Interactive Effects of Temperature and Precipitation on Global Economic Growth

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Abstract

A damage function measures quantitatively how aggregated economies respond to climate change and it have been used as a powerful tool to provide trajectories of future economic development. However, the specification of the damage function remains highly contentious. In this paper we extend the conventional damage function by introducing interactive terms between temperature and precipitation. Our new specification allows for heterogeneous responses to climate change in different climate conditions, making possible the response to temperature change dependent on precipitation levels, and vice versa. The results show that all temperature, precipitation, as well as their interaction are statistically significant factors affecting economic growth. The most sensitive economy to climate change is the combination of cold temperature with excessive precipitation, in which case, either reduced rainfall or a warming trend could benefit economic growth considerably such as in Canada and Northern Europe countries. Compared to cold climate economies, economies with moderate to warm climates are more resilient to precipitation change, which could possibly be attributed to their adaptation to climates characterizing high variability in precipitation.

By estimating historical impacts of temperature changes, we find that except for countries in high latitudes in the Northern Hemisphere that benefit from the warming, massive negative impacts are found in most countries in the world, with the Northern Africa and Southeast Asia being affected the most. We also find that only 17 countries report significant precipitation trends—13 of them experience more precipitation and the remaining 4 report drying trends. The wetting trends are found beneficial to dry regions, such as Russia, and harmful to wet regions, such as Canada and the US. On the other hand, the drying trends are found ubiquitously damaging to local economies which tend to have modest precipitation in the first place.

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New records of increasing temperatures have been observed globally every year, resulting in wide-ranging damages in a wide range of areas, for example agricultural and industrial output, ecosystems, and public welfare, see [1–3]. Damages are not experienced equally across countries; instead, global warming has widened global inequality for which wealthiest countries, despite their stronger ability of adaption and more resilient economies, are less adversely influenced, or even stand to benefit, whereas poorer countries of which economies are more vulnerable experience the largest reduction in economic growth [4, 5].

The impact of climate change on economic output has been empirically estimated by the damage or response function which relates climate explanatory variables to economic levels or growth rates in the literature. Significant nonlinear effects of temperature on economic growth have been widely reported in current climate-economic studies (see e.g. [4–7]). A global universal optimal temperature is found at which economic growth peaks, suggesting that cold countries would benefit while warm countries experience damage from additional warming.

The effects of precipitation on the aggregated economy are less discussed. In general, precipitation can have both positive and negative effects on GDP. On the positive side, adequate amounts of precipitation can support agricultural production, which is an important contributor to GDP in many countries. For example, sufficient rainfall can help to irrigate crops and support the growth of plants and animals. This can lead to higher agricultural yields, which can in turn increase the economic output of a country or region. On the other hand, too much or too little precipitation can have negative effects on GDP. Moreover, extreme weather events, such as drought or flooding, can disrupt agricultural production and damage infrastructure, which can lead to economic losses. For example, a drought can cause crops to fail, leading to reduced agricultural output and lower GDP. Similarly, heavy rainfall or flooding can damage the soil and hence crops and also infrastructures, such as roads, bridges, and buildings, which can also lead to economic losses and lower GDP. Nevertheless, on a global level, there are, to the best of our knowledge, no results that show a significant contribution from precipitation on the economic output. In this paper we show that, in general, precipitation does indeed have an important and significant contribution to a country's GDP. The role of precipitation is even strengthened when we allow temperature and precipitation to interact. This means that the amount of precipitation optimal for an economy depends on the average temperature in the country of that economy.

Moreover, to our best knowledge, the interactive effect between temperature and precipitation is hardly investigated in the existing literature. The intuition behind the interactive terms is that the response to one variable is dependent on the values of the other.

For instance, an abnormally high temperature would likely be less harmful given abundant precipitation than the combination of droughts and heatwaves. Furthermore, interactive terms add curvature to the response surface and allow the response function to be more adaptive to regional characteristics, making possible different climate optimums globally.

Using the baseline framework in ref [6] in addition to our extension we demonstrate the importance of introducing interactive terms between temperature and precipitation to the damage function. The optimal temperature is estimated to be a function of precipitation and vice versa. The function of optimal temperature looks like a quadratic curve, the lowest optimum is reached at a moderate level of precipitation and higher optimal temperatures are associated with extreme precipitations, either extremely dry or wet.

In addition to adding interactive terms to the model, we also investigate alternative ways to specify fixed effects of countries and times, which characterize the time invariant and variant factors affecting economic growth besides climate change. Ref [6] used a country panel regression model in which they controlled for the unobserved variables by time- and country-specific factors additively, i.e., *additive fixed effects*, assuming that abrupt global events, i.e., time-specific factors, such as global recessions and shocks have the same effects on all countries. We relax this assumption by allowing for divergent country responses to global shocks using interactive time- and country-specific factors and our results show improved model estimation better capturing regional characteristics.

In this paper, we make a three-way comparison of models: $i)$ baseline model in ref [6]; $ii)$ model i in addition to temperature and precipitation interactive terms with *additive fixed effects* (AFE); $iii)$ model i in addition to temperature and precipitation interactive terms with *interactive fixed effects* (IFE). We refer to the three models as Burke's model, AFE, and IFE hereinafter. We aim to compare the response surfaces of the three models, and based on which we also demonstrate historical impacts of temperature and precipitation on individual countries over the past six decades.

Climate Evolution

Fig. 1 shows average temperature levels and decadal trends on a country level over 1961–2019. Wide-spread warming is found in all countries with decadal warming rates ranging from 0.05 to 0.40 $^{\circ}C$ per decade. The strength of the warming is likely to be inversely proportional to countries' average temperature. Cold countries in high latitudes of the Northern Hemisphere experience the strongest warming. As latitudes decrease, the warming weakens gradually. Generally, warming in the Southern Hemisphere is milder than in the Northern Hemisphere. The slightest warming is found in Southeast Asia and South America; the strongest warming in Europe, Russia, and Middle East countries.

