Climate shift uncertainty and economic damages

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Focusing on global annual averages of climatic variables, as in the standard damage function approach, can bias 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. We disentangle how much of the missing impacts are due to differences in warming versus heterogeneous damage patterns over space and time. Global damages in 2050 are around 20% higher, when accounting for the shift in the entire distribution of daily mean temperatures at the regional scale. Differences in the shape of daily temperature distributions between climate models transform standard risk rankings based on temperature anomaly, and increase uncertainty across climate models.
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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. The commonly stated rule of thumb: the more disaggregated the data, the higher are the estimated damages [Nordhaus and Yang, 1996, Rudik et al., 2022]. Adaptation may change things, with finer-grained data showing increased capacity to adapt [Heutel et al., 2021]. 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 aggregated models; it also has shortcomings, such as the risk of averaging contradictory effects between regions in terms of damage and warming patterns, or hiding uncertainties within or between climate models. Aggregation, thus, might affect risk ranking between models or the magnitude of structural uncertainty across models. Moreover, aggregation choices can bias results through unobserved mechanisms.

Projections of climate damages in economic models 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. Even 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. Moreover, economists often use a linear relationship between global and regional climate that boils down to an annual regional statistic. Annual averages 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].

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 step 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 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.

Bias-adjusted and gridded climate projections now allow us to compare counterfactual climate to a specific climate scenario at a fine resolution, where 'climate' is defined as the underlying distribution, from which a specific regional temperature distribution over a year is drawn [Waidelich et al., 2023]. A large econometric literature has developed in parallel to infer future economic damages from climate change using observed historical impact from past weather [Dell et al., 2014, Hsiang, 2016, Auffhammer, 2018]. This literature often uses disaggregated daily weather data to estimate dose-response functions of an economic variable of interest to a summary statistics of the high dimensional climate vector [Hsiang, 2016]. But with the notable exception of Rudik et al. [2022], the climate-economic modelling literature mostly ignores the shape of region-specific warming and damage patterns and instead focuses on global averages either for warming patterns, or for damage patterns, or for both, regardless of the level of spatial aggregation—from global [Nordhaus, 1994] to regional [Nordhaus and Yang, 1996] and gridded [Cruz and Rossi-Hansberg, 2021, Krusell and Smith Jr, 2022]. This aggregation might have important consequences, both for establishing our best approximation of future damage and 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 SSPs), model uncertainty (differences in 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), and 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 impact model, 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. We quantify 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 climate models 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, 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. We then apply this resulting regional climate shift uncertainty to the estimation of future climate damages.

We first gather climate and economic data, describe region-specific warming patterns for different climate models, and estimate regional damage patterns. We here focus on average surface temperatures, though the framework applies to any number of different statistics that are usually aggregated from daily to annual levels, including e.g. precipitation patterns. In addition, we illustrate our argument for the year 2050, which is sufficiently close so as not to superficially inflate the results, while also being a relevant time horizon for any number of climate policy considerations. Then, we quantify how much the missing shape-related damage of climate change matters for climate policy and provide a simple statistics to operationalize the finding.

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, under SSP5-8.5, 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 20% 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. Second, we show that the standard risk ranking expressed as the ranking of temperature anomalies between climate models is affected by this shape uncertainty. In SSP5.8-5, the magnitude of scientific uncertainty between climate models is even larger than expected, as standard uncertainty between models is multiplied by shape uncertainty, which further increases dispersion of future possible economic impacts from climate change.

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 using 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-average' 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

[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.

the shape of daily mean temperature distributions unchanged.

Rather than aggregating this data at the global scale, we construct regional 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 [2021] 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.

More details on the climate shift are given in the heatmap in Figure 3. We plot the number of days under actual projections that are both outside synthetic climate and above the median of its distribution. It is negative (positive) when there are less (more) days in projections that are above the median of synthetic

