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Climate shift uncertainty and economic damages

ASSA/AERE

5 January 2026

Credit: romainfillon.github.io

*Questions: gwagner@columbia.edu; gwagner.com/CSU

OVERVIEW

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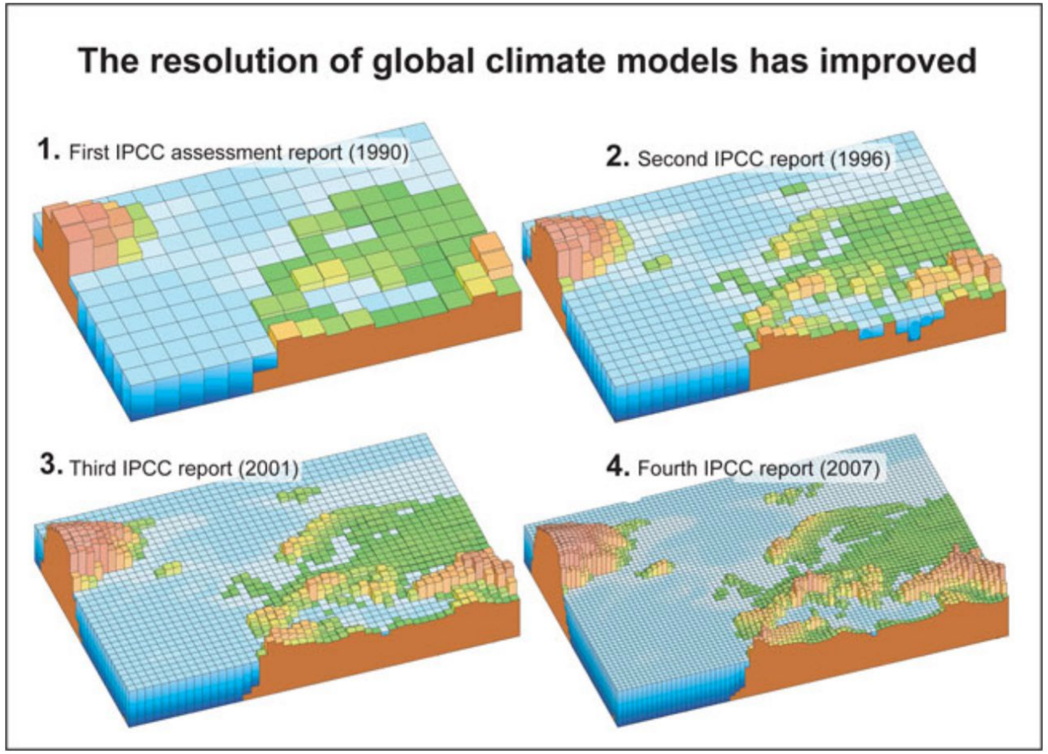

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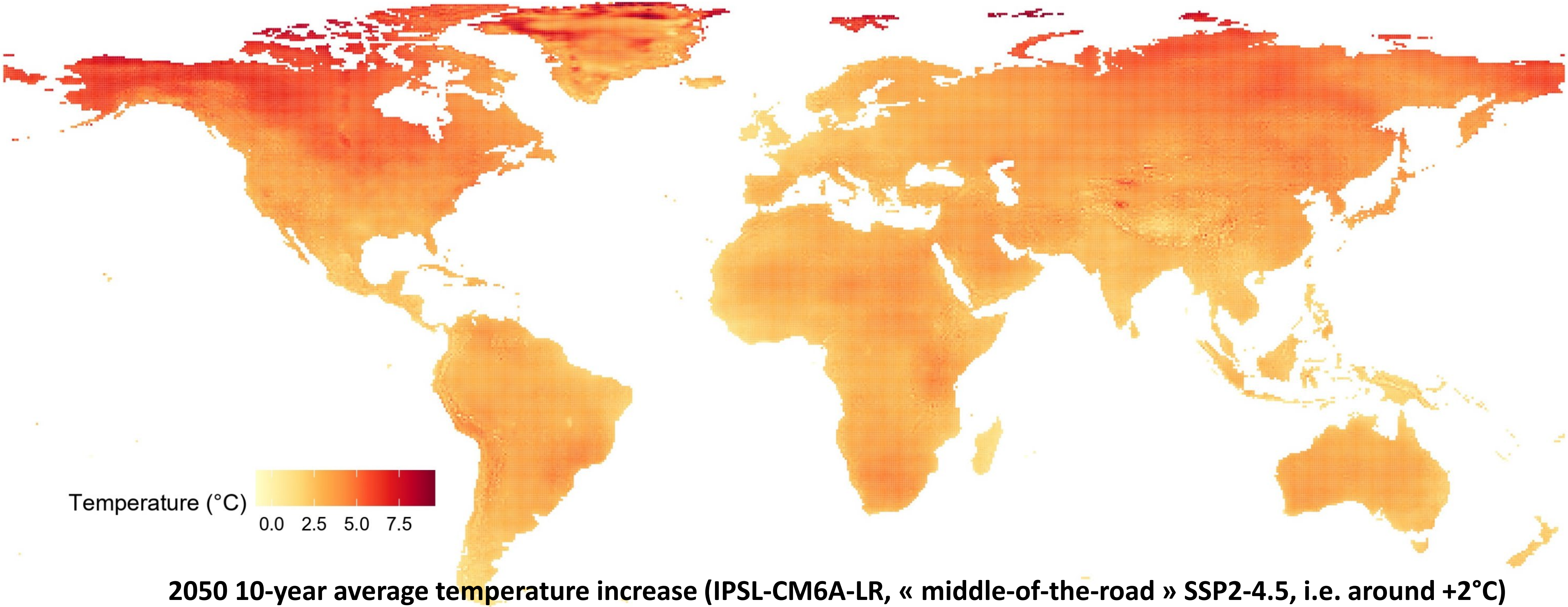
RESULTS:

- Across all scenarios, **2050 global damages are ~25% higher, when accounting for the change in the shape of the entire distribution of daily mean temperatures at the regional scale**.
- Damage are heterogeneously distributed across the world, concentrated in continental areas.

Heterogeneity over space



2050 10-year average temperature increase (IPSL-CM6A-LR, « middle-of-the-road » SSP2-4.5, i.e. around +2°C)

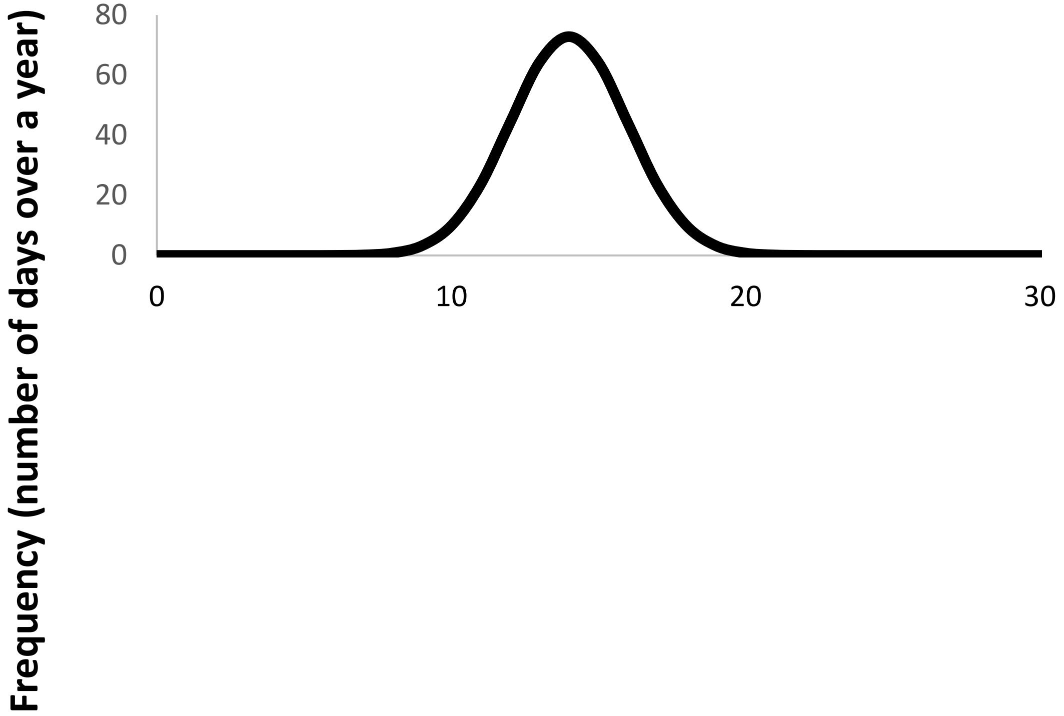
Data winsorized at 99.99% for visualization