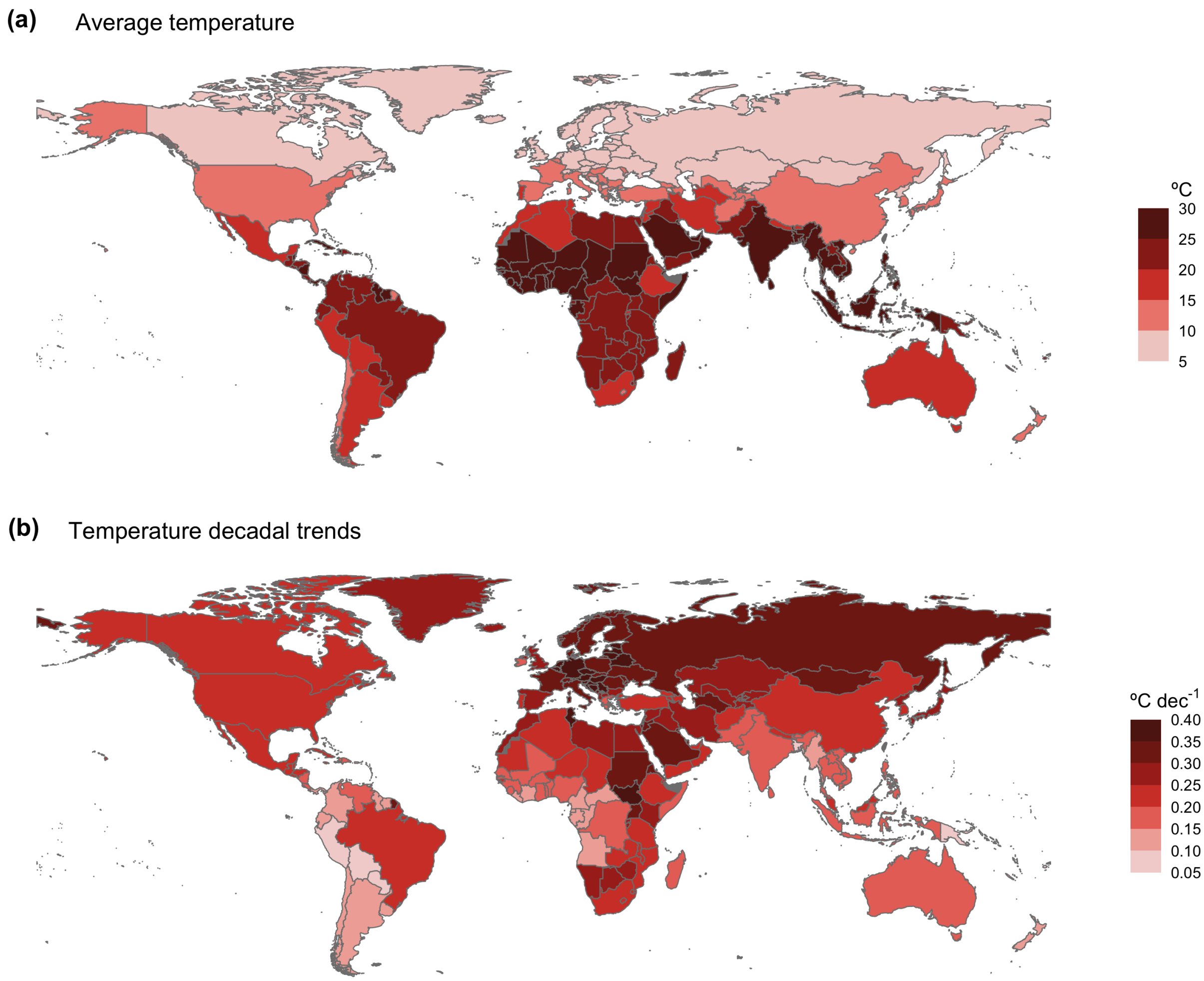

Fig. 1 Country level average annual temperature and decadal trends over 1961–2019. (a) Average annual temperature. (b) Decadal trends regressing each country's annual temperature on linear time trends.

Precipitation trends are not as persistent; unlike the ubiquitous global warming, only ~37% land areas show statistically robust trends at 5% significance level[1] (Fig. 2). Overall, there are 17 countries with significant precipitation trends. However, while only 4 countries have become drier, i.e, Australia, DR Congo, Iraq, and Mongolia, 13 of them have become wetter, primarily located in the High North and Southeast Asia Pacific Islands. Moreover, the wetter trends tend to take place in wet regions and the drier trends in relatively dry regions. These findings are broadly consistent with [8]. Hereinafter, we refer to annual average temperature and annual total precipitation as temperature and precipitation for brevity.

[1]The fraction is calculated as the ratio of the areas of countries with significant precipitation trends over the whole land areas.

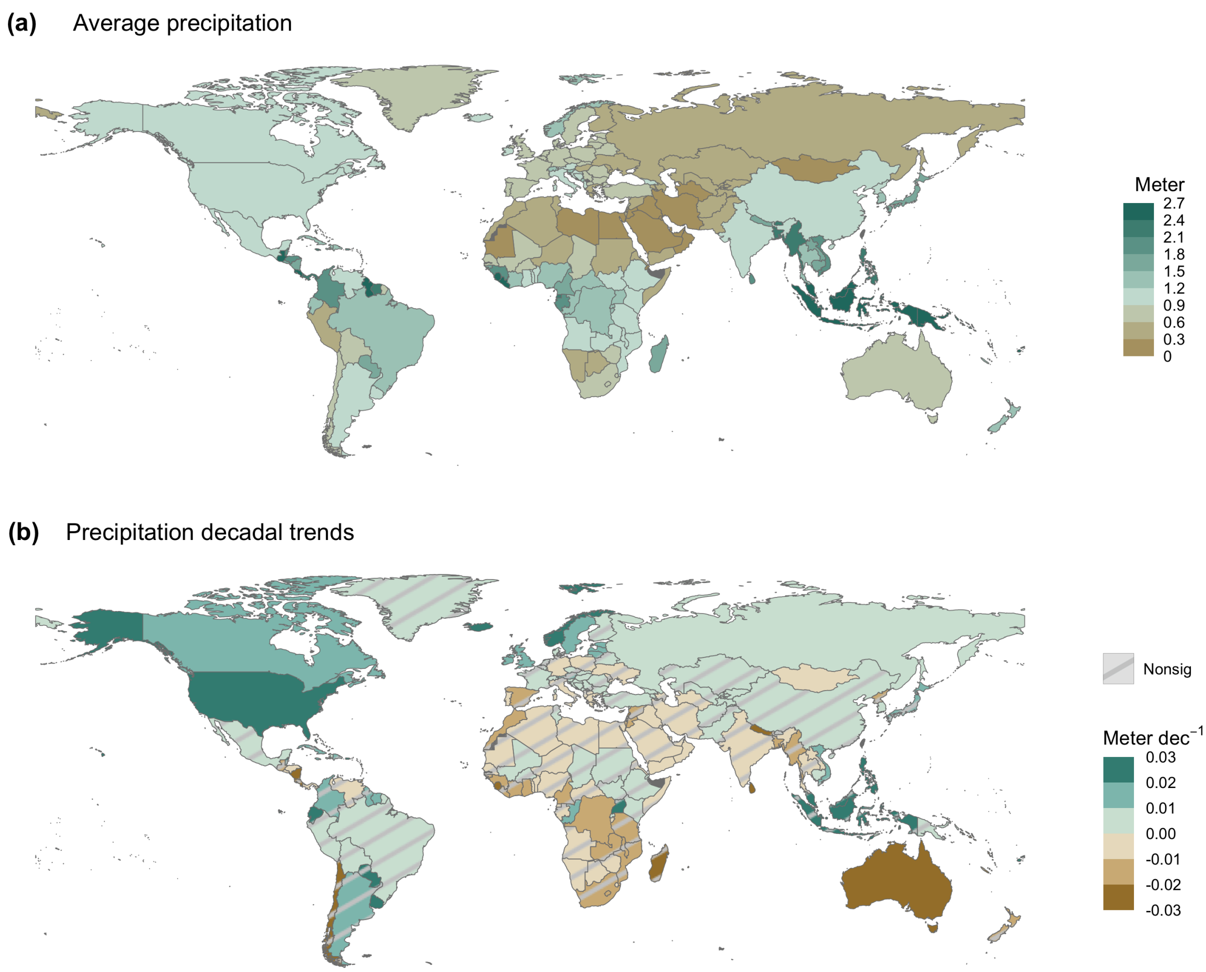

Fig. 2 Country level average annual total precipitation and decadal trends over 1961–2019. (a) Average annual total precipitation. (b) Decadal trends regressing each country's annual total precipitation on linear time trends. Hatched areas indicate that the trends are insignificant at 5% significance level.

Response function

Fig. 3 shows response surfaces for the three models—Burke's model as baseline, and two extended models for comparison. Without interactive terms between temperature and precipitation as in the baseline, the response surface is almost completely flat, dominated by the change of temperature, and with almost no variation due to precipitation changes (panel (c)). On the other hand, introducing the interactive terms increases greatly the sensitivity of the response surface to precipitation, especially in cold climate economies (panel (a) and (b)). The most damaging climate is a cold climate in conjunction with excessive precipitation, e.g., Northern Europe and Canada, in which case either reduced rainfall or a warming trend will bolster economic growth considerably.

