

Reducing forced-signal uncertainty in the INM RAS climate models using a pattern-recognition based approach

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Research Article

Keywords: Forced climate change, climate projections, model uncertainty, emergent constraints, pattern recognition methods

Posted Date: September 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10872092/v1>

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15
16 Submitted to *Climate Dynamics*
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Abstract

Earth System Models (ESM) exhibit a large spread among their simulated future climate projections. Such model uncertainty arises due to different model-specific parameterizations of cloud physics and other processes. Reducing this uncertainty is key to planning societal response to climate change. Previous work addressed this problem via developing model weighting strategies based on the model ancestry, performance, and independence or by applying the so-called emergent constraints, in which the relationship between a model's historical-period (hence, observable) predictor and the climate-projection predictand allows one to reduce the spread of this predictand by using the observed range of the predictor. Here we integrate the idea of emergent constraints with a pattern-recognition based forced-signal estimation methodology — a combination of pattern scaling to identify the CO₂-congruent climate response and the signal-to-noise-maximizing pattern (S/NP) decomposition of the residual, CO₂-detrended variability — to analyze the forced response and reduce the spread of climate projections in near-surface air temperatures among three different versions of a state-of-the-art ESM. The resulting rescaling trained over the historical period using reanalysis products does dial down the intermodel uncertainty in the projected climate warming pattern but fails to constrain a simulated CO₂-congruent climate signal emerging in the second half of the 21st century.

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1 Introduction

The main tool of climate science is complex Earth System Models (ESMs), which are used to both simulate the past and present climates and project the future climate behavior under various emission scenarios. The latest two installments of the coordinated international modeling efforts — the Coupled Model Intercomparison Project phases 5 (CMIP5: Taylor et al. 2012) and 6 (CMIP6: Eyring et al. 2016) — encompass scores of models that have different spatial resolutions and different representation/parameterization of various physical processes, including the processes operating on sub-grid scales (for example, cloud microphysics). These models can, therefore, differ in their internal variability (spontaneous variability generated under constant external forcing), as well as in their response to variable external forcing (such as increasing concentrations of the greenhouse gases in the atmosphere), hereafter referred to as the forced response or forced signal.

The key issue we address in this paper is that of a large inter-model uncertainty in the model projections of future climate change, which hasn't decreased at all since the early modeling efforts of 1990s and through the CMIP5/6 enterprise despite constant and ongoing model development activities (e.g., Knutti et al. 2017; Forster et al. 2020); this has immediate detrimental implications for the societal planning of possible climate-change solutions. One way of dealing with this problem that has recently gained popularity is through the so-called emergent constraints (Hall et al. 2019; Brient 2020) — a methodology in which one looks for a strong linear relationship between the model's historical-period (hence, observable) predictor and the climate-projection predictand to reduce the spread of this predictand by using the observed range of the predictor. For example, Tokarska et al. (2020) followed a regression-based approach to constrain model projections of future warming (in global-mean temperature predictand) using the global-temperature trend over recent decades as a predictor (see also Forster et al. 2013; Jiménez-de-la-Cuesta and Mauritsen 2019; Nijse et al. 2020, among others). A complementary model-weighting approach would assign the loadings to individual-model climate projections based on how close this model reproduces a chosen climate or climate-change characteristic over the historical period (model performance), as well as model independence of other models in the multi-model ensemble (model ancestry) (Knutti et al. 2013, 2017; Gillett 2015; Sanderson et al. 2015a, b, 2017; Lorenz et al. 2018; Brunner et al. 2020; Liang et al. 2020; Kuma et al. 2023).

1 Some weaknesses of the emergent-constraint approach lie in its limited scope (of focusing,
2 typically, on a single scalar predictand, such as global-mean climate response or the strength of a
3 certain climate feedback) and an ad hoc character of the chosen predictors (so that the predictor
4 picked to establish the degree of similarity between the observed and model simulated historical
5 climates may not necessarily constrain the range of projected climate behaviors in a given
6 predictand, as, for example, is the case for the gridded surface-air-temperature predictor, which
7 fails to constrain the future global-mean warming in Liang et al. 2020). Hall et al. (2019) and
8 Brient (2020), among many others, argue strongly that an emergent constraint must be verified by
9 demonstrating the corresponding dynamical relationship established, presumably, through
10 experimentation within a hierarchy of dynamical climate models.

11 We here develop an alternative, data-driven/data-mining strategy in which we seek to use
12 pattern recognition methods in conjunction with a machine-learning (ML) approach to find a
13 transformation that remaps the forced signals in gridded global-scope climate field(s) of multiple
14 climate models (here we used near-surface air temperature) to optimally match the observed
15 (historical) climate evolution of these field(s). These transformations are then applied to the multi-
16 model projections of future climate change under a given emission scenario, thus producing a
17 library of the (multi-model ensemble of) optimally constrained gridded forced-signal time series
18 of the climate field(s) considered, extending through historical and future periods (1880–2100).
19 We hypothesize that applying the proposed procedure to multiple climate models will reduce the
20 spread of their climate projections. This seems likely since various climate feedbacks that control
21 each ESM’s climate sensitivity would be adjusted at the ML model’s learning stage to yield an
22 evolution that best matches the ground truth. We argue that the proposed methodology can be
23 viewed as a data driven parameterization of the climate feedbacks misrepresented or missing in
24 the current generation of ESM models and has thus a potential to elucidate and disentangle the
25 main physical drivers of the model uncertainty.

26 In the following presentation, section 2 describes model simulations, reanalysis products, our
27 pattern-based forced-signal estimation and rescaling methodology, as well as supplementary
28 analysis methods used here. The results are discussed in section 3, which includes an account of
29 the pattern-recognition based forced-signal decompositions in the three models considered, a
30 description of the future projections’ rescaling outcomes and an analysis of the residual future

forced signal undetected by the pattern-based rescaling trained over the historical period. Section 4 summarizes the results and outlines their implications.

2 Data and methods

2.1 CO₂ detrending and S/NP estimates of the forced SAT response in individual models

We analyzed the annual near-surface air temperature (SAT) from the historical (HIST: 1850–2014) and SSP3-7.0 scenario (2015–2100) ensemble simulations of three versions of the Institute of Numerical Mathematics of the Russian Academy of Sciences (INM RAS) climate models — model CM5 (10 members for both HIST and SSP3-7.0), CM6M (10 members for HIST, 5 members for SSP3-7.0), and CM6P (5 members for both HIST and SSP3-7.0). The CM6M is an update of the CM5 model (a member of the CMIP6 ensemble), which has a higher horizontal resolution in the atmosphere ($1.25^\circ \times 1^\circ$ vs. $1.25^\circ \times 2^\circ$) and a different, fully prognostic cloud parameterization scheme (Volodin 2023), resulting in a significant increase of the equilibrium climate sensitivity (3.8K in CM6M compared to 2.1K in CM5; see Gritsun et al. 2024, Volodin et al. 2024). The CM6P model is based on the CM6M one but has a lower resolution in both the atmosphere ($1.25^\circ \times 1^\circ$) and the ocean ($1^\circ \times 0.5^\circ$ vs. $0.5^\circ \times 0.25^\circ$ in both CM5 and CM6M), lower-top atmospheric boundary and readjusted cloud parameterization, which lead to an equilibrium climate sensitivity of about 3.2K.

For each simulation, we formed the SAT anomalies by subtracting the 1880–2005 climatology. The resulting anomalies were further decomposed into the patterns and time series approximating the forced signal in each model. This decomposition was done over five different training periods with the same initial date and different end dates, namely: 1880–2005, 1880–2015, 1880–2025, 1880–2035, and 1880–2045. First, we isolated, in each model, the CO₂-congruent SAT variability by regressing, over a given training period, the individual-model ensemble-mean SAT time series smoothed by the 5-year running-mean boxcar filter onto the annual-mean $\ln(\text{CO}_2)$ time series $p_{\text{CO}_2}(t)$ (see Hébert and Laepple 2025), normalized to have zero mean and unit standard deviation over the 1880–2005 period. The resulting regression patterns $INT_l(x, y)$ and $PAT_l(x, y)$ (different between the models $l=1, 2, 3$), when combined with the $p_{\text{CO}_2}(t)$ time series, represent the CO₂-

1 congruent signal $T_{CO2,l}(x, y, t)$ of each model (both within and outside of the training period, so
 2 over the entire 1850–2100 interval):

$$T_{CO2,l}(x, y, t) = INT_l(x, y) + PAT_l(x, y) (p_{CO2}(t) - \overline{p_{CO2}}), \quad l = 1, 2, 3, \quad (1)$$

3 where $\overline{p_{CO2}}$ is the time-mean of the $p_{CO2}(t)$ predictor over a given training period. The residual,
 4 CO₂-detrended variability $T_{DCO2,k,l}(x, y, t)$, was then computed for each model l and simulation k
 5 as the difference between this simulation's original SAT time series and the CO₂-congruent signal
 6 of the corresponding model:

$$T_{DCO2,k,l}(x, y, t) = T_{k,l}(x, y, t) - T_{CO2,l}(x, y, t). \quad (2)$$

7 Note that the CO₂-detrended ensemble-mean SAT time series has zero time mean over each
 8 training period considered by construction [the actual SAT mean over the training period is equal
 9 to $INT_l(x, y)$ in (1) and is thus subtracted from SAT anomalies on the right-hand side of (2)].

10 We next decomposed the residual CO₂-detrended variability into a set of the signal-to-noise
 11 maximizing patterns (S/NP) and their associated component time series (Wills et al. 2020; Mukhin
 12 et al. 2023; Kravtsov et al. 2025). The requisite fingerprinting patterns (which maximize the ratio
 13 of the ensemble-mean to the total variance) were computed for each model using the training-
 14 interval data and applied to the entire 1850–2100 SAT time series to obtain the S/NP component
 15 projections both inside and outside of the training interval (note that each component has zero time
 16 mean over the training period by construction). Similarly, the S/NP patterns — also computed over
 17 the training interval — provide, when combined with the component projections, a reconstruction
 18 of the corresponding variability outside of this interval, across the entire 1850–2100 period. Thus,
 19 the CO₂-detrended SAT time series $T_{DCO2,k,l}(x, y, t)$ of each ensemble member k of each model l
 20 was decomposed as

$$T_{DCO2,k,l}(x, y, t) = \sum_{m=1}^M SNP_m(x, y) t_{m,k,l}(t) + R_{k,l}(x, y, t). \quad (3)$$

21 For optimal M , typically chosen by selecting the S/NP modes characterized by large signal-to-
 22 noise ratios distinct from the flat tail of the ratios associated with trailing S/NP modes, the
 23 ensemble mean $\langle T_{DCO2,l} \rangle$ of the S/NP filtered SAT time series provides a better estimate of the
 24 forced signal $T_F(x, y, t)$ than the unfiltered ensemble mean, by minimizing the contribution of the
 25 aliased internal variability in the estimated forced signal (Wills et al. 2020; Kravtsov et al. 2025):

$$T_{F,l}(x, y, t) \equiv \langle T_{DCO2,l} \rangle(x, y, t) = \sum_{m=1}^M SNP_{m,l}(x, y) \langle t \rangle_{m,l}(t). \quad (4)$$

For the present simulations, we retained $M=5$ S/NP modes but ended up using $M=3$ modes, as the higher-order modes did not substantially contribute to the estimated forced responses of neither model. In plotting the results of the S/NP decomposition, we normalize the component time series $\langle t \rangle_m(t)$ by their standard deviation and display the dimensional S/NP patterns $SNP_{m,l}(x, y)$ in degrees C. The outcomes of the above pattern-recognition based decomposition of the forced signals simulated by the three INM RAS models are described in section 3.1.

2.2 Forced-signal rescaling to the reanalysis data: Emergent constraints

The main part of our analysis applies the least-squares procedure to rescale the individual-model forced signals by fitting them to the reanalysis data $T_R(x, y, t)$ over the 1880–2005 training period. This procedure was done separately for the CO₂-congruent and CO₂-detrended forced signals. For the former, we find, for each model l , the coefficient b_l that minimizes the residual $R_{CO2,l}(x, y, t)$ in

$$T_{R,CO2}(x, y, t) = b_l PAT_l(x, y) p_{CO2}(t) + R_{CO2,l}(x, y, t) \quad (5)$$

[compare with (1)], where $T_{R,CO2}$ is the CO₂-congruent 1880–2005 SAT anomaly in the reanalysis data. The rescaled CO₂-congruent forced signal $T_{CO2,l}^{(resc)}$ in model l is then given by

$$T_{CO2,l}^{(resc)}(x, y, t) = INT_l(x, y) + PAT_l(x, y) (b_l p_{CO2}(t) - \overline{p_{CO2}}), \quad l = 1, 2, 3. \quad (6)$$

In the same way, finding $c_{m,l}$ to minimize, over the 1880–2005, the residual $R_{DCO2,l}(x, y, t)$ in

$$T_{R,DCO2}(x, y, t) = \sum_{m=1}^M c_{m,l} SNP_{m,l}(x, y) (\langle t \rangle_{m,l}(t) - \widetilde{\langle t \rangle}_{m,l}) + R_{DCO2,l}(x, y, t), \quad (7)$$

where $\widetilde{\langle t \rangle}_{m,l}$ is the time-mean of the $\langle t \rangle_{m,l}(t)$ component over the 1880–2005 period [compare with (4)] gives the rescaled version of the CO₂-detrended variability $T_{DCO2,l}^{(resc)}(x, y, t)$:

$$T_{DCO2,l}^{(resc)}(x, y, t) = \sum_{m=1}^M c_{m,l} SNP_{m,l}(x, y) (\langle t \rangle_{m,l}(t) - \widetilde{\langle t \rangle}_{m,l}) + SNP_{m,l}(x, y) \widetilde{\langle t \rangle}_{m,l}. \quad (8)$$

The rescaled signals in equations (6), (8) therefore show the closest agreement between the model derived estimates of forced signals and the reanalysis data over the period 1880–2005, while also providing corrected extensions of these signals beyond that interval. In this way, they serve as a pattern-recognition-based emergent constraint on the future climate simulated by the models. We hypothesize that this rescaling procedure reduces the uncertainty (spread) in future climate projections simulated by different models. In this work, we test this hypothesis using INM RAS models as illustrative examples (see sections 3.1 and 3.2).