Heterogeneity within a year

Illustrative

Annual distributions of daily mean temperatures

Initial distribution



Daily mean surface temperatures

Heterogeneity within a year

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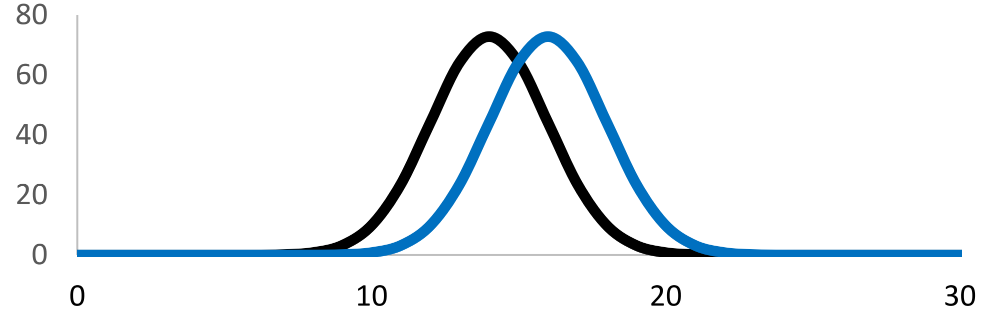

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2°C shape-preserving mean temperature increase

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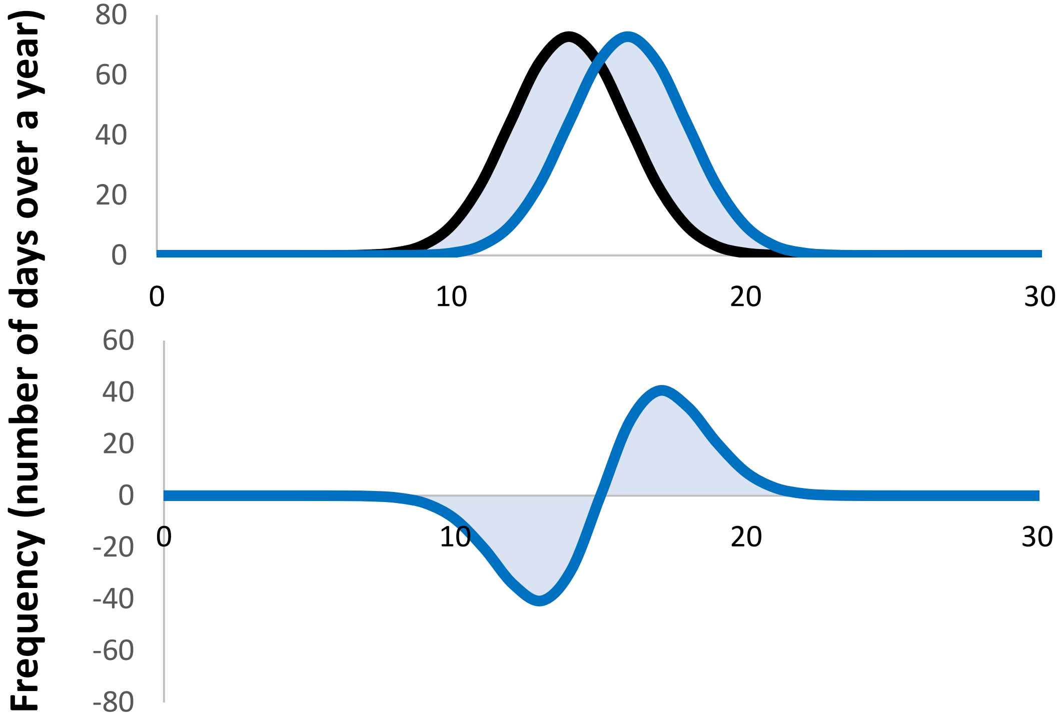

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Climate shift between different distributions

2°C shape-preserving shift

Daily mean surface temperatures

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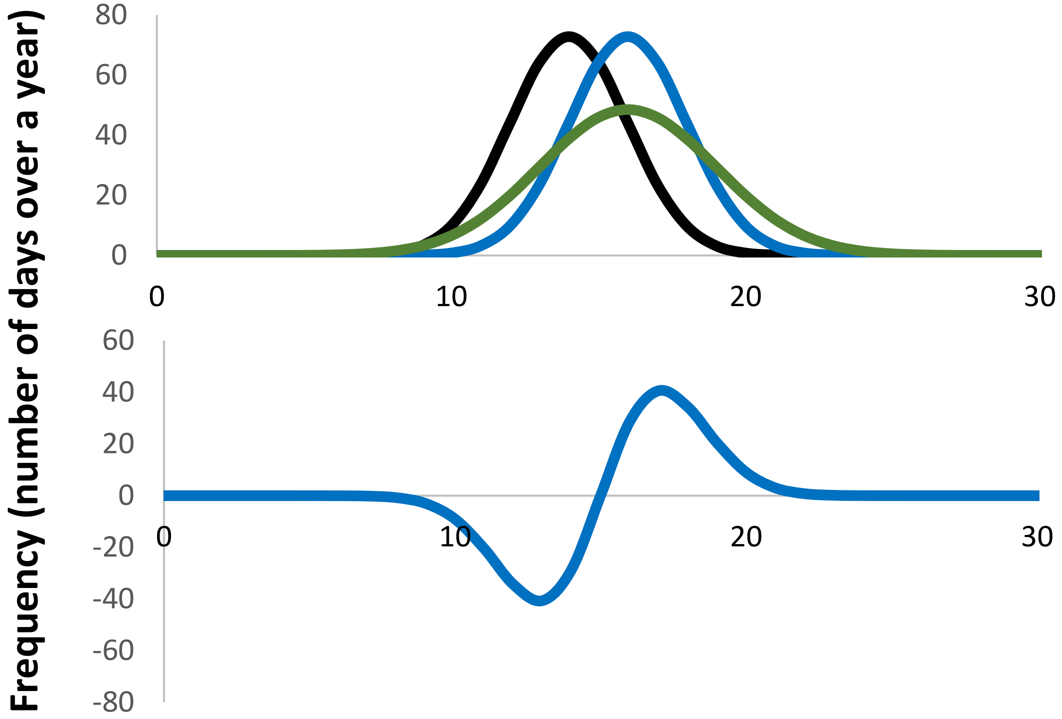

