Climate Damage Projections Beyond Temperature

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Abstract

This paper studies the importance of variables beyond average temperature in determining the macroeconomic impacts of climate change. I assemble a novel dataset of climate variables aggregated at the country-year level from several sources, both for historical data and for projections under future global warming. I find that weather variables at the country-year level are weakly correlated with each other and thus have ample residual variation to estimate the marginal effect of each on per capita GDP. I find that wildfires and tropical cyclones have significant and negative long-run effects on per capita GDP. By 2100, damages from variables beyond temperature represent over 20% of total reduction in per capita GDP, relative to the no-warming counterfactual.

JEL Codes: O33, O44, O47, Q54

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1 Introduction

From a statistical standpoint, the climate can be described as the joint distribution of several variables- such as temperature, humidity and wind speed. Since this distribution is a very high-dimensional object, the economics literature has historically put an emphasis on average temperature as a uni-dimensional proxy for the climate. Existing studies of the macroeconomic impacts of climate change have largely ignored the multi-dimensional nature of the climate. This study aims at filling this gap in our understanding of the macroeconomic consequences of shifting the entire climate distribution, as carbon emissions continue to rise. In particular, throughout this paper I will focus on the consequences for per capita GDP.

Three conditions must be met for a climate variable- other than average temperature- to be relevant in assessing the impact of climate change on GDP. (1) it must not be perfectly correlated with average temperature. Otherwise, all previously estimated effects of average temperature would also completely capture the effects of this additional, hypothetical, climate variable. (2) it must have a significant effect (be it positive or negative) on GDP, or we could just ignore it. (3) it must move with future climate change, or it would not be relevant to our understanding of the effects of climate change (think of earthquakes). Throughout this paper I highlight the climate variables that meet these conditions and the implications of omitting them for climate change damage assessments.

In this paper, I collect historical data and projections under future climate change for twelve variables, which taken together can provide a better approximation of the climate than average temperature alone. The list of variables includes measures of extreme temperatures, cumulative precipitation, flooding, wildfires, wind speed, drought and severe drought, as well as tropical cyclones. First, I show that these variables are generally not strongly correlated with each other at the country-year level and that there is ample residual variation to estimate the marginal impact of each variable separately. In particular, I find that variation in average temperature is weakly correlated with all the other variables considered, and so that ignoring the other climate dimensions may lead to a relevant under-estimate of damages from climate change. Second, I use panel local projections to estimate the cumulative effect of each variable on per capita GDP growth, separating the estimation between variables in levels (e.g. average temperature) and extreme weather realizations (e.g. tropical cyclones). Here I find that only three variables in the assembled dataset have a negative and significant impact on per capita GDP growth: average temperature, wildfires and tropical cyclones. Third, I then extrapolate the estimated effects under future climate projections (ssp5-rcp8.5 for temperature and wildfires, the IPCC A1B scenario for cyclones), and estimate that changes in the two non-temperature variables are projected to imply a reduction in per capita GDP of 12%, and this represents around a quarter of total projected damages to global incomes by 2100 (50.6%). So, while changes to average temperature are the most important driver of projected climate impacts, I find that an accurate quantification of damages does require accounting for all climate dimensions. In particular, there are countries, especially in South East Asia, where not considering the additional impacts of climate change beyond average temperature would imply missing most of the projected damages. Moreover, I find that almost all that effect is driven by an increase in the intensity of cyclones, rather than wildfires.

Importantly, this paper does not include empirical estimates of adaptation to climate change over time, nor does it embed the reduced form effects of climate variables on output within a structural model where households or firms may invest in adaptation. While previous empirical work working with aggregate data has found limited evidence for reduced vulnerability of aggregate output to climate shocks over time (Burke, Zahid, et al., 2024), structural models have instead outlined a relevant role for adaptation (Cruz and Rossi-Hansberg, 2024). Hence, this paper puts more emphasis on the relative contribution of non-temperature variables on total damages, rather than on the exact estimate of those damages.

Finally, to clarify terminology, since the paper does not introduce forward-looking behavior from household or firms, I will interchangeably use *weather* shocks or variables and *climate* shocks or variables. The two are theoretically distinct concept, as the weather corresponds to the draws from the climate distribution. So, for a given variable, the climate is the ex-ante expectation and the weather is the ex-post realization.

Previous literature

This paper builds heavily on existing work, in particular Nath, Ramey, and Klenow, 2024 (henceforth NRK), that uses reduced form estimation of the effect of a change in one climate variables on per capita GDP, as well as future projections of that variable to estimate the impact of future climate change.

I contribute to a vast literature that uses historical data on weather to estimate the effects on GDP of future climate change (reviewed in, among others, Newell, Prest, and Sexton, 2021). Previous work has mostly focused on a single weather variable at a time, or only on few of them together at the same time. Dell, Jones, and Olken, 2012, Burke, Hsiang, and Miguel, 2015, Kalkuhl and Wenz, 2020 and Kahn et al., 2021 all study the effects of temperature on per capita GDP growth. Hsiang and Jina, 2014 and Bakkensen and Barrage, 2025 study empirically the effects of tropical cyclones on long-run growth across affected countries. Bilal and Rossi-Hansberg, 2023 embed empirical estimation of the productivity impacts of extreme temperatures and storms in a spatial general equilibrium model. Castro-Vincenzi, 2022 studies the effect of floods on industrial output with micro-data with global coverage on car manufacturing. Kotz, Levermann, and Wenz, 2024 and Waidelich et al., 2024 study the combined impact of average temperature, cumulative precipitation together with measures of their respective second moments, and a measure of extreme precipitation. In line with this paper, they also find that damages from rising average temperatures represent the large share of total projected damages. The main contribution relative to this previous set of papers is to consider a wider set of weather variables, and estimating their effect using the latest work in climate econometrics from Nath, Ramey, and Klenow, 2024. Akyapi, Bellon, and Massetti, 2022 is similar in spirit to this paper, and it considers a much wider range of weather variables by employing model selection tools from the machine learning literature. A key difference on the estimation side is that Akyapi, Bellon, and Massetti, 2022 use grid-cells as the units of observations for estimation. While this yields benefits in terms of statistical power, it strongly increases identification concerns, coming from the violation of the Stabile Unit Treatment Value Assumption due spillover effects across units. The contribution this paper makes relative to Akyapi, Bellon, and Massetti, 2022 is to extrapolate forward the estimated effects to quantify projected damages from climate change. This, however, requires consistent projections from the same variables that are used in the estimation stage, and these projections are often lacking for many weather variables for which historical data are instead available.

Bilal and Känzig, 2024 uses global time-series in temperature to estimate its effect on global GDP. Their proposed explanation for finding much larger effects than previous comparable work is the link between global temperature variation and local weather extremes. An important difference between their identification strategy and the one used in this paper, which relies instead on local weather variation (as is common in the literature) is that I can use time fixed-effects to control for all time-varying confounders that are constant along the cross-section, instead of having to rely on proxy variables. The contribution this paper makes to their work is to separately estimate the impact on per capita GDP of several of the weather extremes that are impacted by higher global mean temperature, and crucially to estimate their future impacts at the country level under future projections of climate change, which are not available for most measures used in Bilal and Känzig, 2024.

Moreover, this paper is, to the best of my knowledge, the first to study the effect of wildfires on aggregate growth. This finding contributes to a recent literature that quantifies the negative effects of wildfires on mortality (Qiu et al., 2024) as well as hospitalizations and morbidity (Gould et al., 2024).

This paper is organized as follows. Section 2 presents the data used and their sources, as well as descriptive evidence of how global warming affects each climate variable in the data. Section 3 outlines the empirical strategy to obtain consistent estimates of the effect of weather variation on per capita GDP. Section 4 presents the results on damages to per capita GDP by 2100. Section 5 concludes.

2 Data

Variables and measurement

I consider the following twelve weather variables, which I argue can jointly represent the climate:

- Average surface temperature, measured in Degree Celsius.
- Heatwave duration, measured as total number of days within heatwaves. A day belongs to a heatwave if there were at least five consecutive days with TX[1] > 90th percentile (vs. 1981-2010 period) and TX ≥ 30°C.

[1] Maximum daily temperature.

- Coldwave duration, measured as total number of days within coldwaves. A day belongs to a coldwave if there were at least five consecutive days with TN[2] < 10th percentile (vs. 1981-2010) and TN $\leq$ 0°C.

- Cumulative annual precipitation, in millimeters.

- Extreme precipitation days, defined as number of days with rainfall > 99th percentile (vs. 1981-2010 period), not necessarily consecutive.

- Extreme cumulative precipitation, defined as maximum 5-day precipitation, cumulated over the year.

- Flooding, 100-year return period flood depth.

- Wildifires, measured through % of land area burnt during the year.

- Droughts, measured through the SPEI index which varies from +2 (very wet) to -2 (very dry).

- Severe drought events, measured as the annual sum of indicator variables which take value of 1 in the presence of an ongoing drought event (only negatives are used). A drought event starts whenever the SPEI index (accumulation of 12-month) falls below -1 for at least 2 consecutive months and ends when it turns back positive.

- Wind speed, measured in metres/ second, computed as the max, over the year for each cell, of the daily average wind speed in each cell.

- Tropical cyclones, measured in maximum wind speed per square kilometer.

Each variable comes first from 0.5°x 0.5°raster data, which are then aggregated at the country-year level. Whenever a non-linear transformation of the variables is required, in accordance with best practices in the literature, all operations are carried out at the grid-cell level, computed over a year, and only later aggregated over space at the country-year level.

The aggregation over space is done with area-weighting- i.e. for any weather variable x_c in grid-cell c, the country-level variable X_n is computed as:

[2]Minimum daily temperature.

$$X_n = \sum_{c \in n} \frac{x_c \cdot a_c \cdot C_c}{\sum_{c \in n} a_c}$$

where a_c is the area covered by each 0.5°x 0.5°pixel, and C_c is the share of that cell area that falls within the country's borders. The advantage of this choice is twofold: (a) it accounts for the fact that cells near the equator cover a larger area of land, due to the earth surface curvature; (b) by dividing for a country's total area, it accounts for the fact that larger countries are more likely to experience given events on their land simply because they are larger.

Additionally, I aggregate historical and projection data, under ssp5-rcp8.5, on the Köppen-Geiger climate classification system at the 0.5°x 0.5°-level from Beck et al., 2023. The Köppen-Geiger climate classification assigns each local climate to one of 5 major climate classes (Tropical, Arid, Temperate, Continental and Polar), based on a combination of temperature and evotranspiration criteria[3]. I aggregate the Beck et al., 2023 data at the country-year level using an area-weighted mode, so that a country gets assigned to the climate class to which the largest number of pixels within its borders belong to. The map with the country-level aggregated data is shown in Figure A2.

Real annual GDP per capita is measured in constant Local Currency Units.

Data sources

- For average temperature historical data, the source is ERA5 re-analysis data. The time coverage is from 1950 to 2022.
- For cumulative precipitation historical data, the source is the Climate Research Unit at the University of East Anglia. The time coverage is from 1950 to 2024.
- For drought historical data, the source is the SPEI database from the University of Zaragoza. The time coverage is from 1950 to 2022.
- For projections of average temperature, cumulative precipitation and droughts, the source is the World Bank's Climate Change Knowledge Portal. I use the median of the ensemble of the CMIP6 climate models, for both historical data and projections.

[3]See: https://www.britannica.com/science/Koppen-climate-classificationref346013, retrieved on May 25th, 2025.

- For wind speed, the source is Copernicus satellite data, from the CMCC-ESM2 model, for both historical data and projections. The time coverage, for historical data, is from 1950 to 2014.

- Tropical cyclones historical data come from Bakkensen and Barrage, 2025, which in turn process wind data from IBTrACS. The time coverage is from 1970 to 2015.

- For all the other weather variables, the source is the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP). The time coverage for all variables from ISIMIP is from 1960 to 2014.

- GDP per capita in constant local currency units comes from the World Bank's World Development Indicators, consistently with NRK. The time coverage is from 1960 to 2019 since, consistently with NRK, I drop all post-Covid observations of country-level GDP.

For each weather variable (except tropical cyclones), I collect both historical data and projections from 2015 until 2100, under the high-warming scenario of ssp5-rcp8.5 (O'Neill et al., 2016). Future projections of tropical cyclones under climate change are not publicly available. Bakkensen and Barrage, 2025 make available the country-specific scale and shape parameters of the Weibull distribution that will characterize the end-of-century tropical cyclone climate. The projection data from Bakkensen and Barrage, 2025 is not generated under the ssp5-rcp8.5 scenario, but rather the IPCC A1B scenario, which implies slightly lower radiative forcing than under ssp5-rcp8.5 and thus a lower increase in global mean temperature [4].

In order to approximate projections of future tropical cyclone climate for each country, I do the following. First, I linearly interpolate the country-specific parameters of the Weibull distribution of maximum cyclone wind speed from the values under present-day climate to the values under end-of-century climate. This gives a vector of parameters for each country and year. Secondly, for each country, in each year after 2015, I make one draw from the obtained Weibull distribution. Naturally, draws of more devastating cyclones are more likely if global warming implies an increase in the frequency and/or intensity of tropical cyclones, and viceversa. Importantly, an increase in average global temperature does not imply a worsening of the cyclone climate for all countries, with

[4] In terms of radiative forcing, the IPCC A1B scenario is close to rcp7.0.

heterogeneous effects that depend on various local weather patterns (Hsiang and Kopp, 2018).