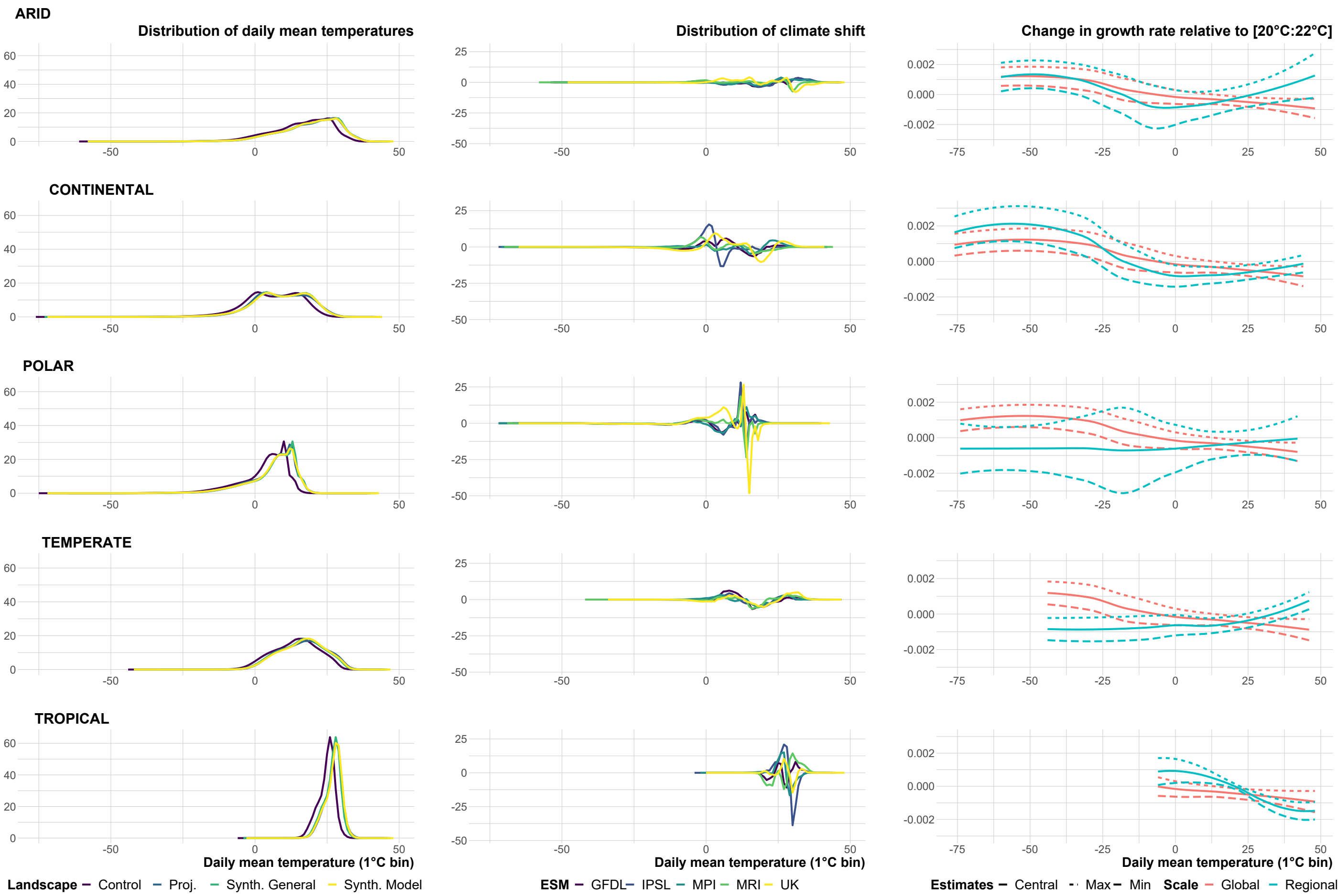

Figure 1. : **Left** Distribution of daily mean temperatures for four climate landscapes. **Middle** Distribution of climate shift, i.e. difference in distribution of daily mean temperatures under projection vs. a synthetic-model climate. **Right** Change in growth rate from one day in this bin relative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

climate. There is no clear sign for this climate shift: climate projections are not unequivocally more right-skewed than the synthetic approach. The sign of the shift is reversed depending on the climate model used.

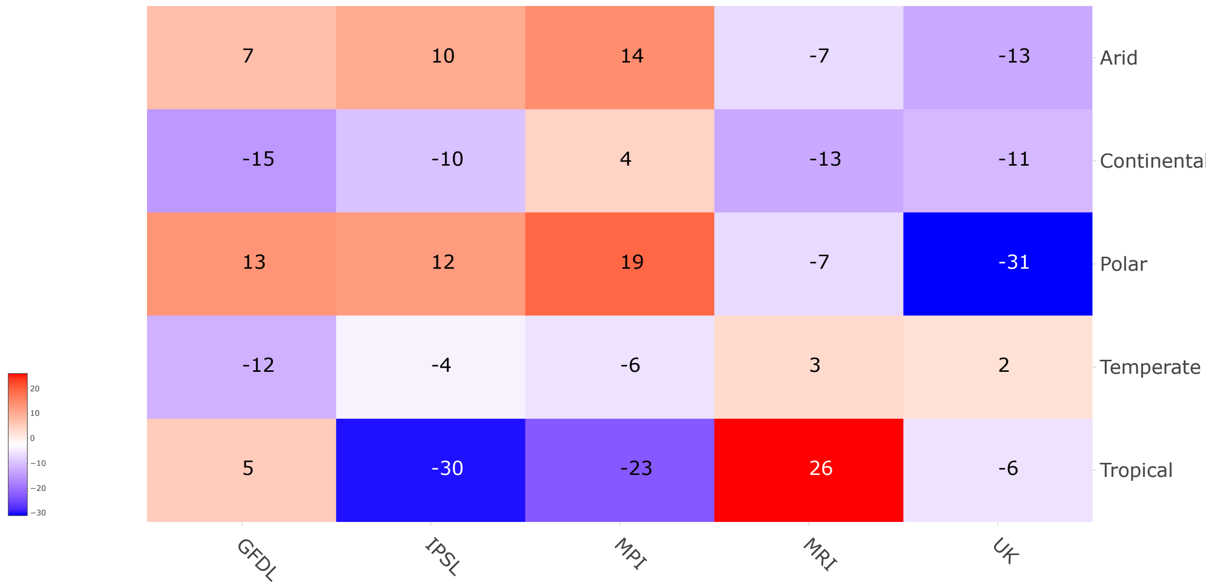

Figure 2. : Days in SSP5-8.5 2050 actual projections for all climate models and DOSE regions that are (1) outside the distribution of synthetic climate and (2) above the median of daily mean temperature distribution in synthetic climate.

