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RIME-X v1.0: Combining Simple Climate Models, Earth System Models, and Climate Impact Models into a Unified Statistical Emulator for Regional Climate Indicators

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Abstract. Many tasks in climate science, including climate impact assessment, scenario analysis, and end-to-end attribution, require efficient methods to translate a wide range of emissions scenarios into regional-scale climate indicators while explicitly accounting for uncertainty. Climate and impact model emulators are statistical models that approximate selected outputs of comprehensive models and can perform this translation. The Rapid Impact Model Emulator (RIME) uses individual simulations from climate or impact models to empirically relate global mean surface air temperature (GMT) levels to regional-scale indicators, enabling the conversion of GMT trajectories, commonly derived from Simple Climate Models (SCMs), into time series of regional climate impacts. Here, we present the Rapid Impact Model Emulator Extended (RIME-X), an extension of the RIME framework that replaces deterministic emulation of individual models along single GMT trajectories with a probabilistic approach. RIME-X combines ensemble simulations of GMT derived from SCMs with warming-level-dependent regional indicator distributions estimated from weighted Model Intercomparison Project (MIP) data. This results in scenario-dependent, time-evolving probability distributions of regional indicators. By jointly quantifying global and regional sources of uncertainty from the start, RIME-X enables systematic exploration of the full space of plausible regional climate impact trajectories under different emissions scenarios. The method is applicable to regional indicators whose distributions are predominantly determined by warming level and provides a computationally efficient framework for uncertainty-aware regional indicator emulation. We provide an open-source Python implementation of RIME-X, including preprocessing workflows for data from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) and support for user-defined indicators.

https://doi.org/10.5194/egusphere-2025-5781
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1 Introduction

Regional impacts of climate change are typically assessed by analyzing simulations of the climate system and its impacts on other systems under assumed greenhouse gas emissions scenarios. This process involves a chain of models: emissions scenarios are generated by integrated assessment models (IAMs), then passed into Earth system models (ESMs) to simulate the response of the climate and Earth system, and finally, the ESM output is translated into sectoral impacts (e.g., on hydrology or the economy) using impact models (Jones et al., 2024). Every step of the modeling chain introduces an additional layer of uncertainty. In this study, we refer to these uncertainties as follows: **Scenario uncertainty** stems from different possible trajectories of future emissions. **Global climate response uncertainty** involves unknowns in key parameters that shape the Earth system's global response to emissions. **Model uncertainty** reflects differences in how various ESMs or impact models represent the response to the same scenario. Finally, **natural variability** arises from the chaotic nature of the climate system, where small differences in initial conditions can amplify over time and lead to different climate outcomes, even when using the same model to simulate the same scenario (Rising et al., 2022; Stainforth et al., 2007; Hawkins and Sutton, 2009). Analyzing the combined uncertainty from these different sources is essential for understanding the full range of possible future climate change, its impacts, and resulting risks. Model intercomparison projects (MIPs) attempt this analysis by using a diverse ensemble of ESMs or impact models to simulate a set of common emissions scenarios. Running the same ESM repeatedly with the same forcing but different initial conditions helps to assess natural variability (Deser et al., 2020). However, MIPs face key limitations. Due to the high computational costs of the ESMs, they can only cover a limited set of scenarios, and often models are not run multiple times to capture natural variability (Edwards et al., 2019). Additionally, MIP ensembles include a limited number of models that often share components, making them "ensembles of opportunity" rather than systematically designed samples of model uncertainty (Masson and Knutti, 2011; Knutti et al., 2010). Other tools have been developed on top of MIP datasets to address their limitations and enable a more efficient and comprehensive exploration of uncertainty in climate projections. Model weighting techniques reweight MIP outputs into probabilistic ensembles, accounting, for example, for model independence and performance against historical observations. This allows a more structured and empirically grounded exploration of model uncertainty (e.g. Brunner et al., 2020b). Simple climate models (SCMs) simulate key global climate indicators like global mean temperature (GMT) or global mean sea-level rise. Their simplicity enables running probabilistic ensemble simulations based on parameter sets constrained by historical observations and known ranges of Earth system parameters, enabling systematic exploration of scenario and global climate response uncertainty (e.g. Meinshausen et al., 2011a, b; Smith et al., 2018; Leach et al., 2021; Gasser et al., 2017; Nauels et al., 2017; Sandstad et al., 2024; Dorheim et al., 2024). Regional climate emulators extend SCMs by translating global climate states into regional climate indicators. The most common method is pattern scaling, which infers linear relationships between GMT and regional variables from ESM data (used in e.g. Frieler et al., 2012; Herger et al., 2015; Osborn et al., 2016; Kitsios et al., 2023; Mathison et al., 2025). Other methods include time slicing, which reconstructs new scenarios by assembling slices from existing simulations (Tebaldi et al., 2022) and impulse response functions, which predict the regional climate response across multiple timescales directly from forcing (Womack et al., 2025; Sandstad et al., 2025). To represent natural variability, emulators often incorporate randomization

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

elements, such as statistical generators (e.g. Beusch et al., 2020; Nath et al., 2022; Quilcaille et al., 2022; Schöngart et al., 2024). These methods support a more holistic bottom-up exploration of scenario uncertainty, global climate response uncertainty, model uncertainty, and natural variability for a set of regional indicators by repeatedly emulating those indicators for multiple scenarios and GMT pathways using emulator instances calibrated on different ESMs. However, this "bottom-up" uncertainty analysis by generative emulation faces practical limitations. Producing large emulated ensembles requires significant storage and manual calibration effort. Many emulators are variable-specific and rely on assumptions about the distribution of the variable or its relationship to GMT, which may influence the uncertainty analysis itself. Moreover, since regional emulators are trained on ESM data, they inherit the “ensemble of opportunity” limitation. To overcome these challenges, we present the Rapid Impact Model Emulator Extended (RIME-X)—a novel, top-down probabilistic emulator designed as a probabilistic extension to the deterministic Rapid Impact Model Emulator (RIME) (Byers et al., 2025). RIME uses available simulations from a climate or impact model to construct a mapping which links GMT levels to values of a regional indicator by extracting values simulated by the model at different GMT levels and interpolating linearly between them. This mapping is then applied to a GMT pathway derived from an SCM to emulate the response of the regional indicator to a given emissions scenario. Individual emulations by RIME are subject to the aforementioned uncertainties. Model uncertainty arises from the choice of the climate or impact model underlying the mapping and natural variability is introduced through the selection of simulation and the specific data points used within this simulation to construct the mapping. Global climate response uncertainty is further incorporated through the selection of GMT time series from the SCM ensemble to which the mapping is applied to generate the emulation. However, these uncertainties are not directly quantified within RIME. RIME-X extends on RIME by directly emulating distributions of regional climate and impact indicators, thereby jointly quantifying all uncertainties associated with RIME emulations. It leverages probabilistic SCM ensembles to generate prior distributions of GMT responses to emissions scenarios, uses weighted MIP data to construct conditional distributions of regional indicators at given GMT levels, and combines these into scenario- and time-dependent distributions of the regional indicators that constitute the emulation. These distributions capture global climate response uncertainty as simulated by an SCM, model uncertainty in the regional response to global climate states across a weighted MIP ensemble, and natural variability across a multitude of simulations in one output distribution. By extracting the regional indicator distribution from weighted MIP data and constraining it with an SCM-derived GMT prior, RIME-X can also help to address common challenges in the probabilistic interpretation of MIP-derived distributions, including inter-model dependencies (Brunner et al., 2020b) and the hot model problem, an observation in CMIP-6 that many models warm faster than expected from other lines of evidence (Hausfather et al., 2022). RIME-X emulations are quickly generated, scenario-flexible, assumption-light, and suitable for the wide range of regional climate and climate impact indicators whose distribution is mainly dependent on the GMT level—including those with non-normal distributions or nonlinear behavior, such as precipitation or temperature extremes (Philip et al., 2020). The emulator supports indicators aggregated using various weighting approaches (e.g., area-weighted, population-weighted, or GDP-weighted) over a user-defined region (such as a continent, country, subdivision, grid point, or custom region) and for user-specified periods (which could span multiple years, a season, a month, a day, or any custom-defined period). In this paper, we describe the exact

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

methodology of RIME-X in section 2, explore its limitations, and develop a validation approach in section 3, and conclude in section 4.