The climatic effects of global warming

This section displays the projected changes in the weather variables in my dataset, from what has been historically observed to the high-warming scenario of ssp5-rcp8.5.

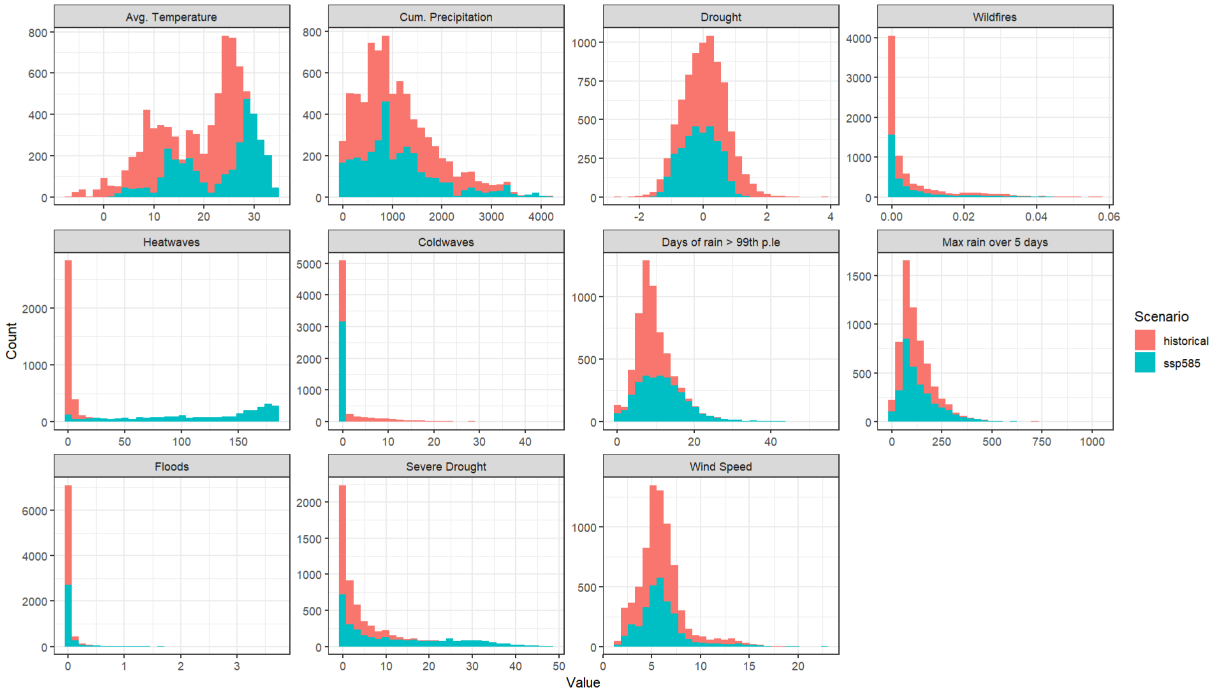
Changes in distribution

Figure 1, in panel (a), displays the different frequency distributions of each variable across historical data and under ssp5-rcp8.5. Notably, we see a shape-preserving shift in scale of the distribution of average temperature. Other notable changes in distribution are the very strong increase in heatwaves, with a corresponding decrease in coldwaves, which are projected to almost disappear. Moreover, we can see an increase in the frequency of extreme precipitation events. This appears consistently across several variables- for cumulative precipitation, for both measures of extreme rain days and for floods. At the same time, also extreme drought events see an increase, going beyond the support of historical observations.

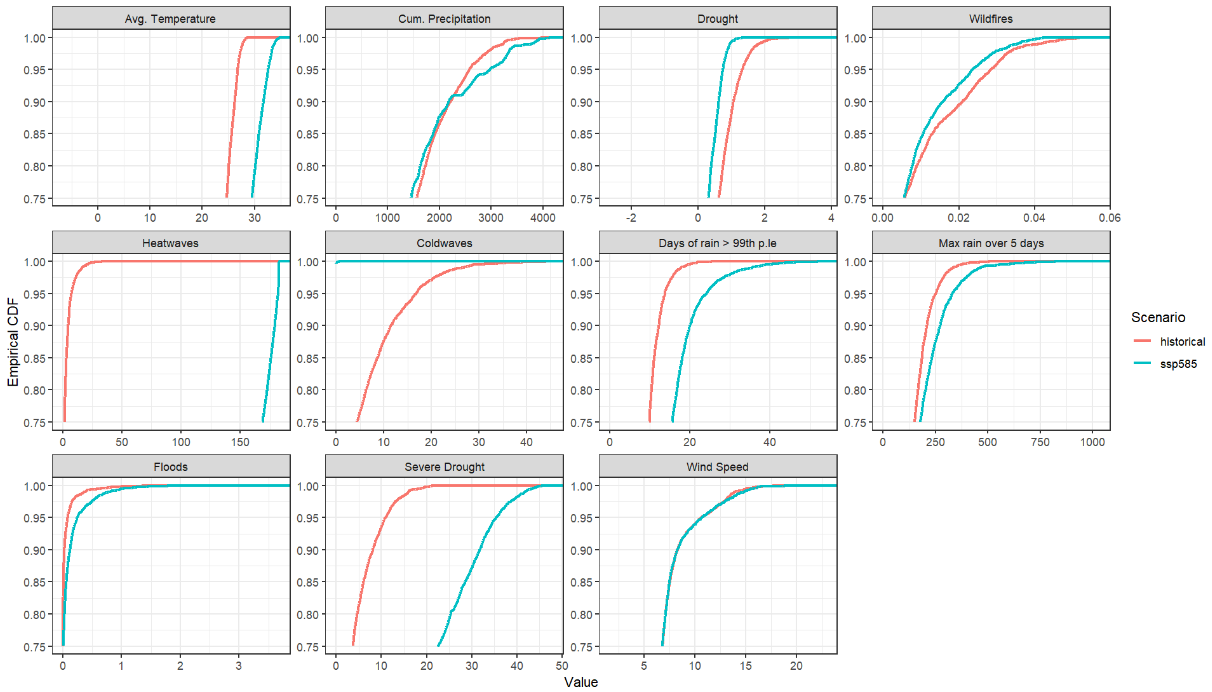
To visualize more clearly the behavior of the extreme values in each distribution across scenarios, Figure 1, in panel (b), looks more closely at the right tail of the frequency distributions of each variable, by plotting the empirical CDFs for each variable in the two scenarios and zooming in on the 75th percentile of each variable. All findings confirm what could be gauged from panel (a). In addition to that, panel (b) shows that extreme wildfires are actually projected to decrease under ssp5-rcp8.5, while little effect is found for maximum wind speed.

Since there are no publicly available end-of-century projections for tropical cyclones, it was not possible to compare the actual distributions of observed vs projected cyclones. Given this constraint, Figure 2 compares the resulting densities after 10,000 draws from 2 country-specific Weibull distributions of cyclone wind speed, for a selected sample of large exposed countries[5]. For each country, the pdf describing the cyclone climate under current parameters is depicted in red, while the blue pdf depicts the cyclone climate under the end-of-century parameters in the A1B scenario. The figure shows how global warming

[5] See Figure A1 in the appendix to see the projected changes for all countries.



(a)



(b)

Figure 1

Notes: In panel (a), the figure displays the frequency distribution for each weather variable in the dataset. The red distributions correspond to observations with historical data, while the green distributions correspond to projection data under the ssp5-rcp8.5 warming scenario. In panel (b), The figure displays the empirical cumulative distribution functions for each weather variable in the dataset, with the y-axis censored below 0.75. The red cumulative distributions correspond to observations with historical data, while the green cumulative distributions correspond to projection data under the ssp5-rcp8.5 warming scenario.

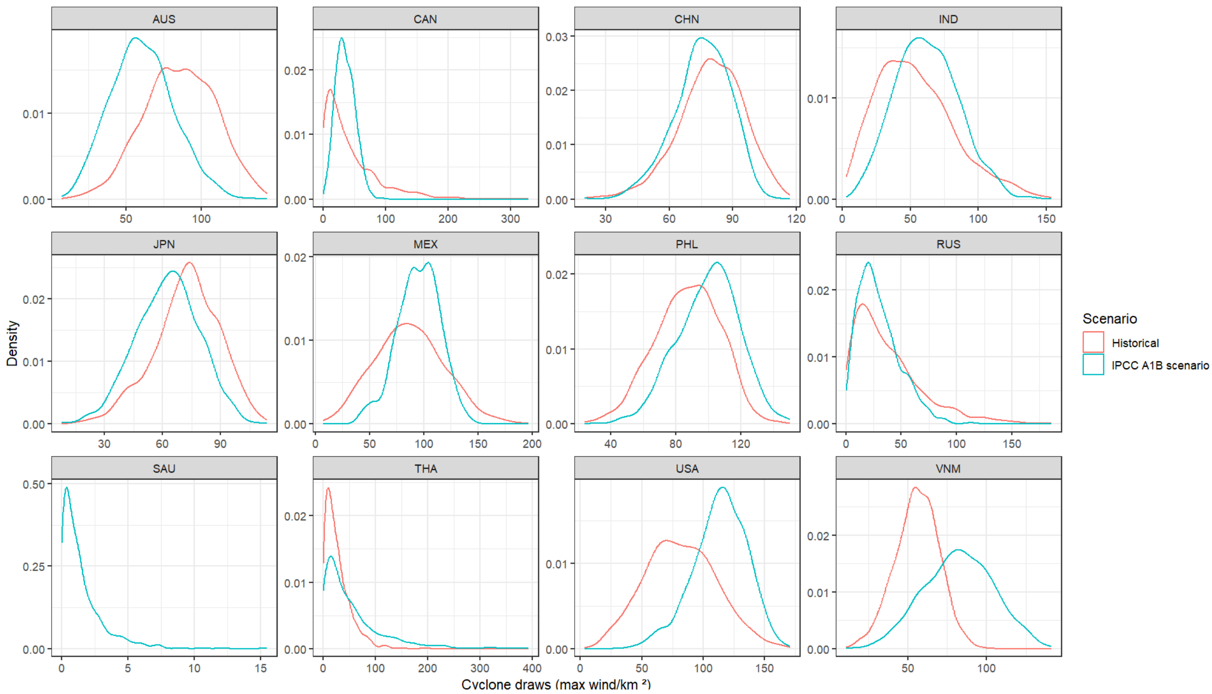


Figure 2

Notes: The figure displays for selected countries the kernel densities for 10,000 draws of cyclone wind speed, measured in maximum wind speed per km^2, from the country specific Weibull distributions, whose scale and shape parameters are provided in Bakkensen and Barrage, 2025. The red densities represent the distribution with Weibull parameters that fit the distribution of cyclones between 1970 and 2015. The blue densities represent the distribution with Weibull parameters that fit the projected distribution of cyclones between 2090 and 2100 under the IPCC A1B scenario.

does not imply a uniform worsening of the cyclone climate for all exposed countries. For example, Australia and Japan are projected to see a reduction in average intensity of cyclone wind speed, while countries like Vietnam and the United States are projected to be more vulnerable to tropical cyclones under global warming. Importantly, countries like Saudi Arabia see too few cyclone strikes under their current climate for their distribution to be parametrized by Bakkensen and Barrage, 2025. They are instead projected to be exposed to cyclones under future warming.

Changes over space

Changes in the global distribution of a variable may mask important heterogeneity across countries. To explore such heterogeneity over space, Figure 3 plots the projected change for each variable from the country's recent historical average (from 2000 to 2010) to the end-of-century average (from 2090 to 2100) under the ssp5-rcp8.5 scenario. The figure shows that average temperature is projected to rise everywhere, with the known pattern of stronger warming in the northern hemisphere. In line with this, heatwaves are projected to increase and coldwaves collapse everywhere. As outlined in Intergovernmental Panel on Climate Change (IPCC), 2021, global warming implies also an increase in global precipitation levels, albeit with more heterogeneity. In particular, southern Europe and North Africa are projected to see a strong decrease in precipitation, in contrast with most other regions around the world. Notably, wildfires and floods are projected to strongly increase in North America and Europe, where the bulk of the innovating countries are. Europe is also projected to see an increase in droughts, while cumulative and extreme precipitation are mostly projected to increase elsewhere. Finally, maximum wind speed is little affected for most countries, suggesting that the limited change in the global distribution was not masking any strong between-country heterogeneity.

3 Empirical strategy

In order to consistently identify the effect of weather variables, I distinguish among weather variables in *levels* and weather variables that measure *extreme* events. I divide the weather variables in my dataset in the two categories as follows.