Daily mean surface temperatures

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2°C increase with actual climate projections

e.g. increase in dispersion (σ) of daily mean temperatures

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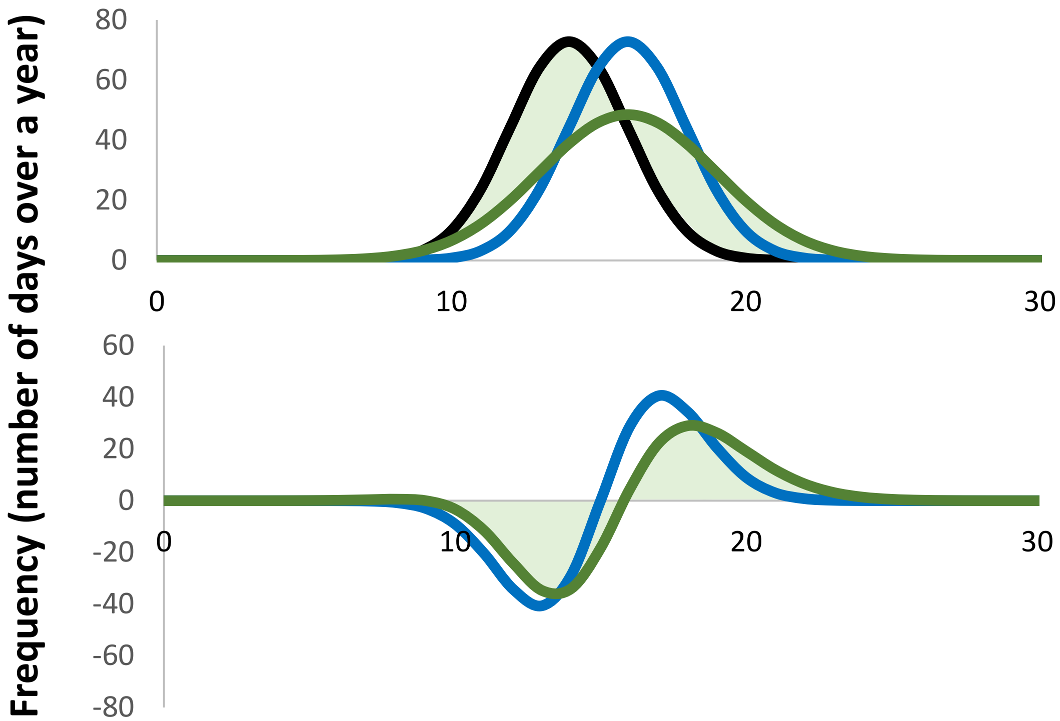

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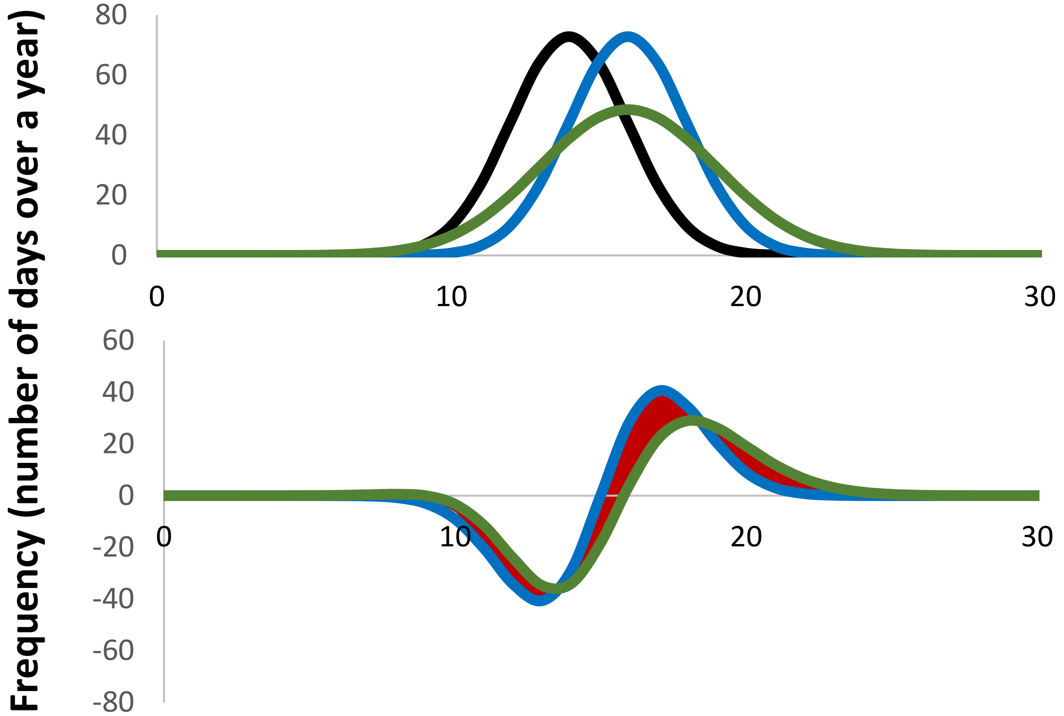

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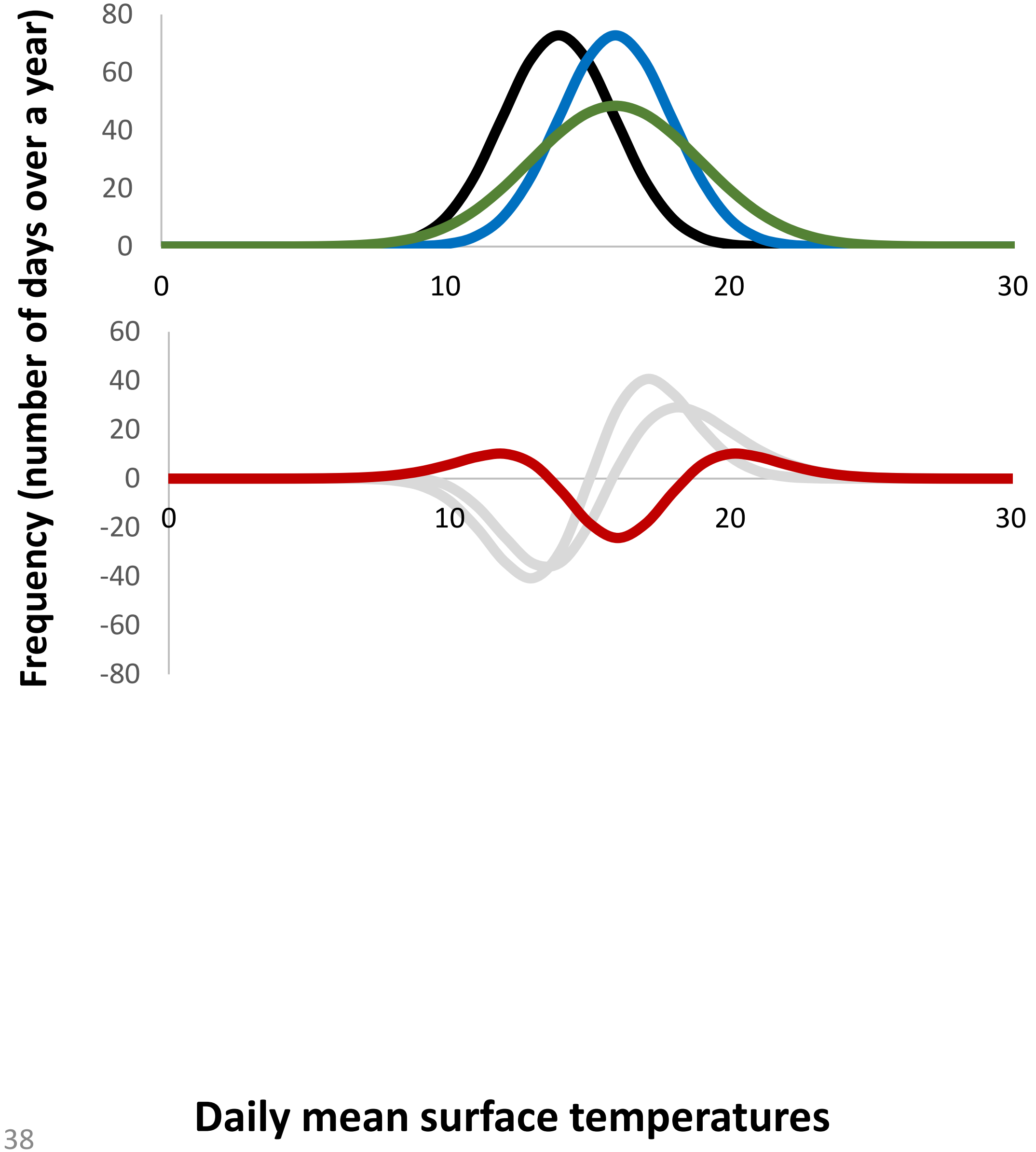