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:

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

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 3 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 bottom left 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 top right 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. The main source of uncertainty that is hidden under the assumption of a shape-preserving mean-shifted synthetic climate stems from structural uncertainty across climate models, i.e. heterogeneity in projected regional warming patterns, and structural uncertainty about the shape of damage patterns, i.e. global versus regional damage estimations.

B. Simple statistics for policy-makers

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, either using 2020 GDP [Kummu et al., 2018], or using SSP scenario to compute 2050 GDP of each DOSE region [Wang and Sun, 2022]. We 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 channel of uncertainty: the interactions between intra-annual warming patterns and damage patterns at the regional scale. On left graph in Figure 4, we plot our estimate of the share of missing growth effects with two approaches: either 2020 GDP or GDP taken from SSP. The underestimation is around 20% lower using SSP projections. On the graph in the middle, we plot our global DD for various ESM and the mean across ESM under regional dam-

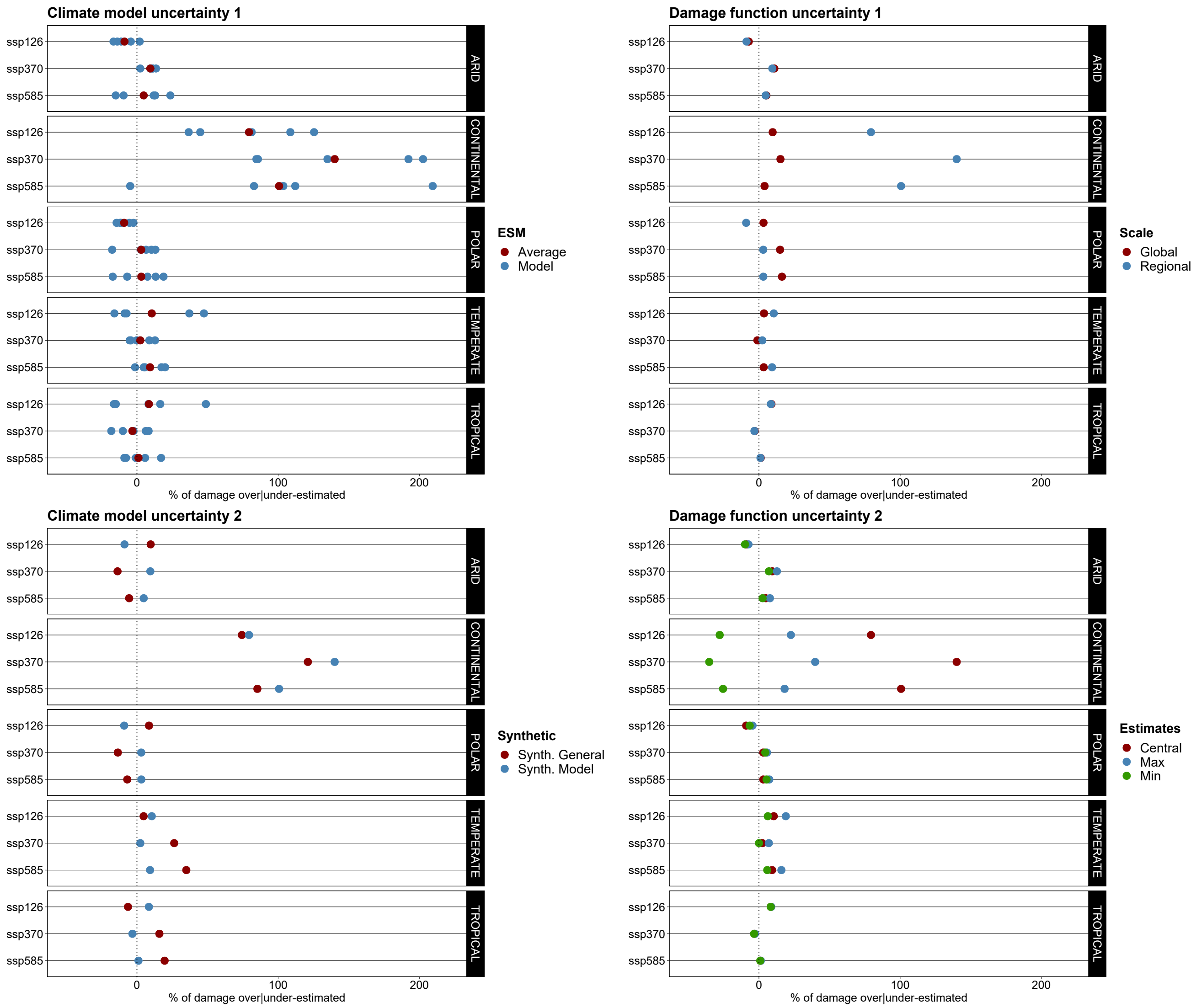

Figure 3. : DD for different specifications, year 2050, all SSP and regions. **Left Top** For each ESM vs. average, using synthetic-model and regional damage **Left Bottom** For synthetic-model vs. synthetic-average, using regional damage, averaging over ESM **Right Top** For global vs. regional damage, using synthetic-model, averaging over ESM **Right Bottom** For central, min. and max. estimates of regional damage, using synthetic-model, averaging over ESM.

ages. The dispersion between climate models is larger than the dispersion across economic scenarii. On the right graph, we plot global DD for two specifications of the dose-response function: either global or regional. Structural uncertainty on the damage function matters as the underestimation is around seven times larger under regional estimates than under global estimates across the three SSP.

