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# EDHEC-CLIRMAP

## EDHEC-CLimate-Induced Regional MAcroimpacts Projector

### The Macroeconomic and Econometric Background



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## Abstract

The EDHEC-CLIRMAP (EDHEC-CLimate-Induced Regional MACroimpacts Projector) is a web-hosted tool developed by the EDHEC Climate Institute. It provides a user-friendly platform for scientists, experts, professionals investors and policymakers to visualise how climate change-induced shifts in average temperature are projected to affect gross regional economic product under various warming scenarios. This document outlines the scientific background underpinning EDHEC-CLIRMAP, with emphasis on the macroeconomic framework, the climate econometric theory, and the *Delta* method elaborated to project future damages over time and space. By integrating the latest subnational economic information with highly-localised climate change simulations from the National Aeronautics and Space Administration, EDHEC-CLIRMAP enables users to intuitively explore the geography of future economic damages – and uncover heterogeneity stories relevant to climate adaptation.

## 1. Purpose of this Document

This document describes the web-based tool EDHEC-CLIRMAP (EDHEC-CLimate-Induced Regional MACroimpacts Projector). In brief, its aim is to provide a user-friendly web-hosted platform for scientists, experts, professionals investors and policymakers to explore and visualise how gross regional economic product is expected to be impacted by climate-change-driven shifts in average temperature. The tool can be accessed here: <https://climateinstitute.edhec.edu/data-visualizations#edhec-clirmap>.

The purpose of this document is to outline the scientific background underpinning EDHEC-CLIRMAP. This includes

- the macroeconomic framework underlying how losses recorded at the unit-level and over the short-run, scale up into wider and longer-term productivity damages at the country-level;
- the econometric theory behind the foundational temperature-gross regional product response functions using real historical data spanning the last 50 years;
- the choice and transformation of climate change simulations with high time and space resolution from the National Aeronautics and Space Administration (NASA); and
- the projection of chronic physical climate risk-driven gross regional economic product (GRP) changes distributed over future epochs, regions, and scenario × global climate models (GCM) ensembles.

Furthermore, we explain which inputs are needed for the projection, how they are fed into the projection engine, and how one should interpret the resulting outputs. The rest of the document is structured as follows.

- §2 summarises the general background and the structure of this tool;
- §3 defines the theoretical macroeconomic framework; §4 describes the quantification of climate-gross GRP functions;
- In §5, the NEX-GDDP-CMIP6 transformation and the development of the Delta Projection Framework are presented;
- §6 discusses the distribution and interpretation of macroeconomic damages; and finally
- §7 outlines caveats and directions to the future evolution of EDHEC-CLIRMAP

## 2. Background and Structure

In this Section we define what is EDHEC-CLIRMAP and what it *is not*.

EDHEC-CLIRMAP is a state-of-the-art projection tool to project geo-economic damages caused by climate change. It builds on a companion EDHEC Climate Institute tool that obtains how the Earth surface temperature responds to various future emissions scenarios<sup>1</sup>. It relies on climate data externally sourced from leading climate data

1 - This is the purpose of the companion web-hosted tool EXCITE (EDHEC Cross-Model Climate Institute Temperature Emulator) developed by the EDHEC Climate Institute (accessible at <https://climateinstitute.edhec.edu/data-visualizations#excite-emulator>) which explores and simulates global temperature trajectories from IAM-derived emissions scenarios.

providers, such as NASA, and applies quantitative methods to provide an empirical estimate of the economic implications of physical climate risk. Its outputs are thus derived from a multi-stage methodology detailed in §4–6, and theoretically grounded in the macroeconomic framework presented in §3.

The objective of EDHEC-CLIRMAP is to allow researchers and non-experts to quickly visualise the heterogeneity of climate change damages on regional economic production under various warming futures. EDHEC-CLIRMAP explicitly focusses on the *chronic* segment of physical climate risks, which refers to the long-continuous shifts in climate patterns – such as gradual changes in average surface temperature – that progressively influence sectoral productivity, asset values, and financial stability. Contemporaneous measures of *acute* risks – i.e., sudden, shorter-term extreme weather events (e.g., hurricanes, floods, wildfires, and heatwaves) that cause immediate shock to infrastructure and supply chains – are not included in the simulated economic damages. This exclusion implies that EDHEC-CLIRMAP outputs are conservative and likely underestimated.

The granular outputs provided by EDHEC-CLIRMAP are the outcome of complex and sophisticated analysis, but they can be aggregated into a simple operational form useful for decision-making and risk management: a damage function. This is the mathematical representation of the non-linear relationship between changes in climate variables – typically mean temperature change relative to the pre-industrial period in °C – and the resulting economic damages – usually modelled as fractional loss in Gross Domestic Product (GDP) consumption – relative to a baseline period or scenario. Damage functions are a key component of climate economics, and are perhaps *the* central module to Integrated Assessment Modelling (IAM), as they are at the heart of the feedback loop between economic output ( $Y$ ), emissions ( $E$ ), changes in temperature,  $\Delta T$ , damages ( $\Omega$ ), and impairment to output ( $\Delta Y$ ) ( $Y \rightarrow E \rightarrow \Delta T \rightarrow \Omega \cdots \rightarrow \Delta Y$ )<sup>2</sup>. After all, without damages  $\Omega$  from rising temperature  $T$ , there is no reason to control polluting emissions  $E$ .

Since the reduction of climate-induced physical damages is what ultimately motivates costly abatement, the damage function must be quantified in a realistic manner. Any cost-benefit assessment of adaptation versus transition strategies also requires a prior understanding of the climate-economy relation. This is therefore another area where damage functions have made their contribution. The first theoretically-grounded damage functions were obtained from expert elicitation (Nordhaus, 2006; Weitzman, 2010). Their estimation has since evolved to become empirically calibrated (Burke et al., 2015) and increasingly informed by intra-country heterogeneity<sup>3</sup> up until today. EDHEC-CLIRMAP, by offering a web-hosted visualisation of future geo-projected gross regional output losses over epochs and warming scenarios, extends this literature by highlighting the granular dimension of global economic climate damages.

In sum, EDHEC-CLIRMAP provides a basis for making more spatially localised projections of chronic physical climate risk-driven economic damages. Our non-linear climate-GRP response functions are obtained using state-of-the-art econometric techniques and are based on high-resolution sub-national economic data over the last 50 years (1970–2018). They have been combined with an ensemble of time- and spatially-resolved NEX-GDDP CMIP6 simulations from 29 distinct GCMs. Under the ‘pessimistic’ SSP5-RCP8.5 warming scenario, we find substantial agreement in the prediction of GCMs of average end-century per capita GRP declines of more than 75% from temperature shifts alone – with the largest effects in regions bordering the equator and the tropics (i.e., West Africa, Central America, South Asia). While broadly consistent with the global GDP damage estimates of Burke et al. (2015), our projections – derived from province-level data – systematically yield larger mean losses. We attribute this divergence to the finer-grained approach we have developed, which better captures localised climate and economic heterogeneity, particularly in terms of small-scale variations in exposure to extreme heat and gross regional economic vulnerability. Our results suggest that nationally-

2 – A major application of climate emulators is the analysis of the feedback loop between economic growth and temperature anomalies in Integrated Assessment Models such as DICE (Nordhaus, 2017), PAGE (Hope, 2011), FUND (Waldhoff et al, 2014) and as summarised in Golosov et al (2014) and Lemoine (2017).

3 – The damage function from Kotz et al (2024) has become a key feature in the enhancement of the 2024 physical risk assessment of the Network for Greening the Financial System (NGFS) Phase-V long-term scenarios for central banks and supervisors. See <https://www.ngfs.net/en>.

derived estimates in Burke et al. (2015) may understate the true economic costs of future physical climate risk, reinforcing and extending the conclusions of Kotz et al. (2024).