2 Methodology

This section introduces relevant notation in section 2.1, followed by the development of the RIME-X approach, which is detailed in section 2.2. Section 2.3 outlines the implementation of the method within the `rime` Python package. Finally, we illustrate the capabilities of the RIME-X method in Section 2.4 by showcasing selected examples of emulations conducted with RIME-X.

2.1 Notation

Climate simulations for a given emissions scenario s, initial condition e, simulated by model m can be formally represented as tensors

$$(V_1, \ldots, V_n)_{\text{lat},\text{lon},t,s,m,e},$$

where each variable V_i (e.g., temperature, precipitation) is defined at spatial coordinates (lat, lon) and time t. To investigate and quantify the development of the regional climate, we look at time series $IM_{t,s,m}$ of indicators IM, defined as functions

$$IM = F(V_1, \ldots, V_n),$$

and aggregated over a specific region r. An indicator IM may represent a direct climate variable, such as monthly temperature; an impact-relevant compound indicator, such as the wet bulb globe temperature; or an impact indicator derived from an external impact model (e.g., a hydrological model), which is forced with the climate variables simulated by the ESM and which outputs quantities such as projected flood depths. The aggregation typically consists of a weighted average or sum over the relevant grid points within a region over a time period. A region may represent a country, an administrative unit, or a single grid cell. The resulting time series describes how a model simulates climate conditions or their impact in a region under the specified scenario.

2.2 RIME-X

RIME-X is designed to probabilistically emulate the response of IM to arbitrary emission scenarios s as a distribution quantifying the associated uncertainties. Formally, RIME-X aims to approximate all quantiles V_p of the distribution of the regional indicator IM, defined by

$$P_{s,y}(IM \leq V_p) = p.$$

The distribution quantifies the uncertainty in the response of the regional indicator IM to a given emissions scenario s in year y, incorporating (i) global climate response uncertainty represented by an ensemble of SCM simulations and (ii) model and natural variability in the mapping from GMT to IM derived from ESM simulations in a MIP (e.g. CMIP or ISIMIP; Eyring

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

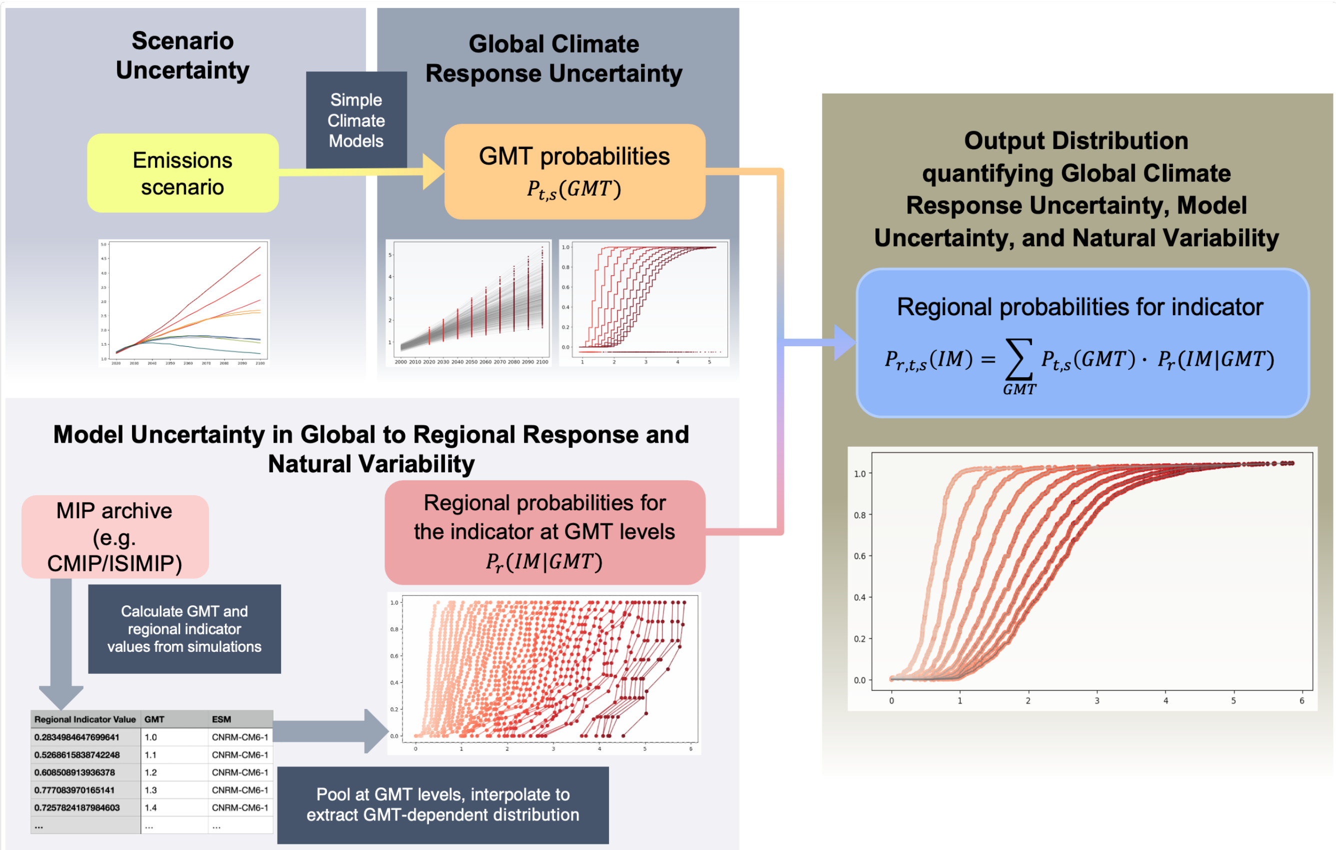

Figure 1. Schematic overview of RIME-X. We extract a scenario-specific GMT distribution from an SCM simulation ensemble and a GMT-specific distribution of a regional indicator from MIP data. Afterwards, we combine the two distributions to form a scenario-specific distribution of the regional indicator. RIME-X estimates quantiles of this output distribution by applying a Monte Carlo sampling procedure to both the GMT and indicator distributions.

et al., 2016; Warszawski et al., 2014), referred to as the training dataset. The estimation of the quantiles V_p in RIME-X is based on all values of IM simulated in the training dataset and all plausible GMT trajectories generated by the SCM ensemble for the target scenario s. RIME-X proceeds through the following three steps, utilizing a discretization of the GMT variable as described in section 2.2.1:

1. **Sampling GMT**: Draw GMT samples from a discretized prior GMT distribution for the scenario s and year y with probabilities $P_{s,y}(GMT)$, derived from the SCM ensemble as detailed in section 2.2.2.

2. **Sampling IM values conditioned on GMT**: For each GMT sample, draw corresponding samples of IM from a distribution of IM conditional on the GMT variable with probabilities $P(IM \mid GMT)$. The conditional distribution

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

is estimated from all values of IM simulated in the training dataset, with each value weighted according to the ESM that produced it, as detailed in sections 2.2.3 and 2.2.4.

3. **Quantile estimation**: Compute the quantile V_p from the IM samples. As outlined in section 2.2.5, RIME-X is effectively an application of the law of total probability, which ensures that the samples of IM behave like samples from the marginal distribution with probabilities $P_{s,y}(IM) = \sum_{GMT} P(IM \mid GMT) \cdot P_{s,y}(GMT)$.

Using a GMT distribution extracted from SCM simulations as a prior to constrain the conditional distribution of IM, derived from weighted MIP data, is expected to help mitigate challenges commonly associated with the probabilistic interpretation of conventional MIP-derived distributions—such as the hot model problem (Hausfather et al., 2022) and model interdependencies (Brunner et al., 2020b).

2.2.1 Discretization of the GMT variable

To approximate both the prior probability for the GMT and the conditional probabilities $P(IM|GMT)$ (without assuming any specific functional forms), we first divide the entire simulated range of GMT from the training dataset into evenly spaced bins of size ΔT; in practice, we typically set $\Delta T = 0.1\,\mathrm{K}$. These bins are denoted as GMT-bins $B_{GMT}(i)$ and span the entire range from $\min(GMT)$ to $\max(GMT)$ as observed in the training dataset. As explained in sections 2.2.2, 2.2.3, and 2.2.5, this binning procedure enables the sampling of GMT values according to discrete probabilities associated with each bin and allows the construction of a conditional distribution for IM, conditioned on discretized GMT values.

