Climate shift uncertainty and economic damages

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October 16, 2024

Focusing on global annual averages of climatic variables, as in the standard damage function approach, can bias aggregate and distributional estimates of the economic impacts of climate change. Here we empirically estimate global and regional dose-response functions of GDP growth rates to daily mean temperature levels and combine them with regional climate projections of daily mean temperatures. We disentangle for various shared socio-economic pathways (SSPs) how much of the missing impacts are due to heterogeneous warming versus heterogeneous damage patterns over space and time. Global damages in 2050 are around 25% higher when accounting for the shift in the shape of the entire intra-annual distribution of daily mean temperatures at the regional scale.
JEL: Q54
Keywords: damage functions, climate risk, uncertainty, climate shift, temporal disaggregation, spatial disaggregation, temperature downscaling

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Knowing how future climate damages might be distributed in time and space is a key research frontier and policy issue for climate scientists, economists, and decision-makers. Projections of endogenous climate damages in macroeconomic models [Fernández-Villaverde et al., 2024] typically rely on reduced-form relationships between climate change and the macroeconomy, which are generally based on *annual* climatic statistics—e.g. mean annual temperatures. Furthermore, models are generally aggregated for that climate variable to be *global*—mean annual global temperatures. In these integrated climate-economy models, carbon emissions are a by-product of regional economic activities. A reduced-form climate module then allows to capture how these carbon emissions turn into global annual mean temperature anomaly, from which regional annual mean temperature anomaly can be down-scaled through a simple linear and time-invariant factor ; a process also called pattern scaling. The regional physical impacts are then interacted with dose-response functions estimated on global data to measure the economic impacts of endogenous climate change. These macroeconomic models are either global [Nordhaus, 1994], regional [Nordhaus and Yang, 1996] or gridded, as in the burgeoning spatial integrated assessment modelling (IAM) literature [Desmet and Rossi-Hansberg, 2024], e.g. Krusell and Smith Jr [2022] and Cruz and Rossi-Hansberg [2024].

The underlying assumption behind these approaches is that the shapes of the spatio-temporal distributions of mean temperatures do not matter. First, with regard to the temporal dimension, the intra-annual shape of the distribution of daily mean temperature is assumed to remain constant: temperature increases due to climate change are shape-preserving increases in annual mean. Second, regarding the spatial dimension, an average increase in temperature at global level is assumed to affect the regional annual distribution by a linear and time-invariant down-scaling factor such as the regional transient response to cumulative emissions [Leduc et al., 2016]. The reality of future regional weather changes, however, seems more complex, for two main reasons. First, natural climate variability over time and space, both from external (e.g. solar cycles) and internal factors (e.g. El Niño-La Niña), might distort future temperature distributions beyond the annual mean [Schwarzwald and Lenssen, 2022]. Second and more fundamentally, the process determining the shape of the weather distribution within a given year for a given regional mean temperature might not be stationary, so that time-invariant relations between annual averages and the intra-annual distribution of weather only imperfectly reflect regional-specific shifts in warming patterns. In North-West Europe, for example, hottest summer days are warming twice as fast as mean summer days [García-León et al., 2021, Patterson, 2023]. That opens the question around the 'right' level of spatial and temporal aggregation for projecting future impacts. Aggregation has advantages, as it comes with statistical robustness, clear identification of causal relationships, and tractability in models where anomaly in climate results from endogenous anthropogenic emissions; it also has shortcomings, such as the risk of averaging contradictory effects between regions both in terms of damage and warming patterns.

In parallel to integrated assessment models with endogenous climate change stemming from anthropogenic carbon emissions, some integrated assessment models use exogenous global circulation model projections to infer the costs of climate change with adapting agents, e.g. spatial IAM such as Bilal and Rossi-Hansberg [2023] and Rudik et al. [2022]. In these models, which incorporate credible climate projections, climate change remains exogenous to economic activities. As a result, the estimates from the two bodies of literature, i.e. endogenous and exogenous, evolve in parallel, yet the effects of this divergence on the aggregate and distributional estimates of climate impacts remain unclear. Our paper aims to shed light on this gap. Indeed, our paper tests the impact of two separate (but related) limitations of many existing studies: the effect of separately fitting models by region on the initial dose response function, and the effect of including regional climate change and projections that sample changes in the entire distribution on future projections using those dose response functions. To disentangle these effects, we here follow a two-step approach. First, we switch from annual average temperatures to the complete daily temperature distribution over a year and show how this affects the heterogeneous distribution of warming patterns between regions, compared to a setting where we assume a shape-preserving shift in mean annual temperatures under a synthetic changing climate. Second, we interact these regional-specific shifts in warming patterns with regional-specific damage patterns, in comparison with a setting where we assume homogeneous damage patterns at the global scale. Indeed, when disaggregating to regional levels, economists often use global damage functions, instead of using estimates from regional-specific damage patterns. Meanwhile, it seems intuitive that a hot day in a relatively warm country has a different impact than the same day in a cold country; Heutel et al. [2021] show this to be the case for U.S. counties. Alongside efforts to measure the non-linear effects of temperature on economic activity, for example with temperature bins [Dell et al., 2014, Hsiang, 2016, Auffhammer, 2018], we measure regional dose response functions, to capture some of the regional idiosyncrasies in the climate-society relation. We focus on a physical idiosyncrasy and estimate regional dose-response functions for each aggregate Köppen-Geiger climatic zone: arid, continental, polar, temperate, tropical.