Weather variables in levels are: average temperature, cumulative precipitation, drought,

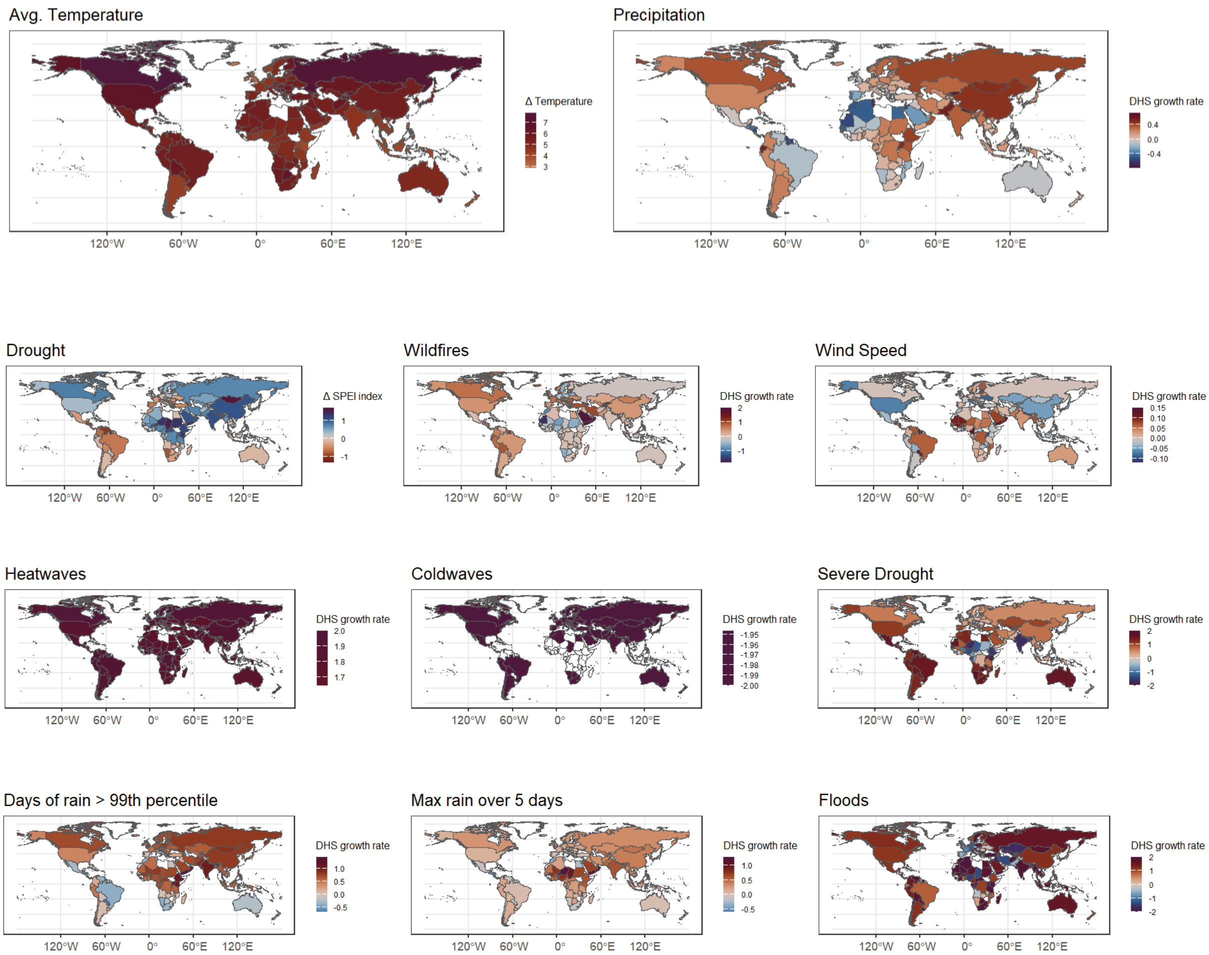


Figure 3

Notes: The figure displays the change, for each weather variable in each country in the dataset, in the sample average between 2000 and 2010 from the sample average between 2090 and 2100 under the ssp5-rcp8.5 warming scenario. For clarity, in this figure the SPEI index has been reversed, so that higher values correspond to stronger droughts. For the variables "Avg. Temperature" and "Drought", the change is measured in the units of that variable (degrees Celsius and SPEI index respectively). For the other variables, the change is computed as the Davis-Haltiwanger-Schuh (DHS) growth rate (Davis and Haltiwanger, 1990). The DHS growth rate for a variable x_t is computed as $\frac{x_t - x_{t-1}}{0.5 \cdot (x_t + x_{t-1})}$, so that it is always $\in [-2, +2]$.

wildfires and wind speed.

Weather extremes are: heatwaves, coldwaves, extreme precipitation days, extreme cumulative precipitation, floods, severe drought and tropical cyclones.

The key difference between the two is that the extremes are measured, as outlined in Section 2, already as deviations from a baseline level of the relevant variable in level - e.g. heatwaves are defined as a sequence of days with a particularly high temperature *relative to the location climate.* All regressions are run separately for each variable. The later results in Figure 4 justify this simplification.

Level variables:

Following NRK, the shocks to each weather variable in levels X in are estimated as the residuals from the following regression:

$$X_{it} = \sum_{j=1}^{p} \gamma_j X_{it-j} + \sum_{j=1}^{p} \theta_j X_{it-j} \cdot \overline{X}_i + \mu_i + \mu_t + \underbrace{\chi_{it}}_{\text{Shocks}} \tag{1}$$

where $\overline{X}_i$ is the sample average of weather variable X in country i, and μ_i and μ_t are country- and time-fixed effects respectively. Standard errors are clustered at the country level.

The effects of each weather variable in levels on log GDP y are then estimated through the following set of local projections, for each variable X:

$$y_{it+h} - y_{it-1} = \beta_0^h \chi_{it} + \sum_{j=1}^{p} \nu_j X_{it-j} + \sum_{j=1}^{p} \phi_j \Delta y_{it-j} + \mu_i + \mu_t + u_{it} \quad \text{for } h = 0, ..., 9. \tag{2}$$

where the persistent effects of the weather shock χ on per capita GDP is given by the sequence of coefficients β_0^h. Lags of the variable in level account for its internal persistence, lags of GDP growth account for serial correlation in GDP growth rates. Standard errors are clustered at the country level. In the main specification, I set the lag length $p = 3$. In appendix section C, I show that the results are robust to using time-varying variables that are constant in the cross-section in place of time fixed effects. In particular, in line with Bilal and Känzig, 2024 and NRK, I control for oil prices, US TFP, US treasury yield and growth in world GDP.

To compute the potential persistence of shocks, I estimate the following set of local projections, for each weather variable:

$$X_{it+h} = \alpha_0^h \chi_{it} + \sum_{j=1}^{p} \psi_j X_{it-j} + \mu_i + \mu_t + \zeta_{it} \text{ for } h = 1, ..., 9 \tag{3}$$

where the persistence of the weather shock χ on the weather variable X itself is given by the sequence of coefficients α_0^h. The contemporaneous effect of the shock in $h = 0$ is normalized to 1.

In appendix section C, I show that different specifications to recover shocks from the weather variables in levels recover very similar time series at the country level (figure A6). I do so for the specifications used in Bilal and Känzig, 2024 as well as in NRK. I also show that the country-level time series for all weather variables display no significant auto-correlation (figure A7).

Extreme variables:

By definition, extreme weather realizations do not persist, so that their impact on per capita GDP can be estimated directly through the following set of local projections for each extreme E, which adapts to my setting the specification for tropical cyclones in Hsiang and Jina, 2014:

$$y_{it+h} - y_{it-1} = \beta_0^h E_{it} + \sum_{j=1}^{p} \phi_j \Delta y_{it-j} + \mu_i + \mu_t + v_{it} \text{ for } h = 0, ..., 9. \tag{4}$$

where the persistent effects of the extreme event E on per capita GDP is given by the sequence of coefficients β_0^h. Importantly, this estimation strategy can only identify the effect of *strikes* for extreme events, and not of the average climatic conditions characterizing the variable in question. For example, if in order to protect themselves from frequent cyclone strikes, firms in a vulnerable country invest in equipment that avoids destruction of capital during the storm, then we may not observe any effect on output. Depending on the opportunity cost of this adaptive investment, then the average cyclone climate may or may not increase growth on average. In any case, that effect will not be identified in the above set of regressions and a structural model is required to quantify the welfare consequences of climate change, as detailed in Bakkensen and Barrage, 2025.

To corroborate the hypothesis that extremes do not persist, I compute the residuals from the regression for each extreme:

$$E_{it} = \mu_i + \mu_t + \varepsilon_{it} \tag{5}$$

Then I estimate their persistence by estimating the following set of local projections:

$$E_{it+h} = \alpha_0^h \varepsilon_{it} + \sum_{j=1}^{p} \phi_j E_{it-j} + \mu_i + \mu_t + \nu_{it} \text{ for } h = 1, ..., 9. \tag{6}$$

which is the equivalent of Equation 3 for the weather extremes.

The results in Section 4 confirm that level variables can display moderate persistence over time, but extremes do not.

The cumulative effects, for both weather variables in levels and weather extremes, on GDP are then given by the Cumulative Response Ratio (CRR), consistently with NRK:

$$CRR = \frac{\sum_{h=0}^{9} \beta_0^h}{1 + \sum_{h=1}^{9} \alpha_0^h} . \tag{7}$$

Hence, the cumulative effect from a weather shock over ten years is given by the area under the impulse response function for GDP, scaled by the area under the impulse response function for weather shock persistence. For fully transitory shocks, like weather extremes, this denominator is ≈ 1.

Heterogeneous weather effects

A notable restriction imposed by the model outlined above is that weather effects are homogeneous across countries. This stands in contrast with several previous papers which mostly focused on temperature-only impacts, such as Burke, Hsiang, and Miguel, 2015 and NRK itself. Prior work, like NRK and Kalkuhl and Wenz, 2020, has used an interaction term between annual temperature variation and the historical average of temperature in a location to quantify heterogeneous temperature effects across locations. Since this paper focuses on the combined impact of several variables that *jointly* describe the climate, rather than a single variable like temperature, there is no obvious counterpart to long-run temperature as an interaction term to study heterogeneity in weather effects. Moreover, the results in Section 4 show that weather shocks within a location are weakly correlated, implying that long-run average temperature will not be an accurate proxy for local climate.

In order to test the hypothesis of heterogeneous weather effects across different local climates, I use data on the Köppen-Geiger climate classification by Beck et al., 2023, aggregated at the country-year level. When I allow for heterogeneous effects of weather shocks, both in persistence and growth impacts, I include an additional set of interaction terms between τ_{it} and the indicator variables for each Köppen-Geiger climate class: $\boldsymbol{\tau_{it}} \cdot \sum_{i \in \{\text{Cold, Temperate, Tropical}\}}$ with the *Arid* climate as the reference category. No country in my dataset has a *Polar* climate, according to the Köppen-Geiger climate classification. More details on the exact specifications used are provided in Appendix B.

The empirical results, for the most part, fail to reject the null hypothesis of homogeneous effects by climate class, both for the persistence of weather shocks and their impacts on GDP growth. I display the effects by climate class in the appendix, in Figure A4 and Figure A5. In light of these results and to favor ease of exposition, I present results from the estimates under homogeneous weather effects.

4 Empirical results

Correlation across variables

In order for variables other than average annual temperature to have a residual impact on aggregate output, they need to not perfectly co-move with average annual temperature. If that were the case, so that average temperature in a country was perfectly correlated with all other weather variables, then average temperature would describe the whole climate in a country by itself. Hence, no additional information about the impact of weather shocks on any outcome would be obtained by regressing an outcome on those other variables. Figure 4 shows that the weather variables in my dataset are far from being perfectly correlated with average temperature, or with each other. The figure plots the correlation matrix for weather shocks across all weather variables in the dataset- both level variables and extremes. Shocks to variables in levels are estimated according to Equation 1, while shocks to extremes are estimated according to Equation 5. Notably, looking at the row corresponding to average temperature, we see that no variable has a correlation coefficient higher than 0.2, which is the correlation coefficient between average temperature and drought. If average temperature were a perfect *principal component* for the climate of a country, then the row corresponding to average temperature would display all coefficients equal to, or very close to, 1. Moreover, no pair of variables displays a correlation coefficient larger than 0.66, for the pair of drought and cumulative precipitation. Notably, even the two measures of extreme precipitation (maximum rain over 5 days vs days of rain above the 99th percentile) do not have a coefficient above 0.5. In sum, Figure 4 implies that there is substantial residual variation across the considered weather variables to estimate their separate impact on GDP.

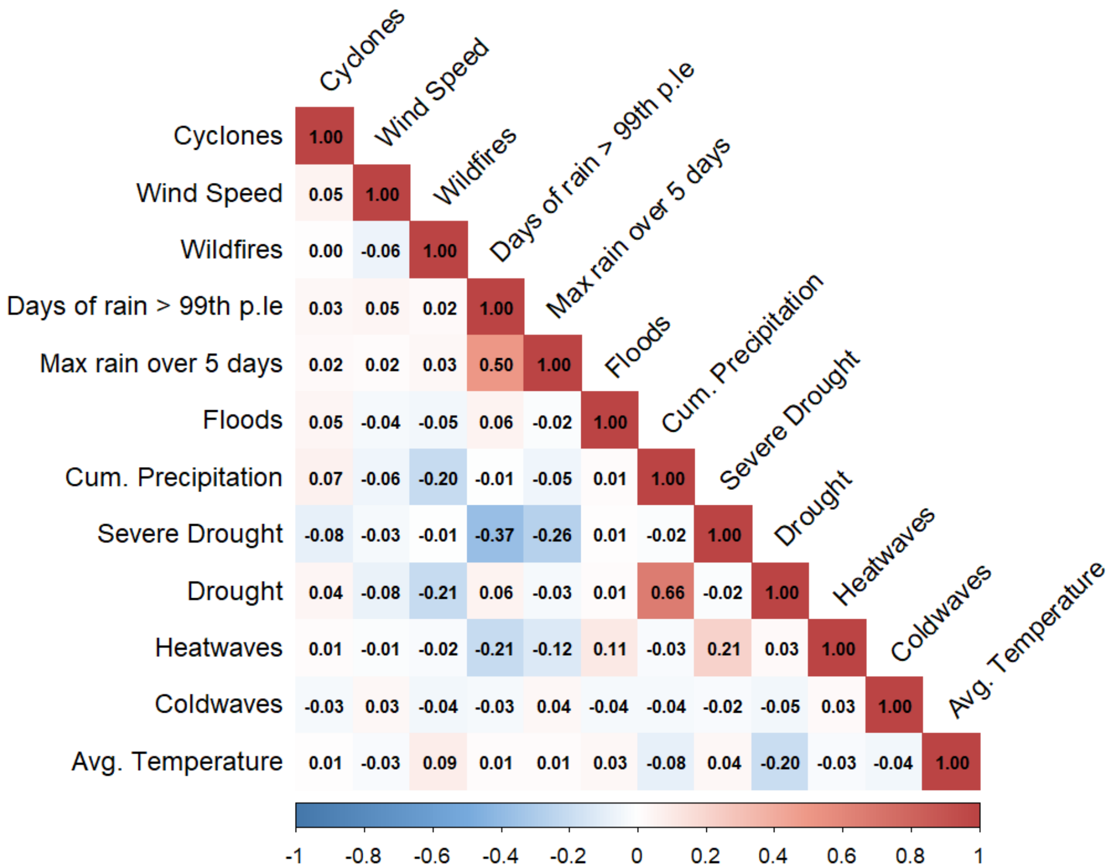


Figure 4

Notes: The figure displays the correlation between the shocks, as defined in Section 3, to each climate variable in the dataset.