2.2.2 Approximating the GMT distribution from SCM ensemble simulations

To quantify global climate response uncertainty to emissions, we approximate the likelihood that in the emissions scenario s and year y a certain GMT level is reached using SCMs such as MAGICC and FaIR, run for the given emissions scenario. SCMs translate greenhouse gas emissions into pathways for globally defined atmospheric variables such as the GMT using a simple carbon cycle model, a set of energy balance equations, distributions of climate system properties from the scientific literature, and observational constraints. They can also be expanded to simulate important variables from other Earth system components such as mean global sea level rise (Meinshausen et al., 2011a, b; Nauels et al., 2017; Leach et al., 2021).

However, as some key climate system properties of the Earth influencing the global climate response to emissions cannot be unambiguously determined, SCMs run many times, making differing plausible assumptions about the values of these properties. As a result, they generate a set of plausible trajectories of certain global variables (primarily GMT), which is probabilistically interpretable due to their systematic parametrization process and can be used to quantify parameter uncertainty in the global climate response of the Earth system to the emissions scenario. Formally, SCMs provide their output as a set of ensemble simulations $GMT(y,s,e)$ for years y, emission scenario s and ensemble members $e \in E$ (which differ from other ensemble members by making different underlying assumptions on the climate system properties). Figure 2 (a) shows an example for such an ensemble simulation. From this data we can approximate the probability of each GMT level being reached in year y and emission scenario s by simply counting the number of ensemble members for the SCM simulation of scenario s

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

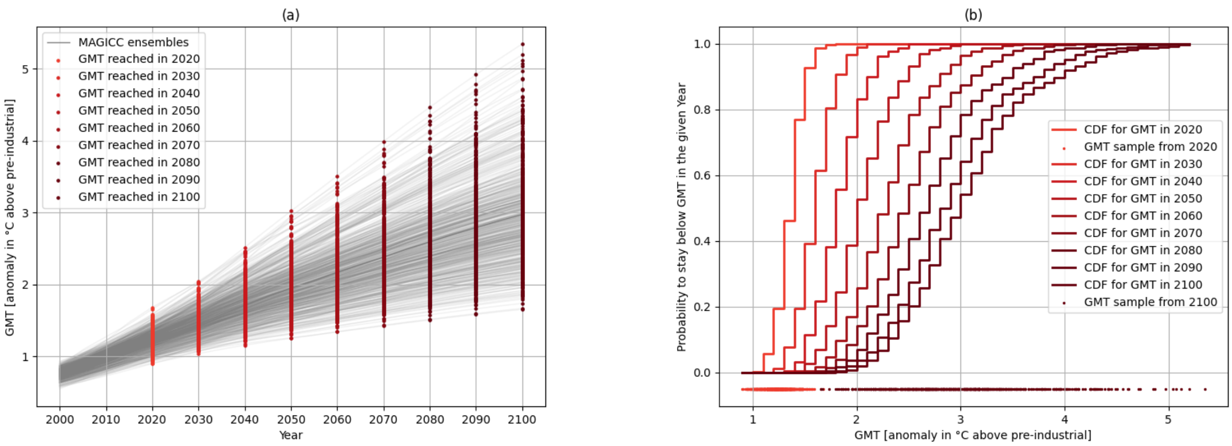

Figure 2. GMT outcomes for 600 ensemble simulations generated with the simple climate model MAGICC for the Climate Action Tracker's current policy scenario are (a) depicted as time series highlighting the GMT levels reached in each simulation in decadal steps and (b) as the corresponding cumulative distribution functions. The dots on the x-axis in (b) show the GMT levels reached in the respective MAGICC ensemble simulations in 2020 and 2100, which are used for the approximation. The step form of the CDF stems from the discretization of the GMT variable.

that lie in a given predictor bin of size ΔT in year y and dividing it by the total number of ensemble members $|E|$, thus

$$P(GMT)_{s,y} = P_{s,y}(T_i \leq GMT < T_i + \Delta T) \approx \frac{|\{e|GMT(y,s,e) \in B_{GMT}(i)\}|}{|E|}.$$

Here, $(T_j)_{j=1..N}$ form an evenly spaced partition of the temperature range in the calibration dataset, such that a temperature bin $B_{GMT}(j)$ is defined for all GMT values x satisfying $T_j \leq x < T_j + \Delta T$. The index i denotes the temperature bin corresponding to the GMT value under consideration. An example of a cumulative distribution function derived with this method can be seen in Figure 2 (b). Note that we can only define probabilities for GMT levels like we do here because we discretized the GMT variable.

2.2.3 Approximating the distributions of regional indicators conditioned on GMT

To estimate the probability of IM conditioned on the discretized GMT level that quantifies model uncertainty in the response of IM to global climate conditions, we first collect all simulated values for IM from the training dataset along with the discretized GMT level at the time the value is simulated. In a second step we group all values for IM in bins $B_{IM}(GMT)$ according to their corresponding GMT levels. We finally assign a weight to all values within each bin according to the ESM they were simulated with using a selected model weighting scheme (more on them in section 2.2.4). We obtain the final conditional probabilities $P(IM \mid GMT)$ of values of IM conditioned on the discretized GMT variable using weighted linear interpolation between the values grouped into each individual bin. Figure 3 shows the cumulative probability functions of the resulting conditional distribution for the 21-year mean of regional temperature in Germany compared to the 2005 to 2015

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

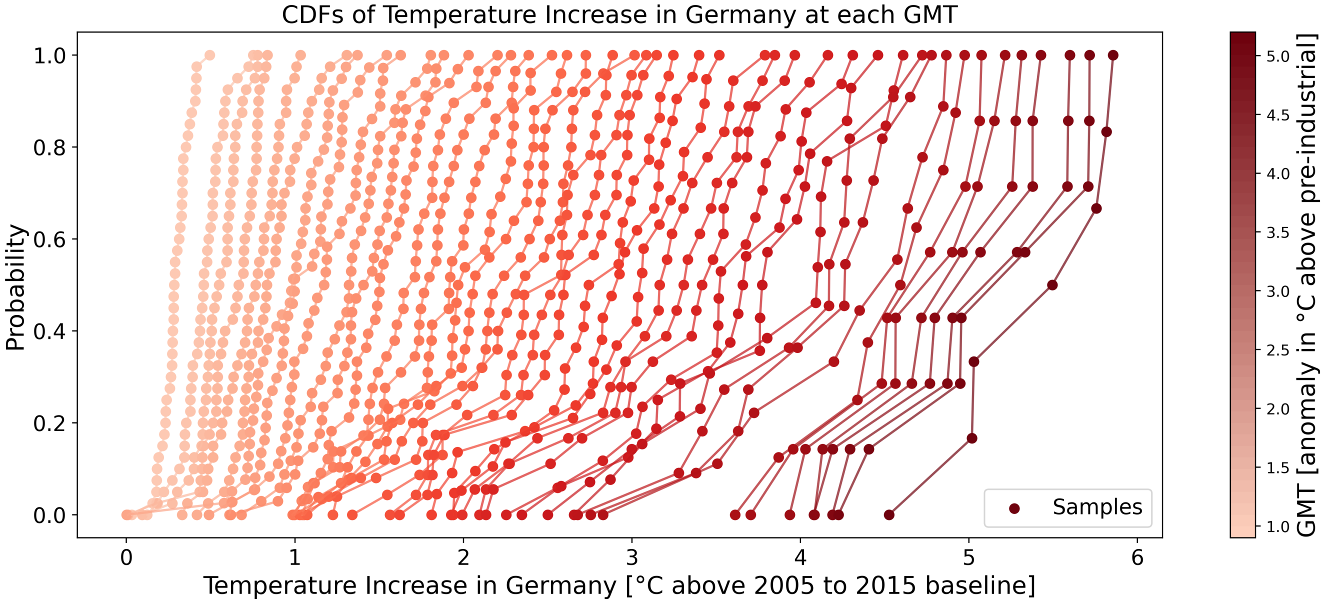

Figure 3. Approximations of the conditional cumulative distribution functions (CDFs) of a regional impact (here the 21-year mean of regional temperature in Germany compared to the 2005 to 2015 baseline) at each GMT level. It is extracted from a subset of the ISIMIP3b input simulations for the tas variable using equal model weighting. The points correspond to samples taken from the ISIMIP simulations.

baseline at each GMT level, as extracted from a subset of the ISIMIP3b input simulations of the tas variable using equal model weighting. Note that we only have the ability to collect several values of IM in bins $B_{IM}(GMT)$ and extract the distribution because we discretized the GMT variable.