These debates over the spatio-temporal aggregation of climate projections might have important consequences, not only for establishing our best approximation of future damage and reconciling different approaches, but also in quantifying the uncertainty surrounding this best guess. Uncertainties in climate-economic modelling abound [Rising et al., 2022, Kotz et al., 2023]. The quantifiable variance of future projections of climate impacts is affected by scenario uncertainty (differences in Shared Socioeconomic Pathways - SSPs), model uncertainty (differences in Earth System Models - ESM - responses to the SSPs), internal variability (spatiotemporally, due to the chaotic nature of the climate and due to regional differences that may be hidden by regional aggregation), any choices made in post-processing or bias-correcting ESM output (including how finely to apply projected changes in climate distributions from ESMs), in addition to regression uncertainty from the dose-response functions, and differences between observational data products used to fit the dose-response function and act as a baseline to which future ESM output is compared. Historically, many studies use global annual average climate variables to estimate and project climate damages, thereby ignoring an important source of internal variability stemming from regional differences in climate states and from only extracting mean changes from ESM projections. Among all uncertainties, we focus on two uncertainties and their interaction: the sensitivity of economic impact projections to an improved sampling of internal variability (through capturing regional differences in impacts) and an improved treatment of ESM output (by capturing changes in the full shape of the temperature distribution instead of annual averages). We take part in uncovering some of the model uncertainties between ESM using the whole shape of warming patterns that is usually reduced by the aggregation procedure on a global and annual scale. We provide a framework based on temperature distributions that can be applied to other climate data, for instance precipitation or maximum temperatures, and a quantification to show how much the regional-specific shift in the shape of warming patterns interacting with regional-specific damage patterns matter empirically, both at the aggregate level and in the distribution of impacts, with the year 2050 as a case study.

Our work yields two main conclusions. First, switching from annual global mean temperature to the regional annual distribution of daily mean temperatures affects the magnitude of the estimates of economic damages: in 2050, using regional damage patterns interacted with the shift in the whole shape of the distribution of daily temperatures yields climate damage at the global scale that are around 25% larger than the damage obtained under the assumption of homogeneous damage patterns over the world and a shape-preserving shift in annual mean daily temperature. Standard aggregation comes with underestimation of future climate damages. This result holds for a variety of more or less carbointensive SSPs: SSP1-2.6, SSP3-7.0 and SSP5-8.5. Second, we show that the distributional effect is not clear-cut. Uncertainty in the change in the shape of the temperature distributions affects all regions of the world in a heterogeneous way, but is particularly strong in continental areas. This result is important for standard climate change adaptation modelled in spatial integrated assessment models. Indeed, they project that adaptation through migration to some regions [Cruz and Rossi-Hansberg, 2024] or greater agricultural output in these regions through structural change [Conte et al., 2021] might reduce the aggregate welfare impacts of climate change and have large distributional implications, with many benefits shifting to the northern hemisphere. The benefits of adaptation to mitigate the aggregate welfare costs of climate change could therefore be overestimated if the regions to which people migrate and where more agricultural output is produced are continental climatic zones, which is the case.

I. Climate and economic data

A. Warming patterns

We compare the distribution of daily mean temperatures in actual climate projections to a counter-factual synthetic projection where the shape of the distribution remains the same while the mean annual temperature increases, a standard assumption in the literature. We build different climate landscapes, where 'climate' is defined as the underlying distribution, from which a specific regional temperature distribution over a year is drawn [Waidelich et al., 2023]. We use CMIP6 bias-corrected and downscaled data at a resolution of 60 arc-minutes from five earth system models (ESM) stored in ISIMIP Protocol 3B [Frieler et al., 2023]: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MPI-ESM2-0, UKESM1-0-LL. ISIMIP subset of climate models and de-biasing techniques were designed to assess impacts of climate change and to span the larger ensemble of CMIP models [Warszawski et al., 2014]. Thus, our illustrative study underestimates inter-model uncertainty among the over 100 CMIP6 models. Data is available for three shared socioeconomic pathways (SSP 1-2.6, 3-7.0, 5-8.5). We construct four different climate landscapes for each SSP. The first is the climate landscape without climate change, the 'control' climate: it is the mean distribution of 'picontrol' time series experiments run over 2006 to 2100 with pre-industrial CO_2 concentration. The second is the landscape from actual climate projections which consists of bias-corrected, downscaled output from five ESMs forced with future emissions from three different SSPs, the 'projection' climate: we use the average of the 10-year distribution around a date to approximately capture the underlying distribution from which the specific weather realization from a specific year is drawn, i.e. 2045-2055 in our example[1]. This landscape samples scenario uncertainty, inter-model uncertainty, and regionally specific changes in the shape of daily mean temperature distributions. The third climate landscape is a 'synthetic-model' landscape, where we add for each temperature observed in the 'control' climate of each of the five ESM the mean of the change in annual temperature in 'projection' climate in this specific ESM. This yields a ESM-specific shape-preserving mean-shifted climate. This landscape samples scenario uncertainty, inter-model uncertainty, and regional differences in mean changes, but keeps the shape of daily mean temperature distributions unchanged. The last climate landscape is a 'synthetic-general' landscape. The difference with the 'synthetic-model' approach is that we sum the mean 'control' climate over all ESM and the mean change in annual mean temperature across ESM. This yields a mean shape-preserving, mean-shifted climate, which aggregates heterogeneity between climate models. This landscape samples scenario uncertainty and regional differences in mean changes while aggregating across ESMs and keeping the shape of daily mean temperature distributions unchanged.