Impacts of weather shocks on economic growth

Figure 5, panel (a) displays the sequence of β_0^h coefficients across horizons h from the estimation of Equation 2, separately for each weather variable in levels. Figure 5, panel (b), displays the sequence of β_0^h coefficients across horizons h from the estimation of Equation 4, separately for each weather extreme. Each coefficient corresponds to the marginal effect of a shock to the weather variable of interest on per capita GDP growth at horizon h. The two variables in levels for which I find significant, and negative effects, on growth are average temperature and wildfires, while for all other level variables I cannot reject the null hypothesis of no effect on growth. The negative effects of a 1°C increase in average temperature accumulate over time, and stabilize around a 2% reduction after 7 years. A one-standard-deviation increase in my measure of wildfires, which corresponds to an approximate increase of 0.9% in burnt area of the country, implies a long-run marginal effect $\approx -3.5\%$ of GDP[6]. In order to gauge potential mechanisms behind these reduced-form effects, Figure A3 presents results from Equation 2, separately for agricultural and non-agricultural GDP. Sectoral output is computed using the cross-country data on value added shares from Comin, Lashkari, and Mestieri, 2021, aggregated into an agricultural and a non-agricultural sector following the classification of sectors in Herrendorf, Rogerson, and Valentinyi, 2014. Per capita sectoral GDP levels are then computed as sectoral share of value added multiplied by per capita GDP from WDI. The coefficients on weather impacts by sector are very imprecisely estimated and do not yield any clear picture on the mechanisms behind the aggregate effects. Importantly, the sample coverage is more sparse when working with sectoral output than with aggregate GDP and so the results are not directly comparable. The only potentially suggestive result is the strong reduction in agricultural output from wildfires- and this provides a potential mechanism explaining the novel finding of aggregate output being negatively affected by wildfires.

Looking at the impact of weather extremes, instead, the long-run effect of a one-standard-deviation increase in cyclone speed implies a long-run effect of $\approx -14.6\%$ of GDP. Finally, a one-day increase in coldwave duration appears to have a small but, surprisingly, positive effect on per capita GDP for two years, but the effect at longer horizons is imprecisely estimated. The effect of all other extremes are not significantly different from zero[7]. In light of these results, in Section 4 I select only average temperature, wildfires and cyclones as the variables whose impacts, when summed together, will represent the total effect of climate change on global GDP. The very low correlations among these variables, as shown in Figure 4, allow me to just sum their separate impacts on GDP as a first-order approximation of their total impact on output. Importantly, these results do not imply that extreme temperatures or extreme precipitation events do not have an effect on aggregate output. Rather, we cannot reject the null of no effect using these measures for those variables. Given the vast literature that finds large and significative effects from those extremes on output and productivity (e.g. Somanathan et al., 2021; Nath, 2025), my

[6]For comparison, a one-standard-deviation increase in average temperature is approximately 8°C, so the comparable long-run reduction in per capita GDP from a temperature shock would approximately -16%.

[7]Results on heterogeneous effects on GDP by local climate class are presented in Figure A4.

results suggest two, not mutually exclusive explanations for the divergence: (a) the exact measurement of the extremes[8] is crucial for detecting their impact on relevant economic variables, (b) aggregating certain variables at the country-level introduces too much noise relative to the signal (see e.g. Damania, Desbureaux, and Zaveri, 2020, for evidence in favor of this hypothesis for precipitation.). I do not pursue further the investigation for this disconnect, but leave it to future research on the topic.

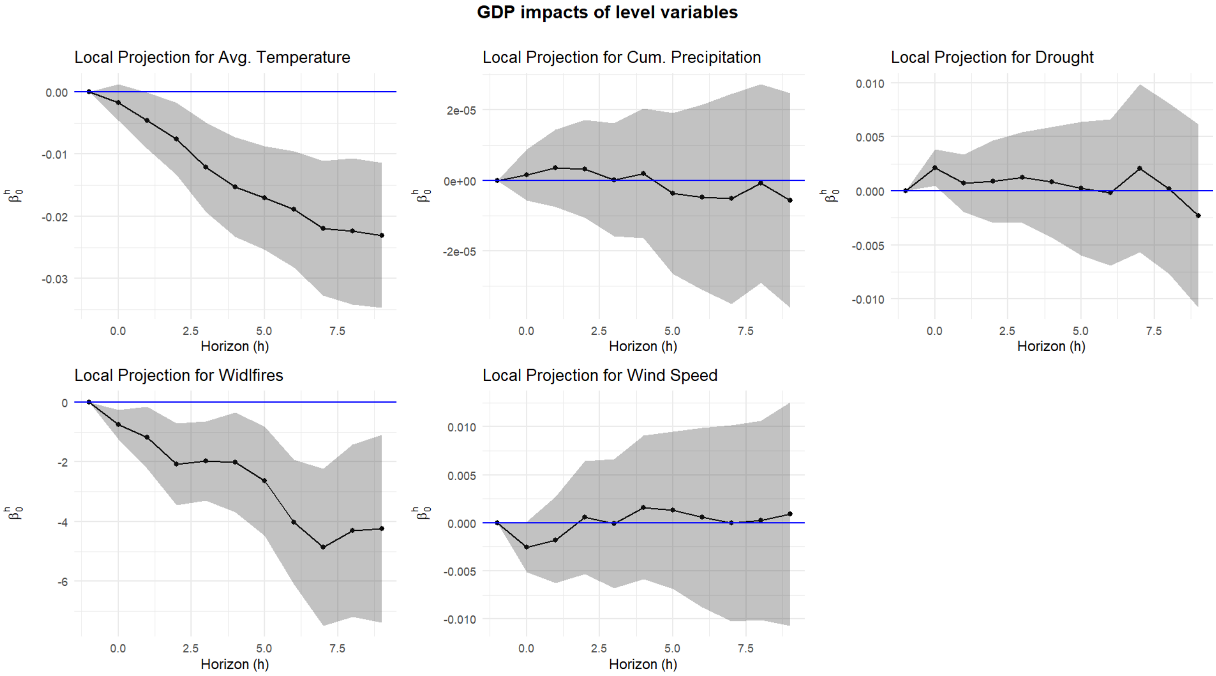
Persistence of weather shocks

Figure 6 displays the sequence of α_0^h coefficients from the estimation of equations 3 and 6, for level variables and extremes respectively, across horizons h. The contemporaneous effect in $h = 0$ is normalized to 1. The figure displays the persistence of a weather shock on the level of the corresponding variable. A fully transitory shock will imply a coefficient of 0 across all horizons, while a permanent shock will have a coefficient of 1 across all horizons, with potentially intermediate persistence in between. Consistently with NRK, I find that average temperature displays but moderate but non-zero persistence. About 20% of a shock to average annual temperature persists after a year, and it dies out within the considered horizon of ten years. The other variable with notable persistence over time is wildfires, where for a 1% increase in burnt area of a country about a quarter of that persists for at least ten years. For the other weather variables in levels, instead, shocks can be described as fully transitory, having zero or limited persistence across horizons. Weather extremes display the expected lack of persistence. Notably, the persistence of cyclones is less precisely estimated and appears to display an oscillating behaviour, but the total area underneath the impulse response integrates to ≈ 1 and thus does not affect the cumulative effect of a cyclone strike on GDP.

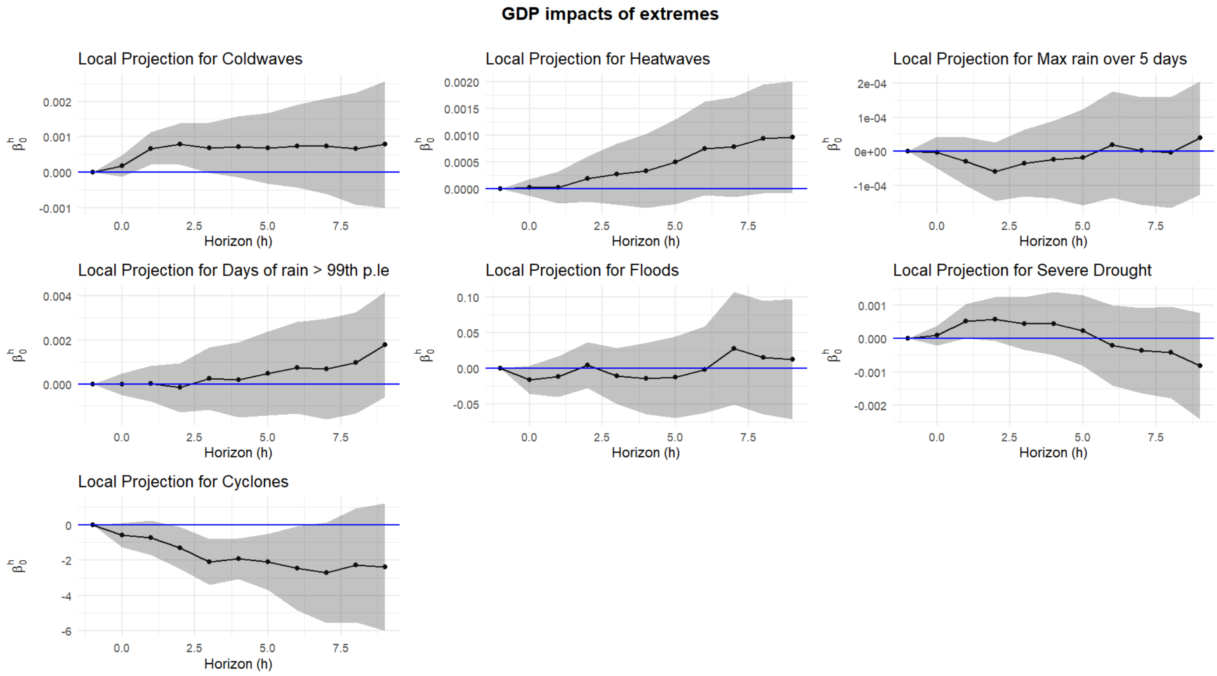
Total climate damages

Having selected 3 variables that have significant impact on per capita GDP, following the results displayed in Figure 5, I then apply to cumulative response ratios in Equation 7 for each of the 3 variables, using projection data until 2100. However, there is an important difference to keep in mind between weather variables in levels and weather extremes

[8]For example, consider the definition of heatwaves used in this paper, as opposed to the number of days that fall in a temperature interval.