2.2.4 Model weighting approaches

When using MIP datasets like CMIP6 or ISIMIP as a training dataset, one has to consider that different models do not necessarily contribute the same number of simulations to those datasets. As a result, the number of values for IM contributing to each bin $B_{IM}(GMT)$ sourced from each model can vary significantly. This variation can lead to an unequal influence of each model on the conditional distribution $P(IM \mid GMT)$. For instance, models that provide more data, either through additional initial condition ensembles or by covering a wider range of scenarios, would have a greater impact on the conditional distributions without model weighting because they contribute more values to the bins, thereby skewing the distributions. To address this bias towards models with more simulations, we implement a weighting mechanism that assigns a weight $w_{m,s}$ based on the source of each value defined by the model m and simulation s. We implement the following three weighting strategies:

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

– **Simulation democracy** corresponds to applying no extra weighting, which results in each simulation having equal influence on the conditional distribution. Consequently, models providing more simulations, either in the form of more initial condition ensembles or covering more input scenarios, have a larger overall impact.

– **Model democracy** ensures that each source model has an equal influence on the conditional distribution. In this approach, simulations from models contributing a larger total number of simulations to the training dataset are given lower weights so that each model has the same impact.

– **Manual weighting** can be combined with the other approaches and allows users to manually assign weights to individual models or simulations. This method can be used to implement model weighting strategies from the scientific literature into RIME-X, which weight models e.g. by how well their simulation of the historical period matches with observations or by how independent the models are from each other (Palmer et al., 2023; Massoud et al., 2023; Brunner et al., 2020b). Manual weighting can also be used to select simulations that capture particular events, such as an AMOC slowdown.

2.2.5 Calculating the final quantiles of the regional indicator distribution

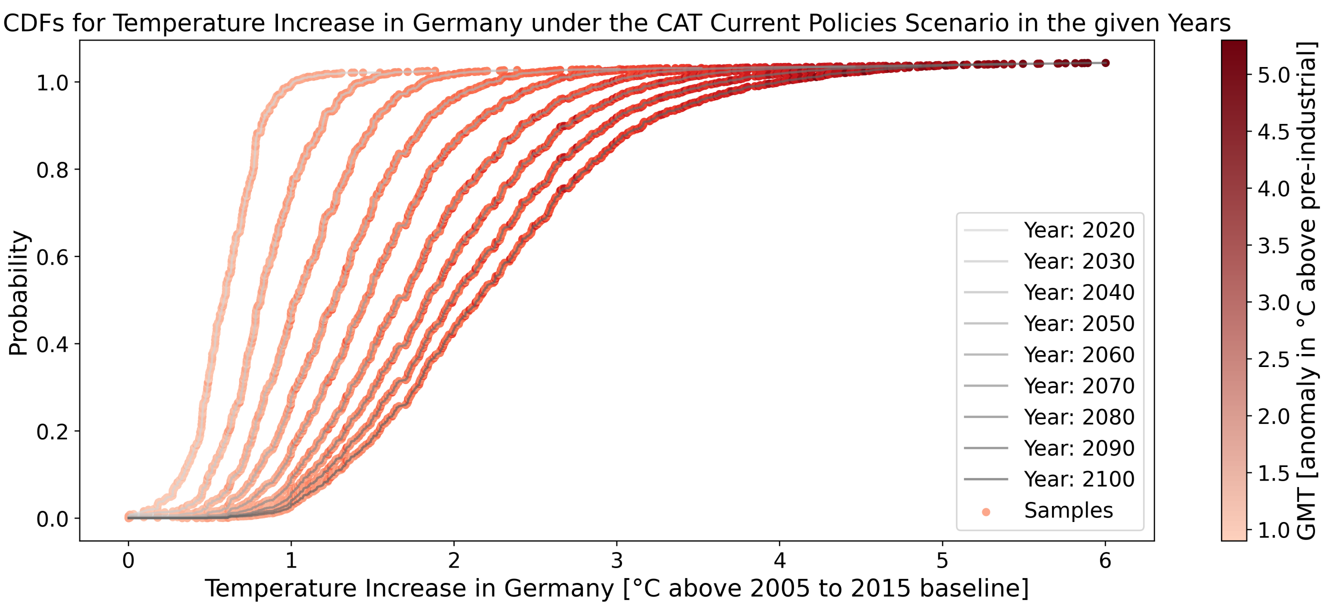

Figure 4. Cumulative distribution functions (CDFs) for the regional impact (here the 21-year mean of regional temperature in Germany compared to the 2005 to 2015 baseline) in the years 2020-2100 when following the Climate Action Tracker's current policy scenario. The shown distribution is a sum of the distributions for the regional temperatures shown in figure 3 weighted by the probabilities of each GMT level in each year, which distribution is shown in graphic (b) of figure 2. Each point corresponds to a sample of the indicator extracted from ISIMIP simulations. The color of the point hints at the GMT level in the simulation at the time the sample was extracted. The applied weighting strategy is simulation democracy.

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

To estimate the quantiles V_p of the distribution of IM we apply Monte Carlo sampling. Specifically, we draw n samples of GMT levels with probabilities $P_{s,y}(GMT)$. For each sampled GMT level, we then draw one value IM with probability $P(IM \mid GMT)$. This results in a set of n samples of IM, from which we compute empirical quantiles. The sampling procedure ensures that the IM values are drawn with probability

$$P_{s,y}(IM) = \sum_{GMT} P(IM \mid GMT) \cdot P_{s,y}(GMT),$$

which represents an application of the law of total probability. Consequently, empirical quantiles derived from the sample set provide a close approximation to the true quantiles of the marginal distribution of IM. Figure 4 illustrates the resulting marginal distribution for the 21-year mean of regional temperature in Germany (relative to the 2005–2015 baseline), constructed using the prior GMT-distribution displayed in Figure 2 and the conditional IM-distribution presented in Figure 3. The number of samples n is a hyperparameter of the RIME-X method. By default, we set $n = 10.000$.

2.3 Implementation

The RIME-X emulator is implemented as an extension of the existing `rime` Python package (Byers et al., 2025). It includes a preprocessing pipeline designed to facilitate the data handling for emulation tasks, with built-in support for downloading simulation output from the ISIMIP repository. The pipeline can also be applied to other MIP datasets, provided they are manually preprocessed into a similar structure as the downloaded ISIMIP dataset. In the first step, the required data is downloaded and converted into NetCDF files containing the target indicator IM in a gridded format, at the minimum necessary temporal resolution. This gridded data is then aggregated regionally using predefined spatial masks. By default, the package includes masks for continents, countries, provinces, and scientifically relevant regions like the IPCC regions (Iturbide et al., 2020), with aggregation weighted by area, GDP, or population. Users may also supply custom regional masks. The regionally aggregated data is transformed into NetCDF files we call quantile maps with dimensions for GMT level, quantile, and region, encoding the conditional distributions described in section 2.2.3. Alternatively, the package supports transformation into grid-point-level quantile maps, with dimensions GMT level, quantile, and spatial coordinates. In this work, we use equally spaced 101 quantile levels and 0.1-degree temperature increments. For quantile emulation, the package provides a dedicated function. It takes as input an ensemble simulation of GMT for a given scenario, a list of years and quantiles of interest, and the regional conditional distribution data preprocessed in the described format. The function returns the requested quantiles of the indicator IM for the specified scenario, years, and regions. In practice, this function first samples a GMT value from the SCM ensemble and a quantile from the quantile map. It then obtains the regional indicator sample by linearly interpolating between the quantile values of the indicator distributions conditional on the two nearest GMT values to the GMT sample in the quantile map, so no temperature binning is needed during prediction.