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QUESTION: How does **aggregation** (space, time) bias empirical estimates of climate damages?

CONTRIBUTION: We divide the world into **regions** (Köppen-Geiger climatic zones).
For each region:

- We obtain climate projections of **daily mean temperatures**.
- We estimate **non-linear** damage functions based on **degree-day** models.
- We combine the two and calculate projected **future damages**.

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We obtain the same results with **aggregated** data (climate projection of annual mean temperature, global damage functions) and calculate the **missing damages**.

LITERATURE

In climate economics, climate change is either:

- **Endogenous:** reduced-form climate module that maps carbon emissions to global annual mean temperature changes at the global (Nordhaus, 1994), regional (Nordhaus & Yang, 1996, *AER*), gridded (e.g. Desmet & Rossi-Hansberg, 2024, *RES*) scale. Then, a linear and time-invariant down-scaling factor allows to map global changes to changes at the relevant scale. Even in more complex recent approaches, for instance with climate emulators (Folini et al., 2024, *RES*, Eftekhari et al., 2024, WP), the final climate output is global annual mean.

Underlying assumptions:

1. **Intra-annual shape of the distribution of daily mean temperature in a given location is assumed to remain constant.**

   But external (e.g. solar cycles) and internal factors (e.g. El Niño) might distort future temperature distributions beyond annual mean (Schwarzwald & Lenssen, 2022, *PNAS*).

2. **Relation between global and regional climate change is assumed to remain constant.**

   But there are 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)

LITERATURE

In climate economics, climate change is either:

- **Endogenous:** reduced-form climate module that maps carbon emissions to global annual mean temperature changes.
- **Exogenous**: use climate projections from earth system models. Climate change remains exogenous to economic activities (Bilal & Rossi-Hansberg, WP; Bilal & Känzig, QJE forthcoming; Rudik et al., WP; Fillon, WP)

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 (largely) unclear.

In climate economics, damages from climate change rely on dose-response functions estimated at the global scale. 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, *Restat*).

CLIMATE DATA

Datasets:

- Most recent **CMIP6** bias-corrected and downscaled climate model projections
- 5 ISIMIP Earth system models to span the larger ensemble [**model uncertainty**]
- Forced with emissions from SSP 1-2.6, 3-7.0, 5-8.5 [**scenario uncertainty**]

Three climate landscapes for each Earth System Model (ESM):

- **Control climate without climate change**.
- **Climate projections**.
- **Synthetic climate**. 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 of that ESM, keeping the shape of daily mean temperature distributions unchanged. This yields a **shape-preserving mean-shifted climate** for **each ESM**.

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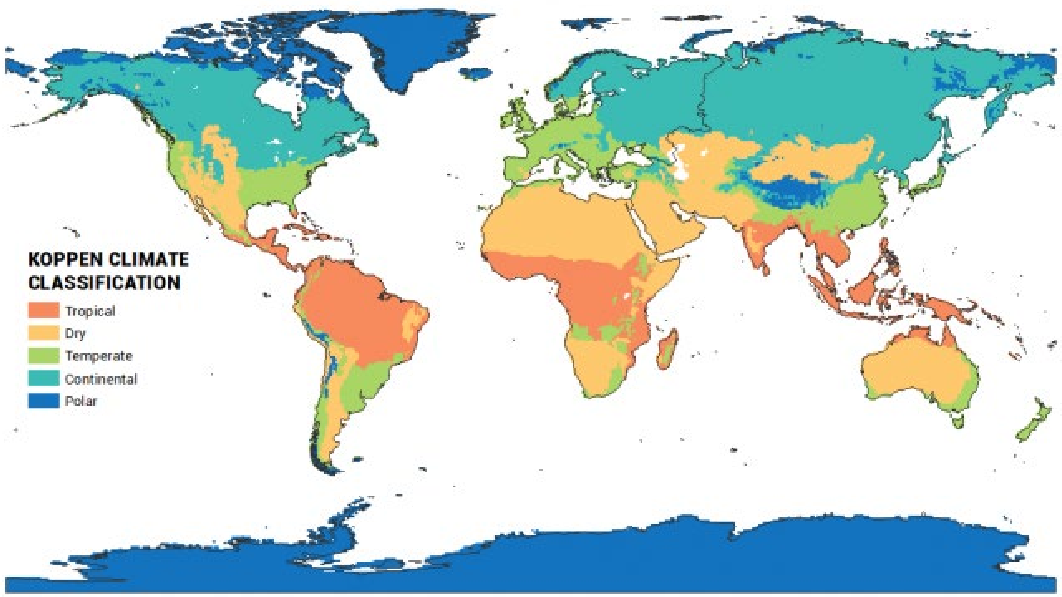
One climate landscape that averages over all ESM:

- **Synthetic climate (ESM average)**. We average the mean 'control' climate over all ESMs and the mean change in annual temperature over all ESMs. This yields a mean shape-preserving, mean-shifted climate that averages heterogeneity between climate models.

ECONOMIC DATA

Data:

- Dataset of subnational GDP per capita DOSE (Wenz et al., 2023, *Scientific Data*)
- Annual distribution of daily mean temperatures from ERA5 climate reanalysis (Hersbach et al., 2020, *QJRMS*), from grid to DOSE-level with population-weighting (99% winsorized)
- Stratification of the sample using Köppen-Geiger climate regions with five categories: arid, continental, polar, temperate, tropical (Beck et al., 2023, *Scientific Data*)