Rather than aggregating this data at the global scale, we construct regional

[1]On the one hand, adding more years around 2050 would enable us to capture more of the internal variability which characterizes 2050 climate [Schwarzwald and Lenssen, 2022], for instance more El Niño cycles. On the other hand, it would come with a costly assumption of perfect symmetry around 2050 in climate change dynamics. By capturing less internal variability, we probably under-count the impact of including regional information.

climate landscapes. Indeed, using a global dataset means that locations in which a given temperature is relatively cold and places in which the same temperature is relatively warm in the two locations fall within the same bin of temperature, which distorts the picture of regional climate shifts, and biases the estimates used to convert these climate shifts into economic damage. We aggregate at the level of five major Köppen regions [Beck et al., 2023]: arid, continental, polar, temperate and tropical. It is reasonable to think that these climate classifications are both good ensembles in terms of warming patterns but also in terms of damage patterns to capture differences between relatively homogeneous regions. If the differences between damage patterns differ for many other reasons (e.g. cultural and political), we capture some of the regional heterogeneity due to climatic conditions. A finer disaggregation would reduce the statistical robustness of the estimates we obtain from our econometric specification below because of limited sample size and variation. When building these climate landscapes, we keep only locations for which we have economic data to estimate dose-response functions below and treat each of these economic region within each climatic Köppen region as a single unit.

B. Econometric estimates of climate damages

For the empirical analysis we combine Wenz et al. [2023]'s Database Of Subnational Economic Output (DOSE v2) with Hersbach et al. [2020]'s climate reanalysis (ERA5). We process the climate reanalysis by first calculating degree-days at the grid-cell level and then aggregating to DOSE regions. We use the combined data to estimate global and regional dose-response functions of GDP growth to daily mean temperatures. We estimate the model:

$$g_{it} = \alpha_i + P_{it}\beta + \sum_{b=1}^{B} n_{bit}\gamma_b + \mu_t + \epsilon_{it}$$

with the growth rate of GDP per capita PPP in USD in administrative unit i in year t as g_{it}, with the number of days with daily mean temperature in the bin indexed b as n_{bit}, and with total annual precipitation P_{it}. Note that here, P_{it} is indeed only a control, focused on global annual values, rather than regionally disaggregated daily ones [Kotz et al., 2022]. The model also includes region fixed effects α_i and year fixed effects μ_t. Errors ϵ_{it} are clustered at the level of countries to account for spatial and temporal autocorrelation. We estimate this model for all regions jointly and for each Köppen-Geiger climate zone k separately. Our main parameters of interest are the coefficients of temperature bins γ_b (for the global model) and γ_{bk} (for the regional models) which represent the non-linear association between daily temperature levels and economic growth. For the regional model, we use a gridded dataset on Köppen climate regions and assign to every administrative unit the share of each climatic zones it is included in based on surface area. The 2°C temperature bins are winsorized at level 99% for econometric estimation to limit the influence of rare events for which we do not have sufficient observations. Furthermore, we follow Cruz and Rossi-Hansberg [2024] and smooth the behavior of the point estimates across temperature bins on the whole temperature distribution in 2050 with degree-two polynomials, assuming that temperature effect on growth changes remains constant above and below our upper and lower bins used for the estimation. We also weigh each point estimate by the inverse of their standard errors to provide a greater weight to the more accurate estimates.

C. Descriptive statistics

Figure 1 gives summary statistics for the warming and damage patterns of each region in 2050 for SSP5-8.5. Graphs on the left plot the distribution of mean daily temperatures for all climate landscapes, taking the average of all five earth system models. The distributions have different shapes, both in terms of their dispersion and their mean. The shifts in the average temperature are also of different magnitude, which is consistent with the observation of spatially heterogeneous global warming. Shifts in shapes are also diverse, and not just because of the initial shape of each distribution as we show on the middle graphs. The middle graphs describe the difference between the 'synthetic-model' and the 'projection' landscapes for different earth system models: for each 1°C temperature bin, it gives the difference in frequency (in number of days) between two distributions. The first distribution is constructed by adding to each daily temperature for each climate model the mean of the annual anomaly observed in that model, thus obtaining a shape-preserving shift in mean, which is the assumption generally made in the literature. The second distribution is taken from climate model projections of daily mean temperatures. These difference can have opposite signs and various magnitude depending on the model considered. The graphs on the right present the minimum, central and maximum estimates of the two global and regional dose-response functions of GDP growth rate to an additional day in a given bin in comparison with a day in the [20 : 22°C] bin, estimated for each region. Our regional dose-response functions reveals different damage patterns than the global dose-response function. For instance, while the positive effect of colder temperatures on GDP growth in the global functions stills holds with regional estimates in the continental areas, the sign of this effect is reversed for polar and temperate areas. For warmer days, in relatively warmer areas, the effect of higher temperatures goes in both directions, i.e. positive effect for arid areas, negative effects for tropical areas, while it is flat in our global estimate that conflates both climatic zones. Disentangling global and regional damage patterns matter for climate policy because it provides a more accurate picture of the spatial and temporal heterogeneity in future climate damage.