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

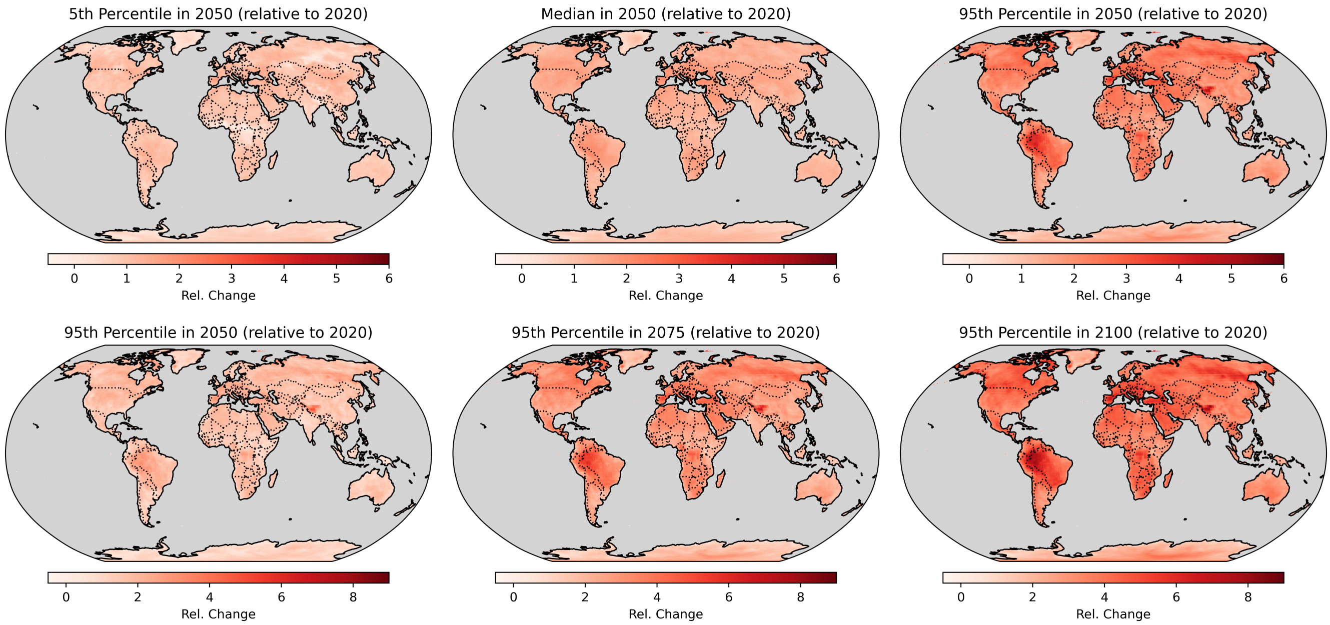

Figure 5. Grid-point-level RIME-X emulations for the CAT Current Policies scenario, illustrating the distribution and temporal evolution of annual maximum temperature. The upper panel shows the median as well as the 5th and 95th percentiles of the indicator distribution in 2050. The lower panel presents the 95th percentile of the distribution for the years 2050, 2075, and 2100, highlighting changes in both magnitude and spatial extent over time.

2.4 Showcase

Here we present selected examples of emulations produced by RIME-X to illustrate its capabilities in capturing the shift in distributions of regional climate indicators. We focus on the Climate Action Tracker (CAT) Current Policies scenario, which exhibits a strong climate signal across various indicators due to its high degree of projected warming. The GMT distribution used as input for the emulations is derived from an ensemble simulation using the simple climate model MAGICC.

To highlight the capabilities of RIME-X, we present the emulated outputs using a variety of visualization formats: In Figure 6, we focus on the temporal evolution of regional indicator distributions. On the right-hand side, we display how the density functions of distributions of selected indicators shift from 2020 to 2100 under the CAT Current Policies scenario. These distributions are approximated by applying a Gaussian kernel density estimate (KDE) to each quantile emulated by RIME-X. On the left-hand side, we show the evolution of the emulated quantiles over time. We highlight the median and the 90% confidence interval. To emphasize the flexibility of RIME-X, we selected a diverse set of emulation cases. Results are shown for a variety of spatial region types and locations (e.g., countries such as Germany and Mexico, provinces such as Guangdong, and IPCC regions such as Southeastern Africa); various indicator types, including direct indicators from the source data (mean annual temperature), indicators derived directly from source variables (cooling degree days and extreme

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

precipitation), and indicators generated using impact models applied to source data (maize yield change). Figure 5 provides a grid-point-level representation of selected percentiles of the emulated distributions of the annual maximum daily maximum temperature indicator (TXx), shown relative to the 2020 median. The upper panel presents the 5th, 50th, and 95th percentiles for the year 2050. The lower panel focuses on the 95th percentile in 2050, 2075, and 2100, highlighting temporal shifts in extreme heat conditions.

The underlying indicator simulations were obtained from the ISIMIP3 repository, using all available simulations (including secondary input) and preprocessed with a 21-year running mean to reduce the effect of natural variability, leading to smoother distributions representing mainly the climatic trend in the indicator. A more detailed description of the specific indicators used can be found in Appendix B.

3 Discussion and Validation

This section discusses the limitations of the methodology of RIME-X in section 3.1 which motivates the development and implementation of an empirical validation strategy in section 3.2.

3.1 Methodological limitations of RIME-X

To develop a validation strategy for RIME-X, we first identify potential conceptual limitations in its methodology. The first step of RIME-X—translating an emissions scenario into a GMT distribution using SCMs—follows established climate science as applied in recent IPCC assessments (e.g. Forster et al., 2021; Riahi et al., 2022). SCMs are highly simplified representations of the climate system that are calibrated against historical observations and have been shown to reproduce the historical period well. Comparisons of SCM projections with ESM projections—our current best tools to project the evolution of the future climate—find no major structural limitations for the GMT variable relevant to the RIME-X framework. However, such evaluations primarily assess consistency with ESM behavior rather than the absolute accuracy of SCM projections and underlying ESM behavior, which means that such validation still cannot guarantee that their application to future climate states delivers adequate projections (Nicholls et al., 2020, 2021; Forster et al., 2021). SCMs guard against overconfidence in projections by simulating large ensembles based on systematically generated, historically constrained probabilistic parameter sets. The parameterization process samples a wide range of plausible responses in key physical processes—such as land–atmosphere interactions and ocean carbon uptake—typically designed to encompass the IPCC-assessed uncertainty ranges (Meinshausen et al., 2011a, b; Leach et al., 2021). These uncertainties are explicitly propagated within RIME-X to inform regional impact projections across multiple emissions scenarios. While we acknowledge that SCMs have inherent limitations, such as unresolved or potentially misrepresented processes following from the strong simplifications in the model structure, they currently provide the best available probabilistic estimates of GMT responses to emissions. The use of probabilistic ensembles that cover IPCC-assessed ranges also guards against introducing bias in any single direction. Given their extensive validation and assessment elsewhere, we consider validation of SCM-based projections to be beyond the scope of this study and treat SCM-based projections as established climate science. The second step—deriving GMT-conditioned regional indicator distributions from