First	Second	Third	Description	Criterion
A			Tropical	Not (B) & $T_{cold} \geq 18$
	f		– Rainforest	$P_{dry} \geq 60$
	m		– Monsoon	Not (Af) & $P_{dry} \geq 100 - \text{MAP}/25$
	w		– Savannah	Not (Af) & $P_{dry} < 100 - \text{MAP}/25$
B			Arid	MAP $< 10 \times P_{threshold}$
	W		– Desert	MAP $< 5 \times P_{threshold}$
	S		– Steppe	MAP $\geq 5 \times P_{threshold}$
		h	– Hot	MAT ≥ 18
		k	– Cold	MAT < 18
C			Temperate	Not (B) & $T_{hot} > 10$ & $-3 < T_{cold} < 18$
	w		– Dry winter	$P_{wdry} < P_{swet}/10$
	s		– Dry summer	Not (w) & $P_{sdry} < 40$ & $P_{sdry} < P_{wwet}/3$
	f		– Without dry season	Not (s) or (w)
		a	– Hot summer	$T_{hot} \geq 22$
		b	– Warm summer	Not (a) & $T_{mon10} \geq 4$
		c	– Cold summer	Not (a or b) & $1 \leq T_{mon10} < 4$
D			Boreal	Not (B) & $T_{hot} > 10$ & $T_{cold} \leq -3$
	w		– Dry winter	$P_{wdry} < P_{swet}/10$
	s		– Dry summer	Not (w) & $P_{sdry} < 40$ & $P_{sdry} < P_{wwet}/3$
	f		– Without dry season	Not (s) or (w)
		a	– Hot summer	$T_{hot} \geq 22$
		b	– Warm summer	Not (a) & $T_{mon10} \geq 4$
		c	– Cold summer	Not (a), (b) or (d)
		d	– Very cold winter	Not (a) or (b) & $T_{cold} < -38$
E			Polar	Not (B) & $T_{hot} \leq 10$
	T		– Tundra	$T_{hot} > 0$
	F		– Frost	$T_{hot} \leq 0$

DAMAGE FUNCTIONS

Empirical specification: “degree-day model” for each Koppen region

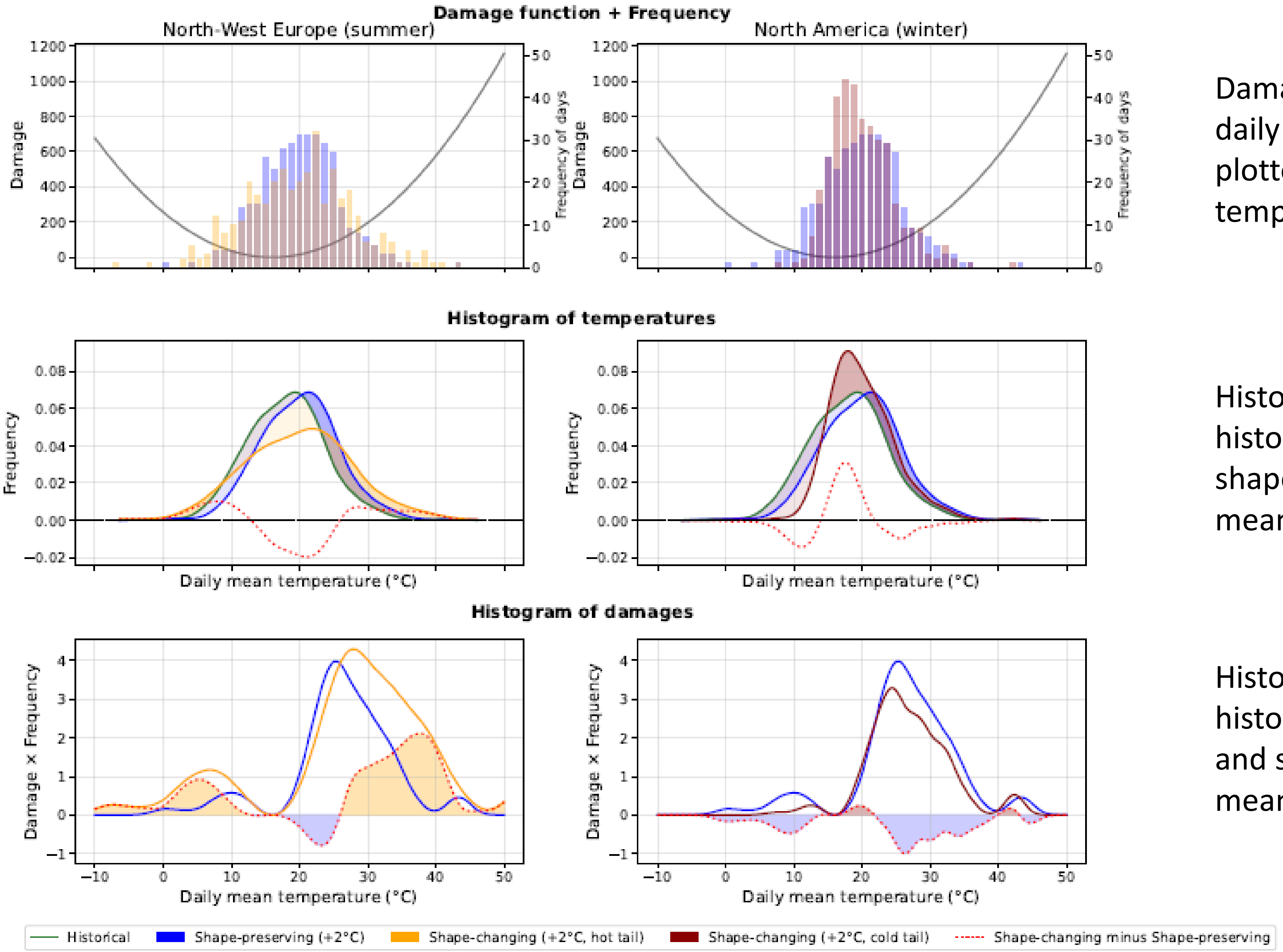
$$g_{it} = P_{it}\beta + \sum_{b=1}^{B} n_{bit}\gamma_b + \alpha_i + \mu_t + \varepsilon_{it}$$

with g the growth rate of *GDP* per capita, total annual precipitation P, number of days n with daily mean temperature in bin b, regional FE α, year FE μ.

In robustness tests we also include region-specific linear time trends.

We smooth the behavior of the point estimates across temperature bins on the whole temperature distribution (Cruz & Rossi-Hansberg, 2024, *RES*).

Examples: European summer & N. American winter



Damage function for different daily mean temperatures plotted against the distribution of temperatures.

Histogram of temperatures for historical, shape-preserving and shape-changing 2°C annual mean temperature increases.

Histogram of damages for historical, shape-preserving and shape-changing 2°C annual mean temperature increases.