For $T_R(x, y, t)$, as in Kravtsov et al. (2025), we used two state-of-the-art reanalysis products which provide gridded proxies of the estimated observed SAT evolution: the National Oceanic and Atmospheric Administration (NOAA) twentieth-century reanalysis version 3 (20CRv3: Compo et al. 2011; Slivinski et al. 2019, 2021) ensemble-mean (restricted to the 1800–2005 period), and a 1880–2005 data set obtained by blending the 20CRv3 and the European Center for Medium-Range Weather Forecasts (ECMWF) Reanalysis of the 20th century (ERA-20C) reanalysis data (Poli et al. 2016). The latter data set was based on the ensemble-mean of the 20CRv3 data prior to 1900 and the ERA-20C data after 1900; hereafter, we’ll still refer to this blended data set as the ERA-20C. In blending the two data sets, the ERA-20C data was adjusted to match the 20CRv3’s 1900–2005 climatology to avoid any discontinuities at year 1900. The backward extension of the ERA-20C data set to year 1880 using the 20CRv3 data set was done to align its temporal coverage with the other data sets used in this study and thus achieve uniform statistical treatment for all of these data sets.

2.3 Identifying and interpreting residual variability in the forced-signal projections outside of the training period

The errors in the estimated future (scenario) forced response of individual models outside of a given training period $T_{predicted}(x, y, t) = T_{CO2,l}(x, y, t) + T_{F,l}(x, y, t)$ [see (1), (4)] were computed by subtracting these signals from the estimate of the future forced response $T_{actual}(x, y, t)$ based on the actual scenario simulations of each model computed as the 5-year running-mean-boxcar-filter smoothed ensemble mean of these simulations. It turns out that the normalized difference $(T_{actual}(x, y, t) - T_{predicted}(x, y, t))/p_{CO2}(t)$ has a nearly constant future pattern (in general, these patterns are different between the three different models) beyond the training period (see

section 3.3.1). This pattern, characterizing the residual p_{CO_2} -congruent forced-signal variability that was unidentified over the training period, was further computed by averaging the p_{CO_2} -normalized SAT differences above over the interval starting 10 years after the end of each training period and ending in 2100. In each case, the residual pattern turned out to have near-zero global mean.

We hypothesize that the residual forced variability undetected by the CO_2 detrending and the subsequent S/NP decomposition and identified as described in section 2.3 is due to the slow adjustment of the climate system to the external forcing that only emerges later in the 21st century. To illustrate this concept, we developed an idealized energy-balance model (EBM) of the Earth's climate, by coupling a rudimentary single-layer gray atmosphere model of the planetary greenhouse effect with a Stommel (1961)-type two-hemispheric ocean box model (see section 3.3.2 and Appendix A). The model was designed to mimic the weakening of the meridional overturning circulation (MOC) in response to changes in the Earth's hydrological cycle induced by the global warming. In principle, such changes become detectable, that is, emerge above the level of internal variability, only in the late 21st century. These experiments thus help explain why pattern-based forced-signal recognition methods, trained on the historical data and even supplemented with the early 21st century scenario data may fail to identify these modes of climate change reliably or to project their future evolution faithfully. The possible existence of such inherently undetectable signals should therefore be kept in mind when applying climate-projection rescaling methods based on the emergent constraints derived from the historical period, including those introduced in the present study.

2.4 Rescaling CM6 simulations by using CM5 simulated climate in lieu of the ground truth

While the reanalysis based forced-signal rescaling of the simulated climates trained over the historical period reduces the spread among the future climate projections of individual models (section 3.2), it does not offer a proof that these rescaled projections are necessarily more realistic than the original, unscaled climate projections, since the future observations are not available. We address this issue by repeating the rescaling analysis of the two CM6 model simulations using the CM5 model simulations in lieu of the ground truth. Here we used the same training period (1880–

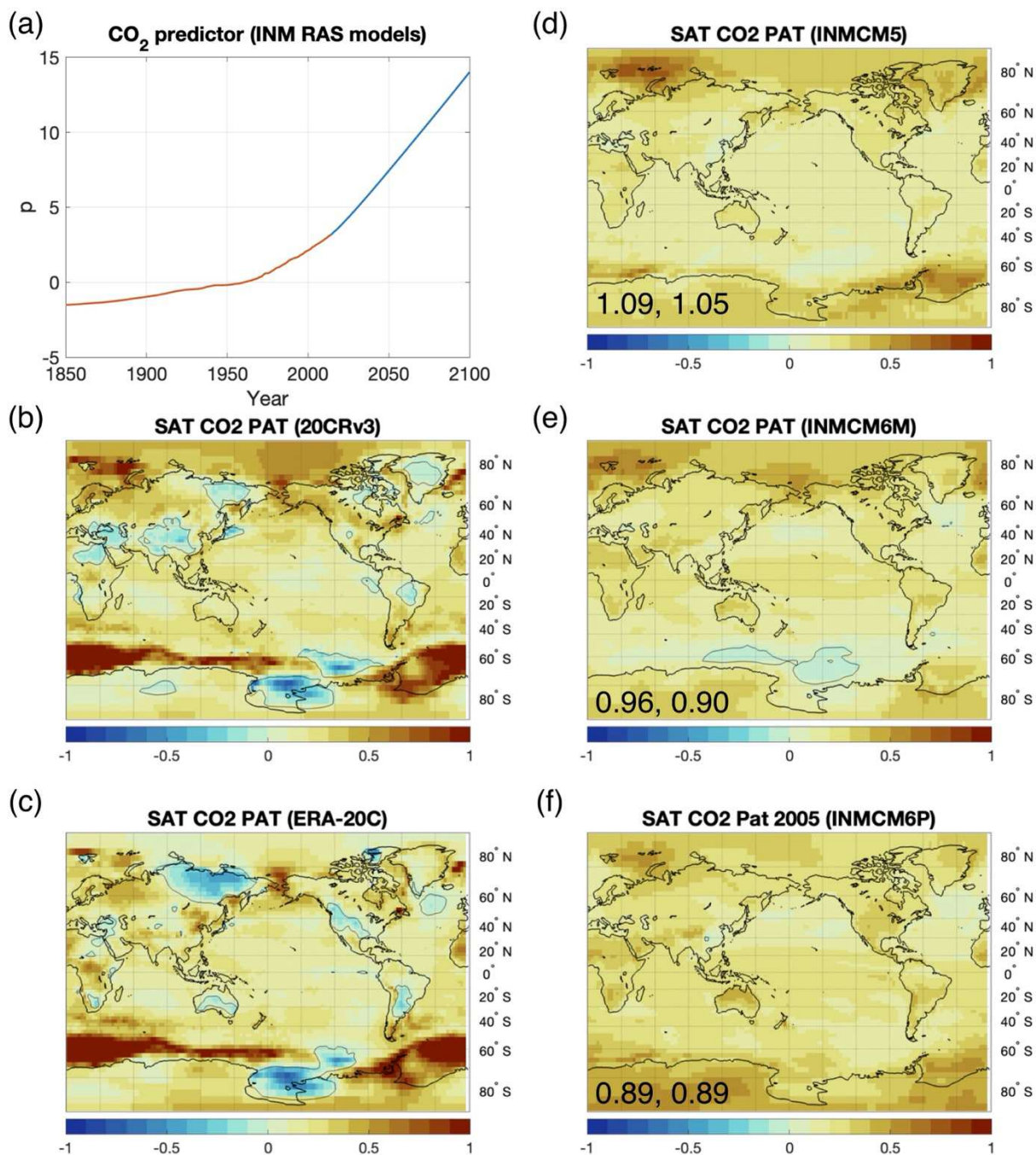


Fig. 1 The centered and normalized (over the 1880–2005 training period) p_{CO_2} predictor (a) and the corresponding regression patterns PAT based on: (b) 20CRv3 reanalysis; (c) ERA-20C reanalysis; (d–f) 5-year moving-average of the 1880–2005 ensemble-mean SAT time series from INMCM5, INMCM6M, and INMCM6P historical simulations, respectively. The numbers in the lower-left corner of the (d–f) panels represent the scaling factors b_l in (5), (6) derived by regressing the 1880–2005 20CRv3 and ERA-20C’s CO₂-congruent signals onto the CO₂-congruent signal of a given model. These scaling factors are later used to scale the model projections of their CO₂-congruent signals. The analogous model patterns based on different training periods are shown in **Fig. S2** of the *Supplementary Information* (while the corresponding intercept patterns are shown in **Fig. S1**).

2025) both to compute the requisite decompositions (of CM6 model simulations) and to run the rescaling regressions (recall that the latter period was confined to 1880–2005 when using the reanalysis data), as it turned out to slightly improve the rescaling results. These experiments confirm (section 3.4) that the rescaling does alleviate the differences between the (estimated) CM6 and (“true”) CM5’s simulated future warming patterns. It also shows that the remaining differences reflect anomalies due to a combination of different model dynamics and the residual forced-signal pattern undetected by the rescaling procedure (as per sections 2.3, 3.3).

Table 1. Fraction of variance (%) in the reanalysis-based CO₂-congruent variability accounted for by the CO₂-congruent variability in the INM RAS models. The coefficients are given for each model (left column) and each training period (top row). The first number in each cell corresponds to the 20CRv3 reanalysis, and the second number — to the ERA-20C reanalysis.

	1880–2005	1880–2015	1880–2025	1880–2035	1880–2045
CM5	58, 48	58, 48	56, 44	54, 42	53, 41
CM6M	46, 36	46, 35	46, 35	46, 34	45, 33
CM6P	54, 49	55, 47	54, 45	53, 44	52, 42

3 Results

3.1 CO₂–S/NP decomposition of the forced SAT response

The CO₂-signal patterns PAT_l [in (1)] of the three INM RAS models based on the 1880–2005 training period (**Fig. 1**, right column) are broadly similar (with spatial correlations all exceeding 0.93 level and thus r^2 values greater than 0.85) and amount to land- and polar-intensified warming across the entire globe. The two CM6 models show a more substantial warming over the tropical belt and a somewhat more pronounced land–sea contrast compared to that in the CM5 model, with the CM6P model exhibiting the strongest CO₂-congruent response. Notably, the CO₂-signal patterns of the two reanalysis products, largely consistent with each other (Figs. 1b, c), are substantially different from the model patterns (see **Table 1**). The model rescaling coefficients b_l [see (5), (6)] shown in panels (d–f) indicate that, on average, the CM5 model warms a bit slower than the reanalysis (rescaling coefficients exceeding unity), whereas the CM6 models warm too fast (rescaling coefficients <1), more so for the CM6P model. Given the dominance of the CO₂ mode in the climate projection of the INM models (see below), this would suggest a slight upward

correction of the year-2100 warming in the CM5 and downward corrections due to the CO₂-signal rescaling in the CM6 models (to be estimated exactly and discussed in more detail later in section 3.2).

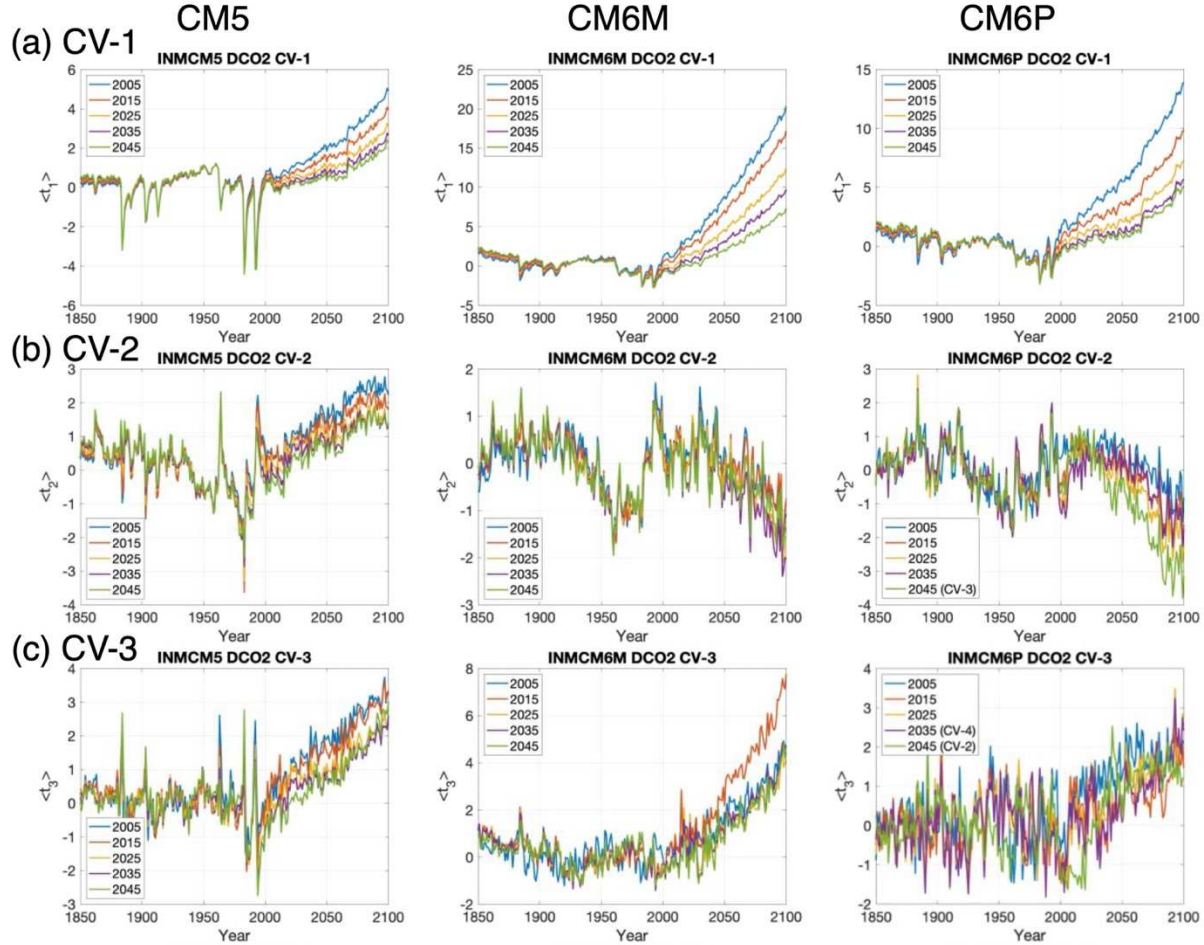


Fig. 2 Unit (ensemble) variance S/NP components 1–3 (panels a–c, respectively) of the CO₂-detrended SAT anomaly data for the INMCM5 (left column), INMCM6M (middle column), and INMCM6P (right column) historical simulations and different training periods, starting at 1880 and going through one of the end dates: 2005, 2015, 2025, 2035, and 2045, as shown in the panel legends.