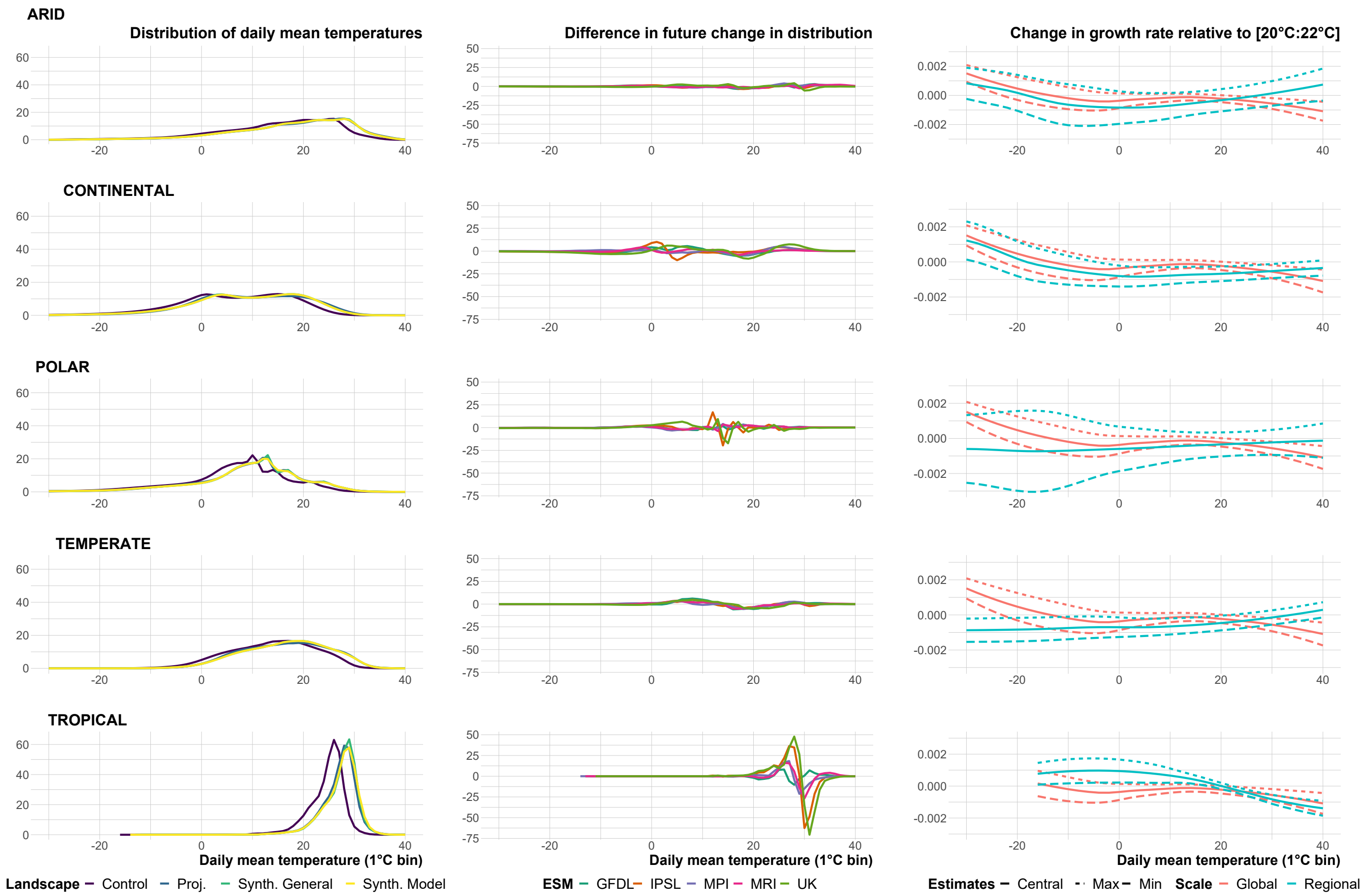

Figure 1. : **Left** Distribution of daily mean temperatures for four climate landscapes. **Middle** Distribution of climate shift, i.e. difference in distribution of daily mean temperatures under projection vs. a synthetic-model climate. **Right** Change in growth rate from one day in this bin relative to one additional day in [20°C : 22°C]. Data are for all DOSE regions, SSP5-8.5, 2050.

II. Quantification

A. *Missing shape-related growth effect of climate change*

We express the GDP growth effect of daily temperatures in climate projections as a share of this effect in synthetic climate, i.e. in a setting where we assume that the shape of the distribution of daily temperatures remains the same when the mean increases. Indeed, we want to measure how much the change in the shape of the distribution of daily mean temperatures matter for the estimation of economic damages. To have a measure that approaches standard climate damages, growth effects in warming climates are expressed with respect to growth effects in control climate. Growth effect at each 1°C bin b is γ_b (γ_{bk}) if we use global (regional) dose-response functions, where k stands for a Köppen-Geiger climate zone. The global growth effect Ω for a given SSP and year in our climate landscape C for a given dose-response function in subadministrative region DOSE d in Köppen-Geiger climate zone k is:

$$\Omega_{ymd}^{glob,C} = \frac{\left(\sum_b \gamma_b t_{bymd}^{C} - \sum_b \gamma_b t_{bymd}^{control}\right)}{\sum_b \gamma_b t_{bymd}^{control}} \;,\; \Omega_{ymdk}^{reg,C} = \frac{\left(\sum_b \gamma_{bk} t_{bymdk}^{C} - \sum_b \gamma_{br} t_{bymdk}^{control}\right)}{\sum_b \gamma_{bdk} t_{bymdk}^{control}}$$