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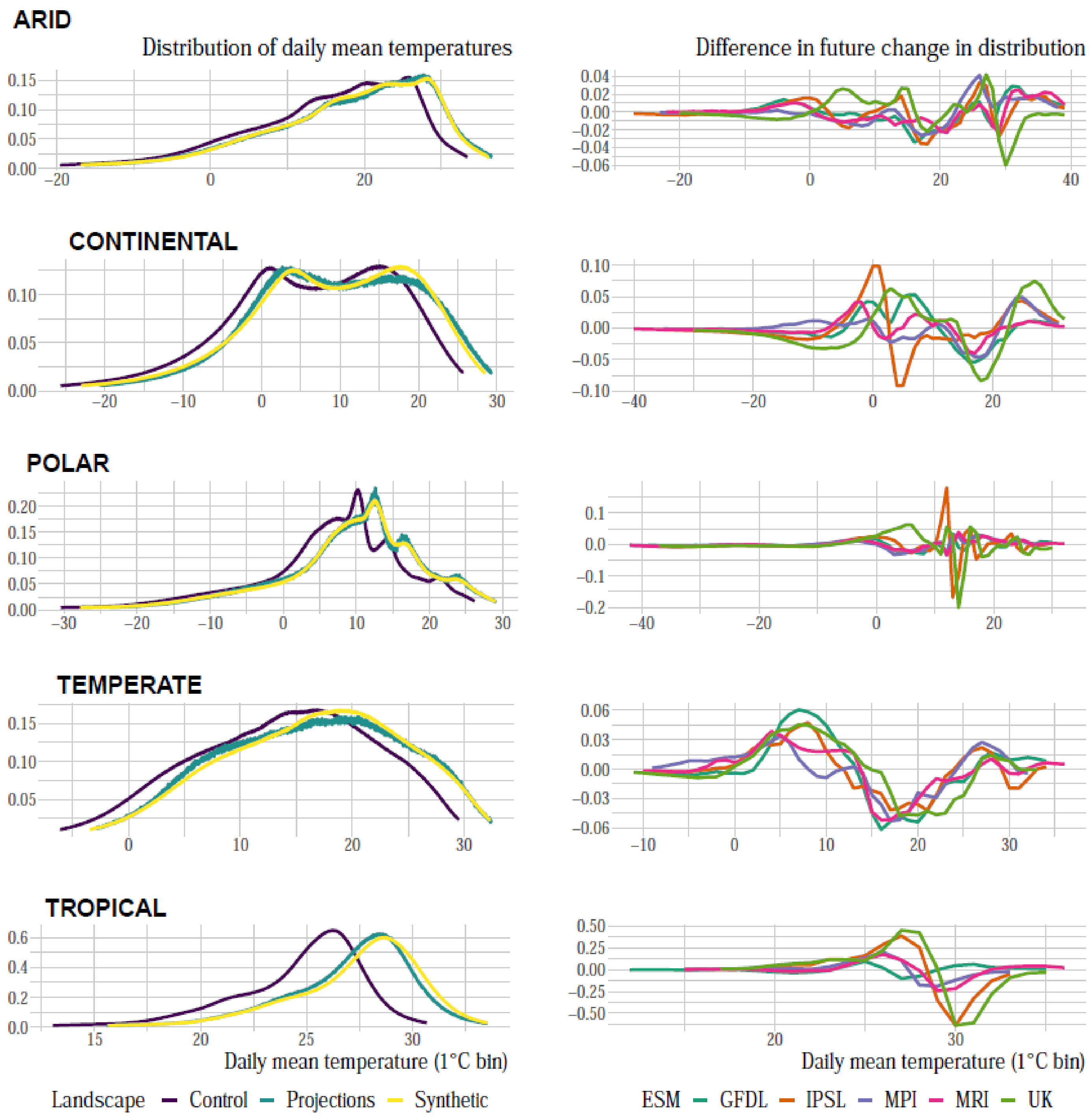

Left Distribution of daily mean temperatures for four climate landscapes.

Right Distribution of climate shift, i.e. difference in distribution of daily mean temperatures under projection vs. a synthetic climate.

Data are for all DOSE regions, SSP5-8.5, 2050. Data is winsorized 1%, x and y-axis differ.

In part significant differences across ESMs.

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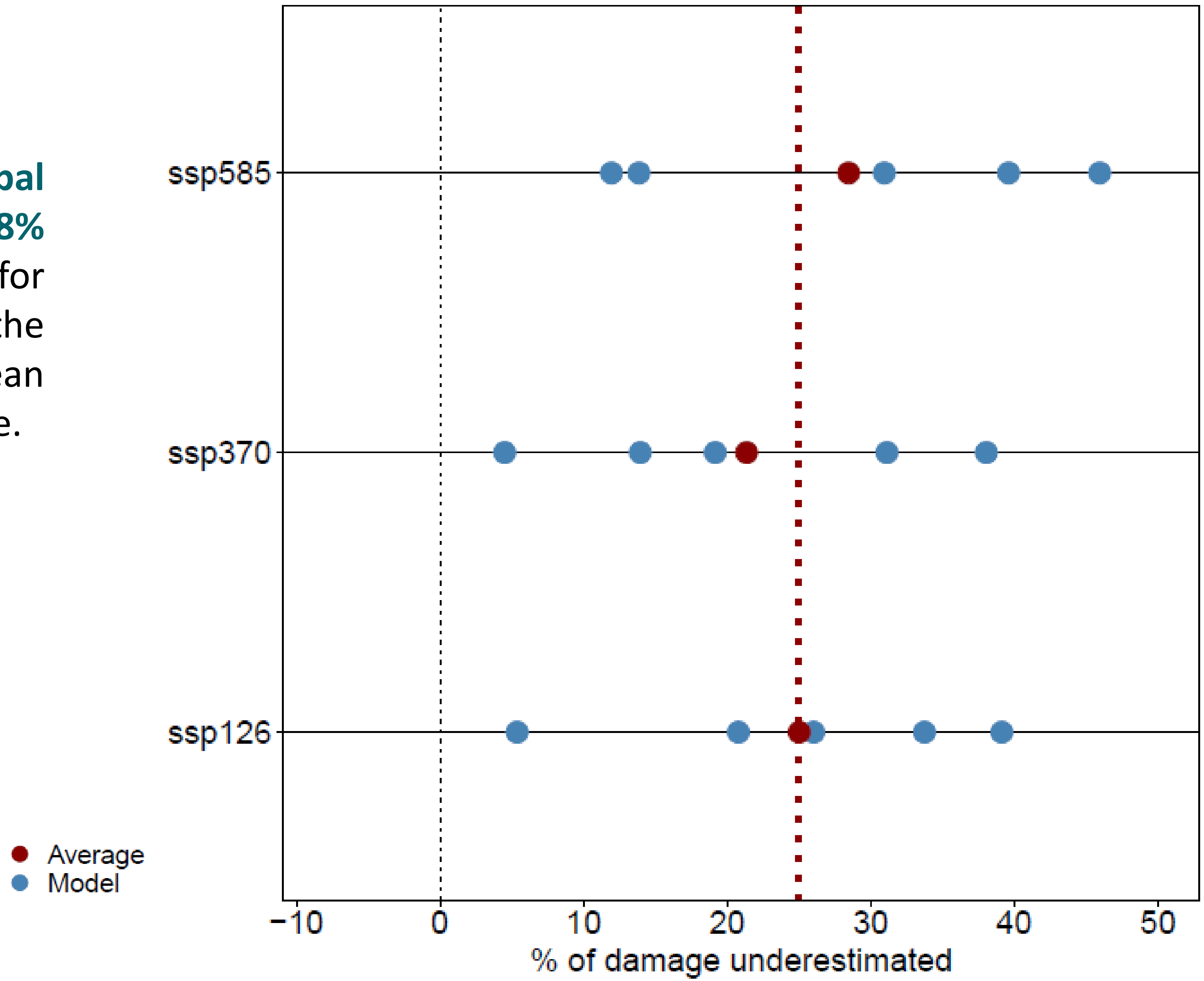
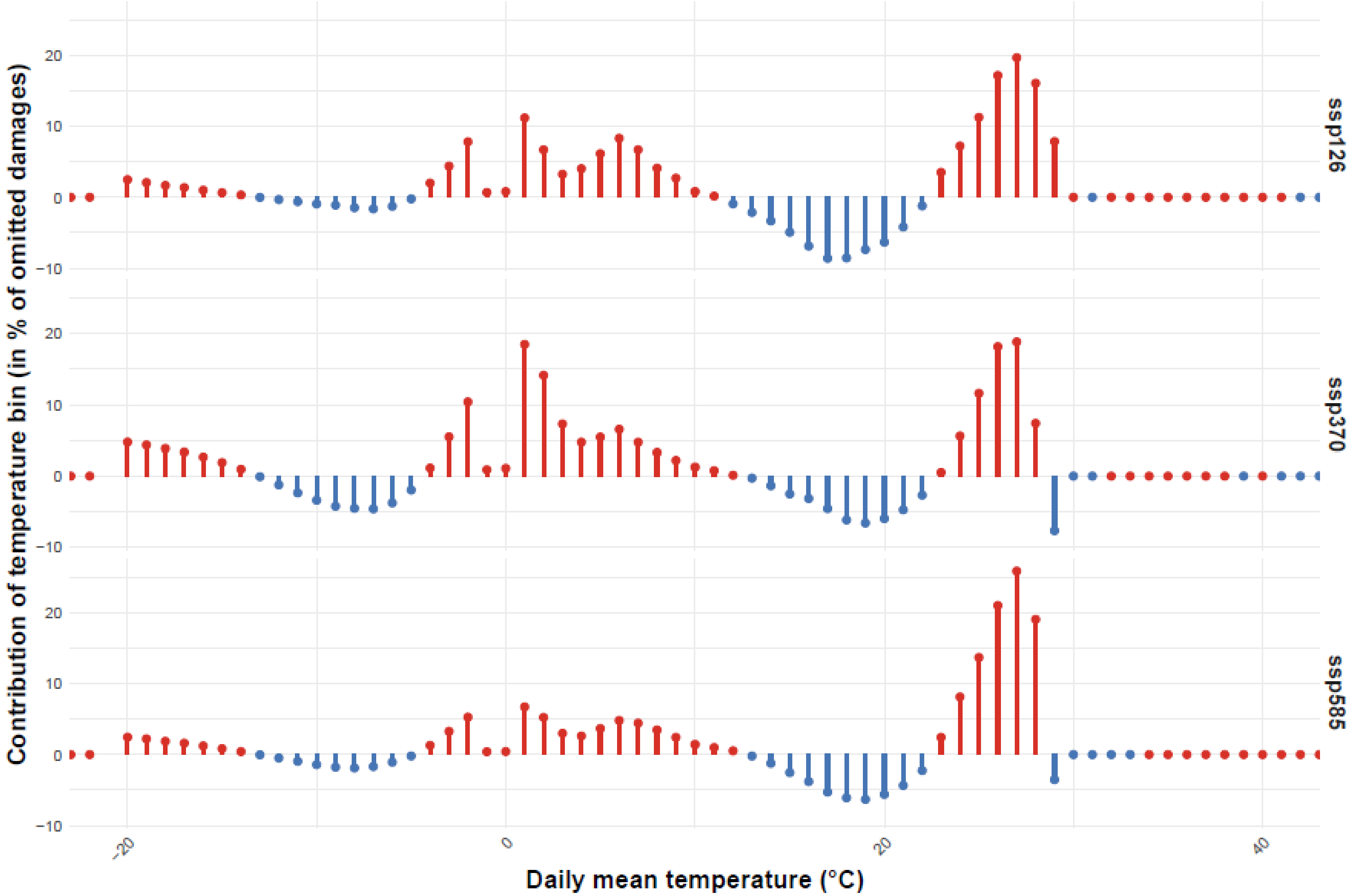
RESULT – AGGREGATE