The p_{CO_2} regression patterns PAT_l for different training periods (including the patterns duplicating those in Figs. 1d–f for the shortest 1880–2005 training period) are shown in **Fig. S2** of the *Supplementary Information*. They are all, again, qualitatively synonymous but exhibit some changes as the end of the training period shifts down from 2005 to 2025, while staying nearly the same for longer training periods. These changes amount to a stronger CO₂-signal-congruent warming for longer training periods. The intercept patterns INT_l (**Fig. S1** of the *Supplementary*

Information) represent the time-mean of the SAT anomaly (with respect to the 1880–2005 period) over a given training period and, naturally, exhibit patterns somewhat similar to the p_{CO_2} regression patterns since the latter dominate the forced warming signal; the INT_l patterns grow from zero for the 1880–2005 period to the magnitudes similar to those of PAT_l patterns for the 1880–2045 period in Fig. S2.

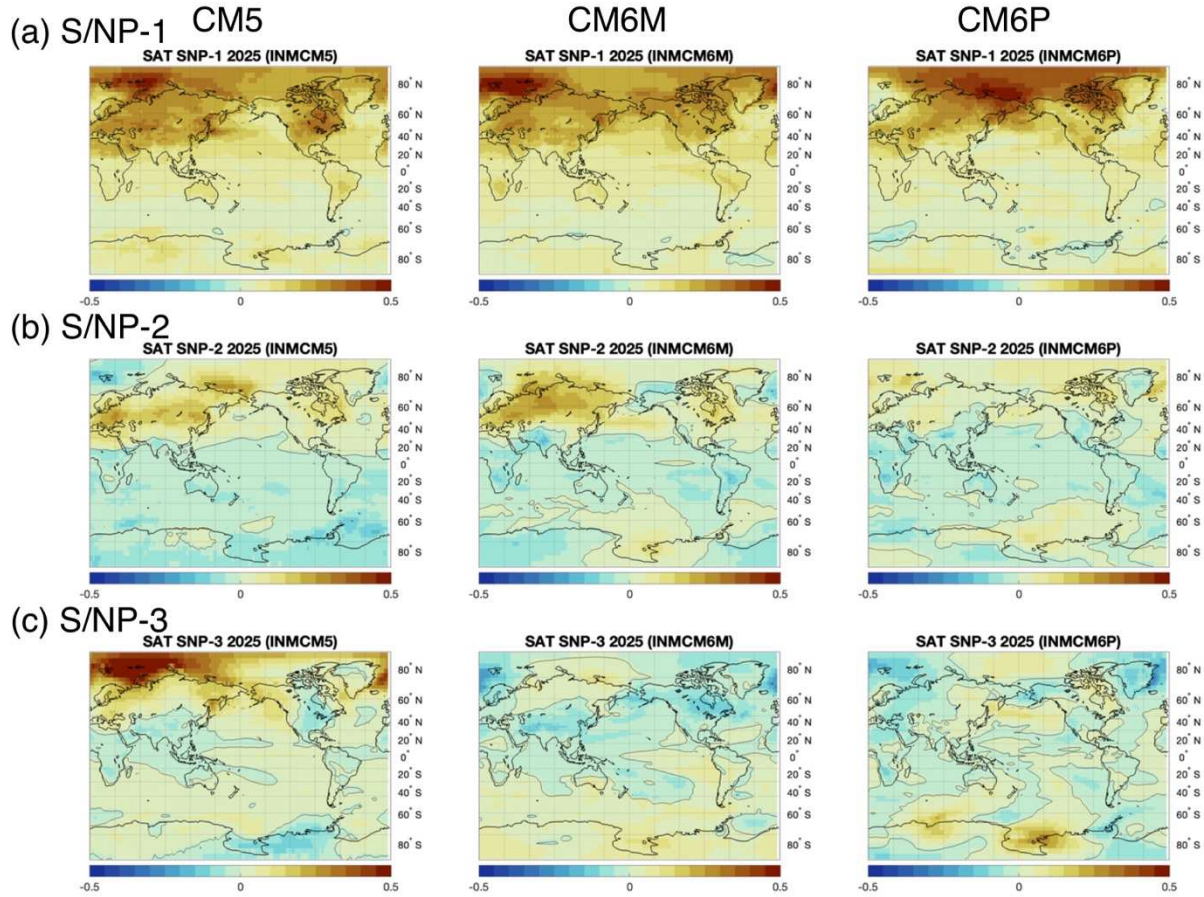


Fig. 3 S/NP patterns 1–3 (rows a–c, respectively) of the CO_2 -detrended SAT data for the INMCM5 (left column), INMCM6M (middle column), and INMCM6P (right column) historical simulations. All patterns are based on the 1880–2025 training period and correspond to the components shown in Figs. 2a–c, respectively. Analogous patterns based on different training periods are shown in **Figs. S3–S5** of the *Supplementary Information* (for S/NPs 1–3, respectively).

The three leading S/NP components of CO_2 -detrended SAT variability in each INM model exhibit a broadly consistent evolution across analyses based on different training periods (**Fig. 2**). The first S/NP component in all three models (Fig. 2a) is characterized by multidecadal variability interrupted by volcanic ‘dips’ in the historical period and a positive trend in the scenario simulations. The CM5 appears to show a markedly stronger volcanic component. The future trends

1 in S/NP-1 are more pronounced in the two CM6 models than in the CM5 model; it should be noted,
2 however, that the differences in the magnitude of these trends between training periods arise
3 largely because the S/NP components are constrained to have zero temporal mean over each
4 training period considered. The S/NP-2 components of different models are dominated by
5 multidecadal trends. They are mutually consistent across the three models during the historical
6 period, but diverge in the future, with weak trends of opposite sign in the CM5 and CM6 models.
7 The S/NP-3 components are structurally more disparate and display, generally, substantially
8 different temporal evolutions over the full record and lower signal-to-noise ratios.

9 These comparison traits are further supported by the examination of the leading S/NP patterns
10 of the CO₂-detrended variability (see **Fig. 3** for the results based on the 1880–2025 training period
11 and **Figs. S3–S5** of the *Supplementary Information* for the analogous — and consistent — patterns
12 associated with different training periods). The S/NP-1 and S/NP-2 patterns are largely consistent
13 between the three models too; the S/NP-3 patterns exhibit more substantial intermodel differences.
14 The S/NP-1 pattern features a global-scope warming amplified in the Northern Hemisphere,
15 whereas the S/NP-2 pattern is characterized by the interhemispheric SAT contrast and has a near-
16 zero global mean (see below).

17 The three INM models show consistent global-mean SAT anomaly (GMSTA) evolution over
18 the historical period but project different levels of global warming by year 2100 (**Fig. 4**), with the
19 CM5 model predicting moderate warming of about 3.5°C and the CM6 models indicating a larger
20 warming of around 5°C (with respect to the 1880–2005 climatology). The combination of the CO₂-
21 congruent signal (1) with the leading three S/NP modes (4) of the CO₂-detrended forced signal (2)
22 provide a good fit to the full simulated GMSTA time series over the entire 1850–2100 period of
23 simulation, irrespective of the training period. The CO₂-congruent signal is a major contributor to
24 the future warming in all cases, but it becomes the dominant contributor as the training period
25 increases. For the CM5 model (Fig. 4, left column), the CO₂-congruent signal is dominant for all
26 training periods, with only a slight correction to the global warming by year 2100 from the S/NP-
27 1 component. For the two CM6 models, the CO₂-congruent signal is more substantially aided by
28 the S/NP-1 component at short training periods, and progressively less so at longer training
29 periods. At the shortest training period, 1880–2005, the CO₂-congruent GMSTA signal is very
30 similar between all the models (rationalizing about 3°C warming by year 2100), but the CO₂-
31 detrended forced signal is weaker in the CM5 compared to that in the CM6 models, thus accounting

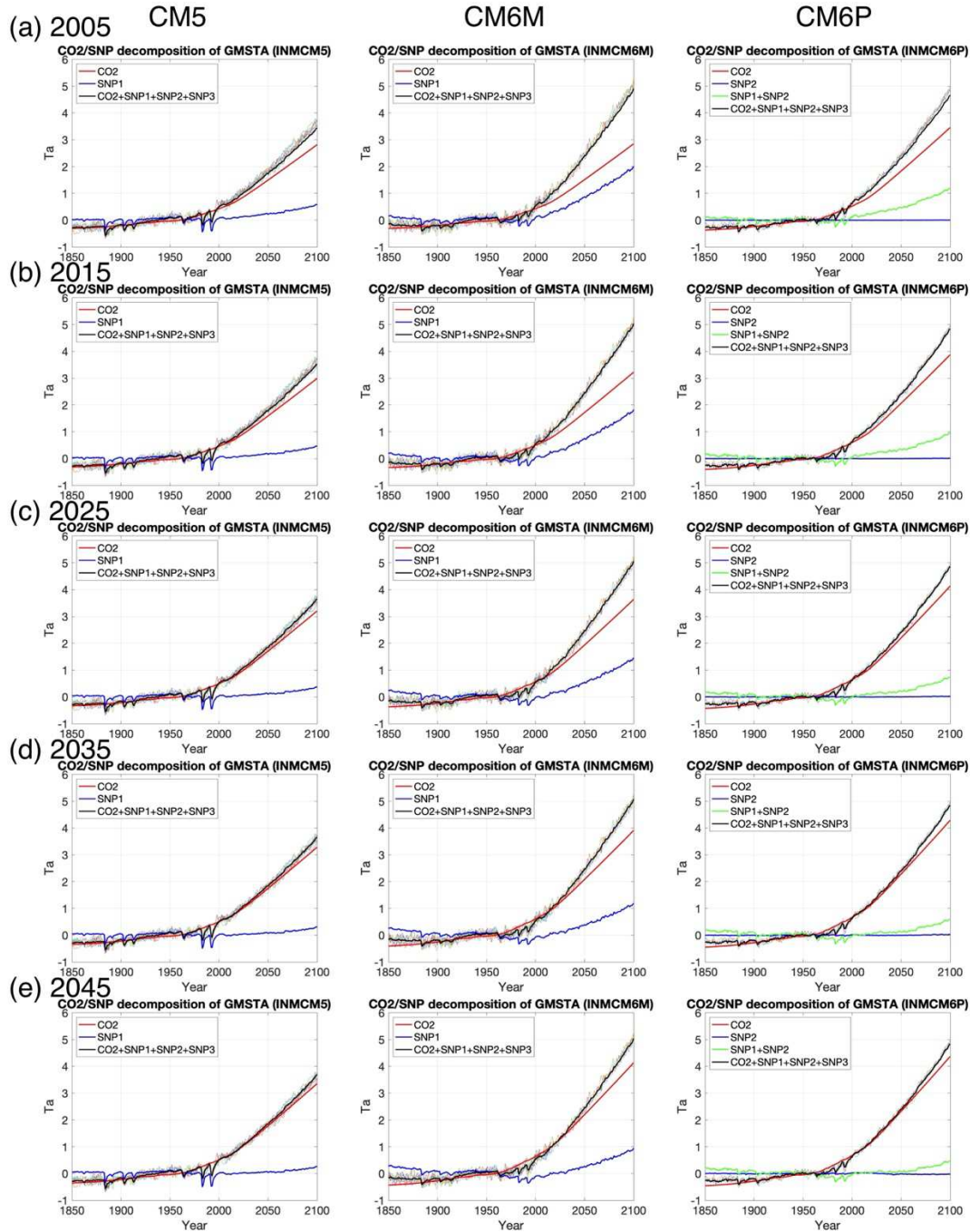


Fig. 4 Global-mean near-surface temperature anomaly time series (GMSTA, with respect to the 1880–2005 reference period) based on the ensemble simulations of the INMCM5 (left column), INMCM6M (middle column), and INMCM6P (right column) models, as well as their decomposition into the CO₂-congruent signal and the S/NP components of the CO₂-detrended (DCO₂) SAT data for different training periods starting at 1880 and ending in (a) 2005; (b) 2015; (c) 2025; (d) 2035; and (e) 2045. Original ensemble simulations are shown by thin curves and the contributions of different components to the estimated forced signal — by thick curves (see panel legends); the sum of these components constitutes the full estimated forced signal (thick black curves).