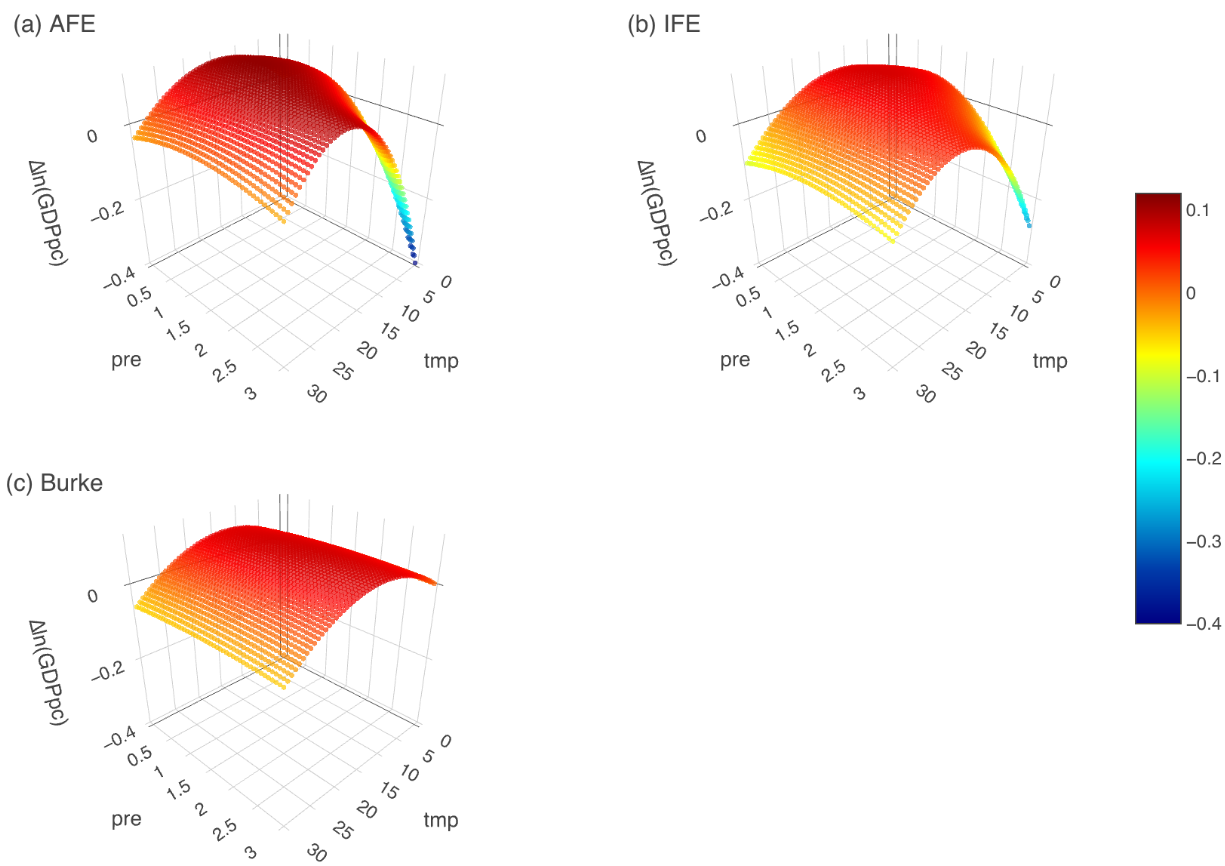

Fig. 3 3D response surfaces with respect to changes in temperature and precipitation. (a) AFE: Burke's model + interactive terms + additive fixed effects; (b) IFE: Burke's model + interactive terms + interactive fixed effects; (c) Burke: Burke's model (baseline); *tmp*: annual average temperature, unit: $^{\circ}C$. *pre*: annual total precipitation, unit: meters; z-axis shows the log difference of GDP per capita. 2D response functions for AFE and IFE can be found in Supplementary Information (SI) Figs. S1 and S2. The 2D response functions are just section planes along different levels of precipitation and temperature.

The larger sensitivity of cold climate economies can also be seen from Fig. 4. When the temperature is at its 10th quantile level, economic growth fluctuates within a range almost six times larger than it does when the temperature is at the median and 90th quantile. Furthermore, and not surprisingly, cold climates tend to have lower level for the optimal precipitation. At the 10th quantile temperature, the growth rate reaches the highest at $\sim$0.8m for annual precipitation (panel (a)). The optimal precipitation becomes larger as temperature increases (panel (b) and (c)). Warm climate economies (with an annual average temperature above $15^{\circ}C$) are more resilient to precipitation variability. The lack of excessive rainfall is not as damaging to them as to cold climate economies, moreover, warm climate economies are less affected by small scale volatility of precipitation. In contrast to the insensitivity to precipitation change, additional warming is the more detrimental hazard to warm climate economies.

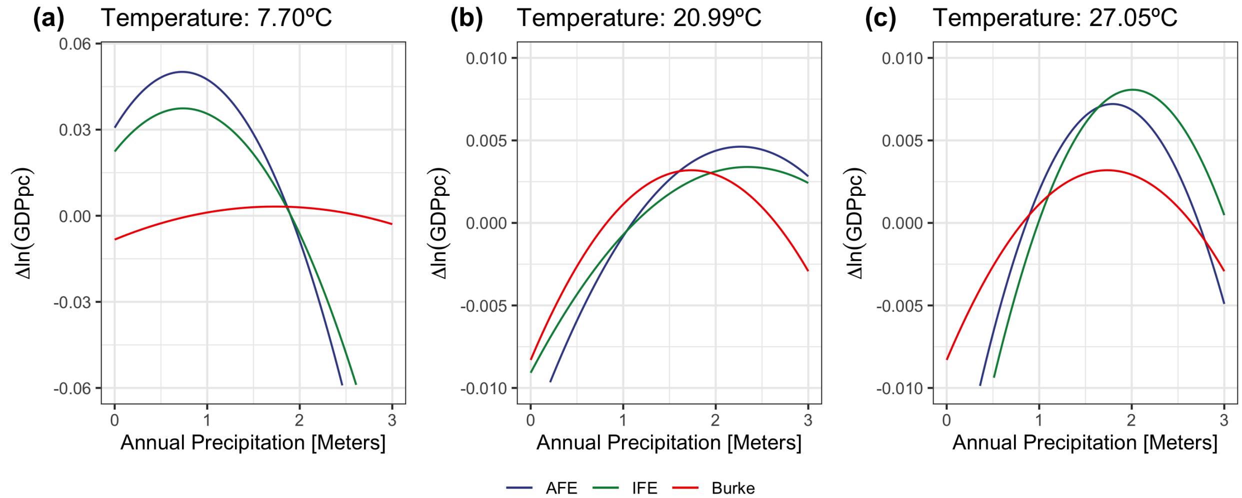

Fig. 4 2D response function to precipitation given fixed temperatures. Temperatures are given as the 10th, 50th, 90th quantiles of all countries' temperature levels in panels (a), (b), and (c), respectively, and the values are shown at the top of each figure. Each panel shows three model specifications: AFE (in blue): Burke's model + interactive terms + additive fixed effects; IFE (in green): Burke's model + interactive terms + interactive fixed effects; Burke (in red): Burke's model (baseline). X-axes show the annual total precipitation in meters; y-axes show the log difference of GDP per capita. Note that since the response function at temperature's 10th quantile varies exceptionally large, we use larger y-axis limits in panel (a) compared to those of panel (b) and (c). See SI Fig. S3 for response functions at more temperature levels.

Responses to temperature change given fixed precipitations are shown in Fig. 5. When the precipitation level is low and medium, the response functions with and without the interactive terms are not distinctively different. In fact, the AFE and Burke's model overlap largely in low to medium precipitation scenarios, whereas IFE displays lower optimal temperatures and smaller sensitivity to additional warming. By contrast, at a high precipitation level, models with interactive terms characterize a higher optimal temperature and show more concave responses to temperature change, meaning larger sensitivity to warming.

Fig. 6 displays the optimal temperature as a function of the level of precipitation and optimal precipitation as a function of temperature. Models with interactive terms show variable optimal values of temperature and precipitation while Burke's model has a fixed optimal value regardless of differences in local climate conditions, with the optimal temperature and precipitation being $12.8°C$ and 1.7m, respectively. By contrast, AFE and IFE models show a large variation of optimal temperatures, ranging from 10 to $20°C$. Note that IFE varies more than AFE does and tends to have lower optimal temperatures at

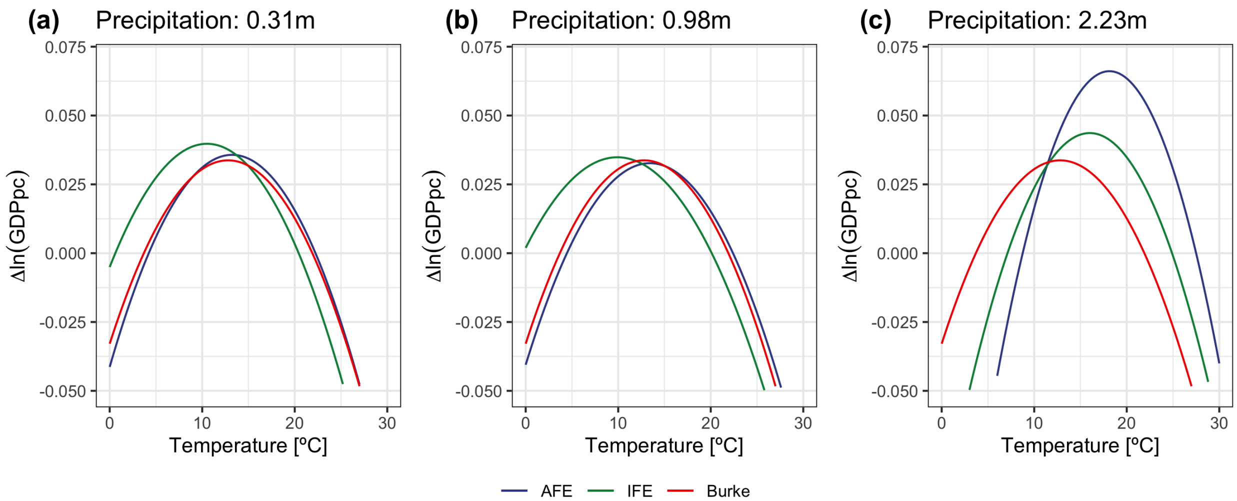

Fig. 5 2D response function to temperature given fixed precipitations. Precipitations are given as the 10th, 50th, 90th quantiles of all countries' precipitation levels in panels (a), (b), and (c), respectively. Refer to Fig. 4 for model specifications. X-axes show the annual average temperature in Celsius degrees ($^{\circ}C$); y-axes show the log difference of GDP per capita. See SI Fig. S4 for response functions at more precipitation levels.