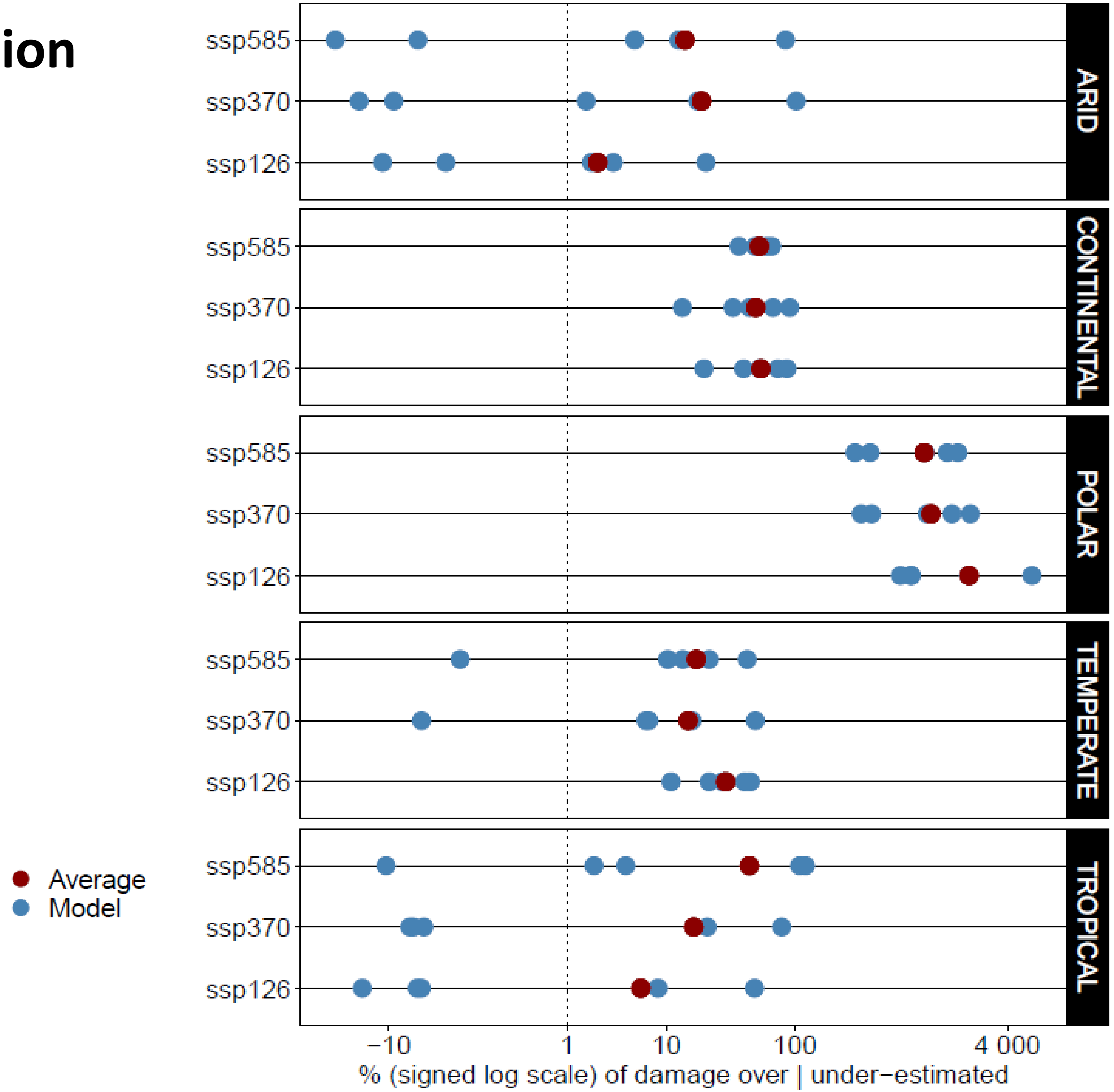
Across all scenarios, **2050 global damages are ~25% higher (21-28% across SSPs)**, when accounting for the change in the shape of the entire distribution of daily mean temperatures at the regional scale.