Table 2. Rescaling coefficients for: (a) CO₂-congruent signal [b_l in (5, 6)]; (b–d) S/NP components 1–3 [$c_{m,l}$ in (7, 8), $m = 1, 2, 3$]. The coefficients are given for each model (left column) and each training period (top row). The first number in each cell corresponds to the 20CRv3 rescaling, and the second number — to the ERA-20C rescaling.

(a)

	1880–2005	1880–2015	1880–2025	1880–2035	1880–2045
CM5	1.09, 1.05	1.03, 0.99	0.93, 0.87	0.89, 0.83	0.86, 0.78
CM6M	0.96, 0.90	0.85, 0.78	0.75, 0.69	0.69, 0.63	0.65, 0.59
CM6P	0.89, 0.89	0.80, 0.79	0.74, 0.72	0.71, 0.69	0.69, 0.66

(b)

	1880–2005	1880–2015	1880–2025	1880–2035	1880–2045
CM5	0.32, 0.33	0.32, 0.34	0.31, 0.33	0.30, 0.32	0.29, 0.32
CM6M	0.60, 0.79	0.54, 0.75	0.39, 0.55	0.31, 0.45	0.25, 0.36
CM6P	0.69, 1.06	0.59, 0.97	0.47, 0.75	0.39, 0.65	0.36, 0.57

(c)

	1880–2005	1880–2015	1880–2025	1880–2035	1880–2045
CM5	0.69, 0.97	0.65, 0.98	0.60, 1.14	0.51, 1.05	0.42, 0.89
CM6M	0.55, 1.54	0.35, 1.35	0.25, 1.16	0.24, 1.05	0.25, 1.06
CM6P	0.29, 0.81	0.49, 1.13	0.50, 0.94	0.53, 0.81	0.17, 0.42

(d)

	1880–2005	1880–2015	1880–2025	1880–2035	1880–2045
CM5	0.04, 0.10	0.25, 0.53	0.21, 0.28	0.23, 0.15	0.34, 0.20
CM6M	0.52, 0.18	1.29, 1.10	1.75, 1.46	1.68, 1.37	1.51, 1.50
CM6P	−0.20, 0.17	−0.21, 0.11	−0.13, 0.02	0.33, 0.72	0.30, 1.08

for a weaker global warming in the future predicted by the CM5 model. As the length of the training period increases, the CO₂-congruent GMSTA signal grows in all models, giving rise to about 3.25°C warming by year 2100 in the CM5 model and around 4°C in the two CM6 models (a bit more in the CM6P model), with the remaining slack of 0.25°C and 1°C (0.5°C in CM6P model) picked up by the S/NP-1. The global-mean SAT associated with the S/NP-2 and S/NP-3 components is close to zero and does not substantially contribute to the GMSTA in none of the cases.

3.2 Pattern-recognition based emergent constraints

We used the pattern-recognition based rescaling (6), (8) of the CO₂-congruent and CO₂-detrended forced signals of the INM RAS models to the 1880–2005 20CRv3 or ERA-20C reanalysis data to constrain SAT future projections of these models. The resulting rescaling coefficients for the dominant CO₂-congruent forced signal (**Table 2a**) are less than unity except for the CM5 model's signals estimated using the two shortest training periods; these coefficients decrease with increasing training period for all models and all reanalysis products, suggesting the downward correction of the estimated future global warming due to rescaling. In general, the rescaling also tends to scale down the contributions to the global warming from the S/NP components of the CO₂-detrended data, in particular from the S/NP-1 component (Table 2b).

3.2.1 Rescaled forced signals in the global-mean SAT

Indeed, comparing the original and rescaled GMSTA forced-signal projections (**Fig. 5**), we observe that the rescaling procedure dials down the projected global warming in all models and greatly reduces the spread between the models, for both reanalysis products used in rescaling and for all training periods. This is especially so for the longer training periods: in particular, the results based on the 1880–2025 and longer training periods (Figs. 5c–e) suggest the constrained estimated global warming to be around 3°C in all models, with the greatly reduced model uncertainty of about 0.5°C or less, due to scaled down contributions from both the CO₂-congruent forced signal and S/NP-1 component of the CO₂-detrended data. Using the longer training periods apparently fine-tunes the pattern identification of the forced climate change due to a combination of the greenhouse-gas forcing and anthropogenic aerosols by encompassing a time interval with a larger

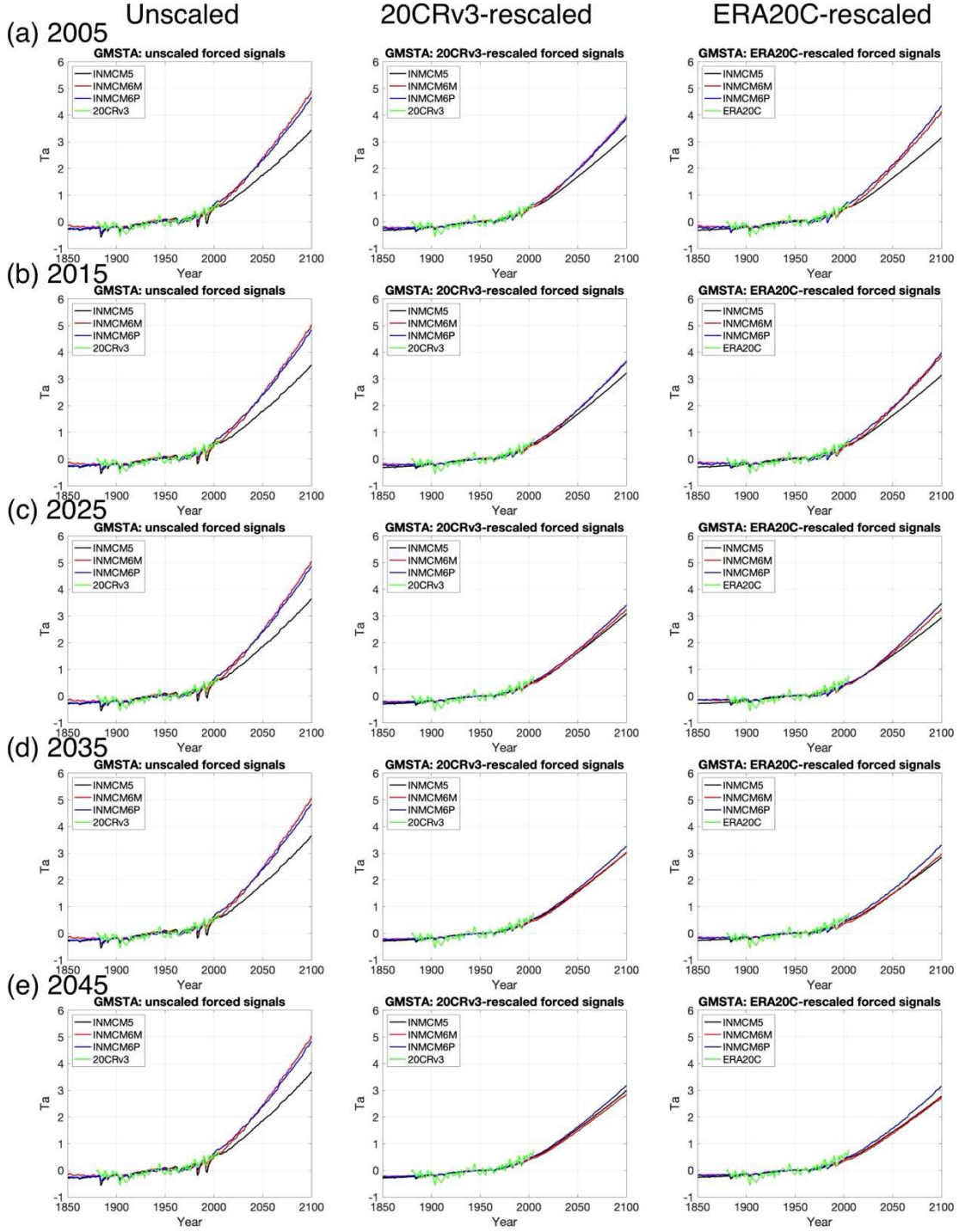


Fig. 5 Unscaled (left column), 20CRv3-rescaled (middle column), and ERA20C-rescaled forced signals in GMSTA for each model and the reanalysis product used to learn rescaling coefficients (6), (7) (see the legend). The rescaling is based on the CO₂-congruent SAT signals and DCO₂ S/NP components computed over the training periods starting at 1880 and ending in (a) 2005; (b) 2015; (c) 2025; (d) 2035; and (e) 2045.

signal-to-noise ratio and thus reducing the biases associated with the other forcing agents (in particular, volcanic aerosols) and the residual internal variability.

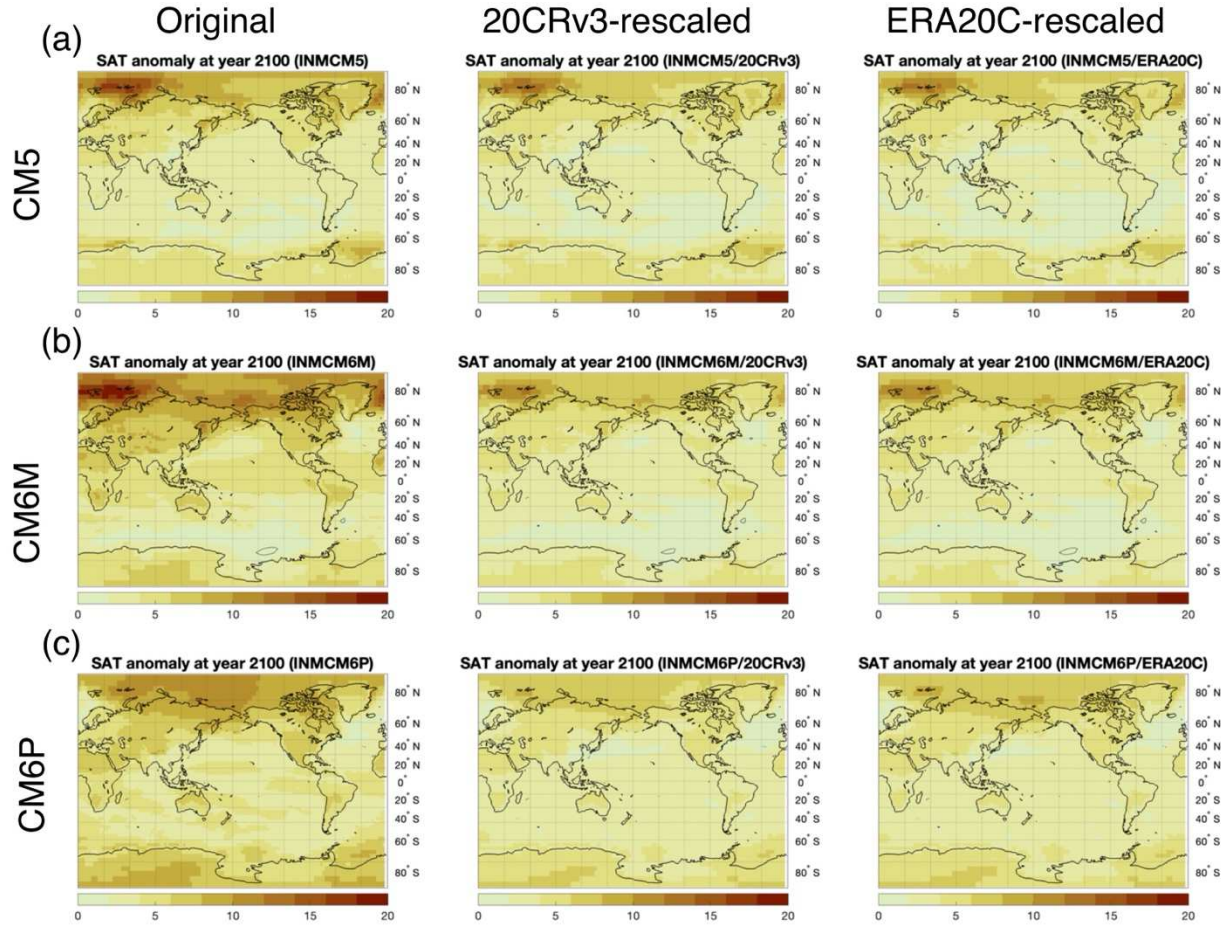


Fig. 6 The forced-signal temperature anomaly (with respect to the 1880–2005 mean) (degrees C) at year 2100 for the individual INM RAS models (top row: INMCM5; middle row: INMCM6M; bottom row: INMCM6P). Shown are unscaled anomalies (left column), 20CRv3 rescaled anomalies (middle column), and ERA-20C anomalies (right column). The rescaling here is based on the CO₂-congruent SAT signals and DCO₂ S/NP components computed over the 1880–2025 training period.