### 3. Theoretical Macroeconomic Framework

Where do we stand theoretically? Our starting place is that climate change is, by nature, a global public-good problem that leaves no productive units or locations unaffected (Schlenker and Walker, 2016). The absence of a formal *control group* has fundamental implications for the impact evaluation approach to climate change, whether historically measured or future projected.

A pioneering theoretical formalisation of the aggregation of cross-climatic damage to productive units was offered in Burke et al. (2015), which we recall hereafter. This serves as the foundation for our theoretical framework, because it models how highly non-linear changes in productivity over short time scales and across many micro-units do scale up into macro-productivity damages – and largely explain the shape of macroeconomic responses over longer periods.

Consider dividing a standard macroeconomic framework into multiple industries, each labelled by an index  $i$ . We assume that all production units within a given industry exhibit uniform responses to temperature shocks<sup>4</sup>. Production within each industry is distributed across different spatial locations, indexed by  $\ell$ , which are further grouped into countries represented by  $L$ . The time dimension is split into short increments, such as hours, denoted by  $t$ , commonly used in micro-level analyses, and longer durations spanning many such increments, like years, represented by  $\tau$ .

Building on the framework of Deryugina and Hsiang (2014), the capital stock, denoted  $K_i$ , and labour input,  $L_i$ , within each industry exhibit productivities  $A_i^K$  and  $A_i^L$  respectively. These productivities depend on the instantaneous temperature  $T_{\ell,t}$  at a specific location  $\ell$  and time  $t$ . Both the total capital and labour employed in industry  $i$  are permitted to vary with changes in temperature. The output price per unit is represented by  $p$ , and  $\alpha$  is a fixed parameter in this simplified production specification. For a given economic unit at location  $\ell$  and time  $t$ , utilising technology set  $i$ , the aggregate production function  $Y_{i,\ell,t}$  can be expressed as:

$$Y_{i,\ell,t}(T_{\ell,t}) = p_i(A_i^K(T_{\ell,t})K_{i,\ell,t}(T_{\ell,t}))^\alpha(A_i^L(T_{\ell,t})L_{i,\ell,t}(T_{\ell,t}))^{1-\alpha} \quad (1)$$

The model posits that the adjustment of capital and labour allocation across locations in response to temperature fluctuations occurs gradually. It is well documented that the amount of time individuals dedicate to work varies with temperature, and this variation is incorporated into the model through changes in labour productivity,  $A_i^L$ <sup>5</sup>. Under competitive equilibrium, the ratio of capital to labour in industry  $i$  at location  $\ell$  and time  $t$  is constant, given by  $\frac{K_{i,\ell,t}}{L_{i,\ell,t}} = \frac{\alpha}{1-\alpha}$ , meaning that capital-to-labour proportions remain fixed and output scales proportionally with the combined amounts of capital and labour allocated to industry  $i$  – indicating constant returns to scale in the production function. Let  $U_{i,\ell,t} = p_i K_{i,\ell,t}^\alpha L_{i,\ell,t}^{1-\alpha}$  represent a scalar quantity measuring the resources devoted to industry  $i$  at location  $\ell$  and time  $t$ . The variable  $U_i$  captures the count of modular production units (firms) assigned to industry  $i$ . Equation (1) can thus be expressed in a simplified form as:

$$Y_{i,\ell,t}(T_{\ell,t}) = \underbrace{(A_i^K(T_{\ell,t})^\alpha A_i^L(T_{\ell,t})^{1-\alpha})}_{f_i(T_{\ell,t})} p_i K_{i,\ell,t}^\alpha L_{i,\ell,t}^{1-\alpha} = f_i(T_{\ell,t}) U_{i,\ell,t} \quad (2)$$

The function  $f_i(T_{\ell,t})$  captures how the productivity of industry  $i$  varies in response to instantaneous temperature changes. This economic model assumes that productivity effects are additively separable across different sectors

4 - This assumption imposes certain limitations. For example, research shows that the way energy demand in productive sectors reacts to temperature depends on a combination of: (i) individuals' sensitivity to weather-related energy use (human factors); (ii) the scale of anticipated climate changes (climatic factors); and (iii) characteristics of buildings and indoor adaptation technologies (infrastructure factors) (Romitti and Sue Wing, 2022).

5 - It is worth mentioning that empirical evidence suggests labor does not shift between industries in response to temperature changes (Graff Zivin and Neidell, 2014).



and geographic areas, considering firms as independent, atomistic agents. Nonetheless, major climatic shifts are expected to generate systemic effects that go beyond the responses of individual firms to localised climate variations. Such systemic impacts stem from extensive spillover effects between firms and from complex price adjustments that arise when climate-related events are correlated over time or space. For example, climate-induced disruptions in a firm's supply chain can amplify economic impacts well beyond the firm's direct exposure. When these effects are significant and cross-border, the empirical strategy used here – which evaluates impacts at the country level independently – may fail to fully capture the wider economic consequences of broad climatic changes. Aggregate output, such as GDP, is calculated by summing production over all industries  $i$  and integrating across all geographic locations within a country and throughout the observed time period. Consequently, the total output in country  $L$  for year  $\tau$  is given by:

$$Y_{\mathcal{L},\tau} = \sum_i Y_{i,\mathcal{L},\tau} = \sum_i \int_{t \in \tau} \int_{\ell \in \mathcal{L}} f_i(T_{\ell,t}) \cdot U_{i,\ell,t} \cdot d\ell \cdot dt \quad (3)$$

The spatial and temporal allocation of production units  $U_{i,\ell,t}$  along with the geographical distribution of atmospheric temperatures, jointly determine the specific temperatures  $T_{\ell,t}$  to which each unit is exposed. Within a given country  $L$  and year  $\tau$ , it is possible to aggregate the instances when individual productive units experience local temperatures  $T_{i,\ell,t}$ , thereby forming a marginal distribution function that characterises temperature exposure for industry  $i$ . It is important to clarify that this marginal distribution function<sup>6</sup> is denoted by  $g_i(\cdot)$ , which has a mean of zero and can be shifted by a location parameter  $T_{L,\tau}$  representing the average temperature in country  $L$  during period  $\tau$ . Thus,  $g_i(T - T_{L,\tau})$  can be interpreted as a histogram reflecting the temperature distribution experienced by the units  $U_i$  over a broad spatial and temporal scale. We assume that, unlike the country-year average temperature parameter  $T_{L,\tau}$ , the shape of  $g_i(\cdot)$  remains consistent across different countries and years<sup>7</sup>.

This assumption endows  $g_i(\cdot)$  with two key properties:

- Firstly, for any given industry, the total measure or 'mass' of productive units, denoted  $M_i$ , corresponds to the integral of  $g_i(\cdot)$  over all temperature values, including those found in historical temperature distributions:

$$M_i = \int_{-\infty}^{\infty} g_i(T - \bar{T}_{\mathcal{L},\tau}) dT = \int_{t \in \tau} \int_{\ell \in \mathcal{L}} U_{i,\ell,t} d\ell dt \quad (4)$$

- Second, the shape of  $g_i(\cdot)$  reflects the distribution of productive units across space and time such that for  $x \in (-\infty, \infty)$ :

$$\int_{-\infty}^x g_i(T - \bar{T}_{\mathcal{L},\tau}) dT = \int_{t \in \tau} \int_{\ell \in \mathcal{L}} U_{i,\ell,t} 1[T_{\ell,t} < x] d\ell dt \quad (5)$$

We can therefore write the total production at the aggregate level in terms of average temperature  $T_{L,\tau}$  expressed at the aggregate level, and  $g_i(\cdot)$ :

$$Y(\bar{T}_{\mathcal{L},\tau}) = \sum_i Y_i(\bar{T}_{\mathcal{L},\tau}) = \sum_i \int_{t \in \tau} \int_{\ell \in \mathcal{L}} f_i(T_{\ell,t}) U_{i,\ell,t} d\ell dt \quad (6)$$

$$= \sum_i \int_{t \in \tau} \int_{\ell \in \mathcal{L}} f_i(T) g_i(T - \bar{T}_{\mathcal{L},\tau}) \cdot dT \quad (7)$$

One no longer needs to track the full spatial and temporal profile of  $U_{i,\ell,t}$ . This is because, provided that the functional form  $g_i(\cdot)$  remains fairly consistent across years  $\tau$ , the annual average temperature  $T_{L,\tau}$  becomes an adequate summary measure of temperature exposure at the aggregate level. Variations in  $T_{L,\tau}$  effectively shift the underlying distribution of temperature experienced by individual units. Burke et al. (2015) showed that

6 - Burke et al (2015) emphasise that this is not a probability distribution since the count of units at each temperature is not normalised by the total units. Instead, it resembles a frequency histogram rather than a probability histogram.

