummu and Kalkuhl databases

Data source	(1) Kummu	(2) Kalkuhl	(3) Kummu
Dep var.	GDP per capita growth		
ΔT	-0.00101 (0.0032)	0.00841* (0.0046)	0.00273 (0.0052)
ΔT*T	0.000236 (0.0002)	-0.000789 (0.0006)	0.000146 (0.0004)
ΔP	-0.00401 (0.0111)	-0.0125 (0.0223)	0.00559 (0.0128)
ΔP*P	-0.00234 (0.0048)	0.00423 (0.0086)	-0.00864 (0.0057)
T	0.00635 (0.0050)	0.000864*** (0.0003)	-0.00320 (0.0098)
T ²	-0.000358* (0.0002)	-0.0000477*** (0.0000)	-0.000138 (0.0004)
P	0.0182 (0.0169)	0.0130** (0.0064)	0.0156 (0.0204)
P ²	-0.00156 (0.0035)	-0.00257 (0.0020)	-0.000601 (0.0044)
Obs.	39881	24991	24078
Adj. R ²	0.131	0.284	0.113
Fixed effects	Region, Year	Region, Year	Region, Year
Cluster (SE)	Country	Country	Country

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Data in columns 2 and 3 shares the same countries and time series. Clustered standard errors at country level in parentheses.

However, we find that the results based on Kalkuhl database are substantially different. The coefficients and statistical significance of the quadratic term of temperature and precipitation in Column (4) of Table S15 are smaller than those in Columns (1) and 2 of Table S15. These results are similar when we use the subnational data (Table S16). Comparing columns (1) and (3) in Table S16 shows that omitting hot and less developed regions substantively changes the regression results. These results confirmed our concern that an incomplete database could not fully capture the effects of weather conditions and cause biased estimates.

The different results of Columns (2) and (3) in Table S16 are attributed to the different currency conversion methods. International dollars deviate most from market dollars in poor countries.

Replacing the Weather Database

Table S17 Regression results based on the ERA5 weather database

Dep var.	(1) GDI per capita growth	(2) GDP per capita growth
ΔT	-0.00356 (0.0053)	0.000437 (0.0031)
ΔT^*T	0.000634 (0.0005)	-0.00000606 (0.0003)
ΔP	0.00510 (0.0076)	-0.00331 (0.0064)
ΔP^*P	-0.00257 (0.0029)	0.000390 (0.0007)
T	0.0140** (0.0067)	0.00513 (0.0055)
T ²	-0.000649* (0.0003)	-0.00000325 (0.0002)
P	0.0232 (0.0154)	0.00480 (0.0114)
P ²	-0.00148 (0.0020)	-0.000303 (0.0008)
AST	-0.00109 (0.0025)	-0.00342* (0.0020)
AST ²	-0.000113 (0.0006)	-0.000482 (0.0006)
ASP	-0.00332** (0.0017)	0.000383 (0.0014)
ASP ²	-0.0000711 (0.0005)	-0.000247 (0.0004)
Edu	-0.000394 (0.0003)	-0.00118 (0.0012)
Pop	0.00138 (0.0051)	0.00581 (0.0084)
Obs.	40711	39881
Adj. R ²	0.13	0.13
Year	1991-2015	1991-2015
Fixed effects	Region, Year	Region, Year
Cluster (SE)	Country	Country

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Clustered standard errors at country level in parentheses.

Second, we replaced our weather database from CRU to ERA5, another widely used weather database in this research field. ERA5 was developed by the European Centre for Medium Range Weather Forecast (ECMWF). It combines satellite and station observations from around the world with the laws of physics encoded in computer models. Therefore, the ERA5 database is able to reduce potential biases from spatial interpolation, missing values, and the discontinuation of weather station observations. However, the weakness of ERA5 is that it is a reanalysis weather database that may not accurately reflect the actual surface weather conditions(12).

The regression results based on the ERA5 weather database are presented in Table S17. Although the coefficient of the quadratic function of temperature and precipitation lost their statistical significance, the coefficient value for economic income is still lower compared to economic output, remaining a greater sensitivity of economic income to weather conditions than economic output.

Using the Weighted Anomaly Standardized Precipitation

Third, we use the weighted anomaly standardized precipitation (WASP) to investigate the variability effect of precipitation on economic growth. The results are presented in Table S18, and we found that although the quadratic function of precipitation lost its statistical significance after using WASP, it remained significant at high precipitation levels.

Table S18 Regression results based on the Weighted Anomaly Standardized Precipitation

Dep var.	(1) GDI per capita growth	(2) GDP per capita growth
ΔT	-0.00401 (0.0048)	-0.000818 (0.0032)
ΔT^*T	0.000427 (0.0003)	0.000208 (0.0002)
ΔP	0.00557 (0.0126)	-0.00488 (0.0109)
ΔP^*P	-0.00198 (0.0047)	-0.00161 (0.0047)
T	0.0150* (0.0081)	0.00807 (0.0053)
T^2	-0.000776*** (0.0003)	-0.000227 (0.0002)
P	0.00924 (0.0220)	-0.00453 (0.0186)
P^2	-0.00453 (0.0038)	0.00111 (0.0032)
AST	0.00270 (0.0030)	-0.00246 (0.0017)
AST^2	-0.000223 (0.0006)	-0.000330 (0.0006)
WASP	0.000150 (0.0018)	0.00247 (0.0018)
$WASP^2$	0.00120 (0.0007)	-0.000519 (0.0004)
Edu	0.00130 (0.0050)	-0.00118 (0.0012)
Pop	-0.000419 (0.0003)	0.00581 (0.0084)
Obs.	40711	39881
Adj. R ²	0.13	0.13
Year	1991-2015	1991-2015
Fixed effects	Region, Year	Region, Year
Cluster (SE)	Country	Country
ME at 1.2 m	-0.0016	-0.0019
..SE	0014	0.013
ME at 5.0 m	-0.036**	0.0066
..SE	0.018	0.019

Note: *p < 0.10, **p < 0.05, ***p < 0.01. ME stands for marginal level effects of weather shocks on economic growth. Clustered standard errors at country level in parentheses.

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