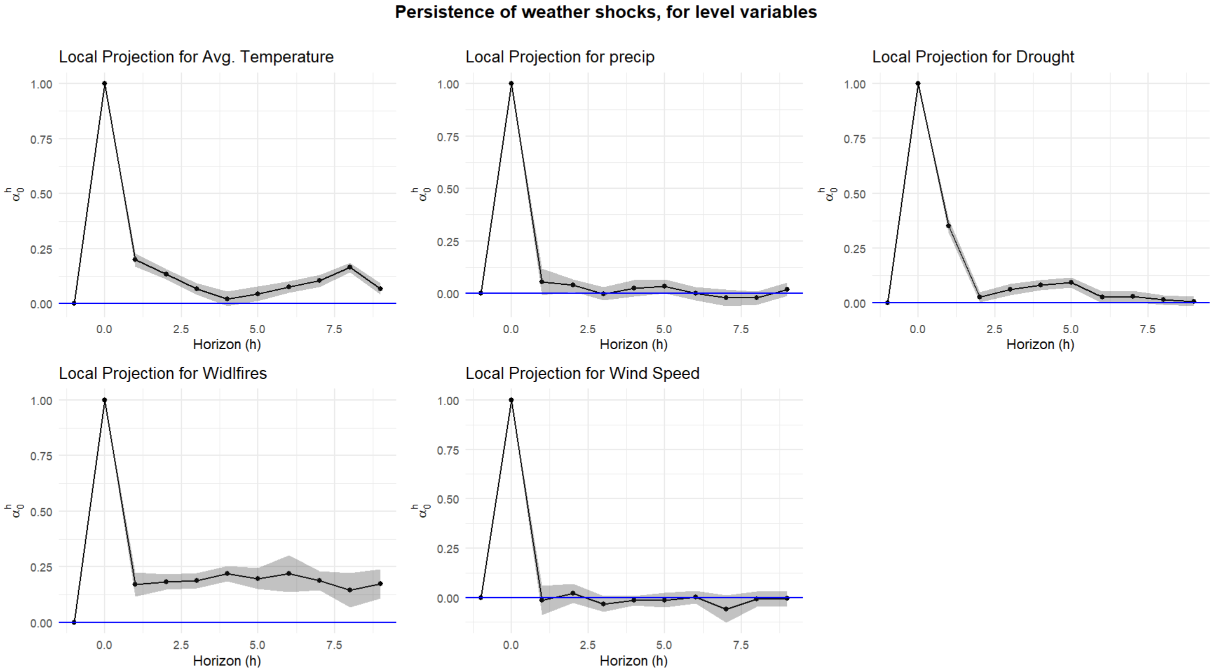
(a)



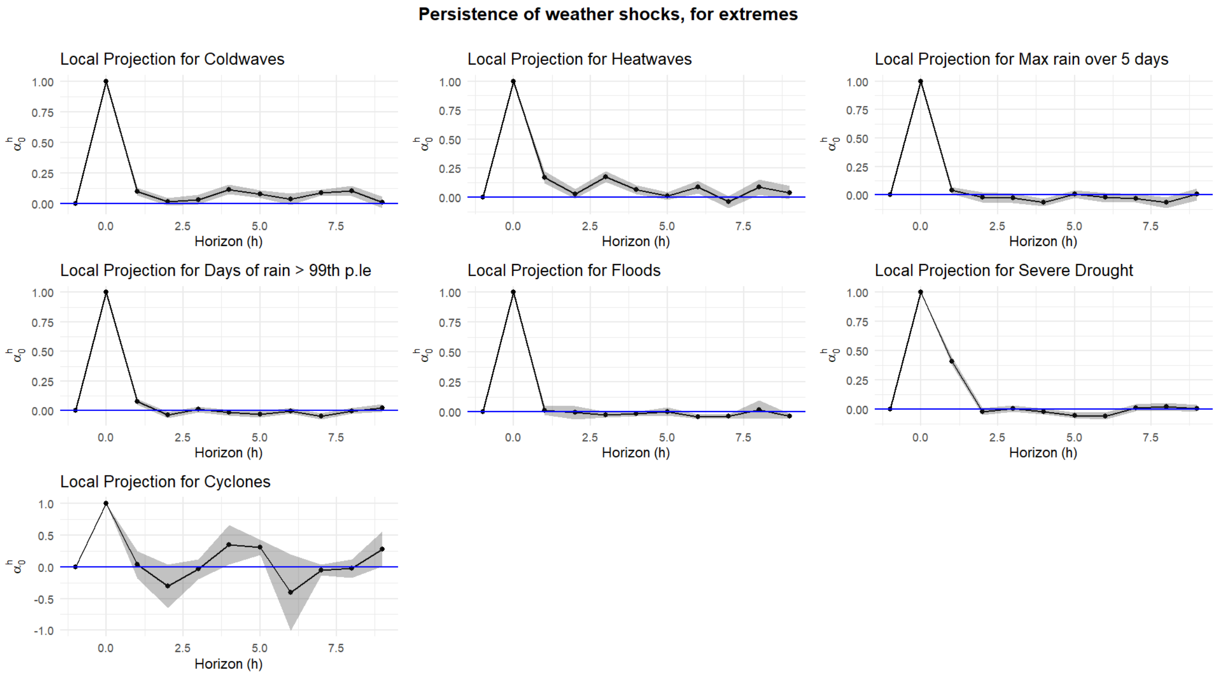
(b)

Figure 5

Notes: Panel (a) presents, for each weather variable in levels, the sequence of β_0^h coefficients from the estimation of Equation 2 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. Panel (b) presents, for each weather extreme variable, the sequence of β_0^h coefficients from the estimation of Equation 4 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. The coefficients and associated standard errors are normalized to 0 in horizon $h = -1$.



(a)



(b)

Figure 6

Notes: Panel (a) presents, for each weather variable in levels, the sequence of β_0^h coefficients from the estimation of Equation 3 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. Panel (b) presents, for each weather extreme variable, the sequence of β_0^h coefficients from the estimation of Equation 6 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. The coefficients and associated standard errors are normalized to 0 in horizon $h = -1$. The coefficients are normalized to 1 in horizon $h = 0$ and the associated standard errors are normalized to 0.

when computing damages from a change in the climate. For level variables- average temperature and wildfires in this case- climate change implies a permanent shift in their level (net of natural year-to-year fluctuations) and thus we can characterize their impacts on per capita GDP through their change in levels only. For extremes- tropical cyclones in this case- climate change implies a change in the distribution from which they are drawn, but the shock of the cyclone strike is transitory even under climate change. That is to say, climate change may imply that a country will tend to have slightly better or worse draws of cyclones each year, but the year following a cyclone a country will not be *adding* to the previous-year cyclone. Temperature, instead, will be increasing on top of the level reached in the previous years. Relatedly, in order to compute the impact of climate change on damages from cyclones, we need to account for cyclone damages under the current climate. This is because a country that is exposed to cyclones will still see an effect of cyclones on its GDP even if its local climate were not to change over time. To do this, I make a draw for each country from the country-specific Weibull distribution also for the years 1970-2015, assuming that the historical distribution is stationary over time. I then apply the CRR from Equation 7 separately to the historical period, which will give an estimate of damages from the current cyclone climate, and then to the projection period, which will give an estimate of damages under the future climate in scenario A1B. The difference between the two cumulative damages will then give the additional impact of climate change on GDP due to its effect on tropical cyclones- naturally, if the distribution in a country stayed the same, that country would not be expected to see any impact from cyclones.

Having outlined how damages are computed, a series of important remarks is in order. First, I compute as damages from climate change those deriving from a change in the distribution of the three selected variables relative to 2015. Given that anthropogenic emissions have already contributed to substantial warming (> 1°C, (Intergovernmental Panel on Climate Change (IPCC), 2021)), the total estimated damages from historical emissions would then be larger. Second, the future path of temperature and wildfires is consistent with the level of radiative of forcing in scenario ssp5-rcp8.5, while the draws of tropical cyclones from the interpolated distributions are consistent with scenario A1B which is consistent with a slightly lower forcing than ssp5-rcp8.5. Thus, to the extent that total damages from cyclones increase with global warming, the total climate damages under the worst-case scenario ssp5-rcp8.5 will be underestimated relative to those presented in this section. Third, damages to GDP are expressed in percent of the counterfactual GDP level without changes in the selected weather variables, and thus they are independent of the level of the counterfactual GDP and of any assumptions about future economic and population growth[9]. Relatedly, because damages to GDP are expressed in terms of percent of the counterfactual, a reduction of $X\%$ indicates that without climate change GDP would have been $X\%$ higher and not that it will be $X\%$ lower than today's level. Finally, because the estimates of GDP impacts from Equation 7 are linear in changes to the selected variables, damages are independent of the levels at which projections of the weather variables start at. That means that end-of-century damages from e.g. higher average temperature in country j only depend on how much average temperature increases between 2015 and 2100 and not on country j's temperature level in 2015 nor the path that temperature follows until 2100[10].

Table 1: Total effects under SSP585, % of GDP in 2100.

	Total effects		
	Total effect, GDP (w)	Total effect, Pop. (w)	Total effect, Patents (w)
Temperature	-35.38	-34.58	-37.42
Wildfires	-0.48	-0.30	-0.25
Cyclones	-11.26	-3.59	-5.26
Total	**-47.12**	**-38.48**	**-42.94**

Notes:
The table shows the projected effects, in percent changes, of unabated global warming on end-of-century per capita GDP. Each row separately displays the projected effects for each selected weather variable. Each column under Total effects uses separate weights: end-of-century GDP under SSP5, end-of-century population under SSP5 and patenting in the USPTO in 2024 respectively. Values rounded to two decimals.

The computation of damages in Table 4 follows NRK, and thus only considers damages to GDP levels coming from climate change. Each column in Table 4 under "Direct effects" applies directly the respective estimated cumulative response ratios of Equation 7 for each weather variable, and computes a weighted average of end-of-century damages across countries. The first column uses end-of-century projected GDP levels by country under ssp5-rcp8.5 as weights, the second column uses end-of-century projected population by country, the third column uses patenting levels in the United States aggregated by country.

[9]Projections of future GDP and population growth only matter, beyond the level of global warming, for the exact weights used in Table 4.

[10]The path of damages to GDP over the years between 2015 and 2100 would instead obviously depend on the actual path followed by temperature and wildfires over that span.

Table 4 shows that the bulk of the projected damages comes from increases in average temperatures, with the average person in 2100 projected to lose about 35% of their income as a result of temperature increases only. The magnitude of temperature damages is very stable across weighting schemes. Wildfires, instead, contribute only marginally to total projected climate damages, with total damages around half of a percent of end-of-century GDP, mostly due to limited changes in projected average rates of burnt land even under the high-warming of ssp5-rcp8.5. Damages from wildfires tend to be concentrated in relatively high-GDP but relatively low-population and low-innovation countries, particularly those located in the Arabian peninsula. Finally, damages from tropical cyclones tend to disproportionally hit high-GDP but relatively low-population countries and total damages from cyclones are estimated to be around 11.7% of end-of-century per capita GDP. Hence, damages from weather variables other than temperature are expected to represent slightly less than a quarter (12.2%) of total damages (50.6%) from climate change by 2100.

Figure 7 displays the distribution of estimated climate change impacts by 2100 across countries. Panel (a) displays the distribution of impacts coming from non-temperature variables, as this is the main focus of the paper. While the majority of countries is projected to suffer negative impacts, the average masks considerable heterogeneity. The countries most exposed to non-temperature damages are mainly located in East and South East Asia- Bangladesh, Thailand, South Korea and Japan- together with Morocco. For these countries, the main driver of the reduction in GDP relative to counterfactual is the additional impact of tropical cyclones. Only a few countries see some modest, positive impacts of climate change. These are located in Sub-Saharan Africa, South America and Northern Europe and they see a beneficial effect from the modest projected reduction in wildfires, while they remain unexposed to tropical cyclones. Panel (b) displays the distribution of temperature-only damages. Since my main empirical specification does not allow for heterogeneous effects, the difference in projected impacts comes only from differences in projected warming at the country level and thus it is countries in the Northern Hemisphere who are projected to suffer the most, since that is the area of the world which will see the strongest increase in average temperatures. Finally, panel (c) displays the distribution of damages from all three variables combined. Since temperature still represents the largest component of projected damages, the spatial distribution of damages resembles that of temperature for the most part, but with the level of damages scaled

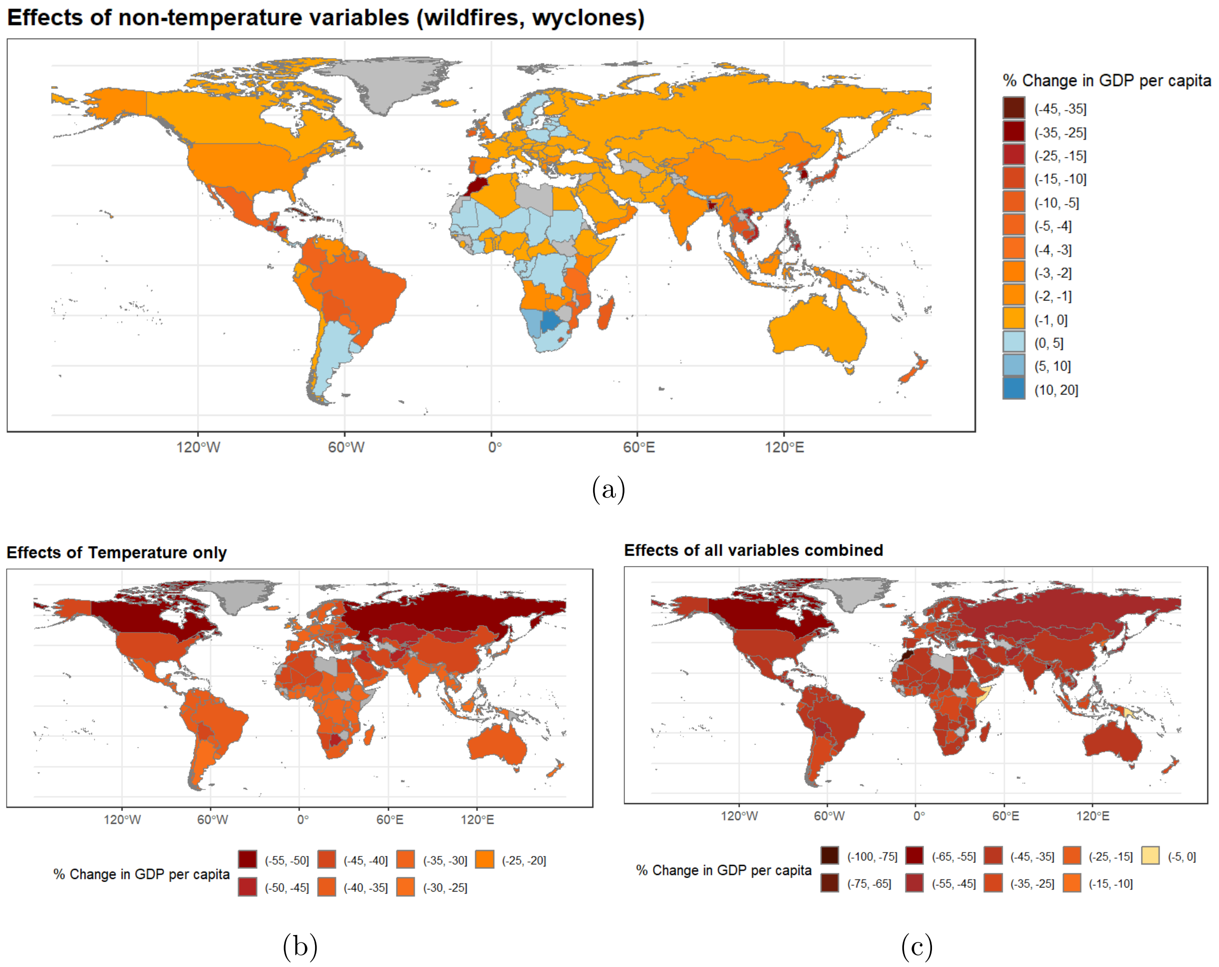


Figure 7

Notes: The maps display the projected effects to country-level in GDP by 2100 under the ssp5-rcp8.5 global warming scenario for the variables average temperature and wildfires and under the IPCC A1B warming scenario for tropical cyclones, separately by weather variable grouping. Panel (a) displays the projected effects due to tropical cyclones and wildfires combined. Panel (b) displays the projected effects due to temperature alone. Panel (c) displays the projected effects due to temperature, tropical cyclones and wildfires combined.

up.