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

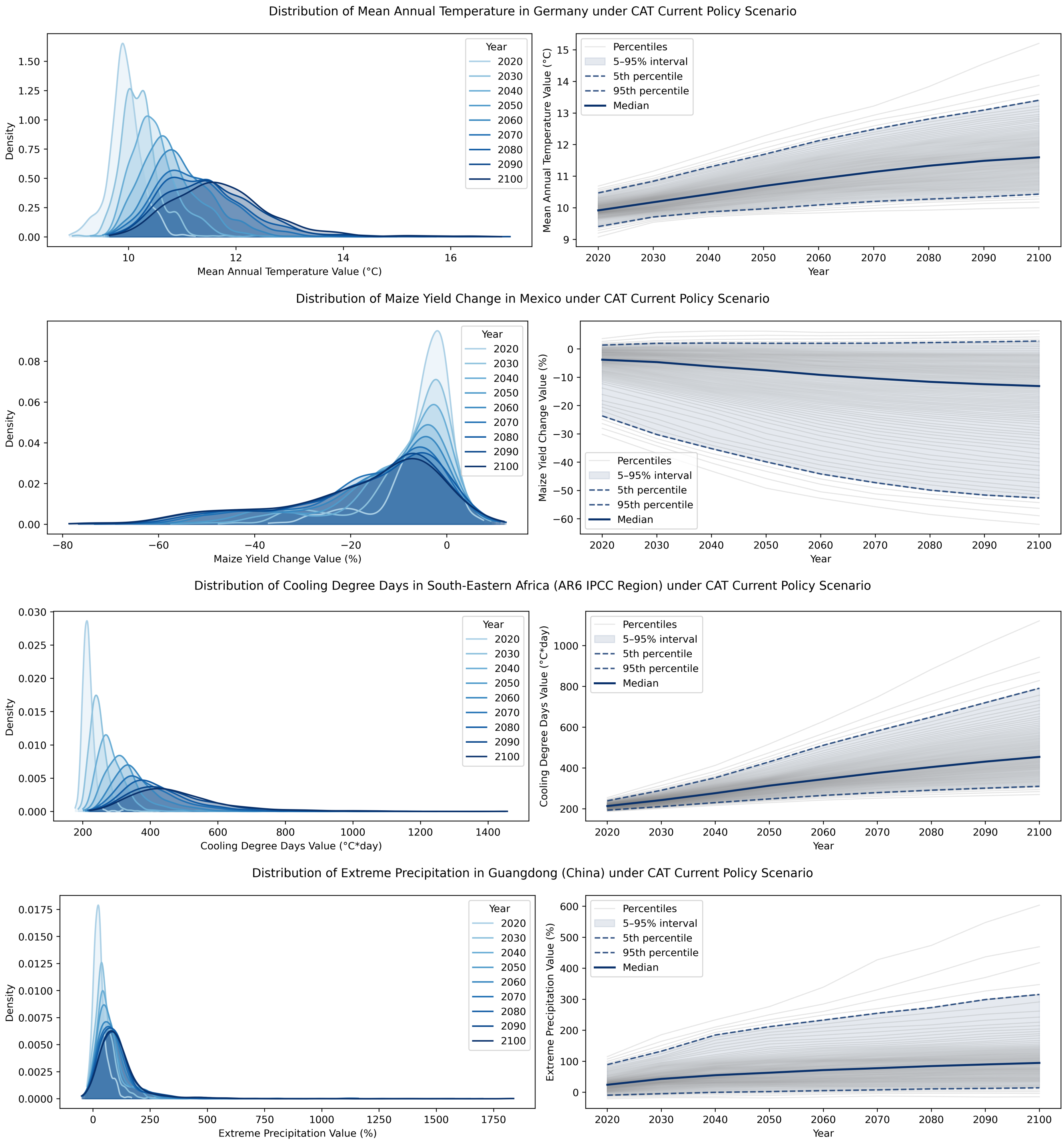

Figure 6. Four examples of RIME-X emulations of the CAT Current Policies scenario illustrating different indicator–region combinations. For each case, the left panel shows the evolution of the indicator distribution over time, while the right panel presents a time series of the percentiles from those distributions. Overall, the distributions tend to widen over time and shift in the direction of the underlying trend, reflecting both increasing model and global climate response uncertainty as well as the projected signal.

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

MIP datasets—presents the main methodological challenge. Here, regional indicator values are binned by GMT to extract conditional distributions, assuming path independence—meaning that responses of regional indicators to climate change depend mainly on the level of GMT, while the trajectory taken to reach that level of GMT and other regional influences like aerosol levels or deforestation are not taken into account. Though supported and applied in the literature for many indicators (Herger et al., 2015; Schleussner et al., 2016; Hausfather et al., 2022), this assumption can introduce biases, particularly for overshoot or stabilization scenarios, and in regions affected by pattern effects, high regional aerosol concentrations, or changes in regional land use (Schleussner et al., 2024; Pfleiderer et al., 2024; Wells et al., 2022; Giani et al., 2024). However, when all scenarios and years are included in the calibration, any loss of predictability due to time lag or related effects will manifest as increased uncertainty (i.e., wider error bars) rather than as an overconfident estimate. Additional limitations stem from the data: MIP ensembles offer a limited number of simulations, often developed using models that share components and are best viewed as "ensembles of opportunity" (Masson and Knutti, 2011; Brunner et al., 2020b; Knutti et al., 2010). While RIME-X can mitigate some of these limitations through model weighting, the underlying epistemic uncertainties persist (Rising et al., 2022; Stainforth et al., 2007). Moreover, many models in the MIP dataset do not reach higher levels of warming, meaning that the regional indicator distributions conditioned on these higher GMT levels are based on an increasingly small and selective subset of models that can provide data at these temperatures. This effect is partly mitigated by the fact that global climate response uncertainty increases with higher emission levels, leading to a wider range of simulated GMT outcomes. As a result, higher-emission scenarios generally sample a broader span of GMT levels, which counteracts—at least to some extent—the reduction in available samples for any specific high-GMT bin. Despite these limitations, MIPs remain the most holistic and flexible datasets for linking global and regional climate responses and are thus the best available foundation for RIME-X's emulation approach, which is designed to be flexible across regions, scenarios, and indicators. The third and final step of RIME-X is a direct application of the law of total probability.

In summary, the first and third steps of RIME-X either rely on well-established methodologies or are mathematically valid. Accordingly, our empirical validation in section 3.2 focuses on the second step: evaluating whether GMT-conditioned regional distributions extracted from MIP datasets can reliably reproduce simulated regional outcomes. This analysis does not, and cannot, address the epistemic limitations of MIP data. Instead, we treat MIP-derived distributions as ground truth and assess whether they can be reconstructed based solely on their dependence on GMT.

3.2 Empirical validation strategy using CMIP6 data

To investigate how reliably RIME-X emulates simulated distributions using GMT-conditioned regional indicator distributions, we adopt a holdout validation framework. The emulator is calibrated on a subset of simulations from *CMIP6* (Eyring et al., 2016), withholding all simulations for the *SSP2-4.5* scenario, which we aim to emulate. For both calibration and ground truth, we use data from the *CMIP6* next-generation archive (Brunner et al., 2020a), which has undergone centralized preprocessing, including interpolation to a common 2.5° × 2.5° latitude-longitude grid. This archive provides over 1,500 simulations from 24 models (see appendix A) covering the historical period and the emissions scenarios *SSP1-2.6*, *SSP4-6.0*, *SSP3-7.0*, and *SSP5-8.5*, enabling robust calibration of the RIME-X emulator. The archive additionally offers more than 150 simulations

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

for the *SSP2-4.5* scenario from the same set of 24 models, which allow us to extract statistically meaningful ground truth quantiles from actual simulations for comparison with our emulated quantiles. For emulator calibration and ground truth preprocessing, the *CMIP6* simulations are spatially aggregated to the country level using masks from the *ISIMIP* archive (Perrette, 2022) and area-based grid cell weights. Temporal aggregation is then performed by applying a 21-year running mean to the regional averages. Countries are chosen as regions for the evaluation due to their heterogeneous sizes, diverse climate zones, and global landmass coverage, thus testing the method's applicability across varied regional characteristics. We use 21-year averages to improve the comparability between the emulated and ground truth distributions by minimizing the impact of outliers due to natural variability. Only simulations from the scenarios *SSP1-2.6*, *SSP4-6.0*, *SSP3-7.0*, and *SSP5-8.5* that share a model and initial condition ensemble with a simulation of the *SSP2-4.5* scenario (including their respective historical simulations) are used to calibrate the RIME-X emulator. We give equal weight to every simulation (see section 2.2.4). All available *CMIP6* simulations for *SSP2-4.5* are used to derive the ground truth distributions. To ensure comparability between emulated and simulated distributions, we use the actual global warming levels from the *SSP2-4.5* simulations to extract the scenario-dependent GMT distribution instead of using an SCM. This departs from the standard RIME-X methodology, which would otherwise rely on warming levels from SCM ensemble simulations (see section 2.2.2). However, SCM ensembles are designed to simulate realistic warming trajectories by assuming observation-based values for key metrics like the transient climate response (Leach et al., 2021), whereas many *CMIP6* models tend to overestimate transient warming rates (Hausfather et al., 2022). Using the same warming levels as the ground truth simulations ensures that deviations between emulated and simulated distributions arise solely from the second step of the emulation methodology, rather than differences in warming trajectories. Consequently, if the emulated distributions closely match the simulated ground truth, we can conclude that RIME-X can use the relationship between GMT levels and regional indicators extracted from the *CMIP6* simulations to produce meaningful regional indicator distributions for the unseen scenario.