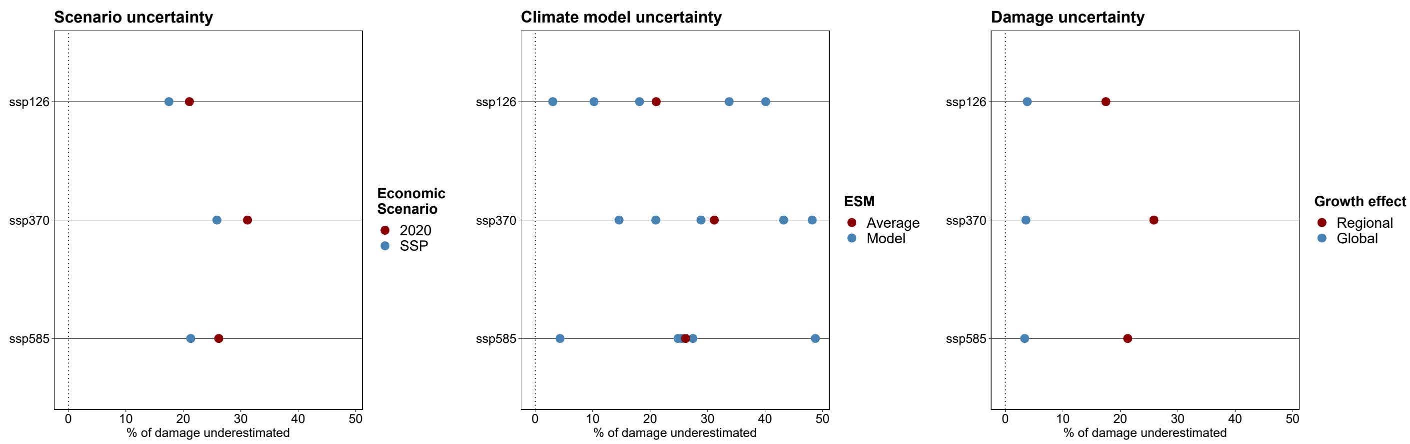

Figure 4. : **Left** Global DD under synthetic-model approach for two aggregation methods, either with 2020 fixed weights or with SSP scenario, for regional damages, average over climate models **Middle** Global DD for each climate model and their average with SSP aggregation method, regional damages **Right** Global DD for each dose-response function and average climate model with SSP aggregation method, regional damages.

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 21.3% under SSP5-8.5 in 2050. The shift in shape matters also for less carbon-intensive pathways: the underestimation is of 17.5% (25.8%) under SSP1-2.6 (SSP3-7.0). 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 modified picture changes mitigation and adaptation policies.

Part of the dispersion between models highlighted above, which is linked to the complete shape of the daily temperature distribution, is generally hidden when we focus on annual average temperatures. This, in turn, is likely to change risk ranking between models. It can also change the magnitude of uncertainty between models. In other words, annual global mean temperature is not a sufficient statistic for climate model uncertainty regarding mean temperatures. In Figure 5, we plot the ranking of each climate model for two measures: the share of underestimated damages highlighted above and the annual mean temperature anomaly in 2050 for each SSP and at the global scale for all DOSE regions [Wenz et al., 2023].

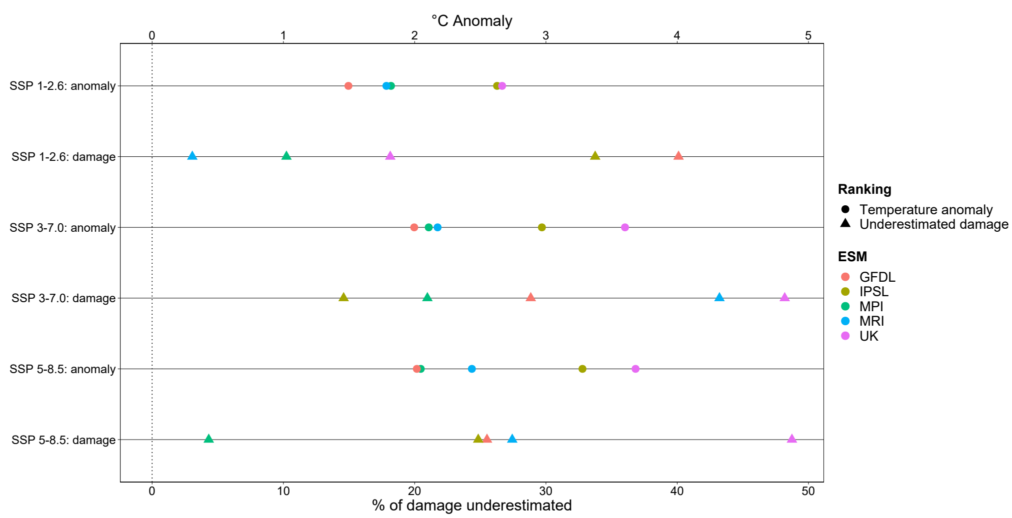

Figure 5. : Risk ranking between climate models for all SSP and all DOSE regions for two key measures: (1) the share of underestimated damage computed with our methodology, (2) the temperature anomaly (in °C).