7 - In reality, the shape of  $g_i(\cdot)$  might vary as the distribution of temperatures that production units encounter changes within countries and years.

this allows for a re-parameterisation in which the complex joint distribution of temperatures and micro-level units is reduced to two elements: the shape of  $g_i(\cdot)$  and the scalar  $T_{L, \tau}$  representing the country-level average temperature – our primary regressor of interest in the econometric framework formalised below in §4. To recap, suppose each function  $f_i(T)$  represents the output contribution of a micro-level productive unit – such as a firm in industry  $i$  – as a function of instantaneous temperature  $T$ . Within a given country, time period, and sector, let  $m_{i1}$  and  $m_{i2}$  capture the proportions of total unit-hours exposed to temperatures below and above a critical threshold, respectively. This formulation implies that temperature exposure across unit-hours follows a distribution given by  $g_i(T - \bar{T})$ , which is normalised to have mean  $\bar{T}$ . Given that  $g_i(\cdot)$  is centred at zero and assuming, as is common in the economic literature, that marginal productivity shocks at the unit-hour level do not propagate significantly across units, the total output  $Y$  can be expressed as the aggregate of industry-level outputs – each obtained by integrating across the full distribution of unit-hours during the specified period and location:

$$Y(\bar{T}) = \sum_i Y_i(\bar{T}) = \sum_i \int_{-\infty}^{+\infty} f_i(T) \cdot g_i(T - \bar{T}) dT \quad (8)$$

When the average temperature  $\bar{T}$  increases, the entire region becomes warmer on average, leading to a rise in  $m_{i2}$  – the share of unit-hours exceeding the critical temperature threshold – for all productive entities situated within the country's borders. This shift results in mounting productivity losses, reflected in a progressive decline in aggregate output  $Y(\bar{T})$ . Equation (8) implies that  $Y(\bar{T})$  evolves smoothly and concavely, with its rate of change determined by the weighted average of the marginal effects of  $f_i(T)$  across industries and temperature levels. The function  $Y(\bar{T})$  reaches its maximum at a temperature below the critical point in  $f_i(T)$  if and only if the productivity losses incurred above the threshold outweigh the gains below it – that is, if the upper slope is more negative than the lower slope is positive, consistent with micro-level findings (Schlenker and Roberts, 2009). These results raise questions about the validity of simply extrapolating nonlinear micro-level temperature responses to the macroeconomic scale (Hsiang, 2010; Heal and Park, 2013). More importantly, while immediate losses in productivity due to temperature variations are expected, their consequences may extend well beyond short-term output fluctuations. For example, temporary downturns in productivity can depress investment in capital formation, potentially altering the long-run growth path of the economy (Dell et al., 2012; Hsiang and Jina, 2014).

Following the approach of Burke et al. (2015), we empirically evaluate the model's predictions using a panel dataset that combines subnational economic output with historical meteorological observations from 1970 to 2018. Building on the national-level econometric framework of Burke et al. (2015), we develop a spatially disaggregated variant that operates at the level of administrative regions – thus aligning our spatial granularity more closely with that of studies such as Kotz et al. (2024).

In an ideal experimental design, the optimal setup would consist of two identical economic regions, one exposed to an exogenous temperature increase and the other left unaffected – allowing for a direct comparison of economic outcomes. Since such a counterfactual is unobservable in reality, researchers approximate it by using temporal variability within the same region, contrasting years with anomalously high temperatures against those with unusually low ones, as driven by stochastic atmospheric fluctuations (Willmott and Matsuura, 2012). In this framework, cooler years serve as a 'control' and warmer years as the 'treatment' (Burke et al., 2015). This within-region, over-time comparison avoids the confounding influences inherent in conventional cross-country or cross-region analyses, which infer temperature effects from economic differences across nations (Nordhaus, 2006).



## 4. Method: Estimating Climate-GRP Functions

### 4.1 Historical Climate and Economic Data

We start our analysis by bringing 50 years of historical economic and climate information together.

**Historical gross regional GDP records.** We take data relating to the gross regional product per capita of various administrative areas from the MCC-PIK Database of Subnational Economic Output (DOSE)<sup>8</sup> (Wenz et al., 2023). Its most recent version provides harmonised data on reported economic outputs from 1,661 subnational regions across 83 countries, with varying temporal coverage from 1960 to 2019. From this, we use a subset: 1970–2018. Sub-national units constitute the first administrative division below national. Recent work has used interpolation and downscaling to yield estimates of sub-national economic output, but reliable data based on official, reported values are lacking. Wenz et al. (2023) instead assembled values from numerous statistical agencies and yearbooks prior to apply harmonisation methods free of linear interpolations for both aggregate and sectoral output. Resulting records have been shown to be temporally and spatially consistent in regional boundaries, enabling coherent matches with geo-spatial climate fields. Following the general literature (Gennaioli and La Porta, 2014; Kalkuhl and Wenz, 2020; Kotz et al., 2021, 2022) and most particularly Kotz et al. (2024), we focus on real subnational output per capita and convert values from local currencies to US dollars to account for diverging national inflationary tendencies and then account for US inflation using a US deflator. Conversions between currencies are conducted using exchange rates from the FRED database of the Federal Reserve Bank of St Louis<sup>9</sup> and the national deflators from the World Bank<sup>10</sup>.

**Historical weather exposures.** The climate exposures of administrative regions are calculated based on 3h 0.25 degree<sup>11</sup> gridded surface temperature and precipitation fields from NASA's Global Land Data Assimilation System<sup>12</sup> (GLDAS – Rodell et al., 2004). GLDAS is a new-generation global high-resolution reanalysis data product developed jointly by NASA, Goddard Space Flight Center (GSFC) and National Centers for Environmental Prediction (NCEP) (Ji et al., 2015). GLDAS incorporates satellite and ground-based observations, producing long and consistent quality-controlled global gridded time series of optimal fields of land surface states and fluxes in near real time. These data also make available other meteorological variables that are not commonly available in other reanalysis data products either as consistent long time series, or at a high-spatial resolution<sup>13</sup>. GLDAS 27 km × 27 km gridded fields are then collapsed into daily meteorological records over the 1970–2018 period, and matched to the spatial and temporal resolution of our GDP realisations using the two-stage method described below:

First, we spatially aggregate the 27 km × 27 km grid-cell-level<sup>14</sup> ( $x$ ) weather exposure estimates to the administrative level ( $i$ ) of GRP records (i.e., level 1 provinces, level 0 being countries) by day ( $d$ ), using the population-weighting method<sup>15</sup> presented below.

We use our network of NASA's GLDAS 27 km × 27 km grid cell coordinates to compute time-invariant weights ( $w$ ) from highly-resolved population density estimates ( $D_{x,w}$ ) taken from downscaled time-invariant 2015 information from the Gridded Population of the World raster dataset<sup>16</sup> (updated version) (CIESIN, 2004). We link each province ( $i$ ) of the dataset with all NASA's GLDAS centroids ( $x$ ) that fall within its boundaries. The population density-weighted daily ( $d$ ) average weather by region ( $i$ ), say for the temperature component ( $T_{i,d}$ ),

8 - Available at: <https://zenodo.org/records/7659600>

9 - Available at: [https://fred.stlouisfed.org/series/AEXUSEU\(2022\)](https://fred.stlouisfed.org/series/AEXUSEU(2022))

10 - Available at: <https://data.worldbank.org/indicator>

11 - Equivalent to ~ 27 km × 27 km grid cells at the equator.