Then, we apply a double difference procedure to find the change in growth effect between synthetic climate and projections. For damage function γ, and synthetic climate: $DD^{\omega}_{ymdk} = 100 * (\Omega^{\omega,projection}_{ymdk} - \Omega^{\omega,synthetic}_{ymdk})/\Omega^{\omega,synthetic}_{ymdk}$, with $\omega \in \{global, regional\}$. This estimate expresses the share the missing shift in shape represents in the standard estimates of damages assumed from shape-preserving synthetic shift in mean. We summarize the values of this estimate for various specifications in Figure 2 below which disentangles various layers of uncertainty. On the top left graph, we plot the dispersion in our DD estimate for each Köppen climatic region and each SSP, for each ESM (in blue) and the average over ESM (in red). This graph captures how for each region the differences between SSP and between climate models drives the impact omitting the whole shape of warming pattern has on the assessment of damages. There is an important climate model uncertainty. Outside continental areas, depending on the climate model used, the sign of the difference between the standard assumption and the full shape of the distribution is either positive or negative. Part of this structural uncertainty between climate models is already captured when comparing climate models at the aggregate annual scale. Thus, on the top right graph, we plot the dispersion between two methods to build our synthetic climate: either using the model-specific control climate and mean aggregate temperature increase to build the new synthetic benchmark, or using the average over different ESM. On the bottom left graph, we plot the difference in our estimates depending on the dose-response function of GDP growth to daily temperatures that is used: either the global dose-response function which combines potentially contradictory effects of changes in temperature distribution over space, or the regional estimates which might capture part of the spatial heterogeneity in damage patterns. On the bottom right graph, we plot our coefficient for the central, minimum and maximum estimates of the regional dose-response function to measure how much parametric uncertainty for a given damage function specification matters in comparison with structural uncertainty about the damage function, i.e. either global or regional. All four sources of uncertainty that are hidden under the assumption of a shape-preserving mean-shifted synthetic climate matter, especially in the continental areas.

B. Aggregate impacts

While we build regional climate landscapes that use the granularity given in climate datasets rather than too aggregated information to discuss climate policy, we seek for global indicators that can easily be applied to aggregate economic models. We compute for each DOSE region within each larger Köppen-Geiger zone the share of missing growth due to disaggregated warming and damage patterns. We use area-weighting to build DOSE-level estimates of missing growth from DOSE*Koppen estimates. We then aggregate the DOSE-level growth effect to the global scale based on the share of each zone in global GDP. We use the synthetic-model approach to build a synthetic climate, assuming that aggregate uncertainty between climate model is already taken into account in the literature studying aggregate annual mean temperatures. Indeed, our study focuses on one

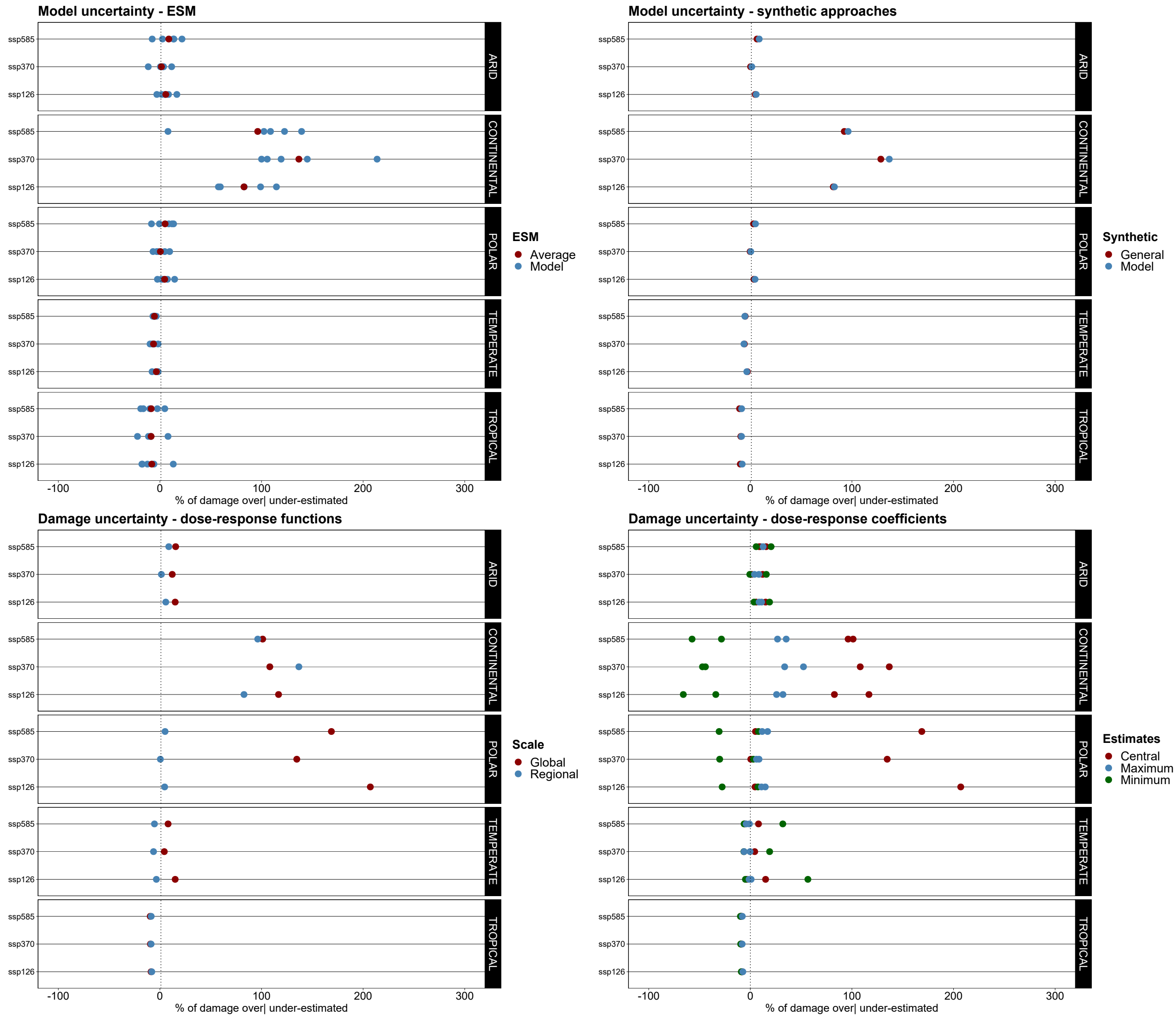

Figure 2. : DD for different specifications, year 2050, all SSP and regions. **Left Top** For each ESM vs. average, using synthetic-model and regional damage **Right Top** For synthetic-model vs. synthetic-general, using regional damage, averaging over ESM **Left Bottom** For global vs. regional damage, using synthetic-model, averaging over ESM **Right Bottom** For central, minimum and maximum estimates of regional damage, using synthetic-model, averaging over ESM.

channel of uncertainty: the interactions between intra-annual warming patterns and damage patterns at the regional scale. On left graph in Figure 3, we plot our estimate of the share of missing growth effects for various ESM and the mean across ESM under regional damages. On the right graph, we plot global DD for two specifications of the dose-response function: either global or regional.