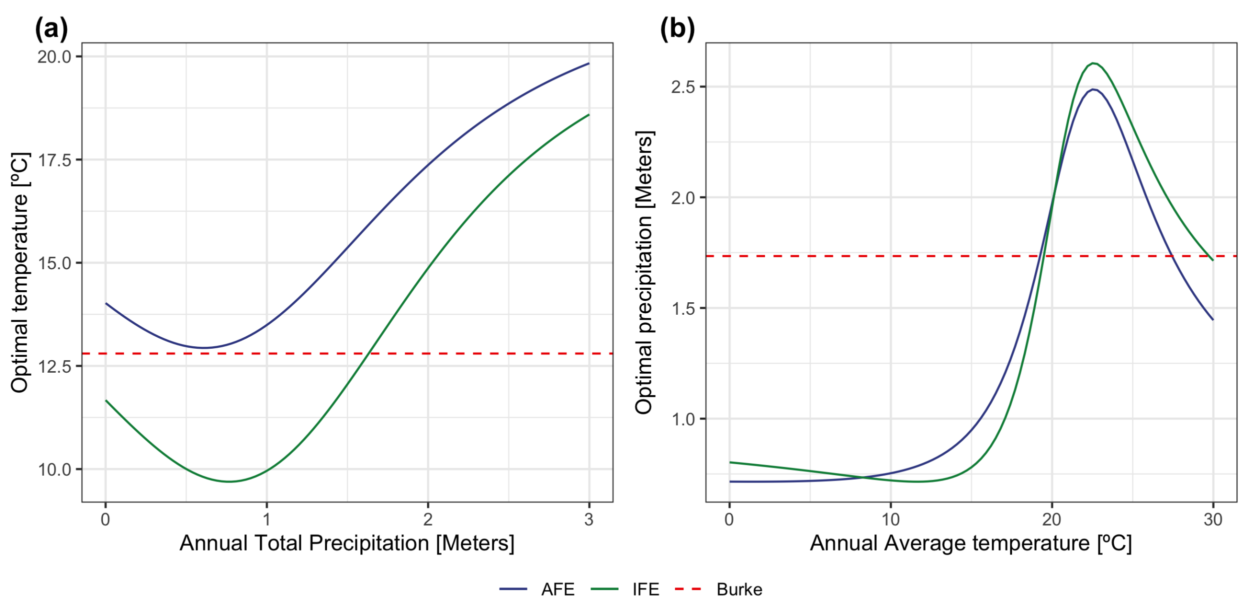

Fig. 6 Optimal temperature and precipitation. (a) Optimal temperature as a function of precipitation. (b) Optimal precipitation as a function of temperature. Three models are shown, AFE, IFE, and Burke in blue, green, and red line respectively. As Burke's model disables variation of the response function of one variable depending on the level of the other, a universal optimal temperature and precipitation are shown as horizontal lines.

fixed levels of precipitation. From extremely dry to extremely wet climates, the optimal temperature decreases at first as precipitation increases and reaches the lowest at about

0.8m of precipitation, located mostly in Western Europe. Additional precipitation beyond that is accompanied by higher optimal temperatures.

Similarly, the optimal annual total precipitation varies between 0.75 to 2.5m depending on the level of temperature. The optimal precipitation varies little when the temperature is between 0 to 12$^{\circ}C$, yet increases drastically given additional warming up to 22$^{\circ}C$ and then starts to decline with further warming. The highest optimal precipitation is found in warm climates where the annual average temperature is between 20 to 25$^{\circ}C$, mostly located in Southern Africa and Latin America. Countries in the Northern Hemisphere outside the subtropics with cold climates tend to have a modest optimal precipitation level, and mostly below 1.0m. Given the general wetting trends in these areas, countries with abundant precipitation above 1.0m, such as Canada and the US, will experience higher rates of economic damage if current trends extends in the future, whereas arid countries, e.g., Russia and Kazakhstan, will benefit from additional precipitation. By contrast, Burke's model applies one fixed optimal precipitation level, 1.7m, to all countries. Given that $\sim$80% countries in the world have precipitations well below the optimum, all of them will benefit from additional precipitation. The disregard for local characteristics of climate circumstances could be problematic as it assumes the same response function for the world's driest and wettest countries.

The difference in the sensitivities and the optimal temperature and precipitation among the models highlights the importance of introducing the interactive terms which enable various reactions to precipitation variability depending on the level of temperature and temperature on precipitation. The interactive terms allow for different response functions in different climate settings. The absence of interactive terms like in Burke's model imposes universally applicable climate optimums and attributes all differences in the climate change consequences to their respective positions on the response function. This overly strict assumption limits the curvature of the response surface, making the model prone to capture the moderate temperature economies and under-represent the consequences of climate change in more extreme climate scenarios.

Historical impacts

Fig. 7 shows the impacts of temperature and precipitation changes separately and jointly over 1961–2019. Generally, high-latitude countries in the Northern Hemisphere have benefited from historical warming, while subtropical and tropical countries have experienced damage. Specifically, the warmer their climate is, the more damage they have suffered from the warming, even though the absolute increase of temperature in warm climates is modest compared to that of high latitude countries (Fig. 1b). AFE and IFE have