12 - Available at: <https://ldas.gsfc.nasa.gov/gldas>

13 - Other reanalysis data products available have either (i) a coarser spatial resolution (e.g. ECMWF-ERA40 and JRA-55, both available from the mid-1950s but at 1.125 deg.) or (ii) a shorter time series (e.g. newly released ECMWF-ERA5 at 0.281 deg. from 1979–present day and NCEP-CFSv2 at 0.205 deg. from 2011–present day).

14 - Latitude ( $Y$ ) and longitude ( $X$ ) values are concatenated ( $Y\_X$ ) to generate a grid-cell string variable uniquely identifying each 0.25 deg. resolved location of weather records; denoted  $x$  hereafter.

15 - We alternatively test the unweighted approach to straightforwardly aggregate NASA's GLDAS grid-cell-level information to the spatial resolution of our GDP records. Estimated responses, available upon request, exhibit slightly weaker statistical power and are less reliable as they do not account for the heterogeneously distributed populations within countries.

16 - Available at: <https://sedac.ciesin.columbia.edu/data/collection/gpw-v4>

is computed from grid-cell-level ( $T_{x,d}$ ) daily climate values matched with locationally-specific population density information:

$$T(i, d) = \frac{\sum_w D_{x,w} \cdot T_{x,d}}{\sum_w D_{x,w}} \quad (9)$$

Second, resulting daily ( $d$ ) weather records matching each region-day are collapsed to the yearly frequency of our GDP observations  $t$ . We thus compute annual measures of heat and moisture exposures – i.e., average temperature values ( $T_{i,t}$  in deg.°C) and cumulative precipitation (in mm/year). These are matched to each region-year output observation. Our raw estimation dataset contains 166 countries  $\times$  year (~9,000 obs.) and 1,661 administrative region  $\times$  year (~82,000 obs.), again spanning the last 50 years (1970–2018).

## 4.2 Econometric Modeling of Climate-GRP Responses

We first econometrically model the responses of per capita gross regional product (GRP) to weather (temperature, precipitation) using a 49-year longitudinal sample of 1,661 sub-national administrative regions level I covering the last 50 years (1970–2018). We use a panel fixed effects (FEs) OLS model<sup>17</sup>, similar to specifications commonly used in the climate economics literature (Schlenker and Roberts, 2009; Burke et al., 2015; Kotz et al., 2024).

Let indices  $r$ , and  $t$  denote sub-national regions and years. Historical data provides annual observations of first-differenced natural logarithm of per capita GRP ( $\Delta Y$ -per-period growth rates in income). We deconvolve the factors that might affect these changes via polynomial functions of temperature and cumulative precipitations ( $P$ ). We estimate the benchmark empirical model:

$$\Delta y_{r,t} = \Delta \ln Y_{r,t} = \mu_r + \nu_t + f[t; \Theta_{z(r)}] + f_T(T_{r,t}) + \lambda_1 P_{r,t} + \lambda_2 P_{r,t}^2 + \epsilon_{r,t} \quad (10)$$

where  $\mu_r$  are region-specific constant terms (fixed effects) that capture unobserved idiosyncratic spatially-varying time-invariant influences (e.g., history, culture or topography). Given the long timespan of our dataset, attributing year-to-year exogenous variations in per capita GRP to weather typically allows the use of low frequency controls such as year fixed effects  $\nu_t$  because they account for abrupt global events (such as shocks to energy markets or global recessions) without over-capturing cyclical temperature fluctuations. In addition to year dummies, gradual changes to individual regions' growth rate, which may be driven by slowly changing factors within an administrative province (e.g, demographic shifts, evolving political institutions etc.), are accounted for via flexible time trends (Dell et al., 2012). Formalised  $f[t; \Theta_{z(r)}]$ , this region-specific<sup>18</sup> time-dependent function aims to capture the unobserved region- and time-varying dynamics that influence per-capita GRP and which are correlated with climate. To do so, we use the Database of Global Administrative Areas (GADM)<sup>19</sup> and spatially intersected grid-cell coordinates with the different sub-national administrative region identifiers in which they fall. Output is GID(0), GID(1) and GID(2) for countries, provinces, and counties/district, respectively. Finally,  $\epsilon$  is a random disturbance term that captures variations in per capita GRP orthogonal to time and spatially varying local climate conditions.

In line with recent micro-level evidence, we explicitly model the temperature impact on output growth in changes rather than levels because of the high degree of serial correlation in GRP data within countries ( $\rho = 0.999$ ), which renders these series nearly perfectly collinear with random walks (i.e., they exhibit unit roots). This characteristic can lead to spurious regression estimates and invalid test statistics (Granger and Newbold, 1974; Angrist and Pischke, 2009; Hsiang et al., 2013). Transforming income values using first differences, and controlling for year fixed effects, as well as country-specific quadratic growth trends, substantially reduces serial correlation in the outcome variable ( $\rho = 0.125$ ). However, since some serial correlation remains even after first

17 - A fixed effects panel model controls for unobserved time-invariant heterogeneity by allowing entity-specific intercepts, isolating the impact of time-varying regressors. For more exhaustive information, see Pretis (2021).

18 - Starting at unity ( $z(r) = 1$  for provinces), zones' size may extend to countries, as well as economic, trade or geographic clusters of countries likely to share that of a common trend.

19 - Available at: <https://gadm.org/data.html>

differencing, we account for this by clustering standard errors at the region level. This adjustment addresses spatial correlation and residual non-independence, following Cameron et al. (2011), and allows for arbitrary autocorrelation patterns within regions. In this framework, each administrative region is allowed to have its own intercept and non-linear growth trend, enabling the effect of temperature on growth to be identified from within-region deviations relative to this trend. Prior research has shown that controlling for income trends and convergence using location-specific trends offers more robust results than relying on autoregressive models (Barro, 2003; Hsiang and Jina, 2014).

Estimated parameters of interest are per-capita GRP growth impacts of the potentially non-linear effects of heat (captured by the function  $f_T(T_{i,t})$ ), and precipitation ( $\lambda$ ). Since idiosyncratic changes in local annual temperatures are often correlated with variations in precipitation (Auffhammer et al., 2013), we jointly estimate the effects of these weather components. Both historical and future economic impacts are likely to be the largest at the temperate extremes. We account for this convexity by estimating non-linear quadratic temperature components  $f_T(T_{r,t}) = \Phi_1 T_{r,t} + \Phi_2 T_{r,t}^2$ , where  $T_{r,t}$  are daily temperature averaged by region-year; allowing for marginal effects of a given amount of warming to vary locationally. More flexible functional forms have also been explored and are summarised in §4.3.

#### 4.3 Uncertainty Handling

We account for empirical uncertainty by varying the functional form both of the temperature component and of the specification of the fixed effects<sup>20</sup>.

**Functional Form of the temperature component.** Given the considerable uncertainty surrounding the shape of the temperature-GDP response function, we test more flexible functional forms specifying its potential impact on output. This includes:

- i. setting higher polynomial orders (cubic, quartic) in a parametric FE-OLS framework;
- ii. regressing restricted cubic splines with varying semi-parametric knots (2-7) capturing N-shaped relations;
- iii. estimating non-parametric smoothed splines estimated via a generalised additive model (Wood, 2004)

with location and time fixed effects. The choice of a non-parametric model would result from a preference to allow the data, rather than parametric assumptions, to determine the shape of the temperature-per capita GRP relationship.

$$\mathbb{E} [\ln Y_{r,t(r)}] = \Psi^T [T_{r,t(r)}; \theta^T] + \mu_r + \nu_t + f[t; \Theta_{z(r)}] \quad (11)$$

where  $\hat{\Psi} = \Psi[\cdot; \hat{\theta}]$  are the fitted temperature splines integrable with average temperature, historically observed and future shifted, over epoch-specific simulations of climate change.