The ranking is not always the same: in SSP1-2.6 for instance, GFDL projects the lowest change in temperature anomaly but the distribution of daily temperatures in GFDL is the one that deviates furthest from the synthetic distribution, which assumes that the shape of the distribution of daily mean temperatures remains the same. Risk ranking between models in terms of climate impact is likely to be modified in this case. In SSP5.8-5 on the other hand, MPI and UK are the lowest and highest among models for both metrics, which suggest that risk ranking might remain the same, but the magnitude of climate uncertainty between models increases as both uncertainties interact. Indeed, UK has the highest temperature anomaly over DOSE regions, and the aggregate climate damage computed from this anomaly is multiplied by the largest underestimated share of damage due to climate shift in the shape of the daily temperatures distribution.

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 level matters. Indeed, switching from annual global mean temperature to a regional annual distribution of daily mean temperatures affects the sign and magnitude of economic damages from climate change. This change comes from heterogeneity in both damage and warming patterns across regions. Disaggregating, 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 acros 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 20% larger than the damage obtained under the assumption of homogeneous damage patterns over the world and shape-preserving shift in annual mean daily temperature. Climate model uncertainty and damage uncertainty matter more in our setting than economic uncertainty about the share of each region in world GDP in 2050. 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 can be used to infer results in regions for which we do not have socioeconomic data to estimate damage functions.

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]. 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.

REFERENCES

M. Auffhammer. Quantifying economic damages from climate change. *Journal of Economic Perspectives*, 32(4):33–52, 2018.

H. E. Beck, T. R. McVicar, N. Vergopolan, A. Berg, N. J. Lutsko, A. Dufour, Z. Zeng, X. Jiang, A. I. van Dijk, and D. G. Miralles. High-resolution (1 km) köppen-geiger maps for 1901–2099 based on constrained cmip6 projections. *Scientific data*, 10(1):724, 2023.

J.-L. Cruz and E. Rossi-Hansberg. The economic geography of global warming. Technical report, National Bureau of Economic Research, 2021.

M. Dell, B. F. Jones, and B. A. Olken. What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature*, 52(3):740–798, 2014.

K. Frieler, J. Volkholz, S. Lange, J. Schewe, M. Mengel, M. d. R. Rivas López, C. Otto, C. P. Reyer, D. N. Karger, J. T. Malle, et al. Scenario set-up and forcing data for impact model evaluation and impact attribution within the third round of the inter-sectoral model intercomparison project (isimip3a). *EGUsphere*, pages 1–83, 2023.

D. García-León, A. Casanueva, G. Standardi, A. Burgstall, A. D. Flouris, and L. Nybo. Current and projected regional economic impacts of heatwaves in europe. *Nature communications*, 12(1):5807, 2021.

H. Hersbach, B. Bell, P. Berrisford, S. Hirahara, A. Horányi, J. Muñoz-Sabater, J. Nicolas, C. Peubey, R. Radu, D. Schepers, A. Simmons, C. Soci, S. Abdalla, X. Abellan, G. Balsamo, P. Bechtold, G. Biavati, J. Bidlot, M. Bonavita, G. De Chiara, P. Dahlgren, D. Dee, M. Diamantakis, R. Dragani, J. Flemming, R. Forbes, M. Fuentes, A. Geer, L. Haimberger, S. Healy, R. J. Hogan,

E. Hólm, M. Janisková, S. Keeley, P. Laloyaux, P. Lopez, C. Lupu, G. Radnoti, P. De Rosnay, I. Rozum, F. Vamborg, S. Villaume, and J.-N. Thépaut. The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049, July 2020. ISSN 0035-9009, 1477-870X. doi: 10.1002/qj.3803.

G. Heutel, N. H. Miller, and D. Molitor. Adaptation and the mortality effects of temperature across us climate regions. *Review of Economics and Statistics*, 103(4):740–753, 2021.

S. Hsiang. Climate econometrics. *Annual Review of Resource Economics*, 8:43–75, 2016.

K. Kornhuber, C. Lesk, C. F. Schleussner, J. Jägermeyr, P. Pfleiderer, and R. M. Horton. Risks of synchronized low yields are underestimated in climate and crop model projections. *Nature Communications*, 14(1):3528, 2023.

M. Kotz, A. Levermann, and L. Wenz. The effect of rainfall changes on economic production. *Nature*, 601(7892):223–227, 2022.

M. Kotz, A. Levermann, and L. Wenz. The economic commitment of climate change. 2023.

P. Krusell and A. A. Smith Jr. Climate change around the world. 2022.

M. Kummu, M. Taka, and J. H. Guillaume. Gridded global datasets for gross domestic product and human development index over 1990–2015. *Scientific data*, 5(1):1–15, 2018.

P. Mérel, E. Paroissien, and M. Gammans. Sufficient statistics for climate change counterfactuals. *Journal of Environmental Economics and Management*, page 102940, 2024.

W. D. Nordhaus. *Managing the global commons: the economics of climate change*, volume 31. MIT press Cambridge, MA, 1994.

W. D. Nordhaus and Z. Yang. A regional dynamic general-equilibrium model of alternative climate-change strategies. *The American Economic Review*, pages 741–765, 1996.

M. Patterson. North-west europe hottest days are warming twice as fast as mean summer days. *Geophysical Research Letters*, 50(10):e2023GL102757, 2023.