5 Conclusion

Excluding damages from variables other than average temperature, and in particular tropical cyclones, may lead to a relevant underestimate of future economic damages from climate change. This paper has found that average temperature does not work as a perfect proxy for the climate at the country-level and that there is residual variation in the other climate variables that is not accounted for when they are excluded. I have found that these other variables may represent over a fifth of total end-of-century damages under high-warming scenario.

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Appendix

Appendix Contents

A Additional data description

Climate data

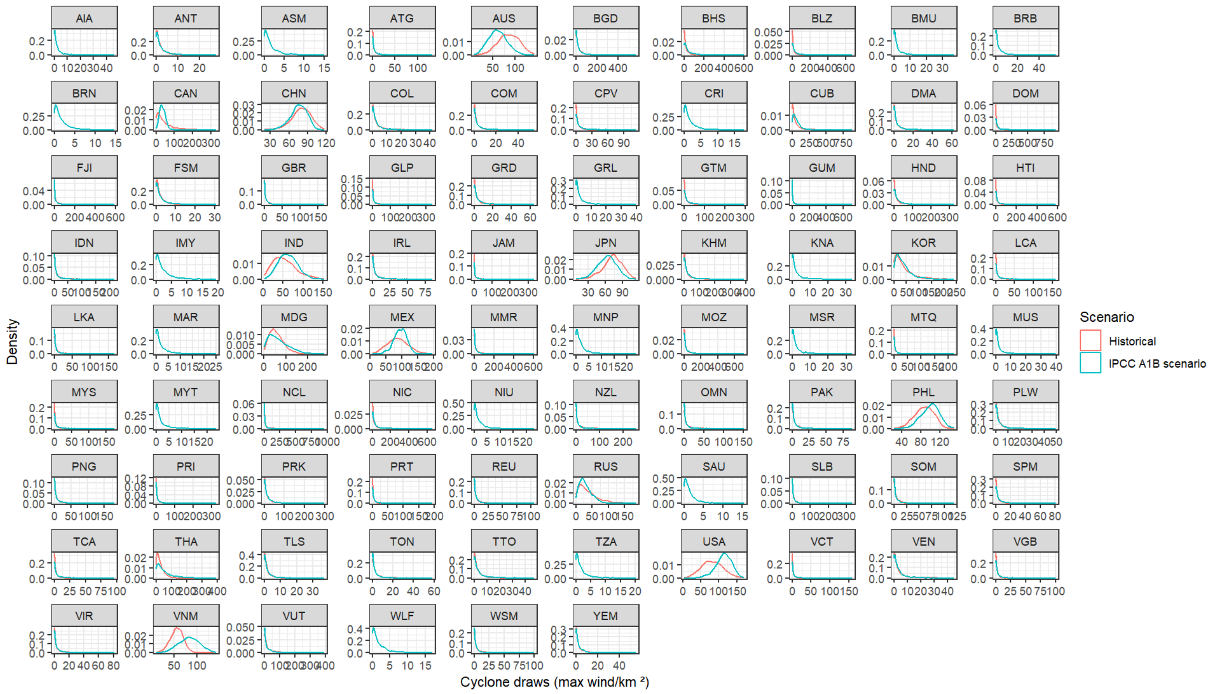


Figure A1

Notes: The figure displays the kernel densities for 10,000 draws of cyclone wind speed, measured in maximum wind speed per km^2, from the country specific Weibull distributions, whose scale and shape parameters are provided in Bakkensen and Barrage, 2025. The red densities represent the distribution with Weibull parameters that fit the distribution of cyclones between 1970 and 2015. The blue densities represent the distribution with Weibull parameters that fit the projected distribution of cyclones between 2090 and 2100 under the IPCC A1B scenario. The figure includes all countries for which data are available in Bakkensen and Barrage, 2025.

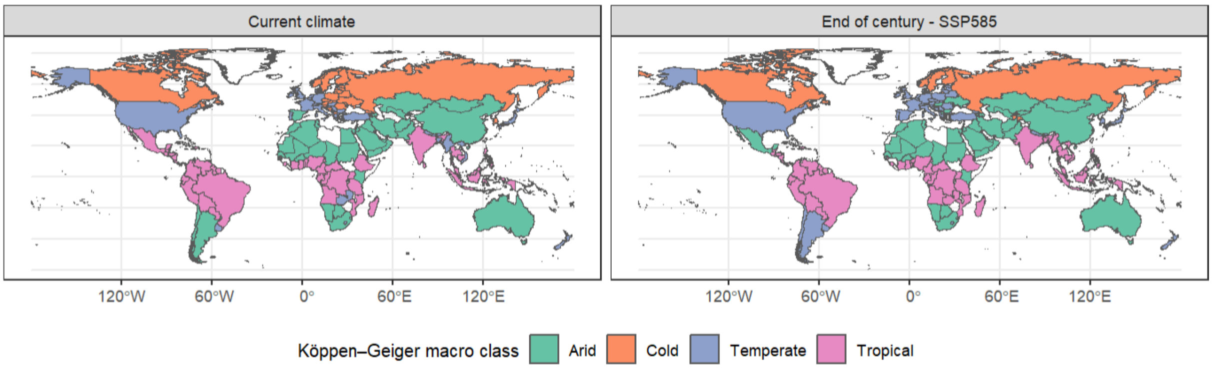
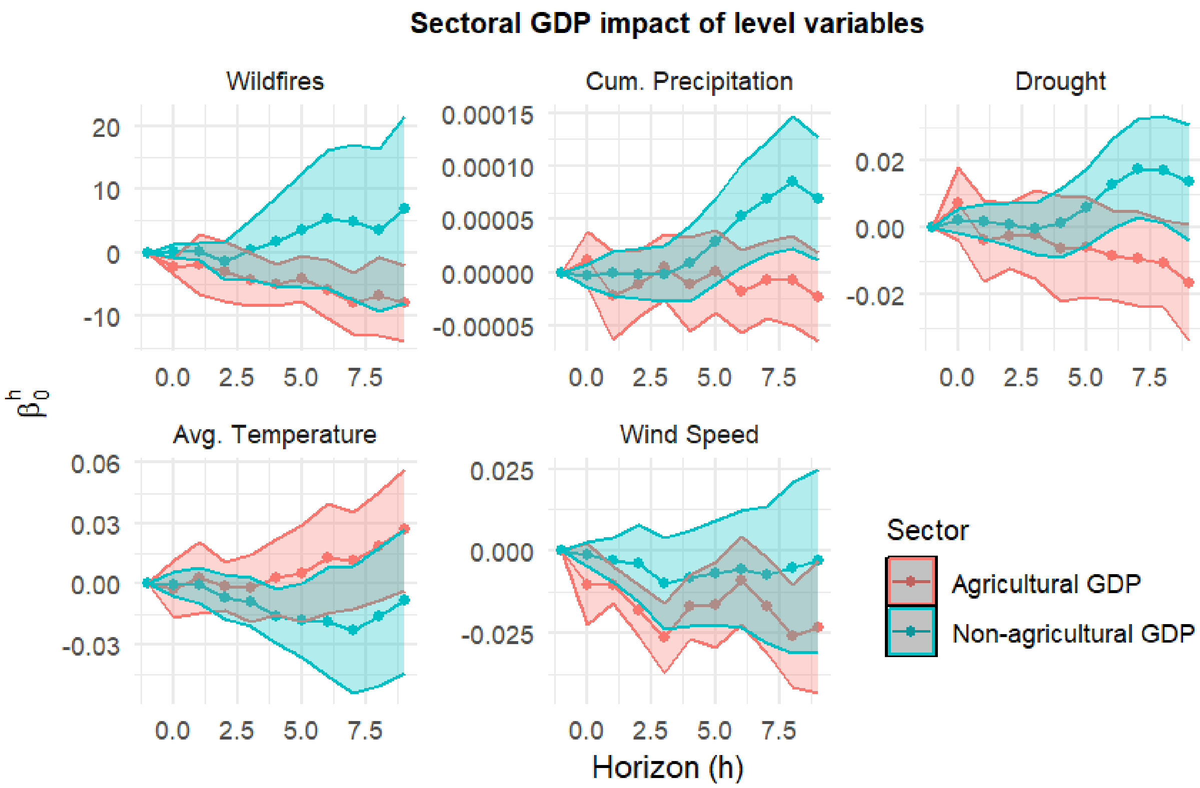


Figure A2

Notes: The maps display the prevalent Köppen-Geiger climate for each country, aggregating by area-weighted mode the grid-cell level data from Beck et al., 2023, separately for current climate (2000-2020) and end of century under ssp5-rcp8.5 (2080-2100).

B Additional empirical results

Results on sectoral GDP



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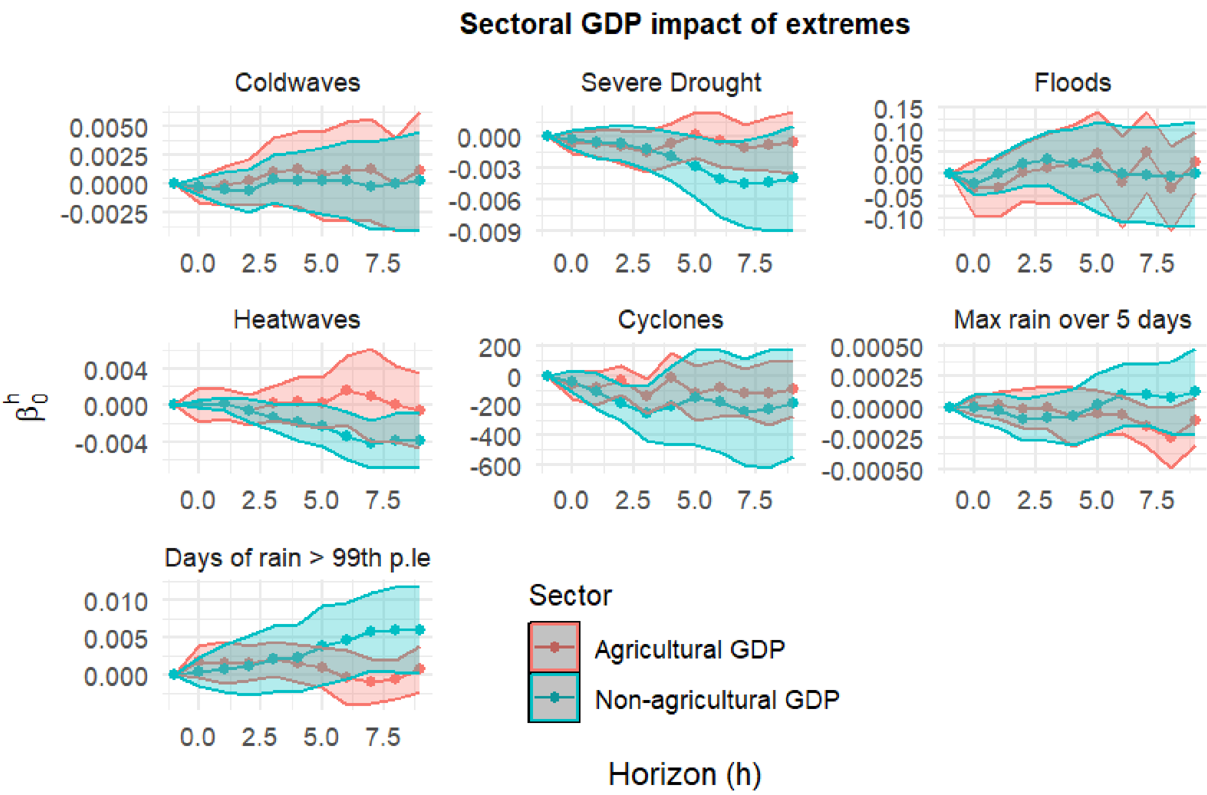


(b)

Figure A3

Notes: Panel (a) presents, for each weather variable in levels, the sequence of β_0^h coefficients from the estimation of Equation 2 separately for agricultural and non-agricultural GDP and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. Panel (b) presents, for each weather extreme variable, the sequence of β_0^h coefficients from the estimation of Equation 4 separately for agricultural and non-agricultural GDP and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. The coefficients and associated standard errors are normalized to 0 in horizon $h = -1$.