3.2.2 The spatial and modal structure of the SAT rescaling signal

To look into the differences in spatial patterns and magnitudes of the projected warming in the original and rescaled INM RAS climate model projections, we focus on the maps of their year 2100 SAT anomalies for each model. An example is given in **Fig. 6**, for the forced SAT signal estimated using the CO₂-congruent component and the CO₂-detrended S/NP components computed over the 1880–2025 training period: a widespread reduction of the unscaled forced SAT anomaly is apparent in all of the rescaled SAT anomalies. We define the rescaling signal as the

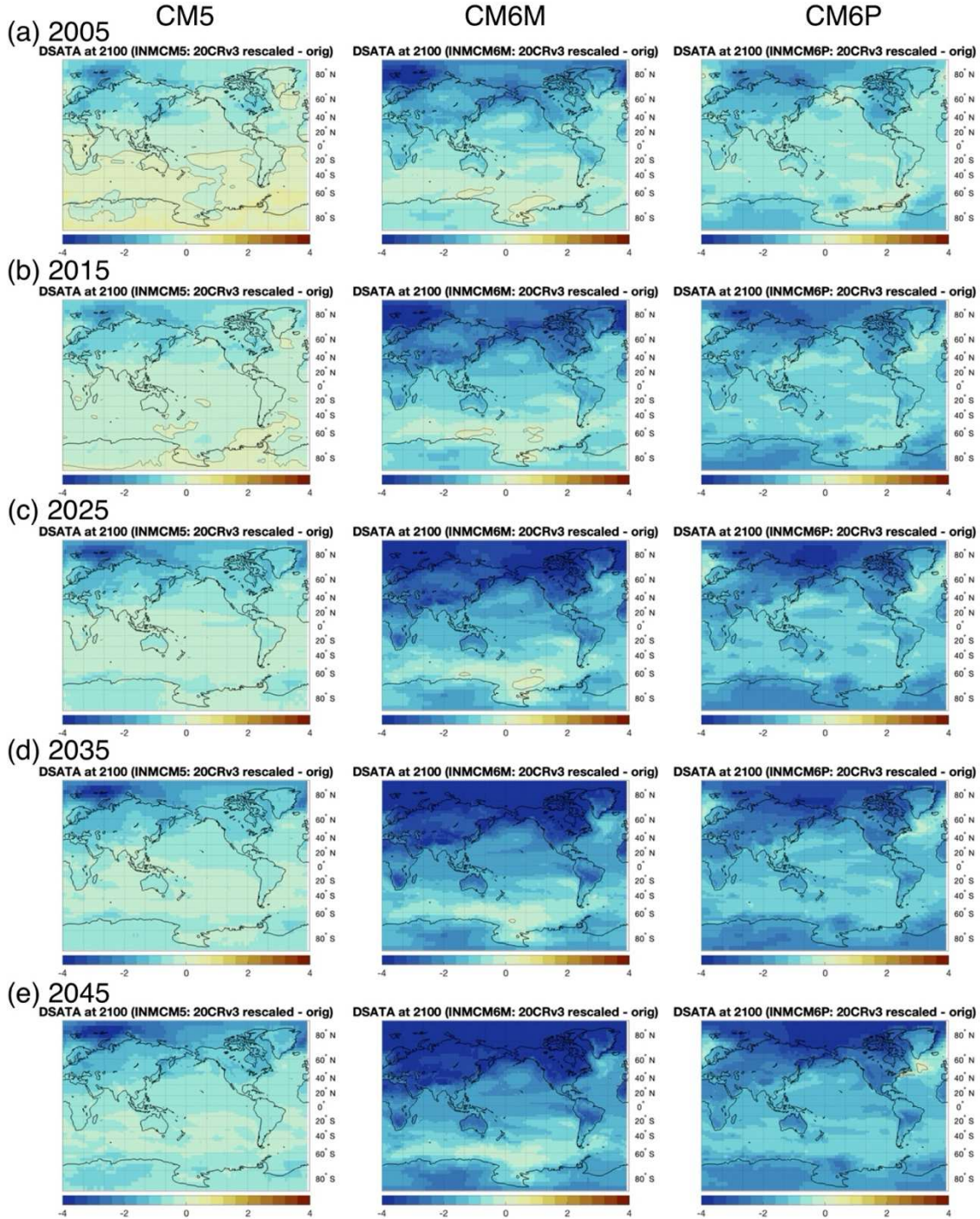


Fig. 7 The rescaling ‘signal’ measured at year 2100 as the difference between the rescaled and original forced-signal temperature anomaly (with respect to the 1880–2005 mean) (degrees C) for the 20CRv3-based rescaling and INMCM5 (left column), INMCM6M (middle column), and INMCM6P (right column) models. The rescaling parameters were estimated using the CO₂-congruent SAT component and DCO₂ SAT S/NP components computed over the training periods starting at 1880 and ending in (a) 2005; (b) 2015; (c) 2025; (d) 2035; and (e) 2045. Analogous results for the ERA20C-based rescaling are shown in **Fig. S8** of the *Supplementary Information*.

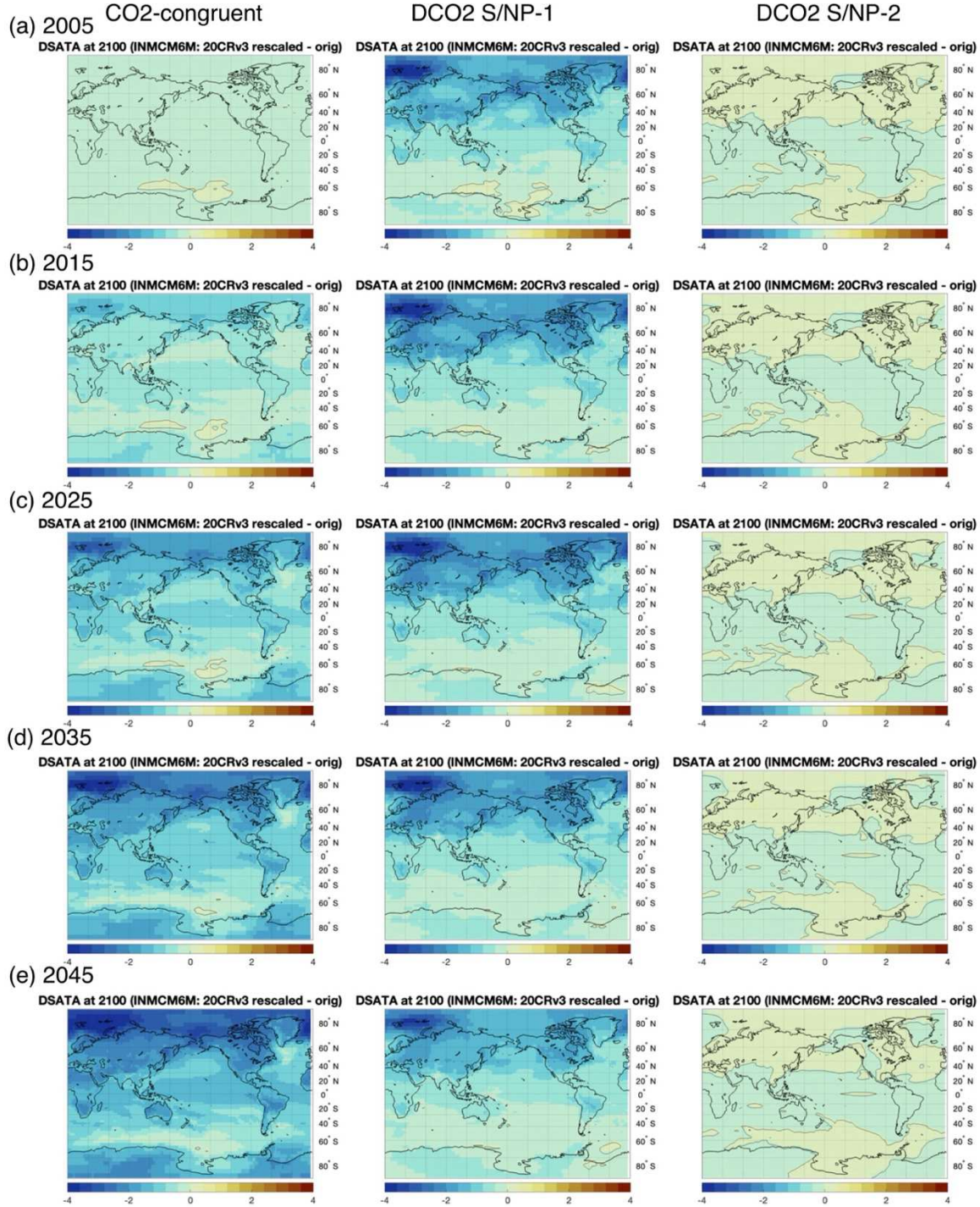


Fig. 8 The contributions to the INMCM6M's 20CRv3-based rescaling signals shown in Fig. 7 (middle column) from the CO₂-congruent component (left column), S/NP-1 component (middle column), and S/NP-2 component (right column). The rescaling parameters were estimated using the CO₂-congruent SAT component and DCO₂ SAT S/NP components computed over the training periods starting at 1880 and ending in (a) 2005; (b) 2015; (c) 2025; (d) 2035; and (e) 2045. The sum of patterns across each row equals the pattern shown in the corresponding row of the middle column of Fig. 7. Analogous 20CRv3 based results for the INMCM5 and INMCM6P models are shown in **Figs. S6** and **S7**, while the ERA20C-based results for all three models — in **Figs. S9–S11** of the *Supplementary Information*.

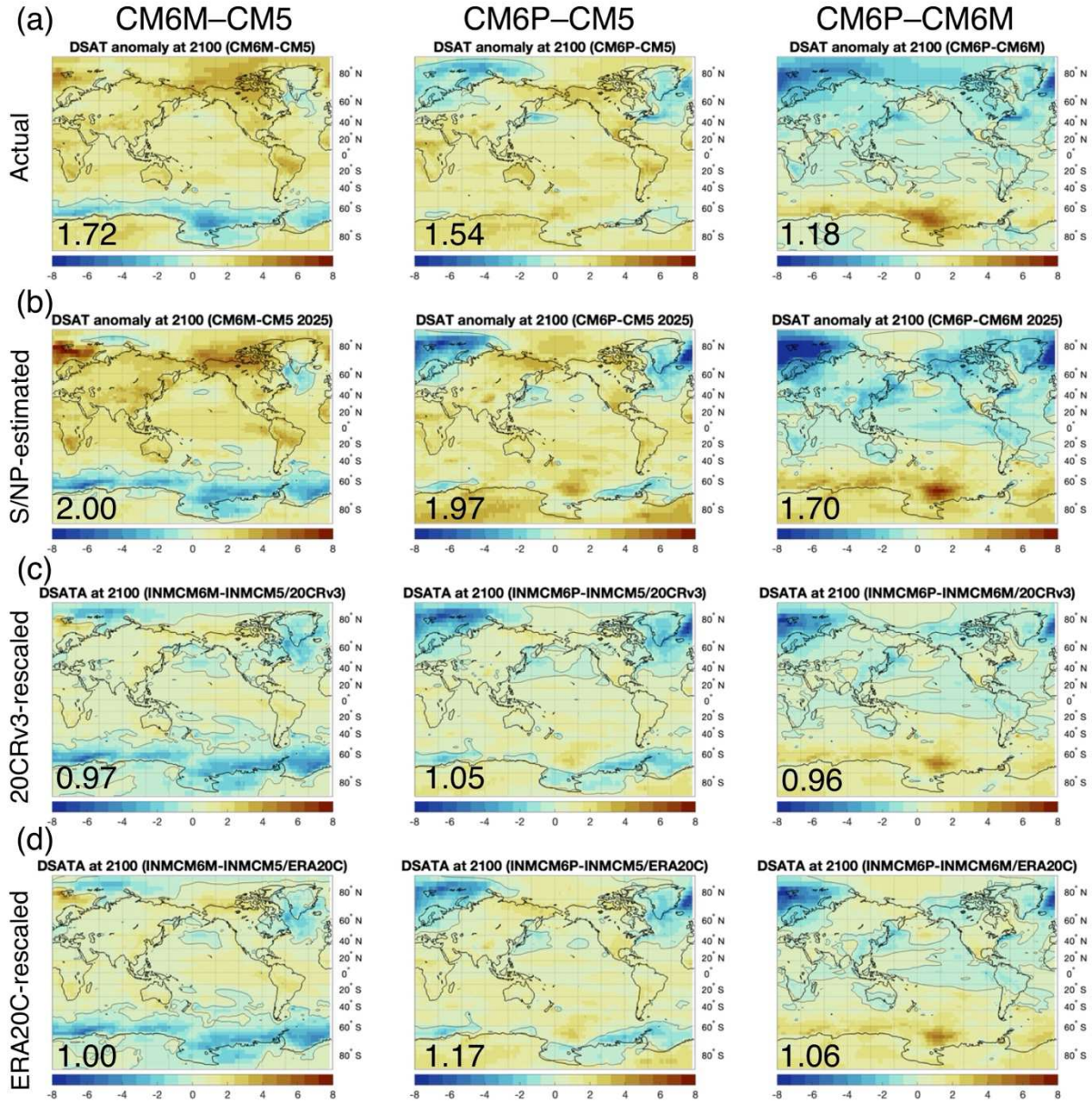


Fig. 9 (Climate projection) model uncertainty, as measured by the difference between the year 2100 (estimated forced signal) SAT anomalies of the CM6M–CM5 models (left column), CM6P–CM5 models (middle column), and CM6P–CM6M models (right column). These differences are shown for: (a) full model simulations (ensemble mean) smoothed by the 5-yr boxcar running-average filter, $T_{actual}(x, y, t)$; (b) unscaled pattern-recognition based forced-signal estimates $T_{predicted}(x, y, t)$; (c, d) scaled versions of the $T_{predicted}(x, y, t)$ associated with the 20CRv3 and ERA-20C based rescaling. The number at the lower-left corner of each panel shows the global root-mean-square value of the corresponding field (degrees C). The results are based on the CO₂-congruent SAT component and DCO₂ SAT S/NP components computed over the 1880–2025 training period. The analogous results based on different training periods are shown in **Figs. S12–S15** of the *Supplementary Information*.