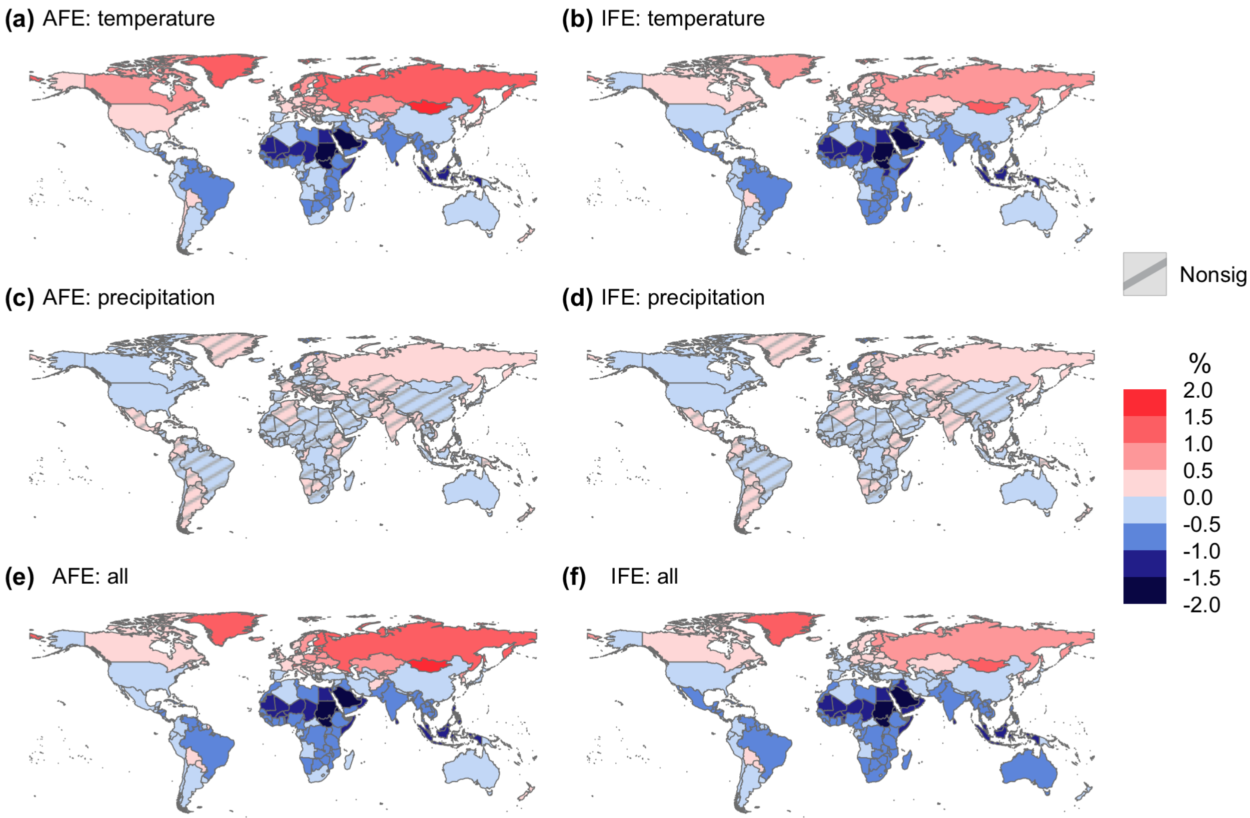

Fig. 7 Historical impacts of temperature and precipitation over the period 1961–2019. The left and right panels correspond to the AFE and IFE models, respectively. (a) and (b) show historical impacts of temperature change; (c) and (d) show impacts of precipitation; stripes indicate nonsignificance of precipitation trends for the country; (e) and (f) show the sum of the effects of temperature and precipitation. The values display the impact on GDP growth. For instance, a value of 1% means that a country's GDP growth rate has increased by 1 percentage point over the period 1961–2019 due to historical climate change. In other words, a country with a growth rate of 3% year^{-1} in 2019 would have a growth rate of 2% year^{-1} if the effects of historical climate change were removed.

generally consistent estimates for the signs of temperature impacts, i.e., positive or negative, though AFE has more optimistic estimates of the benefits. The differences primarily lie in the countries in the temperate climate zone, such as the US and Southern European countries, whose impacts change from positive in AFE to negative in IFE. This change could be attributed to the general higher optimal temperatures in the AFE model at fixed precipitations (Fig. 6a). For instance, AFE and IFE report the optimal temperature for the US being 13.45 and 9.91$^{\circ}C$, respectively. Given the average annual temperature in the US being 13.23$^{\circ}C$, which is smaller than the AFE optimal temperature but larger than the IFE optimal temperature, the warming therefore results in benefits for the AFE model and damages for the IFE model.

Precipitation impacts are generally of a smaller scale compared to those of temperature. AFE and IFE have largely unanimous estimates. For countries with significant precipitation trends, the wetting trend has hampered economic growth in Canada and the US, which have abundant precipitation at the first place, whereas benefited Russia, whose climate is relatively drier; the drying trend has resulted in economic losses in all countries with significant drying trends. A large number of countries cannot conclude significant precipitation impacts due to their weak precipitation trends. Though statistically insignificant, widespread negative impacts are found in Africa and Southeast Asia in addition to the fact that they are also the regions hit the most by global warming.

The overall impacts are generally dominated by temperature change. Overall positive impacts are found in Russia, Canada, and Central and Northern Europe, whereas overall negative impacts are found in Africa, Southeast Asia, Australia, and Latin America. Note that precipitation impacts occasionally trump temperature impacts for some countries, such as the US, Japan, and Chile in the AFE model. All three countries have slightly positive temperature impacts which are offset by negative precipitation impacts. However, under the IFE model, the three countries report negative temperature impacts due to lower optimal temperatures in the IFE and thereby additional warming would be harmful, and they remain to be negative taking into account the precipitation impacts.

Discussion

In summary, the current paper extends the damage function by introducing interactive terms between temperature and precipitation. The new response surface is able to incorporate local climate characteristics and add curvature to the surface. Responses to temperature are different given different precipitation levels, and likewise for responses to precipitation. We find high sensitivity to climate change in cold and high precipitation climate, making it one of the most vulnerable climate types. Moreover, instead of fixed temperature and precipitation optimums in the model without the interactive terms, we present optimal temperature as a function of precipitation, and vice versa. The optimal temperature is the lowest when precipitation is moderate, e.g., in Western Europe, and gets higher when precipitation is extremely high or low, e.g., in Southeast Asia and North Africa.

We further estimate the realized impacts of temperature and precipitation change over the past six decades. We find positive temperature impacts in high-latitude countries in the Northern Hemisphere and widespread negative impacts for subtropical and tropical countries. Precipitation impacts are divergent and of a smaller scale compared to temperature impacts due to the absence of persistent precipitation trends in most countries. Nonetheless, some patterns can still be concluded. Wetting trends are found harmful in countries with abundant precipitations, such as Canada and the US, yet beneficial to dry climates such as Russia. Significant drying trends are found only in four countries which all report negative impacts of less precipitation.

The extension of the damage function is meaningful for society to understand what has happened historically and could be used to provide predictions of future economic scenarios under different climate adaptation policies.

Data and Method

Data

Temperature and precipitation data are obtained from Climate Research Unit Time Series (CRU-TS V4.0, [9]), which provides monthly average temperature and monthly total precipitation data for each $0.5^\circ \times 0.5^\circ$ cell on the globe over the period 1900–2019. We aggregate the 0.5° grid cell climate estimates to country level, weighting by population density in year 2000 using data from the Gridded Population of the World [10].

GDP per capita data are available from the World Bank's World Development Indicators dataset [11], which contains worldwide country level economic development measures between the years 1961–2019. To ensure comparability of the values of economic outcomes in the history, we use constant 2010 US$ GDP per capita. Our full dataset comprises of 8055 country-year observations over the period 1961–2019.

Econometric Model

Suppose that we have the panel data variable $y_{i,t}$ that follows the data generating process (DGP),

$$y_{i,t} = \boldsymbol{\beta}' \mathbf{x}_{i,t} + u_{i,t}, \tag{1}$$

where $\mathbf{x}_{i,t}$ is a $k-$vector of variables and $\boldsymbol{\beta}$ is a $k-$vector of coefficients. This is a homogeneous panel data model. The assumptions we make about $u_{i,t}$ will determine the presence and the nature of unobserved heterogeneity that is allowed.

AFE. Individual and time fixed effects.

$$u_{i,t} = \mu_i + \nu_t + \varepsilon_{i,t}. \tag{2}$$

Here μ_i is the individual fixed effects term that represent the unobserved heterogeneity across cross-section units and ν_t is the fixed time effects that represent the unobserved heterogeneity across time. The term ν_t stands for the shocks that are fixed across cross-section units. In this assumption, we allow the terms that represent unobserved heterogeneity to enter the model in an additive way. For this reason, ref [12] called this model "additive effects model".

IFE. Interactive fixed effects.

$$u_{i,t} = \boldsymbol{\lambda}_i'\mathbf{f}_t + \varepsilon_{i,t}. \tag{3}$$

Here $\mathbf{f}_t$ are $r-$vector of common global shocks that might affect all countries and the $r-$vector $\boldsymbol{\lambda}_i$ are the individual specific loadings. They represent the extent to which the individuals are affected by the common global shocks. This assumption is more general than the FE assumption and it allows the unobserved heterogeneity to enter the model in a multiplicative way. Note that by restricting $\boldsymbol{\lambda}_i = (1, \mu_i)'$ and $\mathbf{f}_t = (\nu_t, 1)'$, we can obtain the FE model back.

The general model specification is given by

$$\begin{aligned}\Delta \ln \left(GDPpc\right)_{i,t} = \beta_1 T_{i,t} + \beta_2 T_{i,t}^2 + \beta_3 P_{i,t} + \beta_4 P_{i,t}^2 + \beta_5 T_{i,t} \cdot P_{i,t} + \beta_6 T_{i,t}^2 \cdot P_{i,t} \\ + \beta_7 T_{i,t} \cdot P_{i,t}^2 + \beta_8 T_{i,t}^2 \cdot P_{i,t}^2 + \theta_{1,i} t + \theta_{2,i} t^2 + u_{i,t}, \\ \text{where } u_{i,t} = \boldsymbol{\lambda}_i'\mathbf{f}_t + \varepsilon_{i,t}\end{aligned} \tag{4}$$

Eqn.(4) relates the log difference of GDP per capita of country i in year t ($\Delta \ln \left(GDPpc\right)_{i,t}$) to a function of annual average temperature ($T_{i,t}$), annual total precipitation ($P_{i,t}$) and time trend (t) in the same year. Temperature and precipitation are the two climate variables discussed most widely in existing literature, mostly focusing on the quadratic polynomials of temperature and precipitation (see e.g.[4–7]). In the current study we introduce the interactive terms between temperature and precipitation to the second degree to investigate how their co-movement affects economic growth. The interactive terms allow for divergent responses to the change of one climate variable dependent on the levels of the other. In other words, this specification makes it possible for different impacts of an additional warming of $1°C$ in arid and humid regions and different impacts of an additional precipitation of 10mm in tropical and Nordic countries. Furthermore, we use country-specific quadratic time trends ($\theta_{1,i} t + \theta_{2,i} t^2$) to capture time varying factors intrinsic to individual countries affecting economic growth, such as technological advancements, demographic shifts, etc. Time- and country-specific fixed effects are represented by $u_{i,t}$ as explained in Eqn.(3).