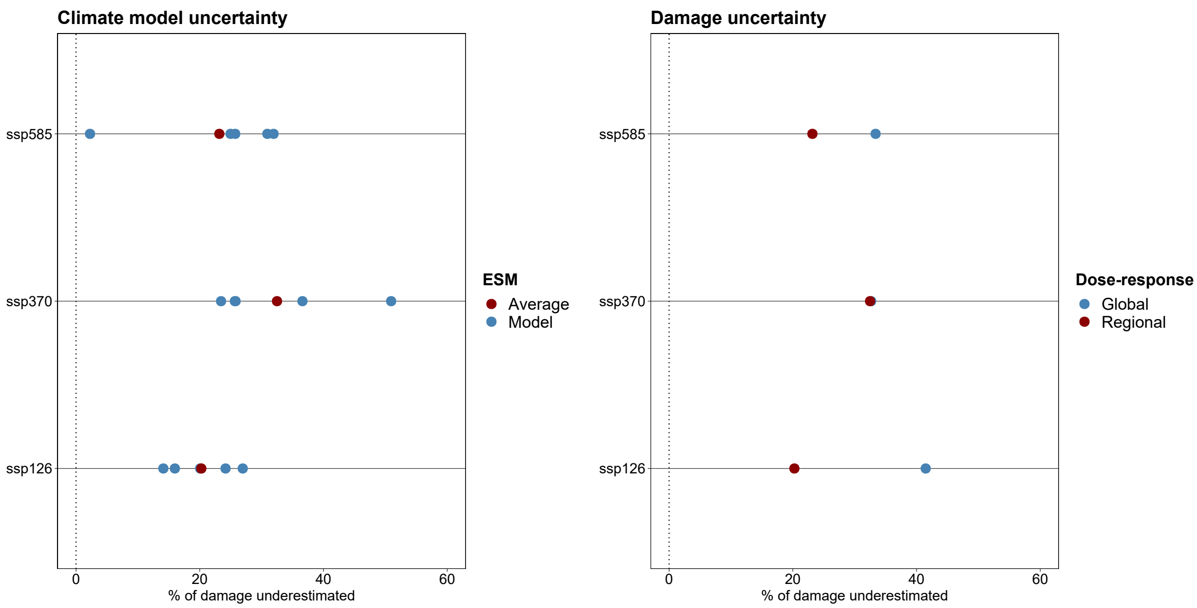

Figure 3. : **Left** Global DD under synthetic-model approach for each ESM and the average over ESM with regional dose-response function **Right** Global DD for each dose-response function, synthetic-model approach and average climate model with regional dose-response function.

The assumption made in the literature of a shape-preserving shift in mean annual global temperature interacted with global damage patterns thus yields biased estimates of future economic damages of climate change. For all climate models and across various specifications of damage patterns and economic scenarios, this bias is an underestimation of future damages: accounting for the shift in regional shape would increase the actual damage by around 25% under all concentration pathways in 2050. The shift in shape matters also for less carbon-intensive pathways. Both uncertainty between climate models on the shape of regional warming patterns and uncertainty on the damage patterns matter. Their interaction is likely to significantly alter the temporal and spatial distribution of the economic damage caused by climate change. This change in the aggregate picture of climate impacts should encourage greater mitigation and adaptation. But what about the distributional effects?

C. Distributional impacts

We have focused on the aggregate impact of this omitted shift in regional daily temperature shape. Now, when we look in more detail at the distribution of damage, we see that there is no perfect correlation with income: the countries most affected by these shifts in the patterns of intra-annual weather distribution are not necessarily the poorest. In fact, the opposite is true, even if the data are widely scattered. In Figure (4) below, we show on the left that, for certain DOSE regions, climate impacts are in fact lower when using climate projections with intra-annual temperature distributions with regional response functions than in a synthetic approach using a mean-shifted shape-preserving climate. In particular, we show on the right graph that gives the distribution of omitted impacts for each quantile of the 2015 distribution of DOSE regions in terms of USD GDP per capita that this applies to the poorest 20% of regions, even if the distribution is fairly skewed.

Uncertainty about changes in the shape of regional temperature distributions interacts with regional damage functions mainly concerning continental regions, as we show on Figure (5), in line with estimates from Figure (1). This is particularly important if less significant impacts are expected in these regions, notably on agricultural productivity, but also on regional amenities, which could justify adaptations that reduce the total cost of climate change. The welfare benefit of these adaptations would be particularly reduced if it turns out that these re-