3.2.1 Results and Discussion

Figure 7 shows the average normalized mean absolute error (ANMAE) of each percentile of the emulated distribution compared to the corresponding percentiles of the ground-truth simulated distribution for each country. Results are shown for (a) annual average regional surface temperature relative to the 1995–2014 baseline under *SSP2-4.5* (in °C), and (b) annual average regional precipitation relative to the same baseline and scenario (in percent). The average normalized mean absolute error $ANMAE_r$ for region r quantifies the error between the emulated p-percentiles $e^r_y(p)$ (where p is a whole number between 1 and 99) in the years $y \in Y$ (here ranging in 5-year steps from 2025 to 2090) and the corresponding simulated percentiles $s^r_y(p)$. The $ANMAE_r$ is calculated as

$$ANMAE_r = \frac{1}{|Y|} \sum_{y \in Y} \frac{\sum_{p=1}^{99} |e^r_y(p) - s^r_y(p)|}{\max s^r_y(p) - \min s^r_y(p)}. \tag{1}$$

This metric represents the average deviation of each emulated percentile from its corresponding ground truth simulated percentile, expressed as a share of the full spread of simulated indicator values. We find that over all countries and both indicators, the $ANMAE$ between the emulated and simulated quantiles ranges from 1% of the model spread to 8% of the

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

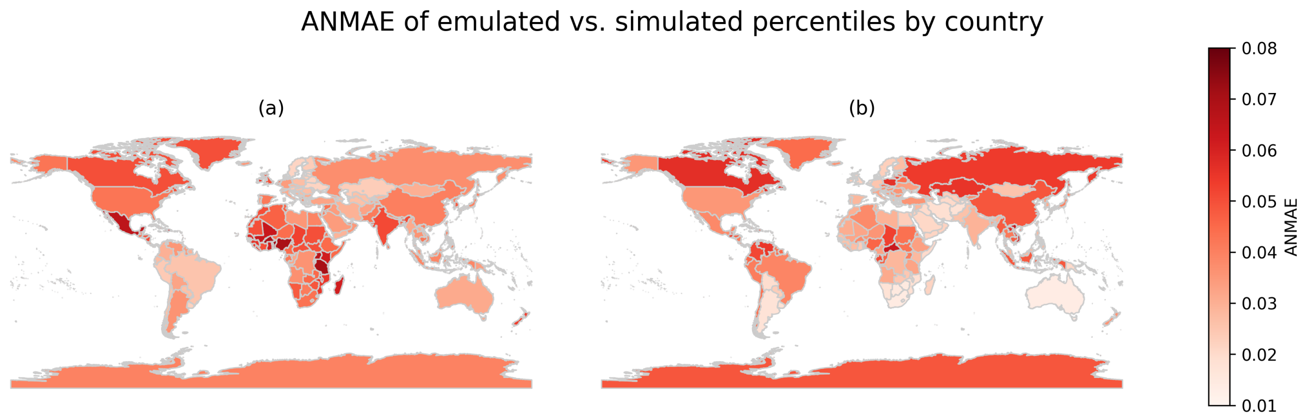

Figure 7. The average normalized mean absolute error ($ANMAE$, see section 3.2.1) of emulated vs. simulated percentiles in each country. Panel (a) shows the annual average regional surface temperature compared to the 1995-2014 baseline for *SSP2-4.5* in °C, and panel (b) shows the annual average regional precipitation compared to the 1995-2014 baseline for *SSP2-4.5* in percent.

model spread. For the regional temperature indicator investigated in panel (a) in Figure 7, Sweden has the lowest $ANMAE$ of around 2.1%, Cambodia has the median $ANMAE$ value of 4.2 %, and Benin has the maximum $ANMAE$ value of 7.2 %. For the regional precipitation indicator investigated in panel (b) in Figure 7, Australia has the lowest $ANMAE$ of around 1.4 %, Qatar has the median $ANMAE$ of around 3.1 %, and the Central African Republic has the maximum $ANMAE$ of 6.3 %. Figure 8 displays Q–Q plots comparing the percentiles of the emulated and simulated distributions for each year. The plots reveal some deviations between the emulated and simulated quantiles. However, such deviations are partially expected, as the 98 percentiles of the simulated distribution are estimated from only around 150 samples—a relatively small sample size that introduces uncertainty in the ground truth quantiles. As a result, even a perfect emulator would still exhibit some deviation in the Q–Q plots due to this sampling variability. To quantify the magnitude of the expected deviations due to the sample size, we estimate the simulated ground truth distribution using a Gaussian kernel density estimate. From this estimated distribution, we repeatedly (1000 times) draw sets of 100 samples and compute the percentiles for each sample set. We then record the range within which the percentiles from these samples deviate from the percentiles of the simulated distribution. This range represents the expected deviation due to the unstable estimation of the ground truth from a limited number of samples and is added to Figure 8 as a bright blue shadowing. We observe that while emulated and simulated quantiles mostly fall within the expected range of sampling deviations, they exceed this range in some cases. This suggests that the methodological limitations discussed in section 3.1 can introduce systematic biases. However, as shown in Figure 7, these biases remain modest, with average deviations typically reaching between two and six percent of the model spread and reaching at most around eight percent even in the worst-affected regions. Overall, deviations between emulated and simulated ground-truth distributions remain one to two orders of magnitude smaller than the inter-model spread in *CMIP6* and are often within the range of expected deviations due to the limited sample size from which the ground-truth quantiles are extracted.

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

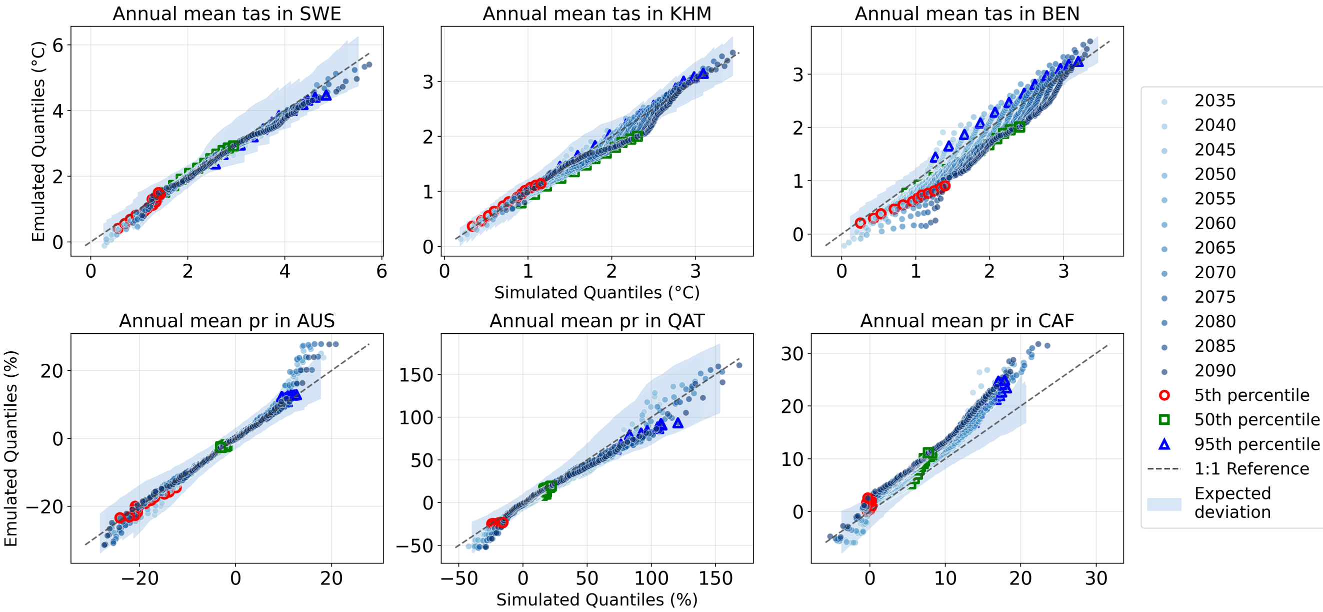

Figure 8. Q-Q plots showing the emulated and simulated percentiles from the CMIP6 ensemble. A perfect emulator and perfect knowledge of the simulated distribution would result in all points lying on the diagonal line included in the Q-Q plot. However, even if RIME-X were perfect, we would still expect a deviation of the emulated percentiles from the simulated percentiles as a result of the imperfect knowledge of the simulated distribution we have to estimate from around 150 samples. The expected deviation is quantified in the shaded area. From left to right the examples illustrate the emulator performance for regions where the emulator showed the best, median, and worst performance as measured by the average normalized mean absolute error ($ANMAE$, see section 3.2.1). In the first row we show the emulated and simulated percentiles of the annual average regional temperature (tas) compared to the 1995-2014 baseline in °C for selected regions, where (a) corresponds to Sweden (SWE), (b) to Cambodia (KHM), and (c) to Benin (BEN). In the second row we show the emulated and simulated percentiles of the annual average regional precipitation change indicator (pr) in °C for selected regions, where (a) corresponds to Australia (AUS), (b) to Qatar (QAT), and (c) to the Central African Republic (CAF).