J. Rising, M. Tedesco, F. Piontek, and D. A. Stainforth. The missing risks of climate change. *Nature*, 610(7933):643–651, 2022.

I. Rudik, G. Lyn, W. Tan, and A. Ortiz-Bobea. The economic effects of climate change in dynamic spatial equilibrium. 2022.

K. Schwarzwald and N. Lenssen. The importance of internal climate variability in climate impact projections. *Proceedings of the National Academy of Sciences*, 119(42):e2208095119, 2022.

P. Waidelich, F. Batibeniz, J. A. Rising, J. Kikstra, and S. Seneviratne. Climate damage projections beyond annual temperature. 2023.

T. Wang and F. Sun. Global gridded gdp data set consistent with the shared socioeconomic pathways. *Scientific Data*, 9(1):221, 2022.

L. Warszawski, K. Frieler, V. Huber, F. Piontek, O. Serdeczny, and J. Schewe. The inter-sectoral impact model intercomparison project (isi–mip): project framework. *Proceedings of the National Academy of Sciences*, 111(9):3228–3232, 2014.

L. Wenz, R. D. Carr, N. Kögel, M. Kotz, and M. Kalkuhl. Dose–global data set of reported sub-national economic output. *Scientific Data*, 10(1):425, 2023.

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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 5 Koppen regions r and climate model m, i.e. the distribution of all t_{bymr} daily mean temperatures in year y, bin b, region r, model m, in four different climates C $\in \{control, projection, synthetic-model, synthetic-average\}$.

- Control climate, without climate change $T_{mr}^{control}$
- ISIMIP projections $T_{mr}^{projection}$
- Synthetic model with model average
  $t_{bymr}^{synthetic-model} = t_{bymr}^{control} + mean_b(t_{bymr}^{projection} - t_{bymr}^{control})$
- Synthetic model with total average
  $t_{byr}^{synthetic-average} = mean_m(t_{byr}^{control}) + mean_{bm}(t_{bymr}^{projection} - t_{bymr}^{control})$

Let us define a climate shift indices: $CSI_{bymr} = t_{bymr}^{projections} - t_{bymr}^{synthetic-model}$.

The Köppen region of use are:

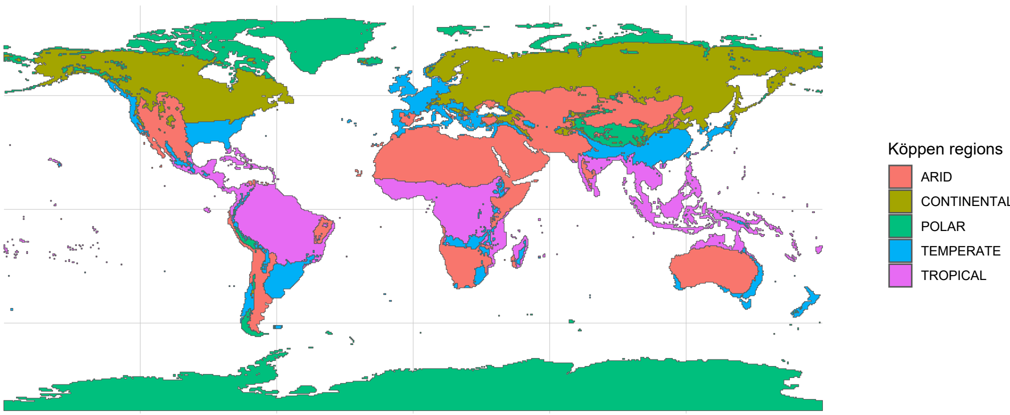

Figure 6. : Köppen climatic zones.