Applying the first derivative rule to Eqn.(4), we obtain the optimal temperature (T^*) and precipitation (P^*) as follows

$$\begin{aligned}
\frac{\partial \Delta \ln (GDPpc)}{\partial T} &= 0 \;\Rightarrow\; T^* = -\frac{\beta_1 + \beta_5 P + \beta_7 P^2}{2(\beta_2 + \beta_6 P + \beta_8 P^2)} \\
\frac{\partial \Delta \ln (GDPpc)}{\partial P} &= 0 \;\Rightarrow\; P^* = -\frac{\beta_3 + \beta_5 T + \beta_6 T^2}{2(\beta_4 + \beta_7 T + \beta_8 T^2)}
\end{aligned} \tag{5}$$

The historical impacts of temperature ($\delta_{i,T}$) can be estimated by subtracting the start year economic growth from the end year economic growth fixing precipitation at its average level given by (6). Similarly, the historical impacts of precipitation ($\delta_{i,P}$) can be estimated by (7).

$$\begin{aligned}
\delta_{i,T} &= (\beta_1 + \beta_5 \overline{P}_i + \beta_7 \overline{P}_i^2)\Delta T_i + (\beta_2 + \beta_6 \overline{P}_i + \beta_8 \overline{P}_i^2)\Delta T_i^2 \\
\Delta T_i &= T_{i,\overline{2019}} - T_{i,\overline{1961}} \\
\Delta T_i^2 &= T_{i,\overline{2019}}^2 - T_{i,\overline{1961}}^2 \\
\overline{P}_i &= \sum_t P_{i,t}
\end{aligned} \tag{6}$$

$$\begin{aligned}
\delta_{i,P} &= (\beta_3 + \beta_5 \overline{T}_i + \beta_6 \overline{T}_i^2)\Delta P_i + (\beta_4 + \beta_7 \overline{T}_i + \beta_8 \overline{T}_i^2)\Delta P_i^2 \\
\Delta P_i &= P_{i,\overline{2019}} - P_{i,\overline{1961}} \\
\Delta P_i^2 &= P_{i,\overline{2019}}^2 - P_{i,\overline{1961}}^2 \\
\overline{T}_i &= \sum_t T_{i,t}
\end{aligned} \tag{7}$$

where $T_{i,\overline{1961}}$ and $T_{i,\overline{2019}}$ stand for the average annual temperature over the first and last decade of the time period 1961–2019. Similarly, $P_{i,\overline{1961}}$ and $P_{i,\overline{2019}}$ are the average annual total precipitation over corresponding periods. When calculating the historical impact of temperature for each country, we fix its precipitation level at the country's average precipitation over the whole period 1961–2019. Likewise, for the historical impacts of precipitation for each country, we fix the temperature level at its average level over the period.

Estimation Result

A stationary panel is essential to ensure a standard limiting distribution and therefore a robust inference for parameters. We start with 170 countries and after applying Phillips-Perron unit-root test for each country, we leave with 6505 country-year observations from

123 countries with stationary log difference GDP per capita data at 1% significance level. Temperature is trend stationary and precipitation is constant stationary.

Table 1 summarizes regression results for the three model specifications. Note that for AFE and IFE models, all variables are significant, including temperature, precipitation, and their interactive terms, while in absence of the interactive terms, the linear precipitation term is not significant.

Table 1 Regression table for three models.

	Estimate	Std error	t stat	Pval	Pval.symbol
			Additive Fixed Effects (AFE)		
T	0.01426	0.00427	3.33654	0.00085	***
T^2	-0.00051	0.00016	-3.26312	0.00111	**
P	0.11927	0.04447	2.68192	0.00734	**
P^2	-0.08335	0.03040	-2.74151	0.00613	**
$T \cdot P$	-0.01066	0.00451	-2.36463	0.01808	*
$T^2 \cdot P$	0.00027	0.00014	1.89741	0.05782	.
$T \cdot P^2$	0.00740	0.00265	2.79239	0.00525	**
$T^2 \cdot P^2$	-0.00017	0.00006	-2.81627	0.00487	**
			Interactive Fixed Effects (IFE)		
T	0.01125	0.00387	2.90457	0.00368	**
T^2	-0.00048	0.00013	-3.84366	0.00012	***
P	0.10527	0.05269	1.99802	0.04571	*
P^2	-0.06558	0.02653	-2.47171	0.01345	*
$T \cdot P$	-0.01064	0.00505	-2.10465	0.03532	*
$T^2 \cdot P$	0.00029	0.00014	2.11550	0.03439	*
$T \cdot P^2$	0.00606	0.00231	2.61889	0.00882	**
$T^2 \cdot P^2$	-0.00015	0.00005	-2.69837	0.00697	**
			Burke's model (Baseline)		
T	0.01041	0.00254	4.10029	0.00004	***
T^2	-0.00041	0.00009	-4.40119	0.00001	***
P	0.01326	0.00869	1.52564	0.12715	
P^2	-0.00382	0.00156	-2.44545	0.01450	*

[1] T: annual average temperature, measured in $°C$; P: annual total precipitation, measured in meters.
[2] Significance symbol representation: *** indicates $p < 0.001$, ** for $p < 0.01$, * for $p \leq 0.05$, . for $p \leq 0.1$, and no symbol if $p > 0.1$.

References

[1] Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, *52*(3), 740–798. https://doi.org/10.1257/jel.52.3.740

[2] Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, *353*(6304). https://doi.org/10.1126/science.aad9837

[3] Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, *32*(4), 33–52. https://doi.org/10.1257/jep.32.4.33

[4] Burke, M., Davis, W. M., & Diffenbaugh, N. S. (2018). Large potential reduction in economic damages under UN mitigation targets. *Nature 2018 557:7706*, *557*(7706), 549–553. https://doi.org/10.1038/s41586-018-0071-9

[5] Diffenbaugh, N. S., & Burke, M. (2019). Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(20), 9808–9813. https://doi.org/10.1073/pnas.1816020116

[6] Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239. https://doi.org/10.1038/nature15725

[7] Pretis, F., Schwarz, M., Tang, K., Haustein, K., & Allen, M. R. (2018). Uncertain impacts on economic growth when stabilizing global temperatures at 1.5C or 2C warming. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *376*(2119), 20160460. https://doi.org/10.1098/RSTA.2016.0460

[8] Feng, H., & Zhang, M. (2015). Global land moisture trends: drier in dry and wetter in wet over land. *Scientific Reports 2015 5:1*, *5*(1), 1–6. https://doi.org/10.1038/srep18018

[9] Harris, I., Osborn, T. J., Jones, P., & Lister, D. (2020). Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Scientific Data*, *7*(1). https://doi.org/10.1038/s41597-020-0453-3

[10] CIESIN. (2000). Gridded Population of the World (GPW), v4.

[11] WDI. (2020). World Bank—Word Development Indicators.

[12] Bai, J. (2009). Panel Data Models With Interactive Fixed Effects. *Econometrica*, *77*(4), 1229–1279. https://doi.org/10.3982/ECTA6135

Supplementary Information for Interactive Effects of Temperature and Precipitation on Global Economic Growth

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Estimation Method

Accurate estimation and inference of $\boldsymbol{\beta}$ in (1) depends on what we assume about $u_{i,t}$. If we assume FE, then we can use classical methods to estimate the (1). For instance, we can define

$$\overline{y}_{i,.} = \frac{1}{T}\sum_{t=1}^{T} y_{i,t}, \quad \overline{y}_{.,t} = \frac{1}{N}\sum_{i=1}^{N} y_{i,t}, \quad \overline{y}_{.,.} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} y_{i,t}$$

and let

$$\tilde{y}_{i,t} = y_{i,t} - \overline{y}_{i,.} - \overline{y}_{.,t} + \overline{y}_{.,.}.$$

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We can rewrite (1)-(2)

$$\tilde{y}_{i,t} = \boldsymbol{\beta}'\tilde{\mathbf{x}}_{i,t} + \tilde{\varepsilon}_{i,t}, \tag{S1}$$

where $\tilde{\mathbf{x}}_{i,t}$ and $\tilde{\varepsilon}_{i,t}$ are defined similarly to $\tilde{y}_{i,t}$. This transformation of the model eliminated the fixed effects from the model. We can estimate (S1) by pooled OLS. This is called the within estimator.