RESULT – Daily Distribution

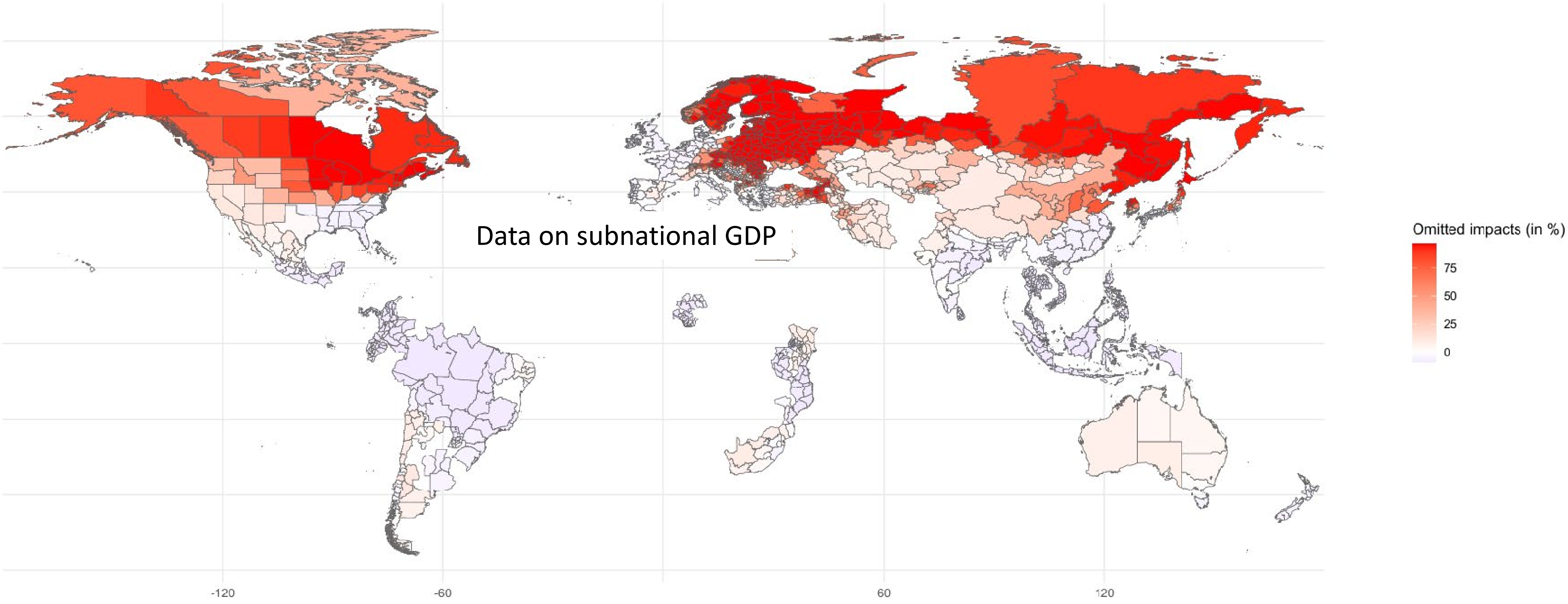


RESULT – Regional Distribution



RESULT – Regional Distribution

Most omitted impacts are in the Northern continental areas



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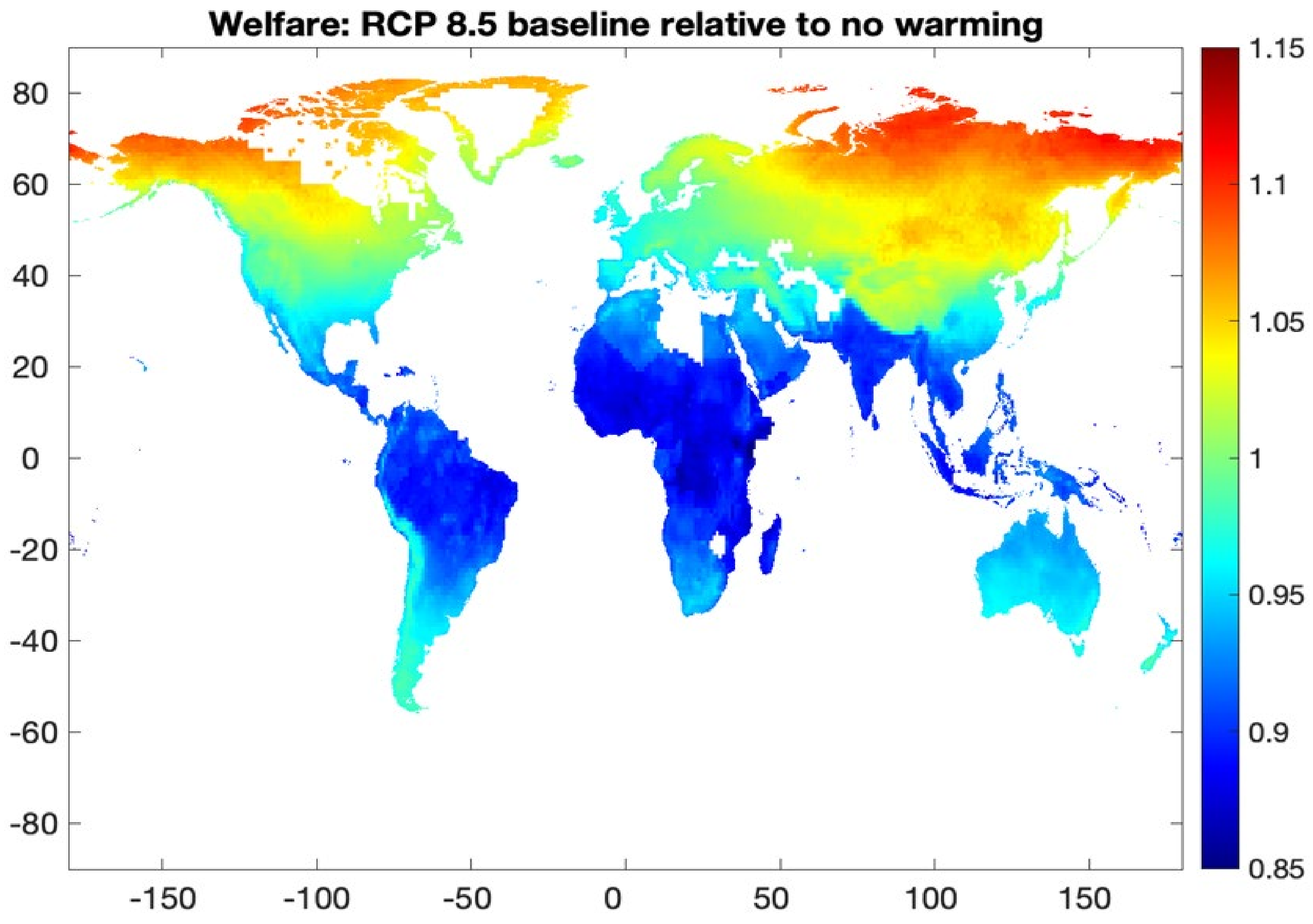
RESULT – Regional Distribution

This matters because we usually assume that aggregate welfare losses at the global scale mask benefits in cold countries in the Northern Hemisphere (e.g. Cruz & Rossi-Hansberg, 2024, RES)



RECAP

METHOD: we combine at the **regional** scale

1. Warming patterns from climate projections of annual distribution of **daily mean temperatures**.

2. Damage patterns empirically estimated with non-linear damage functions.

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2. Results are robust across ESMs and SSPs.
3. The picture of the distribution of damages over the world is affected: northern continental areas show the largest damages from intra-annual changes in temperature patterns.

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PERSPECTIVES

Uncertainty and aggregation in climate economics

Future projections of climate impacts are affected by

1. **internal climate variability**
2. **uncertainty in socioeconomic impact models**
3. **scenario uncertainty** (differences between SSPs)
4. **model uncertainty** (differences between ESMs)

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Next steps:

- Model uncertainty, scenario uncertainty
- Additional costs of climate variability (Kotz et al. 2021, Linsenmeier 2022, Waidelich et al. 2024)

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