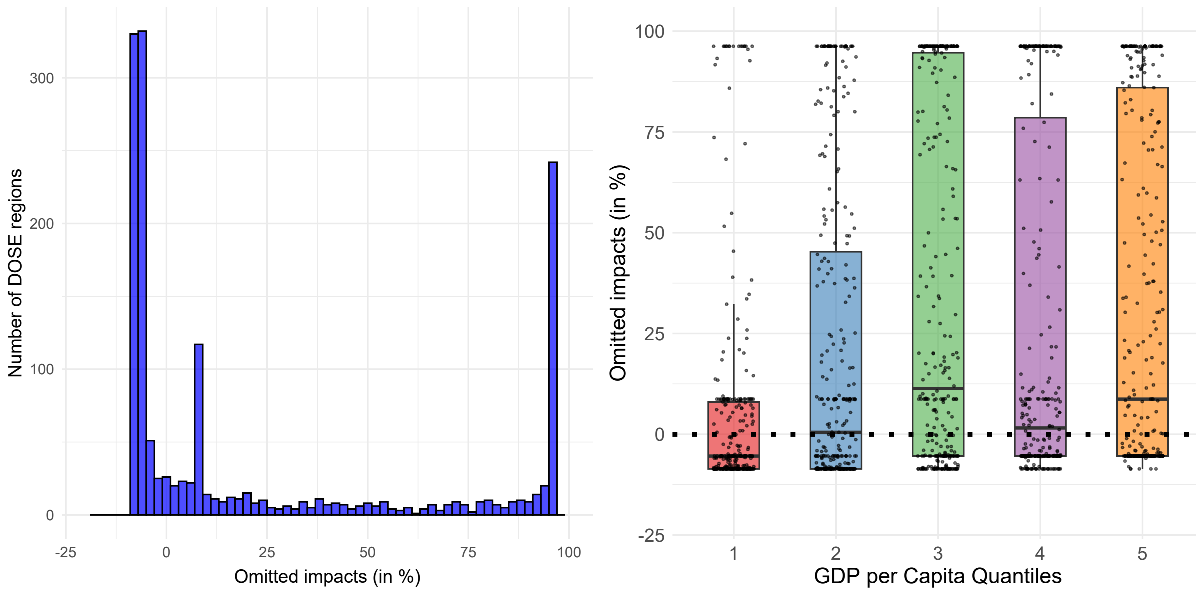

Figure 4. : Estimates are for year 2050, SSP5-8.5. **Left** Distribution of impacts (in % of current estimates) across DOSE regions **Right** Distribution of impacts across and within 2015 USD GDP per capita quantiles of DOSE regions. The colored bars span the interquartile range for each quantile. The black lines represent the mean for each quantile.

gions have very significant welfare changes: impacts on growth up to 100% higher than estimates based on global dose-responses interacted with shape-preserving projected climates.

III. Conclusion

If climate-society relationships were linear, then aggregating would not make any difference. But since they are nonlinear, what happens at the regional and intra-annual levels matters. Indeed, switching from annual global mean temperature to a regional annual distribution of daily mean temperatures affects the magnitude of economic damages from climate change. This change comes from heterogeneity in both damage and warming patterns across regions. Spatio-

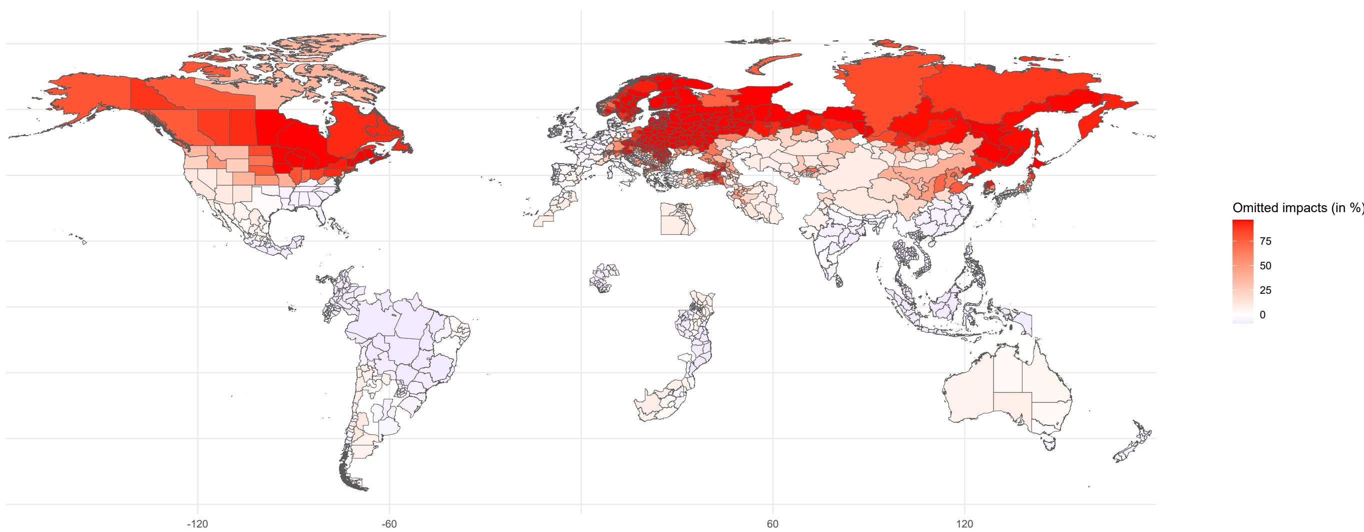

Figure 5. : Map of DOSE regions with their associated missing-shaped related climate impacts, as a share of 2050 estimated growth impacts along SSP5-8.5.

temporal disaggregation, thus, reveals how uncertainty between climate models on the whole shape of the distribution of future weather realizations cascades down to regional damage estimates. This shape uncertainty affects risk rankings across models and increases the magnitude of uncertainty between models. Moreover, accounting for daily temperatures rather than annual averages increases the estimation of economic damages, a finding consistent with previous studies [Rudik et al., 2022]. In 2050, under SSP5-8.5, using regional damage patterns interacted with the shift in the entire shape of the distribution of daily temperatures, yields climate damages at the global scale that are 25% larger than the damage obtained under the assumption of homogeneous damage patterns over the world and shape-preserving shift in annual mean daily temperature. The shape uncertainty about shifts in daily temperature distributions and regional damage patterns should therefore be taken into consideration for decision-making.