1 difference between the rescaled and original SAT anomaly pattern at year 2100; this signal is
2 shown for all models and 20CRv3 (ERA-20C)-reanalysis based rescaling in **Fig. 7** (**Fig. S8** of the
3 *Supplementary Information*). All the models show widespread cooling with respect to the unscaled
4 forced signal, smallest for the CM5 and largest for the CM6M model. The cooling signal has the
5 largest magnitude for the results based on longer training periods, with very similar patterns and
6 magnitudes for the three longest training periods (Figs. 7c–e), consistent with Fig. 5.

7 In CM6M model under 20CRv3 rescaling, this signal is dominated, for the shortest training
8 period, by the contribution from the rescaled S/NP-1 component of the CO₂-detrended data (**Fig.**
9 **8a**). As the training period increases, the contribution of the rescaled CO₂-congruent component
10 grows, whereas that of the S/NP-1 component decreases slightly, although remains substantial. By
11 contrast, the contribution of the S/NP-2 component remains small and nearly constant throughout
12 (Figs. 8b–e). Qualitatively, this description applies to the 20CRv3 based rescaling results for the
13 CM5 and CM6P models (**Figs. S6, S7** of the *Supplementary Information*), although the
14 contribution of the CO₂-congruent component is generally larger for the latter model across all
15 training periods. The results based on the ERA-20C rescaling are also largely analogous (**Figs. S8–**
16 **S10** of the *Supplementary Information*). Thus, the rescaling signal is mainly due to a combination
17 of contributions from two different patterns (CO₂ and S/NP-1) comprising the forced signal of the
18 individual models.

19 **3.2.3 Reduction of the model uncertainty due to pattern-based rescaling**

20 The patterns of individual models in Fig. 6 exhibit broad similarities but also show differences
21 in magnitudes and spatial distribution of the estimated forced global warming at year 2100. Such
22 pattern differences between the three pairs of models are shown in **Fig. 9** for the actual simulated
23 (5-year running-mean boxcar smoothed ensemble-mean) SAT anomalies (a), as well as for the
24 unscaled and rescaled forced signals estimated using our pattern-recognition based extrapolation
25 (b–d); the latter estimates are associated here with the 1880–2025 training period (see **Figs. S12–**
26 **S15** of the *Supplementary Information* for analogous results based on other training periods, which
27 show very similar difference patterns, especially for longer training periods).

28 Note first that the actual (Fig. 9a) and predicted (Fig. 9b) forced-signal anomalies, while being
29 clearly well correlated, do exhibit quantitative differences characterized, in particular, by
30 overestimated loadings in the predicted model-difference patterns over the Northern Hemisphere

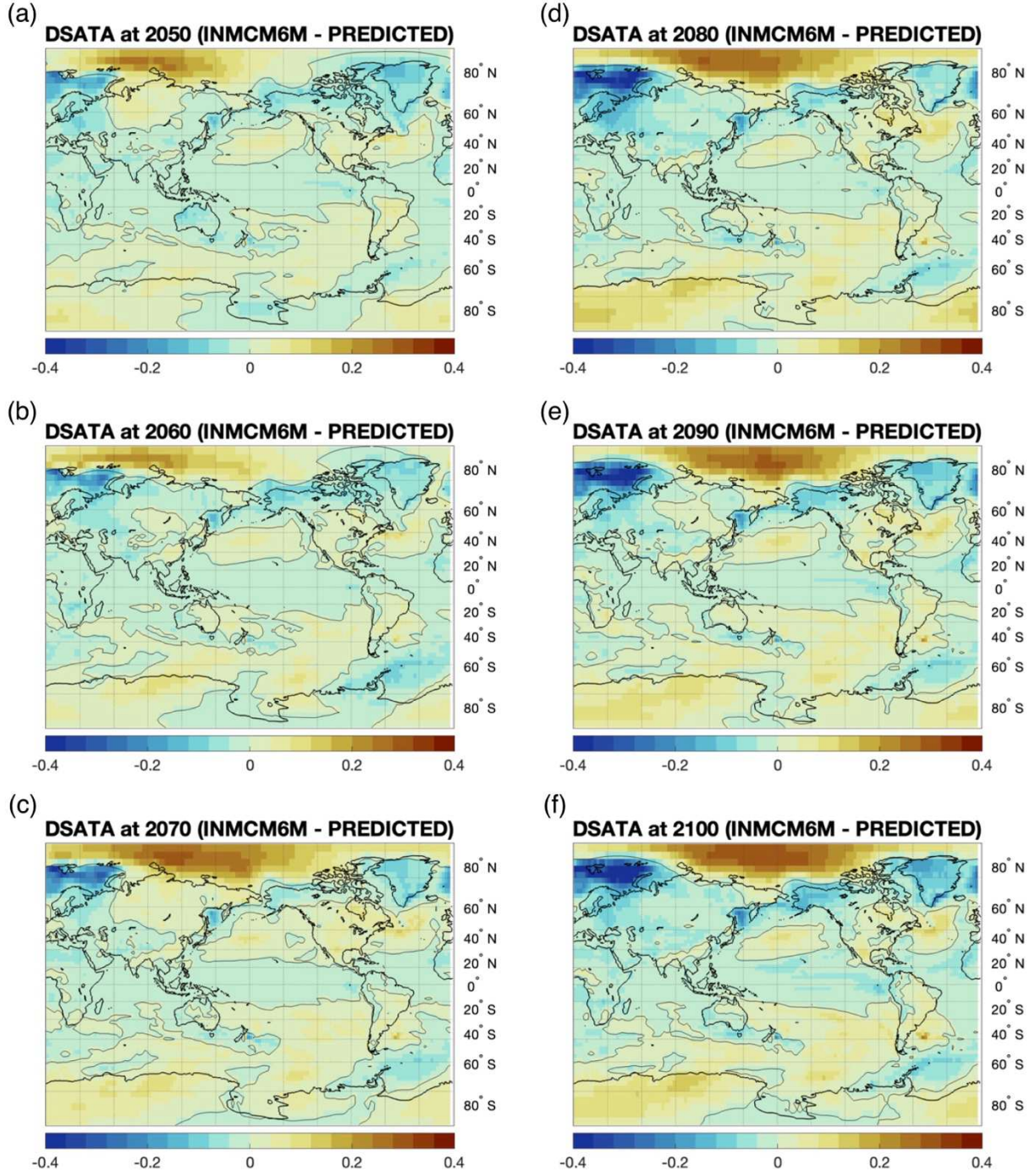


Fig. 10 Scaled SAT differences between the $(T_{actual}(x, y, t) - T_{predicted}(x, y, t)) / p_{CO_2}(t)$ for the INMCM6M model at (a) 2050; (b) 2060; (c) 2070; (d) 2080; (e) 2090; and (f) 2100. $T_{predicted}(x, y, t)$ estimation is based on the 1880–2025 training period.

(see **Fig. S16** of the *Supplementary Information*). These discrepancies are due to the forced-signal component undetected by our pattern-recognition analysis. This component is further discussed in section 3.3.

The differences between the rescaled predicted patterns (Figs. 9c, d) are smaller than those between the original, unscaled predicted patterns (Fig. 9b), reflecting the reduction of model uncertainty by as much as a factor of two due to rescaling, consistent with GMSTA behavior in Fig. 5. However, the (alleviated) patterns of the differences between the individual models seem to still persist even under rescaling, which points to the inability of the scaling procedure to eradicate the structural differences between the individual-model forced responses.

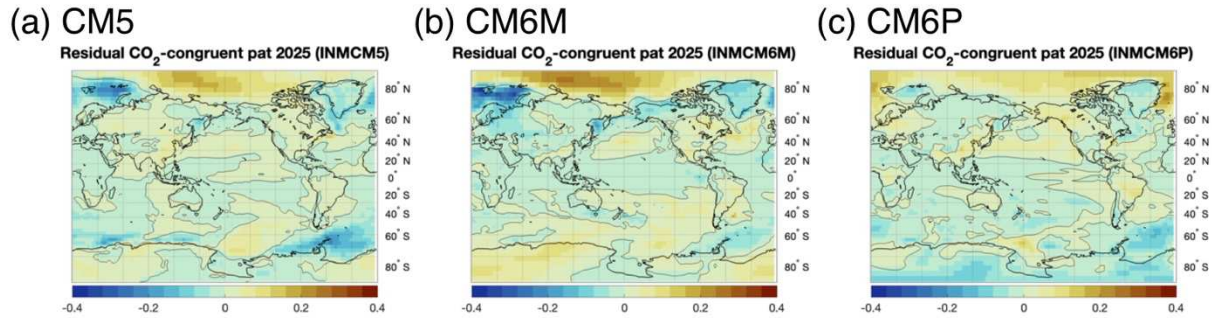


Fig. 11 Residual CO_2 -congruent SAT pattern data in the (a) INMCM5; (b) INMCM6M, and (c) INMCM6P historical simulations obtained using the forced signal prediction based on the 1880–2025 training period (the analogous results based on different training periods are shown in **Fig. S17** of the *Supplementary Information*). The patterns were computed by time averaging the scaled difference $(T_{\text{actual}}(x, y, t) - T_{\text{predicted}}(x, y, t))/p_{\text{CO}_2}(t)$ over the 2035–2100 period, where $T_{\text{actual}}(x, y, t)$ was defined as the 5-yr boxcar running-average ensemble-mean SAT in the actual model’s projection of the future climate. This scaled difference remained approximately constant across each validation period (see an example in Fig. 10).

3.3 Undetected climate-change signal

3.3.1 Identification of the missing signal

The residual, undetected future-climate forced signal introduced in section 3.2.3 was identified using a procedure described in section 2.3 by computing the p_{CO_2} -scaled differences between the actual ensemble-mean model projection of the future climate and the forced signal computed using our pattern-recognition analysis under different training periods. An example of such a scaled SAT difference pattern evolution is shown in **Fig. 10** for the CM6M model’s SAT simulation and the

SAT forced-signal estimate based on the 1880–2025 period, featuring a near-constant (scaled) SAT difference anomaly missing from our forced-signal estimate. The SAT pattern of the scaled difference was then estimated by averaging the patterns shown in Fig. 10 and analogous patterns for other years between 2035 and 2100. This procedure was repeated for all models, with resulting SAT difference patterns of the undetected CO₂-congruent residual forced signal displayed in **Fig. 11** (and in **Fig. S17** for the analogous results based on other training periods). These SAT difference patterns for all models and all training periods turn out to have a near-zero global mean, which explains the excellent match between our estimated global-mean forced SAT signal and the simulated global-mean temperature in Fig. 4 despite our forced-signal estimation procedure missing the residual forced mode discussed here.

The residual SAT difference patterns are relatively robust across the analyses based on the different training periods, but especially so for the longer training periods ending in 2025 or later (Figs. S17c–e). These difference patterns are also relatively similar between the different models featuring, for example, anomalously warm Arctic yet a cold SAT anomaly over the Barents Sea and Greenland, as well as over the Weddell Sea. The difference patterns over the North Atlantic are consistent with the surface signature of a slowed down Atlantic Meridional Overturning Circulation (AMOC: Yan et al. 2019; Rahmstorf 2024), with positive SAT anomalies in midlatitude North Atlantic and negative anomalies further north. Note, however, that despite these qualitative similarities, the differences between the residual forced signals of individual models are large enough to provide a sizable downward correction of the intermodel uncertainty compared to that estimated by our forced-signal pattern-recognition based detection and extrapolation (compare Figs. 9a and 9b).

3.3.2 Interpretation: Idealized EBM results

We hypothesize that the undetected p_{CO_2} -congruent variability identified in section 3.3.1 may arise from dynamical delays associated with the adjustment of slow components of the climate system, such as the oceanic MOC, to changes in forcing linked to anthropogenically driven reorganizations, for example to the shifts in hydrological cycle. This concept is illustrated here using an idealized EBM model (Appendix A), which is intended not as an accurate representation of the real climate system but rather as a process-based metaphor for possible climate behaviors. The model simulates a global warming of about 5°C by year 2100 relative to the preindustrial

global-temperature level (**Fig. 12b**) yet continues to warm further until year 2150 despite the constant GHG forcing after year 2100 (Fig. 12a) reflecting the ongoing thermodynamic adjustment of the model ocean thermocline.