An accurate estimation method under the assumption IE is proposed by Bai [1]. The difficulty comes from the fact that both $\mathbf{f}_t$ and $\boldsymbol{\lambda}_i$ are unobserved and cannot be eliminated from the model by transformations of the variables alone. Hence the component $\boldsymbol{\lambda}_i'\mathbf{f}_t$ needs to be estimated. Bai [1] proposes an iterative principal components based approach. Given an initial estimate for $\boldsymbol{\beta}$, say $\widehat{\boldsymbol{\beta}}$, we can write

$$\widehat{u}_{i,t} = y_{i,t} - \widehat{\boldsymbol{\beta}}'\mathbf{x}_{i,t}$$

we start with an initial estimate of $\mathbf{f}_t$, say $\widehat{\mathbf{f}}_t$ can be taken as the r largest eigenvectors of $\sum_{i=1}^{N} \widehat{\mathbf{U}}_i\widehat{\mathbf{U}}_i'$, where $\widehat{\mathbf{U}}_i = (u_{i,1}, \ldots, u_{i,T})'$ is the $T-$ vector of residuals. An initial estimator for the loadings can be obtained by

$$\widehat{\lambda}_i = T^{-1}\widehat{\mathbf{F}}'(\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}})$$

with obvious definitions for $\widehat{\mathbf{F}}$, $\mathbf{Y}$ and $\mathbf{X}$. Once $\widehat{\mathbf{f}}_t$ and $\widehat{\lambda}_i$ are obtained, a second step estimator for $\widehat{\boldsymbol{\beta}}$ can be obtained by estimating

$$y_{i,t} = \boldsymbol{\beta}'\mathbf{x}_{i,t} + \widehat{\lambda}_i'\widehat{\mathbf{f}}_t + error \tag{S2}$$

Then a second step of residuals can be obtained, which can be used again to obtain second set of estimators for $\mathbf{f}_t$ and $\boldsymbol{\lambda}_i$. This process continues until convergence. The resulting estimator for $\boldsymbol{\beta}$ has very good properties under certain assumptions. This procedure is explained in detail in ref [1].

List of Figures

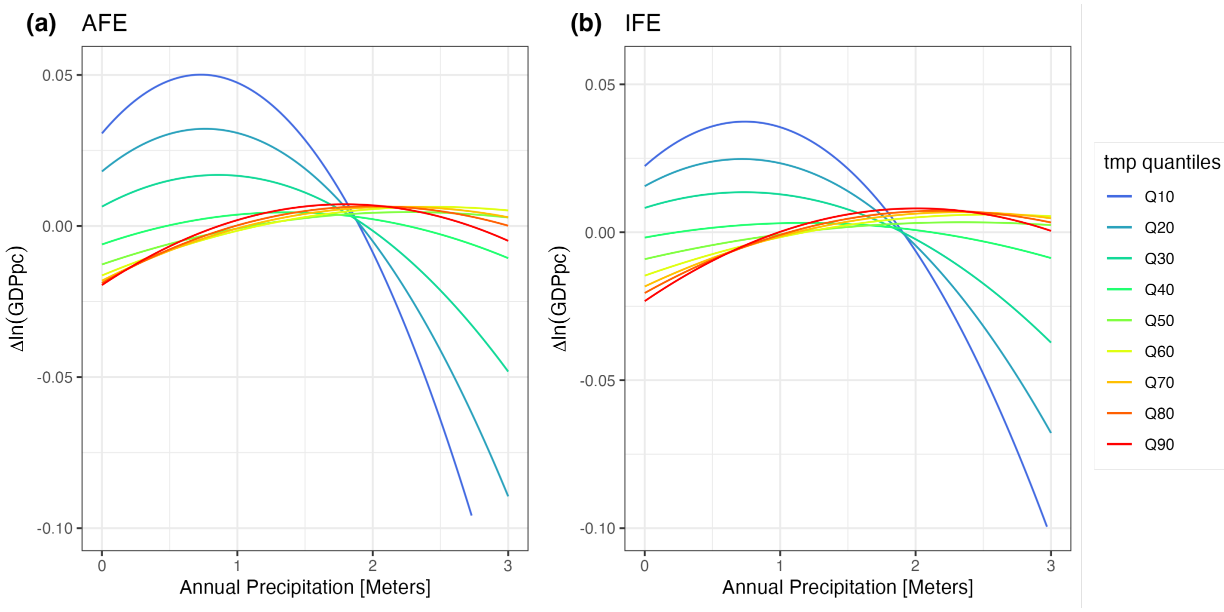

Fig. S1 2D response function to precipitation given fixed temperatures. Temperatures are given as multiples of the 10th quantiles of all countries' temperature levels, i.e., the 10th, 20th, 30th quantiles, until the 90th quantile etc. (a) AFE: Burke's model + interactive terms + additive fixed effects; (b) IFE: Burke's model + interactive terms + interactive fixed effects; Burke's model is without interactive terms, meaning its response function does not vary with temperature levels. Therefore we did not plot the response function for Burke's model here.

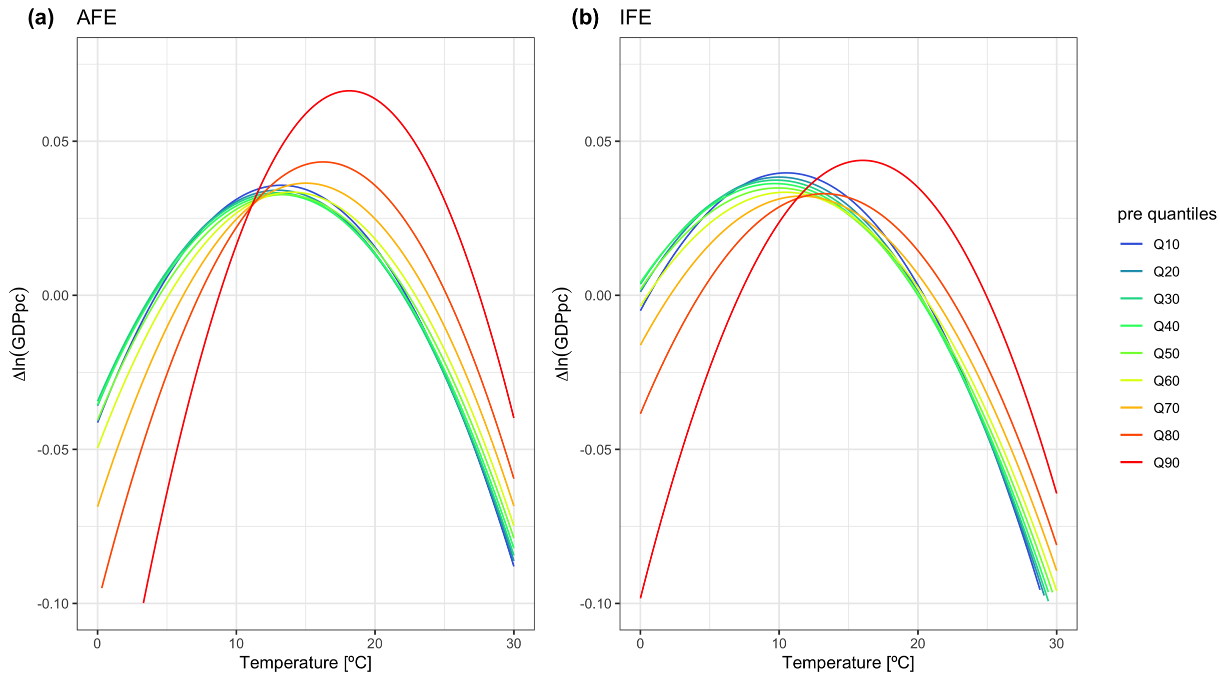

Fig. S2 2D response function to temperature given fixed precipitations. Precipitations are given as multiples of the 10th quantiles of all countries' precipitation levels, i.e., the 10th, 20th, 30th quantiles, until the 90th quantile etc. (a) AFE: Burke's model + interactive terms + additive fixed effects; (b) IFE: Burke's model + interactive terms + interactive fixed effects;