**Functional Form of the FEs.** Other omitted variables influencing both trends in temperature and economic output may affect the results. Starting from a simple FE structure of region-specific linear time trends (i.e.,  $f[t; \Theta_{z(r)}] = \Theta_{r,1}t$ ), we test how the log of per-capita GRP responses vary with:

- i. increasing Chebychev polynomial orders from quadratic to octic (8th) ( $f[t; \Theta_{z(r)}] = \sum_{j=2}^8 \Theta_{z(r),j} t^j$ ) and
- ii. variation in the spatial clustering of the flexible trend function ( $z(r)$ —from administrative areas level 1 to countries, and extending towards multi-regional or national clusters of economic or geographic areas likely to share that of a common trend).

We started off using Burke et al. (2015)'s preferred specification (quadratic country-specific time trends) and set an equivalent quadratic region-specific time trends version ( $\Theta_{r,1}t + \Theta_{r,2}t^2$ ). This approach is motivated by the need to flexibly capture non-linear dynamics in regional growth rates over time. Since the dependent variable

20 - Associated results, however, are not provided in this document but available upon request.

is the derivative of income, each region is allowed its own level and non-linear trend in growth, and the impact of exogenous changes in temperature and precipitation on growth is identified from within-region deviations from this trend (McIntosh and Schlenker, 2006).

## 5. Method: NEX-GDDP-CMIP6 Transformation and Elaboration of the *Delta* Projection Framework

This Section summarises how we elaborated the *Delta* projection framework from applying transformation to climate simulation data.

### 5.1 NEX-GDDP-CMIP6 Processing

The NEX-GDDP-CMIP6 simulations serve as essential inputs to our analysis. Below we detail the transformations we apply.

***Simulations of shifts in temperature exposure driven by climate change.*** Large-scale processing of high-resolution time- and spatially-downscaled climate projections from NASA Earth Exchange Global Daily Downscaled Projections<sup>21</sup> (NEX-GDDP CMIP6). NEX-GDDP CMIP6 is an ensemble of 32 GCMs. These are simulated under the Coupled Model Intercomparison, Phase VI (CMIP6 – Eyring et al., 2016) exercise. Their outputs are biased-corrected and daily downscaled to a 0.25 deg. grid. Climate projections are then truncated to the geographic extents of sub-national provinces from the Global Administrative Database following the same population density-weighting methods as for historical data in Section §4. After this processing, they are used to calculate the weather variables for historical and future (2030, 2040, mid-century etc.) epochs, each according to a climate scenario. The resulting series of GCM-simulated values of each variable are averaged over the 20 years straddling each mid-point (2031-2050 for 2040 etc.). After taking the inter-epoch difference between historical and future means, this gives us an ensemble of 'Deltas' values for each weather factor specific to scenarios, GCMs and epochs.

Since estimates of the economic effects of climate change are GCM-sensitive, we simulate median impacts from a wider set of GCMs. Other sources of uncertainty come from downscaling and from bias-correction which can potentially alter local climate projections in CMIP6 (Lafferty et al., 2023). A final concern is that a subset of CMIP6 GCMs may be "too hot", because their representation of cloud feedbacks give rise to higher-than-consensus ECS or TCR estimates.<sup>22</sup>(Sherwood et al., 2020; Tokarska et al., 2020; Zelinka et al., 2020). To mitigate bias, we follow Hausfather et al's (2022) recommended procedure of excluding models with TCR and ECS outside "likely" ranges (1.4–2.2°C, 66% likelihood, and 2.5–4°C, 90% likelihood, respectively). This leaves us with an ensemble of 'Delta' values simulated from 15 "likely" GCMs – the full list is provided in Table 1 below – that we feed into our preferred GRP model (econometrically calibrated using real historical data spanning the last 50 years in Section §4 as part of our projection exercise).

Table 1: Classification of GCMs to correct Hausfather et al (2022)'s hot model problem

GCM	ID	Model Classification
ACCESS-ESM1-5	1	likely
BCC-CSM2-MR	2	likely
CESM2	3	not likely
CESM2-WACCM	4	not likely
CMCC-CM2-SR5	5	likely
CMCC-ESM2	6	likely

21 - NEX-GDDP CMIP6 is available at: <https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6>

22 - The equilibrium climate sensitivity (ECS) is the global temperature increase after an instantaneous doubling of the CO<sub>2</sub> concentration; the TCR (Transient Climate Response) is the global warming after 70 years of a 1% per annum increase in CO<sub>2</sub>.

CNRM-CM6-1	7	not likely
CNRM-ESM2-1	8	not likely
CanESM5	9	not likely
EC-Earth3	10	none
EC-Earth3-Veg-LR	11	not likely
FGOALS-g3	12	likely
GFDL-CM4	13	likely
GFDL-ESM4	14	likely
HadGEM3-GC31-LL	15	not likely
IITM-ESM	15	not likely
INM-CM4-8	16	likely
INM-CM5-0	17	none
IPSL-CM6A-LR	18	likely
KACE-1-0-G	19	none
KIOST-ESM	20	none
MIROC6	21	likely
MIROC-ES2L	22	likely
MPI-ESM1-2-HR	23	likely
MPI-ESM1-2-LR	24	likely
MRI-ESM2-0	25	likely
NorESM2-LM	26	likely
NorESM2-MM	27	none
TaiESM1	28	none
UKESM1-0-LL	29	not likely

Note: This model classification is based on Hausfather et al's (2022) recommended procedure of excluding models with TCR and ECS outside "likely" ranges (1.4–2.2°C, 66% likelihood, and 2.5–4°C, 90% likelihood, respectively). That leaves us with 15 "likely" GCMs that form the basis of our macroeconomic impact modelling and which accounts for the 'hot models' identified in the last generation of climate model simulations in CMIP6. For a more exhaustive review of this problem, see Hausfather et al (2022).

Source: Our elaboration at EDHEC Climate Institute.

## 5.2 A Simple Damage Projection Framework: the *Delta* Method

Our fitted regional GDP model in Equation 10 facilitates projection of long-run GRP per capita changes associated with climate change-driven shifts in the temperature. We provide below a simplified formalisation of our projection framework: the Delta method.

Use  $\mathbf{x} = \{\mathbf{T}\}$  to denote the main weather covariate: temperature. Recall that in Section §5, we computed and concatenated GCM-simulated values of this factor's exposure. We did this for an ensemble of future 20-year averaged values corresponding to the climate epochs' midpoints being analysed (2021–2040, 2031–2050, ..., 2099). Then, following the same temporal parametrisation as for an historical baseline period (1995–2014), we calculated the inter-epoch differences to construct local region-specific shifters ( $\Delta\mathbf{x}$ ). Finally, we added these offsets to the 1995–2014 historical mean of the same sub-national predictors ( $\mathbf{x}$ ) to construct projected future climate values:  $\mathbf{x} = \mathbf{x} + \Delta\mathbf{x}$ . The latter are combined with our fitted econometric model estimated in Section §4 to project GRP per capita changes induced by these region- and epoch-specific climate shifters.