To our knowledge, we provide the first comparison between various approaches to spatial and temporal aggregation regarding impacts of changes in mean surface temperatures on economic activity and quantify how much these often-overlooked aggregation procedures matter empirically. We believe that this procedure can be reasonably translated horizontally and vertically. Vertically, this framework can be applied to other economic damages stemming, for instance, from changes in maximum or minimum daily temperatures. Horizontally, the framework could be used to infer results in regions for which we do not have socioeconomic data to estimate damage functions. In this work, we have kept the DOSE regions for the sake of consistency. But using Köppen-Geiger climatic zones, i.e. widely available physical data, to build ensembles and generalize the results over these ensembles could be a useful detour at first, alongside a necessary deepening in the availability of socioeconomic data, particularly in Africa.

Our analysis also comes with limitations. In particular, our estimation of regional damage functions is based on the idea that differences in the economic damage caused by weather—and therefore by climate change—is intimately linked to climatic zones. However, there are many factors that go well beyond geographical determinism that we do not explore here. Furthermore, Earth System Models are imperfect, and some may not be able to capture well the shape (or changes in the shape) of the temperature distribution [Kornhuber et al., 2023]. When it comes to estimating the future damage of climate change, other approaches use annual temperature [Bilal and Känzig, 2024] and thus avoid the problem of time-fixed effects, which erase a large proportion of the impacts. The question of aggregation is less of an issue in this case, as these approaches consider annual temperature to be a sufficient statistic for estimating impacts. Nevertheless, the question of the relevance of past natural variability as a proxy for global annual climate change based on complex processes and rising carbon concentration remains. This question is left for future research. Finally, while we studied variations of warming patterns in space and time, and variation of damage patterns in space, we have left out the question of variation of damage patterns in time under a 'swinging climate' [Mérel et al., 2024]—i.e. adaptation to shifts in climate. How might a given daily temperature yield different damages in any particular region under a different climate, as the region moves away from its normal climatic zone? Lastly, that raises the question of how adaptation might interact with the entire distribution of climatic factors, a question left for further research.

Acknowledgement

Romain Fillon thanks the Fulbright Program (France) for funding his research stay at Columbia University. The authors thank François Bareille, Adrien Delahais, Célia Escribe, Céline Guivarch, Radley Horton, Adam Sobel and especially Kevin Schwarzwald for fruitful comments on earlier versions of this work. Computations were performed on the Columbia University Research Grid.

Appendix A. Building climate landscapes

We scale the frequency of observations by the share of land area in each cell using GPW4 dataset. We compare changes in shapes of daily mean temperature distributions T_{mr} in five Köppen regions r and climate model m, i.e. the distribution of all T_{mr} daily mean temperatures in region r and model m, in four different climates C. Climate C are: a control climate, ISIMIP projections, the synthetic distribution with model average, the synthetic distribution with average over models. We bin the temperature distributions t at 1°C: $f(.)$ is a function that bin the distributions. Our final landscapes for each year are:

- Control climate, without climate change $T_{mr}^{control} = f(t_{mr}^{control})$
- ISIMIP projections $T_{mr}^{proj} = f(t_{mr}^{proj})$
- Synthetic model with model average are built by adding the difference between binned projections and control climate
  $T_{mr}^{synth.model} = f\left(t_{mr}^{control} + T_{mr}^{proj} - T_{mr}^{control}\right)$
- Synthetic model with total average are built by adding the difference between binned projections and control climate, averaged over all models m in ensemble M
  $T_{mr}^{synth.general} = f\left(t_{mr}^{control} + mean_M(T_{mr}^{proj} - T_{mr}^{control})\right)$

Let us define a climate shift indices for a given year: $CSI_{mr} = \hat{T}_{mr}^{proj} - \hat{T}_{mr}^{synth.model}$, which gives for each bin the difference in the frequency of this degree-day in the projections with respect to the synthetic shape-preserving mean-shifted climate for each ESM.

Appendix B. Köppen regions

The Köppen region of use are:

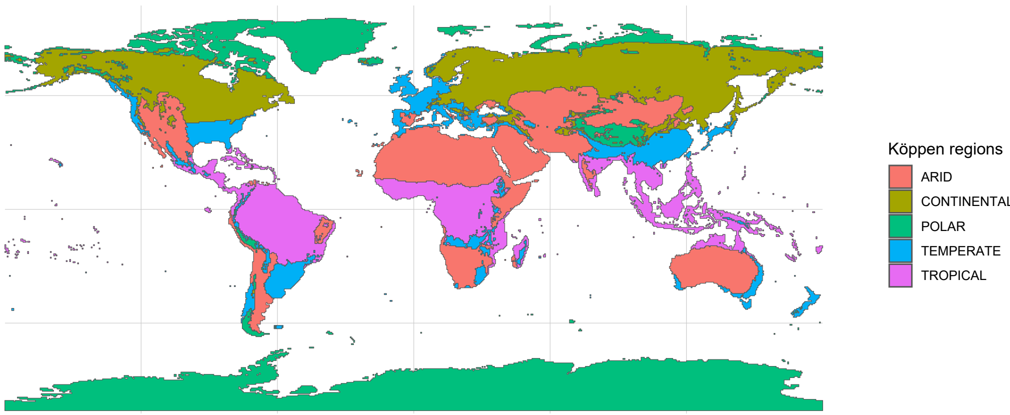

Figure 6. : Köppen climatic zones.

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