Appendix B. Some graphs

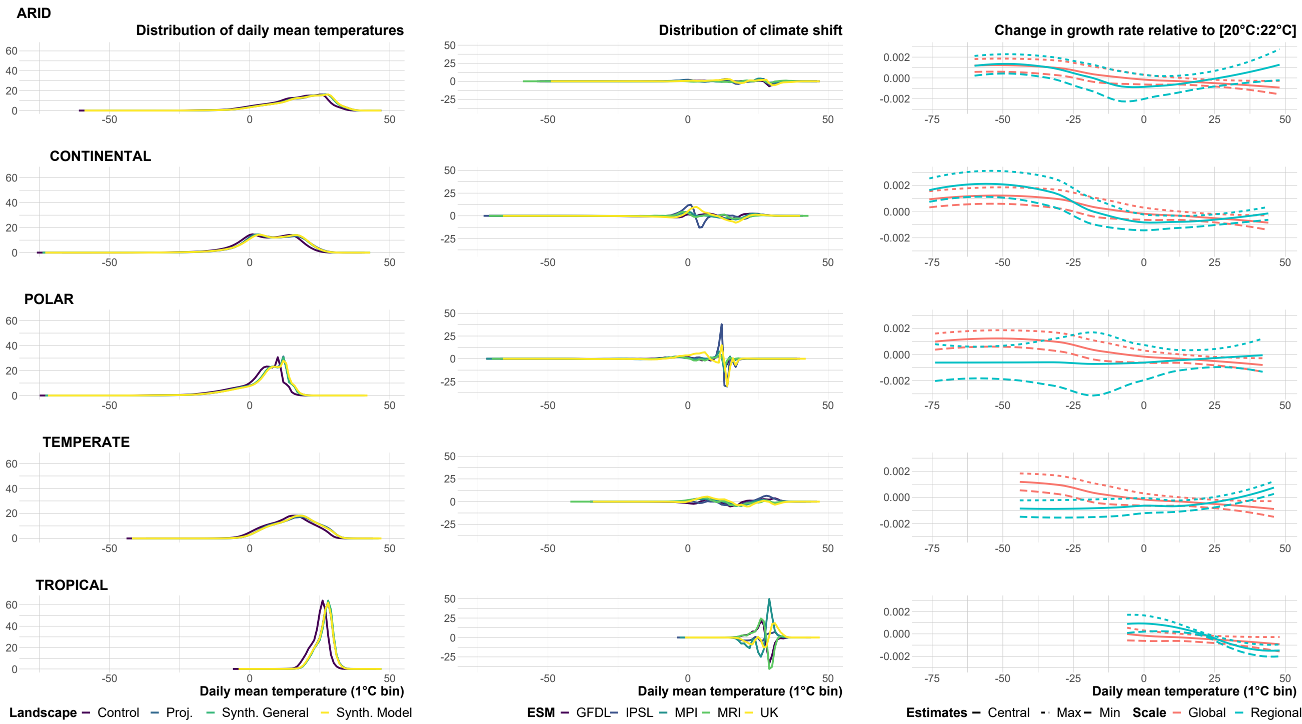

Figure 7. : SSP1-2.6 **Left** Distribution of daily mean temperatures for four different climate landscapes. **Middle** Distribution of climate shift, i.e. difference in distribution of daily mean temperatures under projection vs. a synthetic-model climate. **Right** Change in growth rate from one day in this bin relative to one additional day in [20°C : 22°C].

Appendix D. Final statistics

We give the values for the share of each climatic region in GDP for different scenarii used in this paper: either fixed 2020 GDP share, or SSP-dependent GDP share. From GDP gridded data at 5 arc-min resolution: GDP is upscaled based on surface area for grid zones that are spread over several Köppen regions.

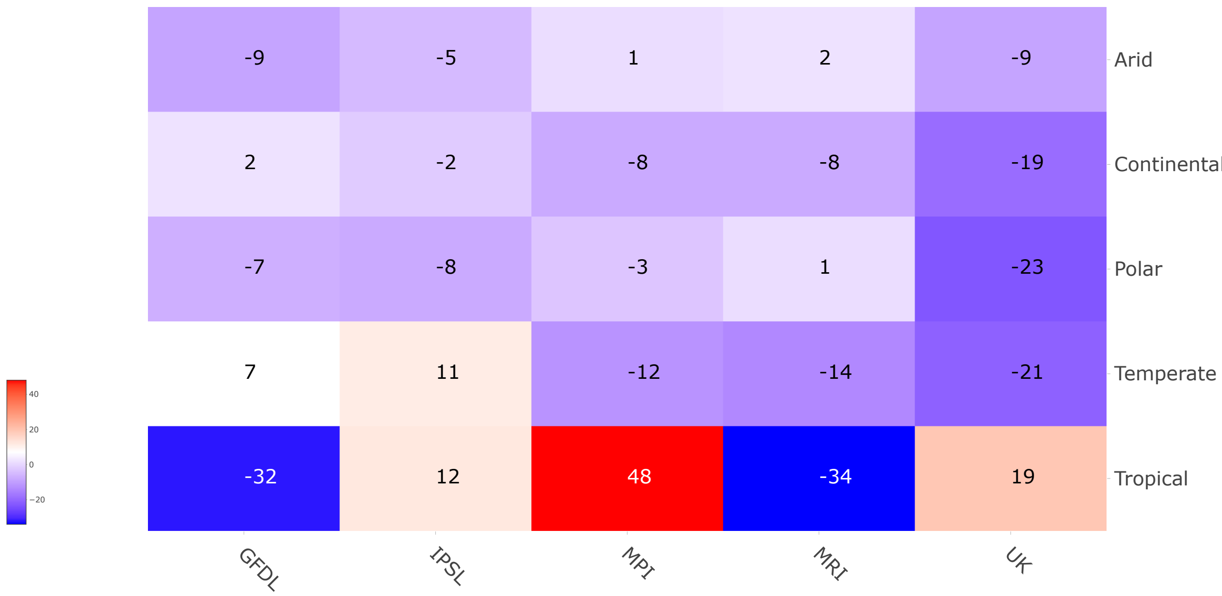

Figure 8. : Heatmaps for SSP1-3.6 year 2050 actual climate projections, for all climate models and regions. Number of days both outside the synthetic-climate distribution and above its median.