For communication purpose, we reduce the temperature functional form  $f_T(T_{r,t})$  from §4.2 to one simple semi-elasticity<sup>23</sup> ( $\beta^T$ ) of a linear temperature variable – instead of the actual polynomial function characterising  $f_T(T_{r,t})$ . A simple projection framework for region  $r$  in future epoch  $t^*$  can be formulated as:

$$\tilde{y}_{r,t^*} = \hat{\mu}_{i,r} + \hat{\nu}_{t^*} + f[t^*; \hat{\theta}_{z(r)}] + \hat{\beta}^T \tilde{\mathbf{T}}_{r,t^*} \quad (12)$$

23 – Basically, a semi-elasticity measures the percentage change in a dependent variable in response to a one-unit absolute change in an independent variable – e.g., if  $y$  and  $x$  denote dependent and independent variables (respectively), the semi-elasticity of  $y$  with respect to  $x$  is  $\ln y \frac{dny}{dx}$ .

and for our historical benchmark period  $t^0$ :

$$y_{r,t^0}^0 = \hat{\mu}_{i,r} + \hat{\nu}_{t^0} + f[t^0; \hat{\theta}_{z(r)}] + \hat{\beta}^T \bar{T}_{r,t^0} \quad (13)$$

Facilitating computation of our primary impact metric: the projected fractional change (%) in GRP per capita as the inter-epoch difference ( $y_{r,t^*} - y_{r,t^0}$ ) in outputs; such that the sub-national region  $\times$  weather factor  $\times$  epoch combination of climate shift-induced % change in regional GRP per capita can be computed as:

$$\Psi_{r,t^*} = \hat{\beta}^T [\tilde{T}_{r,t^*} - \bar{T}_{r,t^0}] \quad (14)$$

Where  $T_{r,t^*} = T_{r,t^0} + \Delta T_{r,t^*}$ . This leaves us with an ensemble of region-specific simulations  $\Psi_{r,t^*}$  that we distribute across the following vectors:

- (i) 15 'likely' GCMs;
- (ii) moderate (2-4.5) or vigorous (5-8.5) SSP-RCP warming scenarios; and
- (iii) future epochs (2030, 2040, ..., 2100).

The burgeoning availability of SSP-RCP-specific GCM simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6) presents a unique opportunity to incorporate the most advanced time- and spatially-downscaled warming projections into our geo-economic modelling. Within a given country, we assume regions to be heterogeneously exposed to climate deltas, leading to equally heterogeneous economic impacts. §4 describes the spatial coverage of administrative province-level gross regional product time-series data in the raw DOSE product. It is to be noted that spatial gaps in sub-national output for some African and Middle Eastern countries remain, leaving an incomplete geographic coverage globally<sup>24</sup>. This is an obstacle that Kotz et al. (2024) faced. To project climate-driven economic damages in administrative regions lacking DOSE data, we apply a two-step approach:

- First, by spatially intersecting the missing administrative regions with their respective ensembles of GCM-simulated localised Deltas derived from outputs of the NEX-GDDP CMIP6 processing in Section §5.
- Second, by combining these with our globally estimated non-linear semi-elasticities deemed theoretically suitable to capture the sign and shape of the general temperature-output relationship from all countries.

We thus obtain a synthetic 'enhanced' vectorised projection matrix linking predicted per capita GDP impacts to each administrative province. This approach has the advantage of offering consistent coverage across all 3,672 sub-national regions globally, while providing empirically valid damage estimates.

## 6. Distribution and Interpretation of Macroeconomic Damages

This section presents and decomposes the projected damage estimates on regional economic production. *These are the precise outputs shown on the EDHEC-CLIRMAP tool map accessible here:*

<https://climateinstitute.edhec.edu/data-visualizations#edhec-clirmap>.

In this exercise, shifts in temperature exposure from both high- and moderate-warming scenarios (SSP5-RCP8.5 and SSP2-RCP4.5, respectively) are considered. Although they differ in terms of economic trajectories and climate stringency forecasts, both sets of climate models predict vigorous warming to cause substantially more extreme high temperature circa-2050.

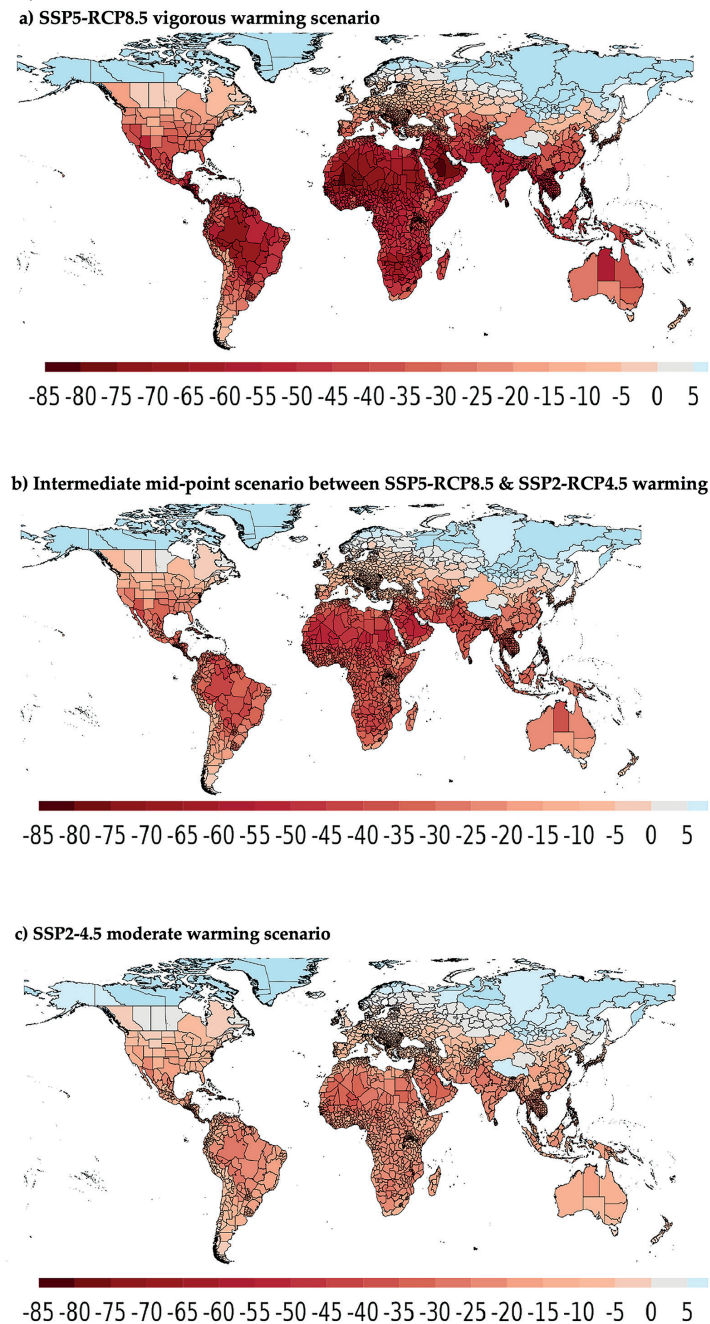
The EDHEC-CLIRMAP web module could but does not provide a graphical summary of model responses in the form of globally aggregated percentage damages. The reason is that global averages are less reliable for

24 - Among its limitations, the global DOSE dataset of reported sub-national economic output exhibits both temporal and spatial inconsistencies, with coverage restricted to 83 countries. A key characteristic of DOSE is its strict reliance on officially reported macroeconomic data from diverse national statistical offices and yearbooks, as Wenz et al (2023) deliberately excluded interpolation methods to address data gaps. While this approach ensures fidelity to observed values, it also results in discontinuous time series, particularly in under-reported provinces. Moreover, challenges related to administrative boundary consistency persist due to historical changes, which can lead to spatial mismatches when integrating with geospatial climate data, as discussed in §5.



investors seeking regional solutions. Estimates of global damages have granular origins that EDHEC-CLIRMAP chooses to exploit. We look more holistically at the spatial, temporal, climate model, and scenario distribution of projected GRP changes. Ultimately, delivering information on subnational economic damages predicted over time is both the explicit aim and the competitive edge of the EDHEC-CLIRMAP tool. Next, we detail how-to-interpret examples of outputs shown in Panels a, b, and c of Figures 1 and 2.

Figure 1: Projected climate-change impacts



Notes: Projected climate-change impacts (%) on per capita gross regional product from shift in average temperature alone, 2099 epoch relative to constant historical 1985-2004 temperature means, multi-model medians of 15 'likely' CMIP6 GCMs.