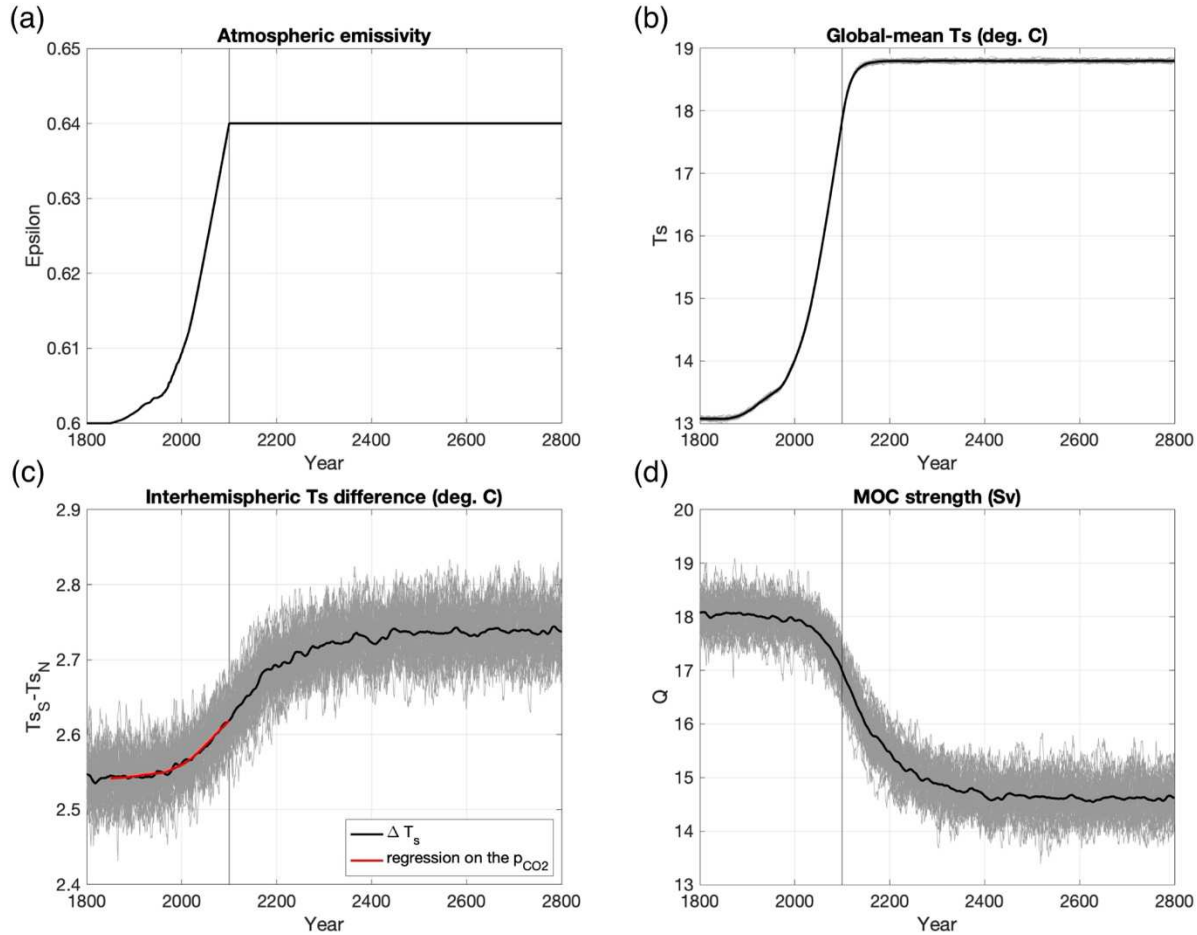


Fig. 12 Results from an idealized EBM model climate-change experiment. (a) (Prescribed) time dependence of the atmospheric emissivity ϵ , with temporal shape following that of the p_{CO2} predictor; (b) global-mean surface temperature time series (degrees C); (c) the interhemispheric surface-temperature difference ΔT_s (degrees C); (d) strength of meridional overturning circulation (MOC) (Sv). Heavy solid curves show the ensemble-mean over 50 independent simulations with different noise driving, while thin gray curves show the results from individual simulations. The red curve in (c) is the ΔT_s reconstruction obtained by regressing the actual ΔT_s time series onto the p_{CO2} predictor over the 1850–2100 period. Vertical line marks year 2100.

This p_{CO2} -congruent warming signal is easily detectable over the historical period (due to very high signal-to-noise ratio under the chosen model parameters), mimicking the forced climate change signal detected in the INM RAS climate models by our pattern-based identification methods. In contrast to this major climate-change signal, the model also exhibits

global-warming forced changes in its hydrological cycle causing the slowing down of its MOC (Fig. 12d), which starts around year 2025 and levels off only by year 2400. The slower MOC forces the interhemispheric temperature contrast (Fig. 12c), which, however, only rises above the background of internal climate variability by mid-21st century, making this p_{CO_2} -congruent adjustment mode effectively undetectable in the historical data, analogous to the residual p_{CO_2} -congruent variability discussed in section 3.3.1.

We note here that the EBM model of Appendix A exhibits an expected rich spectrum of possible behaviors under different parameter settings, including multiple steady states and future transition to the salinity-dominated mode under higher values for p_0 , as well as self-sustained multidecadal oscillations with the choice of longer MOC adjustment delay parameter τ (for example, for $\tau = 30$ years). These conceptual possibilities of climatic tipping points and internal oscillations have been discussed before and their quantitative assessment are beyond the scope of this paper, especially given a highly idealized, *ad hoc* nature of the present EBM model.

3.4 Intermodel rescaling

We now repeat the rescaling analysis of the two CM6 model simulations using each of the ten CM5 model simulations in lieu of the ground truth (see section 2.4). The (ensemble-mean) results presented in **Fig. 13** confirm that the rescaling does alleviate the differences between the (estimated) CM6 and (“true”) CM5’s simulated future warming patterns. In particular, it cuts the difference between the year 2100 global-mean temperature anomaly of the CM6M and CM5 models by about 40% (from 1.4°C to ~1°C) and removes most of the global-mean temperature difference between the CM6P and CM5 models (Fig. 13a), with spatially nonhomogeneous but uniformly negative rescaling signals (Fig. 13d). The CM6–CM5 difference maps using unscaled (Fig. 13b) and rescaled (Fig. 13c) estimates of the CM6 future climate SAT anomaly reconfirm the overall global-wide reduction of the intermodel differences by 15% (from 2°C to 1.7°C) and 35% (from 1.64°C to 1.05°C) for the CM6M and CM6P models, respectively. Note that these difference patterns and the associated uncertainty reduction factors are different from those associated with the reanalysis-based rescaling in Figs. 9 for a few reasons.

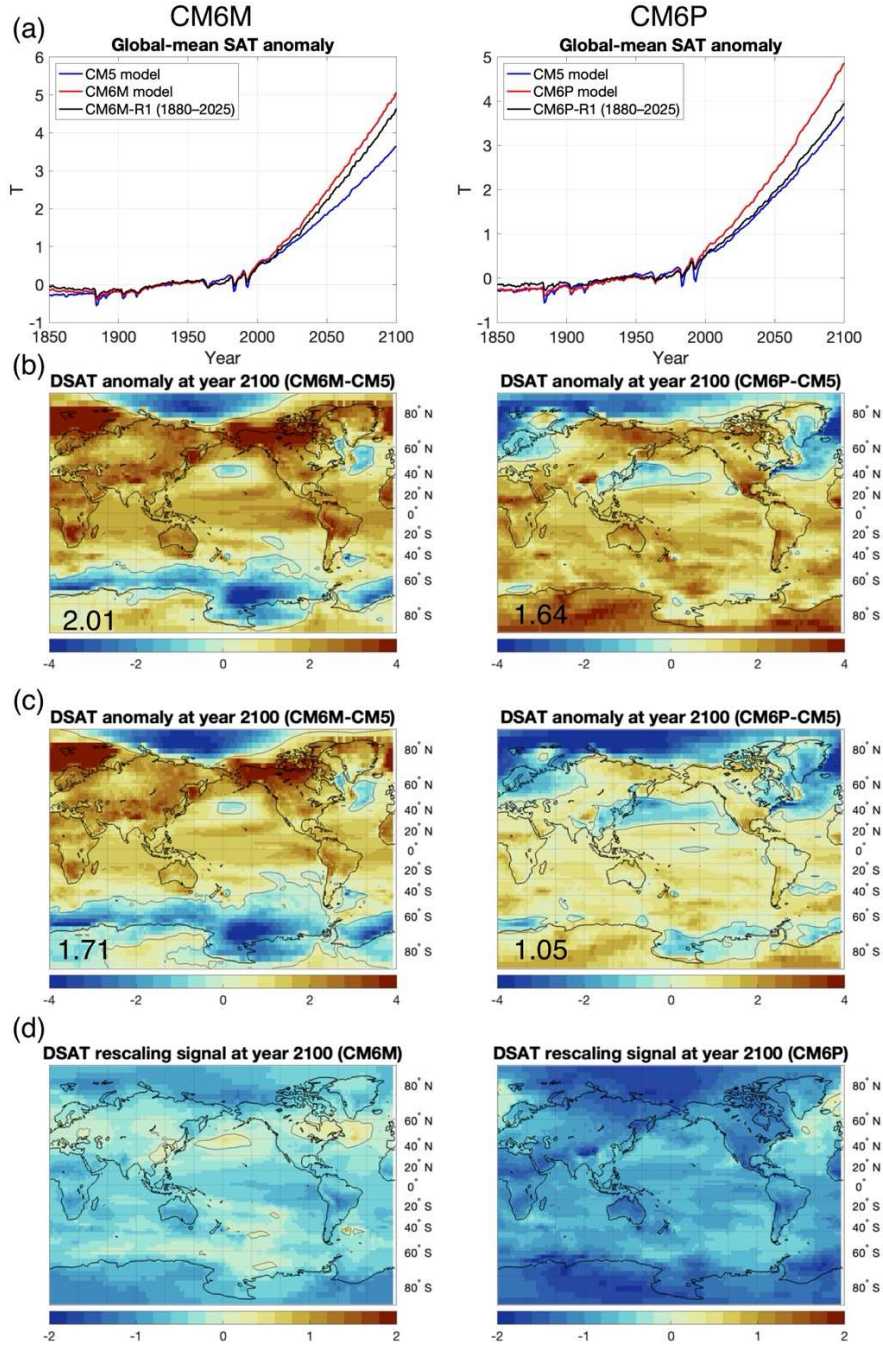


Fig. 13 Pattern-recognition based rescaling of the CM6M (left column) and CM6P (right column) model simulations using the CM5 simulated (historical and future) climates as ground truth: (a) unscaled and rescaled global-mean temperature anomaly time series [with respect to the 1880–2025 mean] (see legend for details); (b) the difference between the unscaled S/NP-extrapolated CM6 forced-signal and the CM5 (ensemble-mean) temperature anomaly at year 2100; (c) the same as in (b) but using the rescaled CM6 forced signals; (d) the rescaling signal — the difference between rescaled and unscaled CM6 temperature anomalies at year 2100. The rescaling here is based on the CO₂-congruent SAT signals and DCO₂ S/NP components computed over the 1880–2025 training period. The number at the lower-left corner of each panel shows the global root-mean-square value of the corresponding field. Units are degrees C. **Figures S18 and S19** of the *Supplementary Information* show analogous results for the rescaling based on the CM6M and CM6P “ground truth.”

First off, the CM5 based rescaling produces different rescaling coefficients for the CO₂-congruent and DCO₂ S/NP-1 components (which dominate the rescaling signal) — (0.85, 1.04) for CM6M and (0.79, 0.94) for CM6P — as compared to the values based on the rescaling to reanalysis (Table 2). The latter (corresponding) CM6M and CM6P values are (0.75, 0.39) and (0.74, 0.47) for the 20CRv3-based rescaling and (0.69, 0.55) and (0.72, 0.75) for the ERA20C-based rescaling. Second, the year 2100 SAT differences in Figs. 9a, b are either those between the actual model simulated anomalies (Fig. 9a) or between their estimated, pattern-recognition based forced-signal extrapolations (Fig. 9b), whereas the differences in Fig. 13 are between the extrapolated CM6 forced signals and the actual CM5 simulations. The latter differences thus incorporate the structural differences between the CM6 and CM5 CO₂-congruent and CO₂-detrended forced signals (such as the belt of negative SAT differences between CM6 and CM5 simulations over the Southern Ocean — compare the left columns of Figs. 9 and 13b, c), as well as the residual forced signal undetected by our pattern recognition procedure trained over the historical period (section 3.3). This signal is immediately apparent in the Northern high-latitude difference patterns in Figs. 13b, c, which are the negative twins of the patterns in Figs. 11b, c.

Analogous rescaling results using either CM6M or CM6P model simulations as the ground truth (**Figs. S18 and S19** of the Supplementary Information, respectively) confirm the general tendency for the rescaling procedure to reduce (or at least to not increase) the model uncertainty, except in one case of the CM6P rescaling to the CM6M ground truth (Figs. S18), where the rescaling drives the CM6P's model's projected climate further away from the CM6M simulated climate. This result reinforces the need to test the rescaling procedure proposed here in a larger multi-model ensemble using the standard cross-validation strategies (e.g., Immorlano et al. 2025).

4 Summary and discussion

4.1 Summary

We estimated the forced near-surface air temperature (SAT) response in the historical (1850–2014) and SSP3–7.0 (2015–2100) future scenario ensemble simulations of the three versions of the INM RAS climate model (CM5, CM6M and CM6P) using a combination of the CO₂ detrending (Hébert and Laepple 2025) and subsequent signal-to-noise maximizing pattern (S/NP) filtering (Wills et al. 2020; Kravtsov et al. 2025). The pattern recognition used five different

1 training intervals — 1880–2005, 1880–2015, 1880–2025, 1880–2035, and 1880–2045 — and
2 supplied, in each case, the estimates of the SAT forced response both within and beyond these
3 intervals through year 2100. The main thrust of the paper is to provide a proof-of-concept
4 demonstration of the utility of the novel linear method that rescales each of the above forced-signal
5 components to best match the observed historical climate evolution in serving as an emergent
6 constraint on the models’ future climate projections.