Table 1—: Share of each Köppen-Geiger zone k in world's GDP under various assumptions

Region	Arid	Continental	Polar	Temperate	Tropical
2020	0.17	0.206	0.003	0.479	0.142
SSP1	0.176	0.158	0.002	0.444	0.22
SSP3	0.188	0.169	0.002	0.446	0.196
SSP5	0.178	0.16	0.002	0.441	0.219

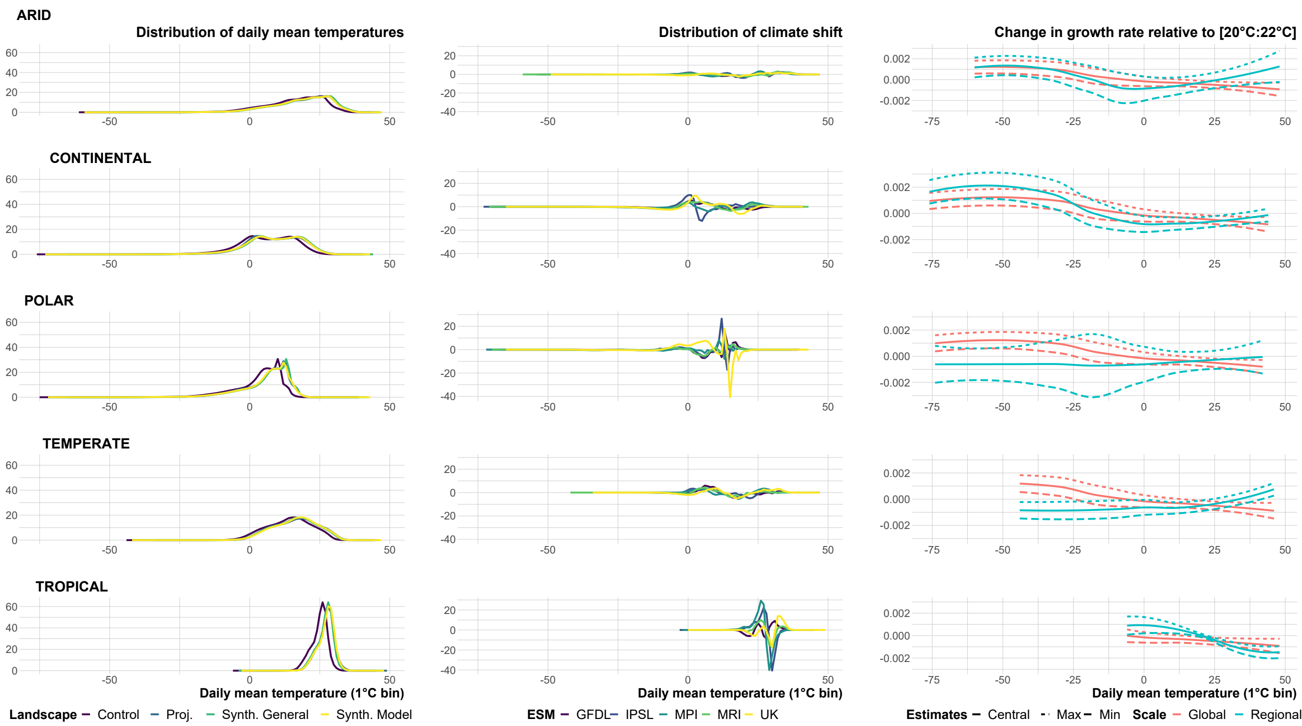

Figure 9. : SSP3-7.0 **Left** Distribution of daily mean temperatures for four different climate landscapes. **Middle** Distribution of climate shift, i.e. difference in distribution of daily mean temperatures under projection vs. a synthetic-model climate. **Right** Change in growth rate from one day in this bin relative to one additional day in [20°C : 22°C].

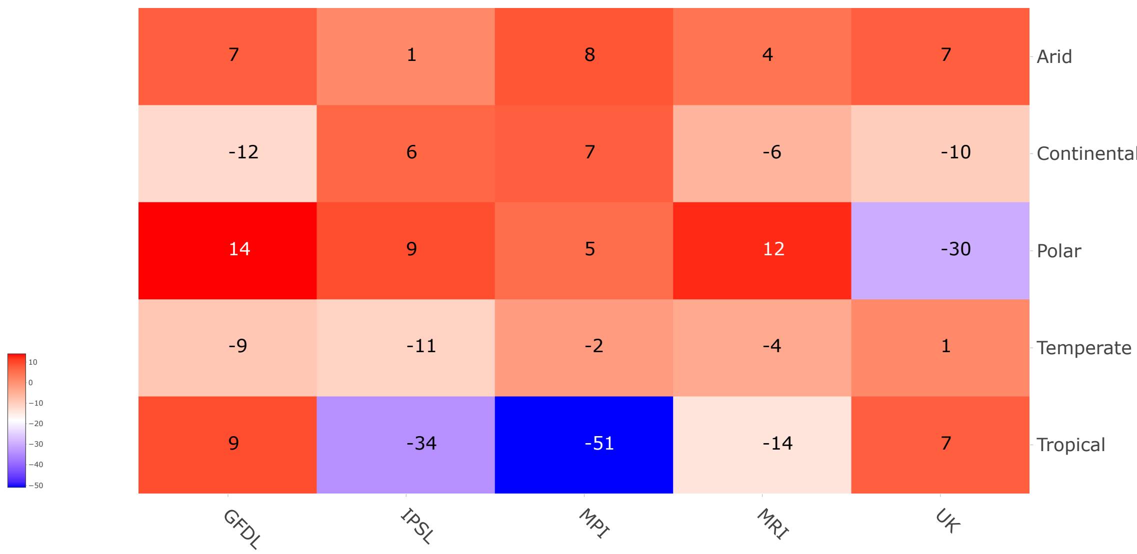

Figure 10. : Heatmaps for SSP3-7.0 year 2050 actual climate projections, for all climate models and regions. Number of days both outside the synthetic-climate distribution and above its median.