Note that the intermediate scenario is computed directly at the source as the midpoint average between the SSP5-8.5 and SSP2-4.5 future temperature trajectories. Source: our elaboration at EDHEC Climate Institute.

To project future physical risk-driven GRP per capita changes, we combine outputs from §4 [=temperature-GRP per capita response functions, our ensemble of semi-elasticities] with those from §5 [=region-specific simulations of climate 'Deltas', our local quantity 'shifters'].

Panel a of Figure 1 shows the spatial distribution of the multi-model median impacts at future epoch 2099, from our ensemble of 15 "likely" SSP5-RCP8.5 GCM realisations. Impacts, or induced changes (%), are expressed relative to a baseline period – here, constant historical 1985–2004 temperature means – which is equivalent to projecting the current economic system into a warmer future simulated by GCMs × climate scenarios. From shift in average temperature alone, province-level end-century median per capita GRP declines are recorded for most countries despite striking heterogeneous magnitudes spanning the 5–85% range. Interspersed with isolated regions of negligible losses (0–5%), the largest damages are concentrated in areas overlapping the tropics or near the equator – particularly central Africa, America and Asia.

Across most countries, there is strong empirical agreement that climate change leads to net declines in per capita GRP, with the magnitude of these losses increasing as the absolute latitude of a country's centroid decreases. This geographic pattern is consistent with previous findings from the agricultural sector, where the impacts of climate change on crop yields have been shown to align with agroclimatic zones (Sue Wing et al., 2021). A small number of regions display modest net increases in per capita GRP, which can be attributed to two key factors:

i. exposure to relatively low baseline average temperatures – placing these regions on the ascending (left-hand) side of the empirically estimated inverted U-shaped response function corroborating Burke et al. (2015)'s non-linear estimates<sup>25</sup> in sign and magnitude – and

ii. comparatively smaller projected temperature changes ( $\Delta$ ) in higher-latitude areas under CMIP6 scenarios.

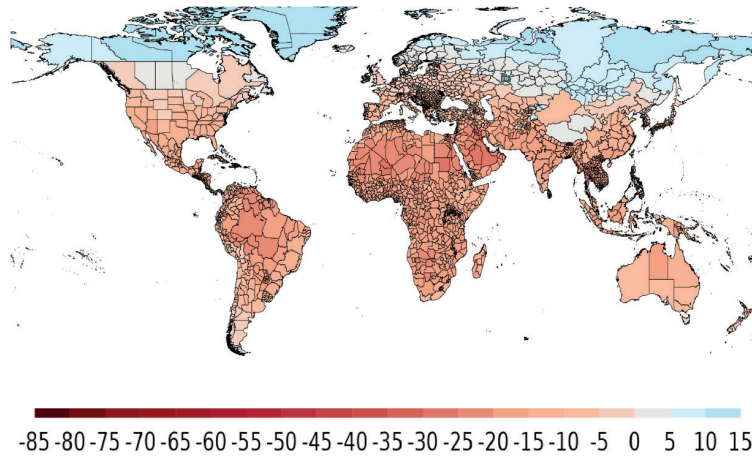
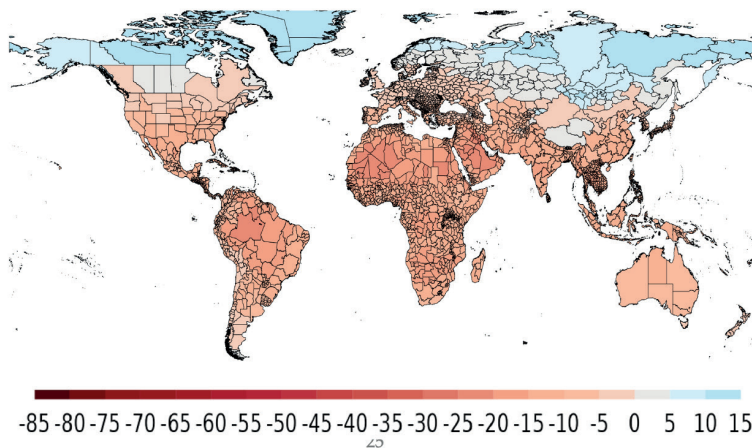
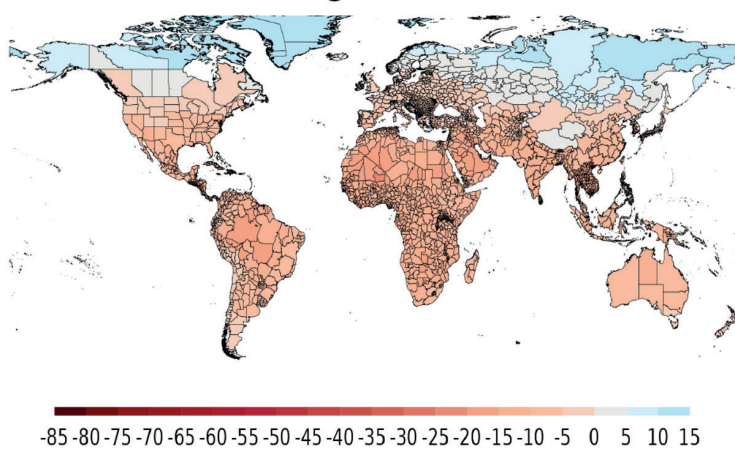
In an SSP2-RCP4.5 scenario, projected temperature changes are relatively moderate. Panels b and c of Figure 1, corresponding respectively to an intermediate warming case between SSP5-RCP8.5 and SSP2-RCP4.5, and a moderate warming realisation under SSP2-RCP4.5, display spatial patterns of projected per capita GRP damages that are consistent with higher-emissions scenarios, albeit at reduced intensity. Similarly, damages projected for the mid-century period (2041–2060), as shown in Figure 2, exhibit comparable spatial patterns to end-of-century projections, though with reduced magnitude, reflecting the lower cumulative warming implied by the temporally shorter *treatment effect*<sup>26</sup>.

Both studies account for heterogeneous intra-country population allocation and spatially aggregate grid-cell-level weather exposure by province/country via a weighted collapsing method incorporating time-invariant sub-national population density statistics from the Gridded Population of the World dataset (2015 Version) (CIESIN, 2004).

25 – Differences between this study and Burke et al (2015) mainly relate to the elaboration of climate variables. Here, we calculated sub-national provinces' climatic exposures based on 3h 27 km × 27 km gridded surface temperature and precipitation fields from GLDAS (Rodell et al, 2004) collapsed into daily climatic records over 1970–2018, and matched to the period of our gross regional output realisations (see §4 Methods). Burke et al (2015) instead used reconstruction data from the University of Delaware containing 0.5 degree gridded monthly average meteorological fields over 1960–2010.

26 – This typically refers to the causal impact of climate factors on micro-level outcomes, which, when aggregated, produce broader macroeconomic changes. It borrows from causal inference terminology – a specifically the idea of a discrete treatment effect – but instead of a controlled experiment quantifiable via a Difference-in-Differences approach, the "treatment" is the continuous exposure to a changing climate that leaves no location untreated globally (Schlenker and Walker, 2016). In an ideal experimental design, two identical economies – one exposed to an exogenous temperature rise, the other not – would allow direct comparison of outputs; in practice and to overcome the public good problem of climate mentioned above, this is approximated by exploiting year-to-year temperature variation within the same country (Willmott and Matsuura, 2012). Under the macroeconomic framework in §3, cooler years within a country serve as the empirical 'control,' while warmer years represent the 'treatment' (Burke et al, 2015). This temporal, within-country approach avoids cross-national comparisons, which are susceptible to confounding factors, distinguishing it from cross-sectional analyses that infer temperature effects from inter-country economic differences (Nordhaus, 2006).