7 All models simulate very similar forced climate evolution over the historical period but display
8 some divergence in their future projections. For each model, the estimated forced response over
9 the 1850–2100 is well approximated by a combination of the model-specific CO₂-congruent
10 forced pattern and three additional patterns describing CO₂-detrended variability, of which the
11 first is clearly dominant, although residual CO₂-congruent variability not detected by our
12 methodology must also be considered, as discussed below. Within each model, the estimated
13 forced-signal patterns are relatively robust to the choice of the training period. These patterns are
14 also qualitatively similar across models, while differing quantitatively, for example in the
15 amplitudes of their regional centers of action; such differences reflect inter-model variation in
16 effective climate sensitivity and in the spatial patterns of forced climate change.

17 Pattern-recognition based rescaling of the future climate scenarios obtained by the optimal
18 linear matching of the estimated forced-signal evolution to the observed SAT variability over the
19 historical 1880–2005 period (provided by the 20CRv3 or ERA-20C reanalysis proxies) results in
20 a downward revision of the future global warming simulated by the models (by as much as 2°C in
21 the global-mean) and reduces the model uncertainty (intermodel spread) of the future climate
22 projections to a small fraction of a degree in the global mean and by as much as 50% in terms of
23 the root-mean-square SAT difference between the models. The model uncertainty is most reduced
24 in the forced signals identified using the three longish training periods (1880–2025, 2035, and
25 2045), possibly due to the fact that the overlapping patterns associated with volcanic and
26 anthropogenic forcing are better differentiated over the added (early twentieth century) periods
27 (2015–2025, 2035, or 2045) in which the latter forcing dominates. In spite of this success, however,
28 the pattern differences between the original model scenarios still persist — even if in a somewhat
29 muted form — in the rescaled model scenarios.

1 The forced signal estimates *all* fail to detect a largely CO₂-congruent *future* climate signal
2 associated with the SAT pattern that has a near-zero global mean (and so does not contribute to the
3 global-mean warming). These residual signals (computed by forming the differences between the
4 smoothed ensemble-mean of the actual model simulations and the pattern-based extrapolated
5 estimates of the future forced signal) share some common features across all three models, which
6 include a warm anomaly over the Arctic and regional cool anomalies over the Barents Sea,
7 Greenland and Weddell Sea, as well as a dipolar SAT signature over the North Atlantic possibly
8 associated with a weakened Atlantic Meridional Circulation (AMOC: Yan et al. 2019; Rahmstorf
9 2024). Despite these similarities, the residual forced signals of individual model are distinct
10 enough to provide sizeable corrections to the future warming pattern’s intermodel uncertainty
11 estimated by our pattern-recognition based extrapolation, which, in its unscaled form, slightly
12 overestimates the actual intermodel uncertainty (yet reduces it after rescaling). The patterns
13 associated with the residual forced signal start to arise in year 2050 but become most evident and
14 fully developed by 2070. They are apparently masked enough by the SAT response to the volcanic
15 forcing and the internal variability in the historical data to be undetectable by our pattern
16 recognition methods even when the early scenario data are included in the training period, which
17 is a clear limitation of the proposed pattern-based emergent constraint methodology. We used an
18 idealized energy-balance climate model (EBM) to offer an interpretation of the forced, largely
19 CO₂-congruent variability undetectable until late in the 21st century as the one caused by the
20 adjustment of the oceanic meridional overturning circulation (MOC) to the intensification of the
21 global hydrological cycle associated with the anthropogenic climate change.

22 Finally, we repeated our pattern-recognition based adjustment procedure to constrain the CM6
23 model simulations using the CM5 simulated historical and future climates in lieu of the ground
24 truth. This rescaling does shift the CM6 future warming patterns closer to the future patterns of the
25 CM5 model but fails to eradicate structural differences in these patterns, including, of course, the
26 differences associated with the residual forced signal (discussed above) that is undetected by our
27 pattern recognition scheme trained over the historical period. The analogous rescaling results
28 obtained by using one of the CM6 models as ground truth also suggest the general reduction of the
29 intermodel uncertainty due to rescaling but contain counterexamples that reinforce the need to test
30 the rescaling procedure proposed here in a larger multi-model ensemble using the standard cross-
31 validation strategies (e.g., Immorlano et al. 2025).

4.2 Discussion

Recent work (Armor et al. 2024 and references therein) has questioned the utility of the emergent constraints for the future global-mean temperature based on its historical post-1970 trends (which was initially proposed to avoid uncertainties associated with the aerosol forcing when using historical periods that start earlier: e.g., Jiménez-de-la-Cuesta and Mauritsen 2019; Nijse et al. 2020; Tokarska et al. 2020). In a nutshell, the patterns of the recent and future warming simulated in CMIP5/6 models are similar, leading to a tight linear relationship between the post-1970 global warming and climate sensitivity, thus forming the basis for the corresponding emergent constraint. These patterns, however, exhibit a common bias with respect to the observed post-1970 temperature trends, which feature an accelerated warming in the western equatorial Pacific and cooling in the eastern tropical Pacific (ETP) and Southern Oceans (Wills et al. 2022), with a plausible substantial contribution from the unforced, internal low-frequency variability absent or misrepresented in climate models (cf. Kravtsov et al. 2018, 2024). Armor et al. (2024) showed that the atmosphere-only models forced by the observed sea-surface temperature (SST) evolution have an effective climate sensitivity [estimated by using the standard global energy balance framework — and different from the equilibrium climate sensitivity (ECS)] comparable to the one inferred from observations but lower than that derived from the fully coupled simulations (unable to reproduce the observed SST trend patterns), thus ascribing the differences between the two to the so-called pattern effect (the dependence of the Earth’s radiative feedbacks on the pattern of warming). Since this behavior characterized both high and low ECS models, the authors further suggested that the recent observed warming “provides very little information about (the equilibrium) climate sensitivity.” At the same time, Liang et al. (2024) went around this problem by regressing out the ETP-congruent variability before applying the post-1970 observed global-mean forcing trend as a constraint and reported a higher-than-previously-estimated 21st-century (global-mean) warming and reduced intermodel uncertainty.

The present pattern-based rescaling of temperature arguably alleviates these issues by emphasizing the model simulated forced-signal patterns (Figs. 1 and 3) largely uncorrelated with the pattern of the recent model bias (cf. Liang et al. 2024) and by looking at a longer (1880–present) training periods, thus seeking to adjust the long-term model biases resulting from both the imperfect model physics and possible errors in the prescribed model forcings (in particular, aerosol emissions; see, for example, Moseid et al. 2020 and Maher et al. 2026). For the models considered,

our technique decreases the model spread by lowering the upper bound of the model estimated future warming, apparently at odds with the rescaling of Liang et al. (2024). The present method is also simpler (and, potentially, more interpretable) than the recent related strategy developed in Immorlano et al. (2025), which combines the Deep Neural Network emulators of the ESM models fine-tuned to best represent the historical observations of surface temperature via transfer learning. Further analysis using a larger multi-model ensemble is in order.

Acknowledgements This study was partially supported by the state assignment of the Shirshov Institute of Oceanology of the Russian Academy of Sciences (Agreement # FMWE-2024-0017). The work described in sections 3.1, 3.3.1, 3.4 was supported by the Russian Science Foundation project №23-62-10043, <https://rscf.ru/project/23-62-10043>.

Author contributions SK and AG designed the study, AG ran model simulations, SK conducted the statistical analysis and wrote the first draft of the paper, all co-authors contributed equally to the paper's revisions and final interpretation of the results.

Data availability All INM RAS model data used in this paper is publicly available from <https://esm-data.inm.ras.ru> or <https://climdat.inm.ras.ru/climate-data/>. The MATLAB © scripts developed in the course of analysis, as well as the input/output data are available from the authors on request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

1 Appendix A: Idealized energy-balance climate model (EBM)

2 The coupled model introduced in section 2.4 consists of two atmospheric and two oceanic
 3 boxes, one atmospheric and one oceanic box in each of the hemispheres; let's denote the NH
 4 components of the model by the subscript 1 and its SH components by the subscript 2. Neglecting
 5 the atmospheric heat capacity and interhemispheric heat transport, we have, for the atmospheric
 6 energy balance in each hemisphere:

$$0 = \varepsilon \sigma T_{os,i}^4 - 2\varepsilon \sigma T_{a,i}^4 + \lambda(T_{os,i} - T_{as,i}); \quad i = 1, 2, \quad (\text{A1})$$

7 where $\sigma = 5.67 \times 10^{-8} \text{ Wm}^{-2}\text{K}^{-4}$ is the Stefan-Boltzmann constant, ε is the (dimensionless)
 8 atmospheric emissivity ($\varepsilon = 0.6$ in the preindustrial control run), T_a is the upper-tropospheric
 9 temperature, $\lambda = 20 \text{ Wm}^{-2}\text{K}^{-1}$ is the air-sea heat exchange coefficient, and T_{os} and T_{as} are the
 10 sea-surface temperature and near-surface atmospheric temperature, respectively; all temperatures
 11 are measured in K. The latter temperatures are assumed to be linearly related to the ocean
 12 thermocline temperatures T_o and the atmospheric temperature T_a as follows:

$$T_{os,i} = 2T_d - T_{o,i}, \quad T_{as,i} = T_{a,i} + \gamma H_a; \quad i = 1, 2. \quad (\text{A2})$$

13 Here $T_d = 271.25 \text{ K}$ (-1.9°C) is the deep-ocean temperature set at the freezing temperature for
 14 sea water, $H_a = 10000 \text{ m}$ is the tropospheric height, and $\gamma = 6.5 \times 10^{-3} \text{ K m}^{-1}$ is the moist
 15 adiabatic lapse rate. The equations for the ocean boxes are written as

$$\begin{aligned} \rho c D \dot{T}_{o,i} = & R(1 - a_i) - \sigma T_{os,i}^4 + \varepsilon \sigma T_{a,i}^4 - \lambda(T_{os,i} - T_{as,i}) - \rho c |q| (T_{o,i} - T_{o,\sim i}) / \Sigma \\ & + Q \xi_i, \end{aligned} \quad (\text{A3})$$

16 where, again, $i = 1, 2$, the index $\sim i$ is equal to 2 when $i = 1$ and is equal to 1 when $i = 2$, the dot
 17 denotes the time derivative, $\rho = 1000 \text{ kg m}^{-3}$ is the representative ocean density, $c = 4000 \text{ J kg}^{-1}$
 18 K^{-1} is the ocean's heat capacity, $D = 1000 \text{ m}$ is the ocean's thermocline depth, $\Sigma = 2\pi a_E^2/3$ is
 19 the surface area of the ocean-atmosphere interface in each hemisphere (with $a_E = 6.4 \times 10^6 \text{ m}$
 20 being the radius of the Earth) — mimicking the Atlantic sector of the World Ocean, and q is the
 21 interhemispheric volume flux of water (in $\text{m}^3 \text{ s}^{-1}$). The solar constant R is set to the standard value
 22 of $1360/4 \text{ Wm}^{-2}$. To drive the interhemispheric contrast, we set the albedo values for the Northern
 23 and Southern Hemispheres to 0.32 and 0.28, respectively, resulting in the cooler Northern
 24 Hemisphere and warmer Southern Hemisphere. The last term on the right-hand side of (A3)

represents stochastic forcing modeled, in each hemisphere, as the independent Gaussian white noise (at monthly resolution) ξ_i with the amplitude $Q = 2 \text{ Wm}^{-2}$.

Analogous equations for the ocean's salinity in each box S_i are

$$\dot{S}_i = (-1)^i p \bar{S}/D - |q|(S_i - S_{\sim i})/(\Sigma D), \quad (\text{A4})$$

where $\bar{S} = 35\text{ppt}$ is the average ocean salinity, and the sign of the hydrological forcing p (m s^{-1}) is chosen to correspond to the freshening in the Northern Hemisphere and making the water saltier in the Southern Hemisphere. This forcing depends on the global-mean surface temperature to mimic the 7% intensification of the hydrological cycle for each 1°C of global warming:

$$p = p_0 [1 + \delta ((T_{os,1} + T_{os,2})/2 - T_{PI})]. \quad (\text{A5})$$

Here $p_0 = 0.035 \text{ m year}^{-1}$, $\delta = 0.07$, $T_{PI} = 286.24 \text{ K}$ (obtained by model tuning in the preindustrial experiment with the fixed $\varepsilon = 0.6$ to make $p = p_0$).

The interhemispheric ocean water volume flux q is given by

$$q = k[(T_{o,2}(t - \tau) - T_{o,1}(t - \tau)) - (\beta/\alpha)(S_2(t - \tau) - S_1(t - \tau))], \quad (\text{A6})$$

where the coefficient $k = 2 \times 10^7 \text{ m}^3 \text{K}^{-1} \text{s}^{-1}$ is chosen by model tuning, $\beta/\alpha = 4$ is the ratio of the haline contraction and thermal expansion coefficients for sea water and $\tau = 5$ years is the MOC adjustment delay. The positive q corresponds to the present-day MOC with the thermally driven sinking in the Northern Hemisphere and upwelling in the Southern Hemisphere.

We ran the ensemble of 50 experiments of the above model (with Euler time stepping of $\Delta t = 1$ month) under independent random forcing and common evolution of the emissivity $\varepsilon(t)$, which was set to 0.6 during the first 500 years (1351–1850: preindustrial control) of each experiment (started from uniform oceanic-box temperatures of 283 K and salinities of 35 ppt). In the next 250 years (1850–2100: historical and SSP3-7.0 scenario stage), the emissivity was raised from the value of 0.6 to that of 0.64 following the shape of the p_{CO2} predictor and then fixed at 0.64 for another 700 years (2100–2800: final stage).

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