Heterogeneous weather effects

When allowing for heterogeneous weather effects across country-specific climates, as measured by the Köppen-Geiger climate classification system, I estimate the following set of regressions, for each weather variable, distinguishing among weather variables in levels and extremes like in the main text. Shocks to variables in levels and to the extremes are estimated as described in Section 4.

Level variables:

$$y_{it+h} - y_{it-1} = \beta_0^h \boldsymbol{\chi_{it}} + \boldsymbol{\Theta_{\mathbf{it}}}'\boldsymbol{\gamma} + \mu_i + \mu_t + u_{it} \text{ for } h = 0, ..., 9. \tag{8}$$

where $\boldsymbol{\Theta_{\mathbf{it}}} = \{X_{it-j}, \sum_{k \in \{\text{Cold, Temperate, Tropical}\}} \alpha_{1,k}^h X_{it-j} \cdot \mathbb{1}\{k = l\}, \Delta y_{it-j}\ \}_{j=1}^p$

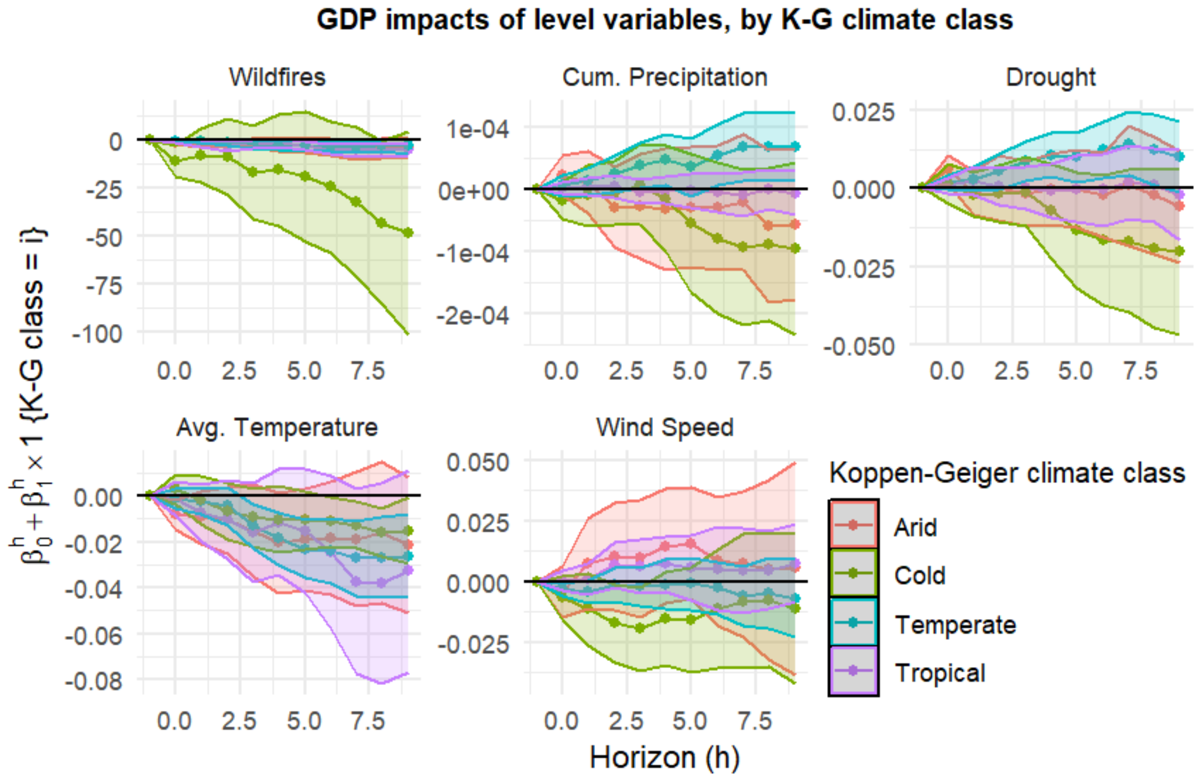
$$X_{it+h} = \alpha_0^h \boldsymbol{\chi_{it}} + \sum_{k \in \{\text{Cold, Temperate, Tropical}\}} \alpha_{1,k}^h \boldsymbol{\chi_{it}} \cdot \mathbb{1}\{k = l\} + \boldsymbol{\Lambda_{\mathbf{it}}}'\boldsymbol{\delta} + \mu_i + \mu_t + \zeta_{it} \text{ for } h = 1, ..., 9 \tag{9}$$

where $\boldsymbol{\Lambda_{\mathbf{it}}} = \{X_{it-j}, \sum_{k \in \{\text{Cold, Temperate, Tropical}\}} \alpha_{1,k}^h X_{it-j} \cdot \mathbb{1}\{k = l\}\ \}_{j=1}^p$

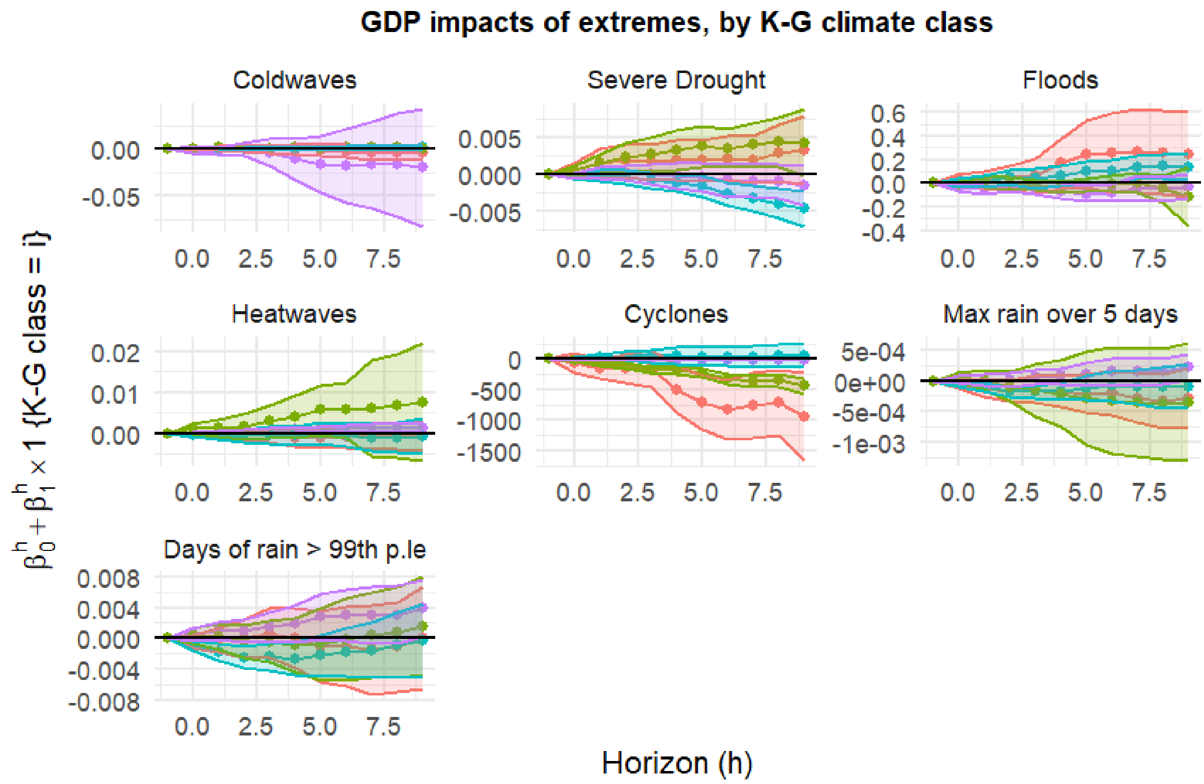
Extreme variables:

$$y_{it+h} - y_{it-1} = \beta_0^h E_{it} + \sum_{k \in \{\text{Cold, Temperate, Tropical}\}} \alpha_{1,k}^h E_{it-j} \cdot \mathbb{1}\{k = l\} + \mu_i + \mu_t + u_{it} \text{ for } h = 0, ..., 9. \tag{10}$$

$$E_{it+h} = \alpha_0^h \boldsymbol{\varepsilon_{it}} + \sum_{k \in \{\text{Cold, Temperate, Tropical}\}} \alpha_{1,k}^h \boldsymbol{\varepsilon_{it}} \cdot \mathbb{1}\{k = l\} + \boldsymbol{\Lambda_{\mathbf{it}}}'\boldsymbol{\delta} + \mu_i + \mu_t + \zeta_{it} \text{ for } h = 1, ..., 9 \tag{11}$$



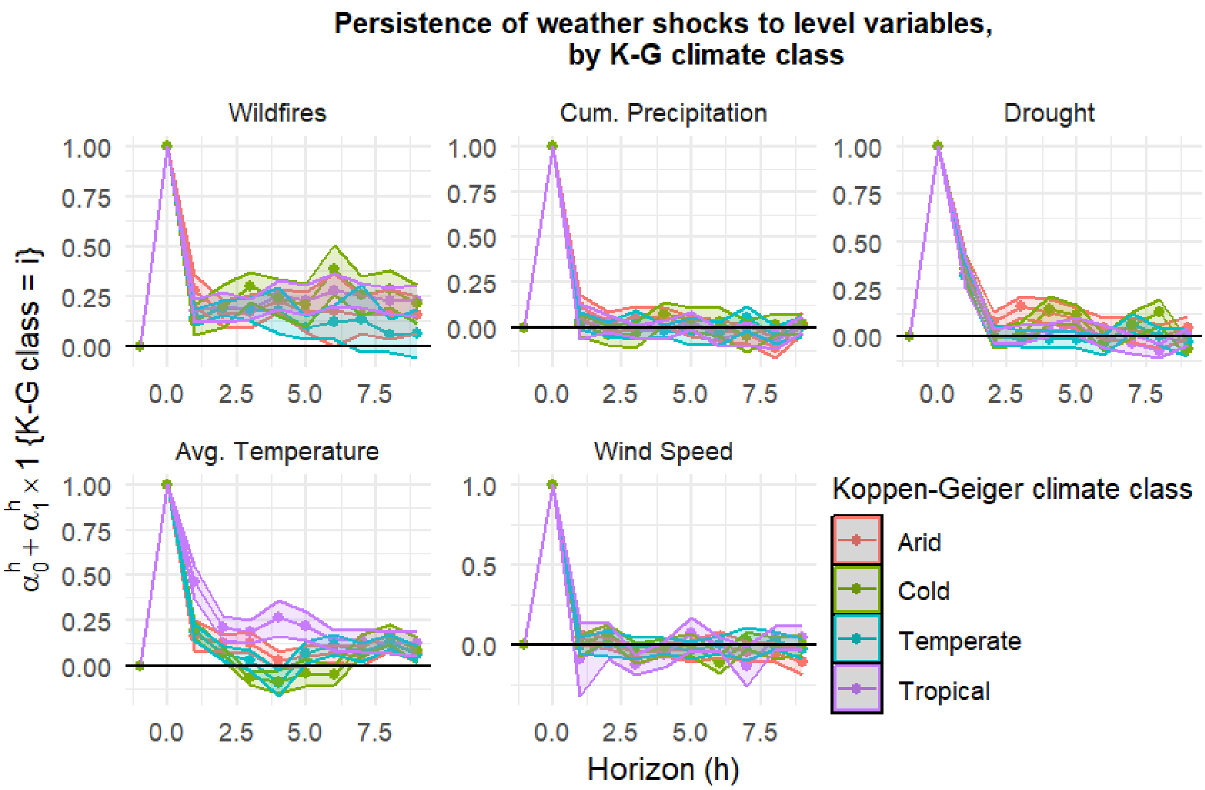
(a)



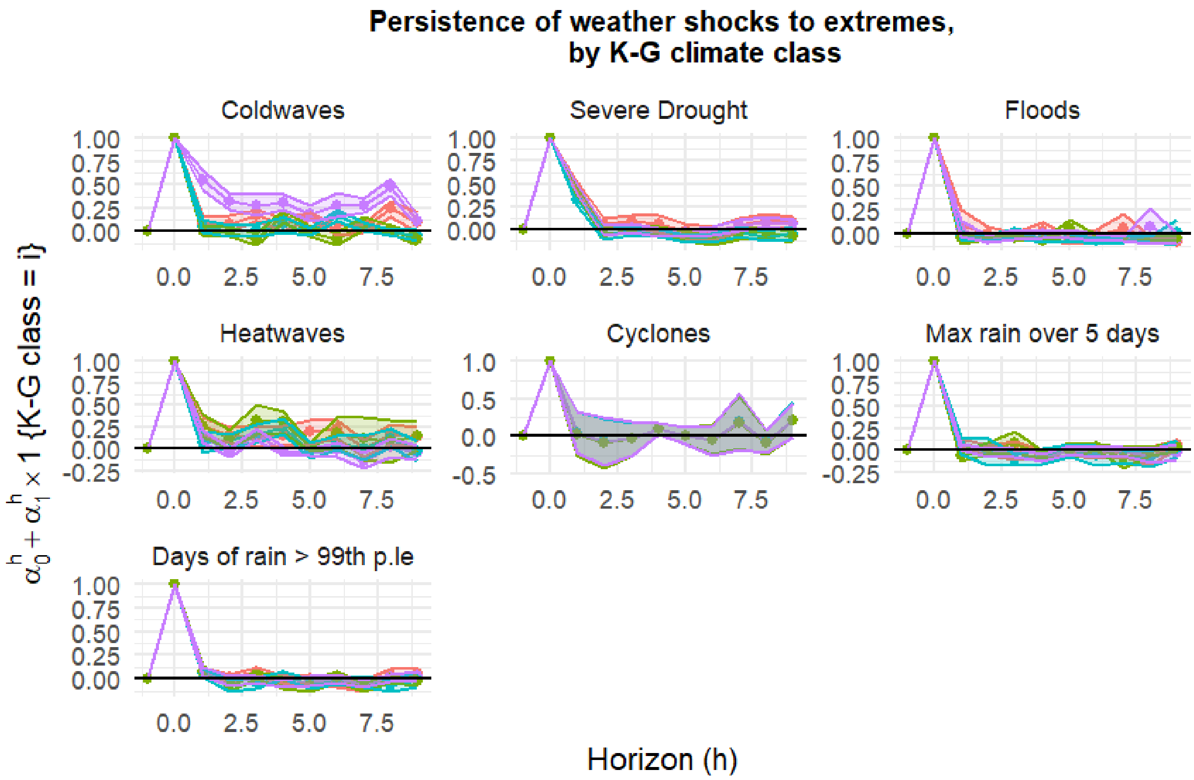
(b)

Figure A4

Notes: Panel (a) presents, for each weather variable in levels, the sequence of β_0^h coefficients from the estimation of Equation 8 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. Panel (b) presents, for each weather extreme variable, the sequence of β_0^h coefficients from the estimation of Equation 10 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. The coefficients and associated standard errors are normalized to 0 in horizon $h = -1$.