Figure 2: Projected climate-change impacts

**a) SSP5-RCP8.5 vigorous warming scenario****b) Intermediate mid-point scenario between SSP5-RCP8.5 & SSP2-RCP4.5 warmings****c) SSP2-RCP4.5 moderate warming scenario**

Notes: Projected climate-change impacts (%) on per capita gross regional product from shift in average temperature alone, mid-century 2041-2060 epoch relative to constant historical 1985-2004 temperature means, multi-model medians of 15 'likely' CMIP6 global climate models (GCMs). Note that the intermediate scenario is computed directly at the source as the midpoint average between the SSP5-8.5 and SSP2-4.5 future temperature trajectories.  
Source: our elaboration at EDHEC Climate Institute.

The geographic patterns revealed in Burke et al. (2015) are empirically confirmed for global regions, though per capita GRP losses appear larger when accounting for both economic and climatic intra-country variability. This finer resolution reveals that heterogeneously developed administrative regions are exposed to uneven level of physical climate risks driven by local environmental conditions, consistent with the results of Mahlstein et al. (2013). Notable zones of particularly high projected impacts include southern Europe, the Southwest US, western Mali, northern Nigeria, and parts of tropical Asia.

Finally, the distribution of projected GRP changes across individual GCMs matters. Estimates of the macroeconomic impacts of climate change are climate model-sensitive (Burke and Emerick, 2016), due to inherent structural differences in how these latter simulate temperature responses to CO<sub>2</sub> emission trajectories. This is further emphasised in Hausfather et al. (2022)'s '*hot model problem*' covering CMIP6 ensemble outputs. SSP2-RCP4.5 moderate GCMs finally exhibit similar but more concentrated patterns of model-specific heterogeneity in the prediction of output damages.

Therefore, these findings are consistent with those of Kotz et al. (2024) suggesting that estimating climate damages first regionally, rather than relying on country aggregates, yields significantly higher estimates of global economic losses, leaving a large place for patterns of spatial differences. This stems from greater accuracy in capturing localised climate and economic heterogeneity, as our approach better accounts for small-scale variations in exposure to extreme climate impacts and gross regional economic vulnerability, particularly in densely populated regions with higher exposure of infrastructures and sectors to climate risks and lower adaptive capacity. If aggregated, country-level estimates of climate damages may understate the true economic cost of future climate shocks.

## 7. Caveats and Evolution of EDHEC-CLIRMAP

The EDHEC-CLIRMAP module provides a basis for making more regionally localised projections of climatically-induced economic damages but is not without caveats. We thus discuss potential dimensions to advance further EDHEC-CLIRMAP in the future.

### 7.1 Caveats

Caveats are primarily associated with the competitively higher spatial resolution of global data set of reported sub-national economic output (DOSE) (Wenz et al., 2023) that was derived by assembling values from numerous statistical agencies and yearbooks prior to apply harmonisation methods free of linear interpolations. First, the 'reported' nature of the DOSE project implies that its internal validity is inherently limited by the accuracy of national and regional administrations in displaying their economic output. Despite the increased spatial and temporal coverage of DOSE in comparison to most pre-existing datasets, data gaps in both dimensions remain, and so the use of satellite-derived data products could be a promising avenue for filling out these gaps. *Spatially*, sub-national output data are lacking for a large number of African and Middle-Eastern countries, suggesting a sampling skewed towards relatively wealthier western regions (over-represented), and leaving an incomplete geographic coverage globally. It is an obstacle faced by Kotz et al. (2024); which we addressed in the projection stage following a two-stage method described in §5. *Temporally*, DOSE tends to be unbalanced with the majority of observations taking place over the last three decades of coverage (1990–2020) compared to the earlier decades (1960–1990). A final limitation is that converting sub-national nominal GRP values in local currencies to real GRP data in USD is not straight-forward, partly due to the lack of auxiliary data at the sub-national level (i.e., GDP deflators are generally unavailable at the global scale).

Moreover, historical fields from GLDAS (Rodell et al., 2004) may suffer from limitations associated with the relatively coarse spatial resolution (27 km × 27 km grid) of this dataset which incompletely captures localised hydrological processes. For instance, used land surface models (Noah-LSM, VIC) rely on parametrisation that oversimplify our representation of complex processes, soil properties (e.g., satellite-based soil moisture or snow cover data) and vegetation types, whereas its atmospheric forcing data (e.g., precipitation, temperature, radiation) from reanalysis may propagate measurement errors throughout the system (Viviers et al., 2024). Similar arguments limit the accuracy of NEX-GDDP CMIP6's ensemble of 29 global climate models (GCMs) simulated under the Coupled Model Intercomparison, Phase VI (CMIP6 – Eyring et al., 2016) exercise. Certain feedbacks, such as those involving ice-sheet dynamics or vegetation-atmosphere interactions, are either poorly represented or absent (Zelinka et al., 2020). This explains the 'hot model problem' discussed earlier in §5 of the paper. Other remaining sources of uncertainty propagation are attributable to downscaling and bias-correction which might potentially alter local climate projections in CMIP6 (Lafferty et al., 2023).

## 7.2 Moving Forward

There are several doors for future extensions of this tool.

- First, the EDHEC-CLIRMAP module provides globally distributed projections of climate change-driven economic damages at the level of administrative-region level I (i.e., provinces, 0 being countries). While this marks meaningful progress, much work remains to reach the next level of spatial disaggregation – estimating economic damages at the county level (i.e., administrative-region level II; N~48,000) – despite the potential for such results to offer breakthrough insights for decision-makers and investors seeking region-specific solutions.
  - Second, projected macroeconomic damages offered are derived from a dominant, yet incomplete representation of chronic physical climate risks: *the long stochastic warming process from temperatures following an upward trend*. Although incorporating a broader ensemble of chronic physical risk indicators (e.g., precipitation extremes, wet-day frequency, temperature variability) is feasible with sufficient time investment, recent findings highlight that their overall contributions to both direct and indirect future productivity losses are likely small compared to the overriding driving force of average temperature (Kotz et al., 2024).
  - Last but not least, there is an obvious, most urgent and critical missing piece in this climate-economy puzzle. In major sectors, the technical aspects of production supply need to be quantified in a warming framework. How has the balance of forces played out historically and geographically? What given both supply and demand determinants, the likely geo-sectoral economic implications are circa-2050? This is a milestone left for future, more ambitious work.
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## About EDHEC Climate Institute

### Institutional Context

Operating from campuses in Lille, Nice, Paris, London and Singapore, EDHEC Business School is ranked in the top ten European business schools. With more than 110 nationalities represented in its student body, some 50,000 alumni in 130 countries, and learning partnerships with 290 institutions worldwide, it is truly international.

EDHEC Business School has been recognised for over 20 years for its expertise in finance. Its approach to climate finance is founded on a commitment to equipping finance professionals and decision-makers with the insights, tools, and solutions necessary to navigate the challenges and opportunities presented by climate change. EDHEC has developed a significant research capacity on the financial measurement of climate risk, which relies on the best researchers in climate finance, and brings together experts in climate risks as well as in quantitative analysis.

The DNA of EDHEC's work has also resided, since its origin, in the ability to generate business ventures, by encouraging spin-offs based on the research work of its teams. EDHEC is currently involved in three ventures: Scientific Portfolio, Scientific Infra and Private Assets, and the soon-to-launch Scientific Climate Ratings.

### Mission and Ambitions

The EDHEC Climate Institute (ECI) focuses on helping private and public decision-makers manage climate-related financial risks and make the most of financial tools to support the transition to a low-emission economy that is more resilient to climate change.

It has a long track record as an independent and critical reference centre in helping long-term investors to understand and manage the financial implications of climate change on asset prices and the management of investments and climate action policies.

The institute has also developed an expertise in physical risks, developing proprietary research frameworks and innovative approaches. ECI is also conducting advanced research on climate transition risks, with a focus on supply chain emissions (Scope 3), consumer choices, and emerging technologies.

As part of its mission, ECI collaborates with academic partners, businesses, and financial players to establish targeted research partnerships. This includes making research outputs, publications, and data available in open source to maximise impact and accessibility.

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