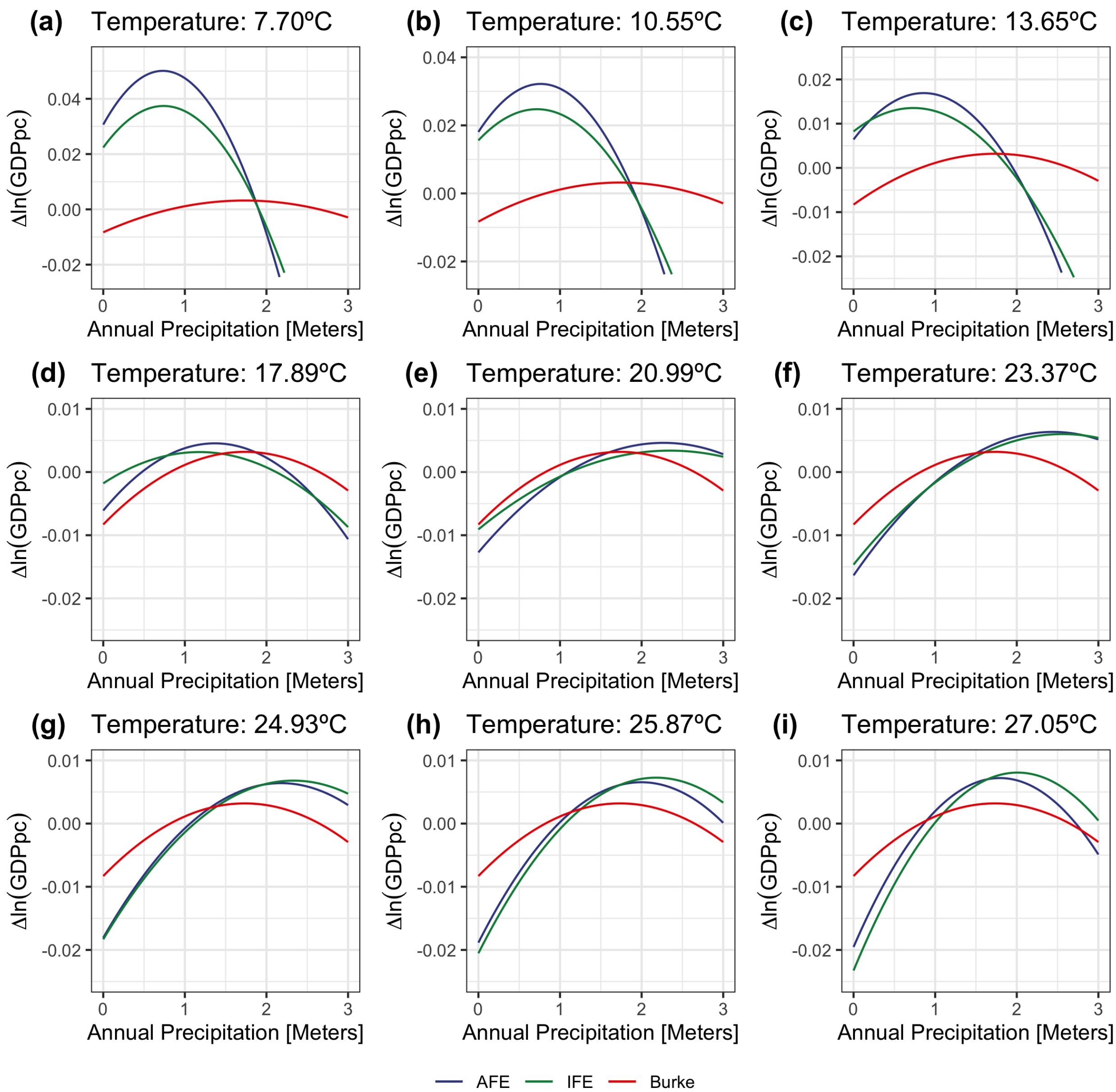

Fig. S3 2D response function to precipitation given fixed temperatures. Temperatures are given as multiples of 10th quantiles of all countries' temperature levels, i.e., the 10th, 20th, 30th quantiles, etc. Each panel shows three model specifications: AFE: Burke's model + interactive terms + additive fixed effects; IFE: Burke's model + interactive terms + interactive fixed effects; Burke: Burke's model (baseline).

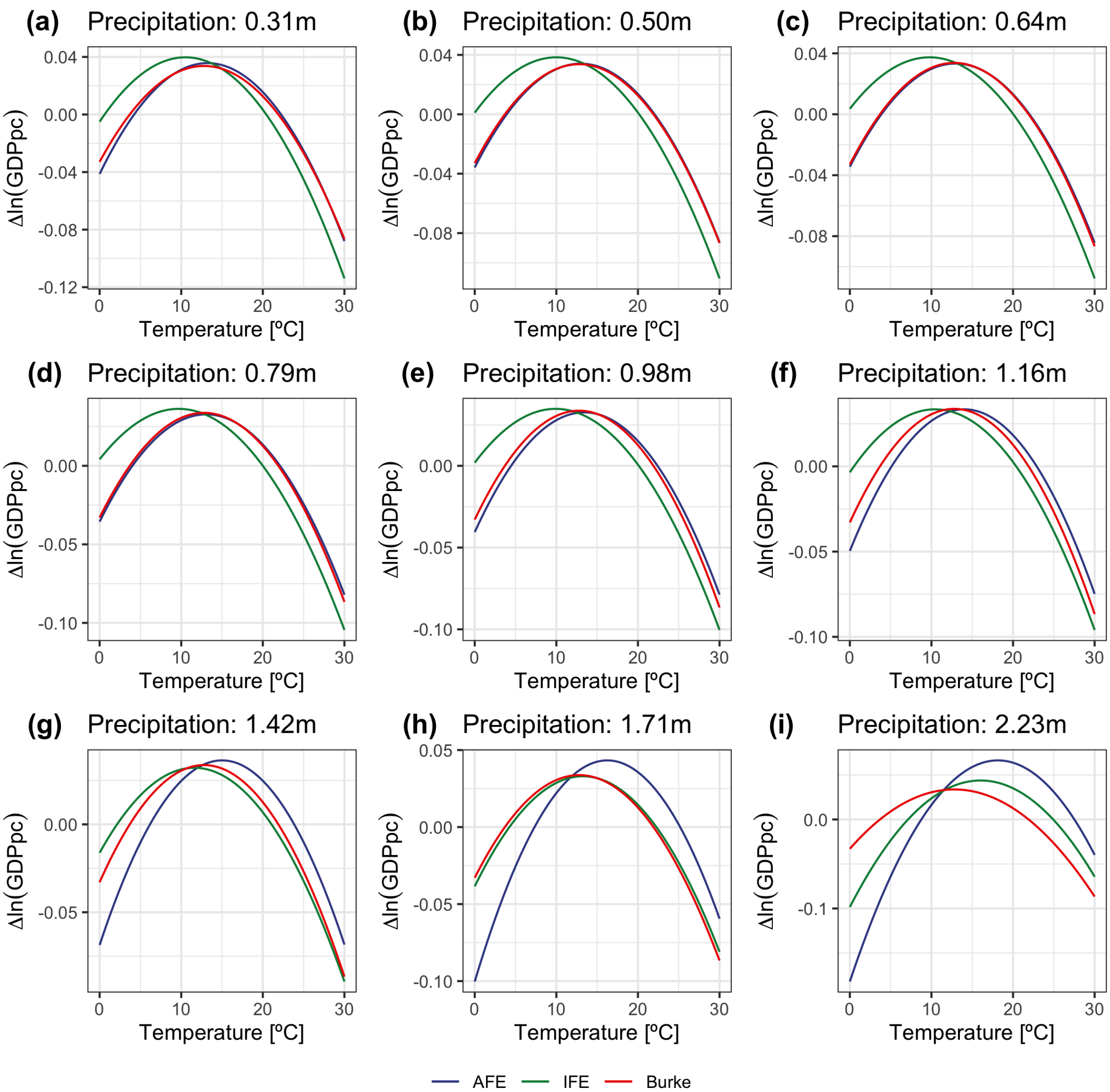

Fig. S4 2D response function to temperature given fixed precipitations. Precipitations are given as multiples of the 10th quantiles, i.e., the 10th, 20th, 30th quantiles, etc. Refer to Fig. S3 for model specifications.

References

[1] Bai, J. (2009). Panel Data Models With Interactive Fixed Effects. *Econometrica*, *77*(4), 1229–1279. https://doi.org/10.3982/ECTA6135