(a)



(b)

Figure A5

Notes: Panel (a) presents, for each weather variable in levels, the sequence of β_0^h coefficients from the estimation of Equation 9 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. Panel (b) presents, for each weather extreme variable, the sequence of β_0^h coefficients from the estimation of **??** and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. The coefficients and associated standard errors are normalized to 0 in horizon $h = -1$. The coefficients are normalized to 1 in horizon $h = 0$ and the associated standard errors are normalized to 0.

C Robustness Checks

Time series properties of the shocks

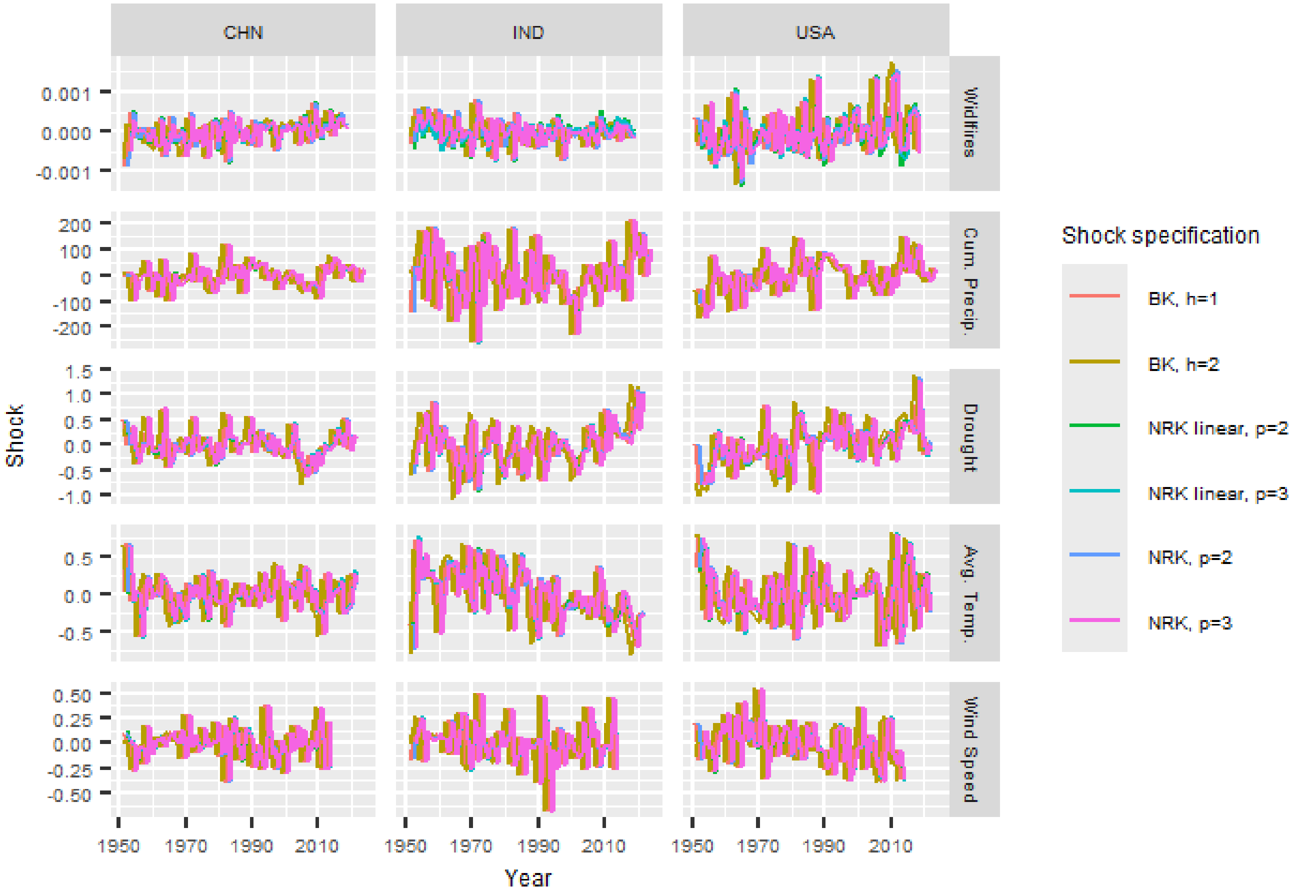


Figure A6

Notes: The figure depicts the time series of identified shocks for weather variables in levels, across different specifications of Equation 1, for the countries of China, India and the United States. *BK* specifications follow Bilal and Känzig, 2024 for different values of the h-step ahead forecast error. *NRK* specifications follow Nath, Ramey, and Klenow, 2024 for different values of the lag length p. *Linear* specifications omit the $\{\theta_j\}$ terms in Equation 1.

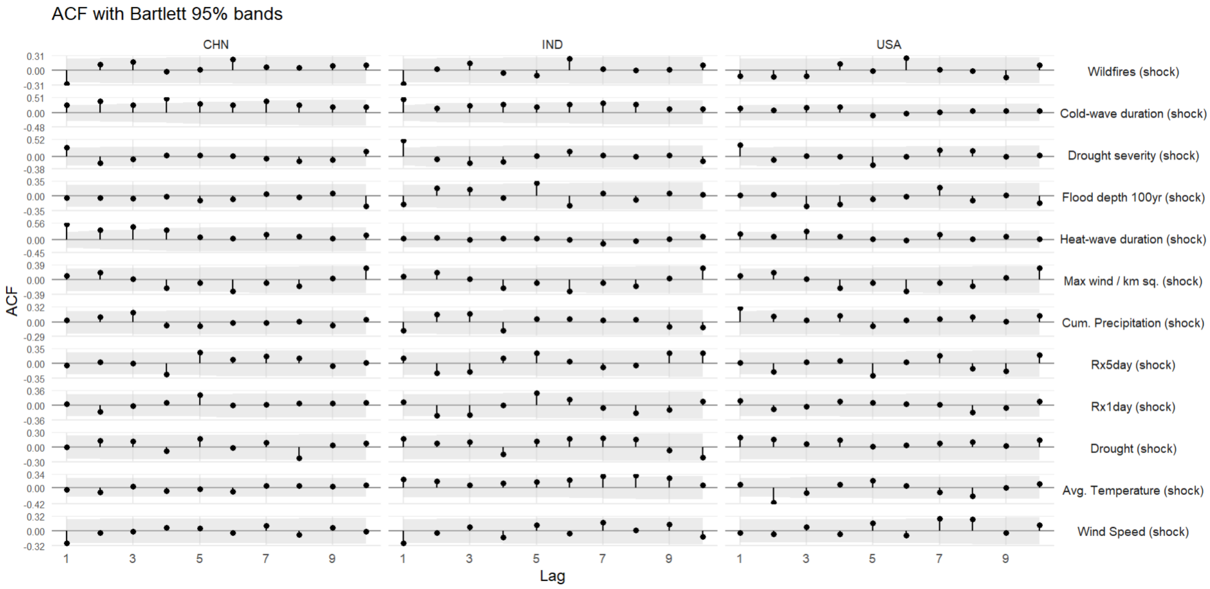
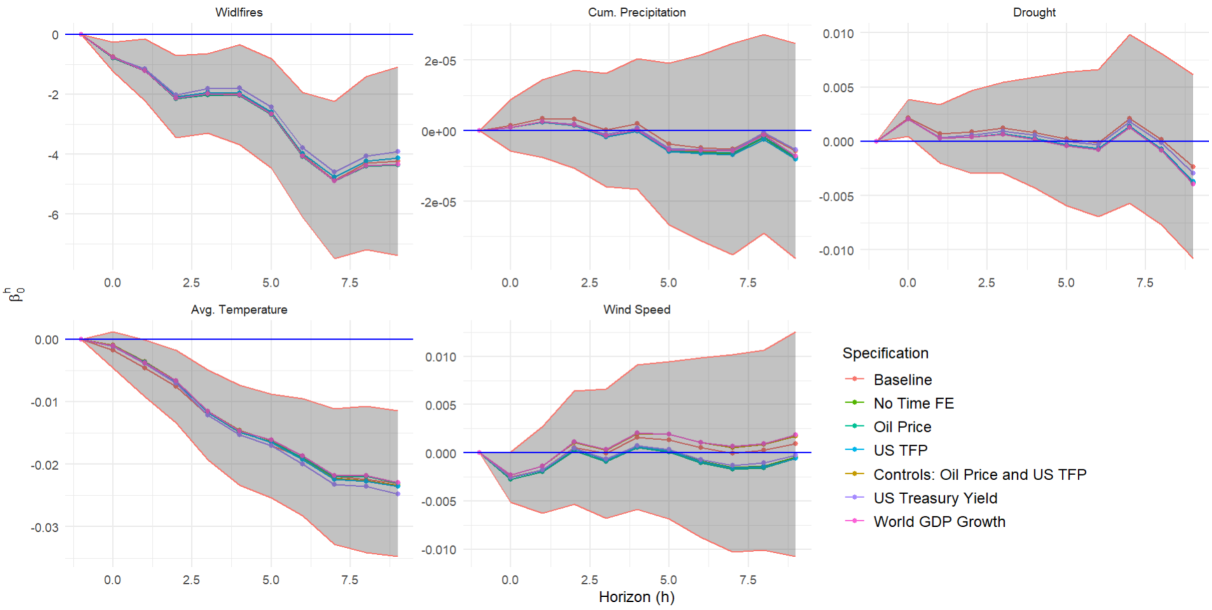
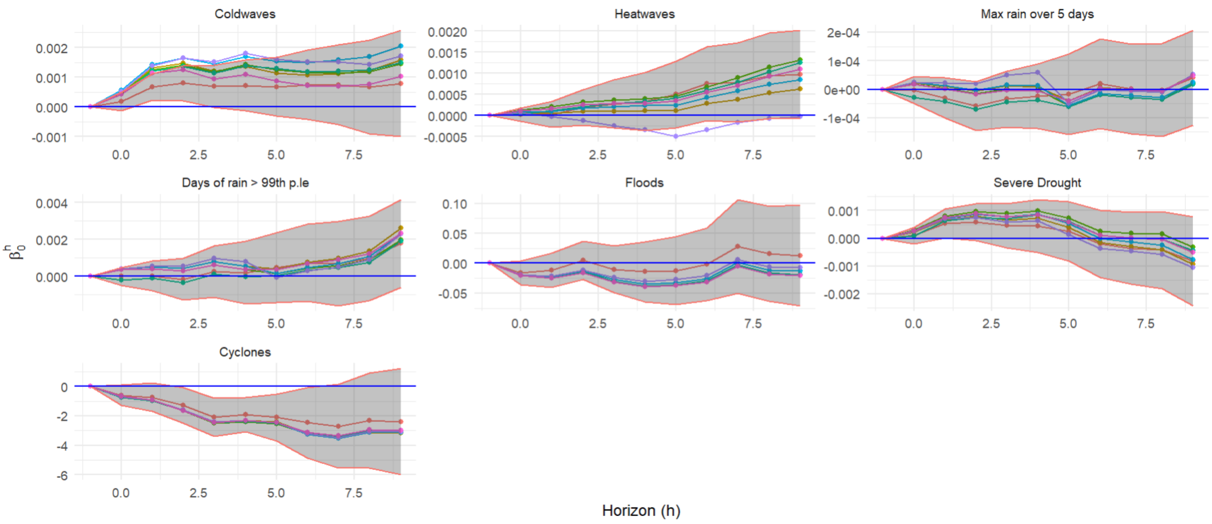


Figure A7

Notes: The figure depicts the auto-correlation function with 95% Bartlett confidence bands for the time series of the identified shocks, according to Equations 1 and 5, for the countries of China, India and the United States.



(a)



(b)

Figure A8

Notes: Panel (a) presents, for each weather variable in levels, the sequence of β_0^h coefficients from the estimation of Equation 3 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. Panel (b) presents, for each weather extreme variable, the sequence of β_0^h coefficients from the estimation of Equation 6 and the associated 95% confidence intervals, across horizons $h = 0, ..., 9$. The coefficients and associated standard errors are normalized to 0 in horizon $h = -1$. The coefficients are normalized to 1 in horizon $h = 0$ and the associated standard errors are normalized to 0.