4 Conclusions

We have developed and validated RIME-X, an emulator that predicts scenario- and time-dependent distributions of regional indicators under climate change. RIME-X applies to any indicator whose distribution is mainly influenced by global warming levels. Unlike ESM emulators, RIME-X emulates distributions of responses directly, integrating uncertainty in the global response to emission scenarios (via SCM ensembles), model uncertainty in the regional response to global climate change (from weighted MIP datasets), and internal climate variability (via multiple simulations from the same model). This enables efficient exploration of projected regional impacts across multi-model ensembles like *CMIP6* or *ISIMIP3*, constrained by plausible global climate trajectories from simple climate models and model weighting to mitigate challenges commonly associated with the probabilistic interpretation of conventional MIP-derived distributions—such as the hot model problem (Hausfather

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

et al., 2022) and model interdependencies (Brunner et al., 2020b). RIME-X is conceived to support users such as researchers and practitioners from, e.g., the finance sector who need fast, flexible, and probabilistic assessments of climate risks across scenarios, regions, and indicators. It enables the exploration of the full range of possible effects of an emission scenario on a regional indicator, including the extreme ends of the risk spectrum. We provide a user-friendly implementation of RIME-X in the Python package *rime*, which includes a preprocessing module that automatically downloads and processes indicators from the ISIMIP repository but also supports processing of custom indicators. We apply RIME-X in the Climate Impact Explorer[1], for which we have already preprocessed a wide range of indicators that will be made publicly accessible.

We validated RIME-X by calibrating it with *CMIP6* simulations for four scenarios (excluding *SSP2-4.5*) for regional temperature and precipitation. We then emulated the distribution of the *CMIP6* ensemble under *SSP2-4.5* and compared the output to the actual *CMIP6* distribution, treated as ground truth. Emulated and simulated distributions matched closely, with percentile deviations averaging 1% and up to 8% of model spread over all countries in the best- to worst-case. However, some limitations can affect RIME-X's accuracy. It assumes that the regional indicator depends primarily on GMT, excluding influences like aerosols or socioeconomic shifts, limiting applicability to indicators where this assumption approximately holds. It also does not account for the path to reaching GMT levels, limiting applicability in scenarios where time-lag effects play a major role for the assessment of regional indicators, such as overshoot scenarios. Moreover, as fewer ESMs reach high warming levels, the robustness of emulations decreases with warming level due to reduced training data. Emulations are also constrained by epistemic uncertainty regarding the limited number of models available to quantify model uncertainty within the training dataset. This epistemic uncertainty is, however, partly mitigated through model weighting and GMT-based constraints. Future work could address some of these limitations—for instance, by conditioning indicator distributions on changing socioeconomic variables like GDP or population, improving robustness at high warming levels using training data with prescribed GMT shifts like, e.g., from the upcoming Tipping Points Modelling Intercomparison Project (TIPMIP; Winkelmann et al., 2025), and testing additional global predictor indicators such as the likelihood of being before or after peak GMT.

Code and data availability. The current version of RIME-X is available on GitHub at https://github.com/iiasa/rimeX (last access: 13 November 2025). The exact version of RIME-X, the pre-processed data and code used to produce the results in this paper is archived on Zenodo at https://doi.org/10.5281/zenodo.17491735 and based on ESM data from the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project (Phase 6), available at https://aims2.llnl.gov/search/cmip6/ (last access: 12 November 2024) and processed according to Brunner et al. (2020) (https://doi.org/10.5281/zenodo.3734128) as well as data from the ISIMIP3b archive, available at https://data.isimip.org (last access: 13 November 2025).

[1]https://climate-impact-explorer.climateanalytics.org, last access: 11 November 2025

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

Appendix A: CMIP6 data used in this study

Model name	Reference	Available scenarios	Experiments
ACCESS-CM2	Dix et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	5
ACCESS-ESM1-5	Ziehn et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	40
AWI-CM-1-1-MR	Semmler et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1
CESM2-WACCM	Danabasoglu (2019b)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	3
CESM2	Danabasoglu (2019a)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1
CMCC-CM2-SR5	Lovato and Peano (2020)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1
CNRM-CM6-1-HR	Voldoire (2019b)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1
CNRM-CM6-1	Voldoire (2019a)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	6
CNRM-ESM2-1	Seferian (2019)	SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	5
CanESM5	Swart et al. (2019)	SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	50
E3SM-1-1	Bader et al. (2020)	SSP5-8.5	1
FGOALS-f3-L	Yu (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1
FGOALS-g3	Li (2019)	SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	4
FIO-ESM-2-0	Song et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	3
HadGEM3-GC31-LL	Good (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	4
HadGEM3-GC31-MM	Jackson (2020)	SSP1-2.6, SSP5-8.5	4
IPSL-CM6A-LR	Boucher et al. (2019)	SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	7
MPI-ESM1-2-HR	Schupfner et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	2
MPI-ESM1-2-LR	Schupfner et al. (2021)	SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	30
MRI-ESM2-0	Yukimoto et al. (2019)	SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	6
NESM3	Cao (2019)	SSP1-2.6, SSP2-4.5, SSP5-8.5	2
NorESM2-LM	Seland et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1
NorESM2-MM	Bentsen et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1
UKESM1-0-LL	Good et al. (2019)	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	5

Table A1. Overview of the CMIP6 models available in the Brunner et al. (2020a) dataset and the scenarios that are available for each model. We used this dataset in sections 3.2 and 3.2.1 for the validations of our method with CMIP6 data.

https://doi.org/10.5194/egusphere-2025-5781
Preprint. Discussion started: 9 February 2026

Appendix B: Definitions of the indicators presented in the showcase

Indicator	Definition	Variables	Models	Scenarios
Mean annual temperature	Annual mean of the `tas` variable aggregated over the region	`tas`	CanESM5, CNRM-CM6-1, EC-Earth3, IITM-ESM, KACE-1-0-G, MPI-ESM-1-2-HR, TaiESM1, CESM2-WACCM, CNRM-ESM2-1, GFDL-ESM4, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0, UKESM1-0-ll	historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, SSP5-8.5
Maize Yield Change	Annual mean of `yieldchange` variable aggregated over all grid points with maize yields.	`yieldchange`	GCMs: MPI-ESM-1-2-HR, GFDL-ESM4, IPSL-CM6A-LR, MRI-ESM2-0, UKESM1-0-ll; Crop Models: CROVER, CYGMA1p74, DDSAT-Pythia, EPIC-IIASA, ISAM, LDNDC, LPJmL, pDSSAT, PEPIC, PROMET, SIMPLACE-LINTUL5	historical, SSP1-2.6, SSP3-7.0, SSP5-8.5
Cooling Degree Days	Annual sum of degrees by which the daily `tas` exceeds 26 °C, aggregated over the region.	`tas`	CanESM5, CNRM-CM6-1, EC-Earth3, IITM-ESM, KACE-1-0-G, MPI-ESM-1-2-HR, TaiESM1, CESM2-WACCM, CNRM-ESM2-1, GFDL-ESM4, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0, UKESM1-0-ll	historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, SSP5-8.5
Extreme Precipitation	Annual sum of mm by which the daily `pr` exceeds the 99.9th percentile of daily `pr` in the 1980 to 2015 reference period, aggregated over the region.	`pr`	CanESM5, CNRM-CM6-1, EC-Earth3, IITM-ESM, KACE-1-0-G, MPI-ESM-1-2-HR, TaiESM1, CESM2-WACCM, CNRM-ESM2-1, GFDL-ESM4, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0, UKESM1-0-ll	historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, SSP5-8.5sss

Table B1. Overview of the indicators shown in Section 2.4 and the variables, models, and simulations from the ISIMIP3 repository used as source data.

Author contributions. NS, QL, PP, and CFS conceived the study. NS and MP developed the methods, with contributions from SS and PP. NS produced the figures, with contributions from AH, SS, and CFS. NS wrote the paper, with contributions from all authors.

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Preprint. Discussion started: 9 February 2026

Competing interests. The contact author has declared that none of the authors has any competing interests.

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