Observation-based estimate of Earth's effective radiative forcing

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Human emissions continue to influence Earth's climate. Effective radiative forcing quantifies the effect of such anthropogenic emissions together with natural factors on Earth's energy balance (Soden et al. 2018; Gregory et al. 2020; Forster et al. 2021, 2024). Evaluating the exact rate of effective radiative forcing is challenging, because it can not be directly observed. Therefore, estimating the effective forcing usually relies heavily on climate models (Forster et al. 2024). Here, we present an estimate of effective radiative forcing that makes optimal use of observations. We use artificial intelligence to learn the relationship between surface temperature and radiation caused by internal variability in a multi-model ensemble. Combining this with observations of surface temperature and the Earth's net radiative imbalance (Loeb et al. 2018, 2021; NASA/LARC/SD/ASDC 2023), we predict an effective forcing trend of $0.72 \pm 0.20\,\mathrm{Wm}^{-2}$ per decade for 2001-2023. Our method enables a new and independent assessment of the observed effective radiative forcing since 1985, that can be updated simultaneously with available observations. We make advances to close the Earth's energy budget on annual timescales, separating the influence of forcing versus the radiative response to surface temperature variations. Effective radiative forcing has substantially increased since 2021 and has not been countered by a strongly negative radiative response, consistent with an exceptionally warm year of 2023 and 2024.

Significance Statement: Effective radiative forcing is the radiative perturbation of the atmosphere due to, e.g., emissions, before surface temperature changes. Quantifying this effect is key to understanding Earth's energy balance, testing climate theories, building climate models, and attributing climate change. Effective forcing cannot be observed and its calculation relies on climate models, which come with biases and assumptions of emissions and cloud processes that are not understood well yet. Here, we develop a new framework to calculate historical forcing that makes minimal use of climate models, by combining artificial intelligence with direct observations. Our forcing estimate indicates a strong upwards trend in the last two decades, can be updated immediately with new observations, and increases our understanding of Earth's recent energy imbalance.

Effective radiative forcing (F) and the radiative response to forcing (R, hereafter referred to as radiation) simultaneously modify the radiation budget of the Earth (N). The simplest energy balance model states that, globally averaged,

$$N = F + R. \tag{1}$$

Only N can be measured by satellites recording the energy flux in and out of the entire Earth system (Loeb et al. 2018, 2021; NASA/LARC/SD/ASDC 2023). A positive effective forcing F (excess energy introduced into the atmosphere) is generally balanced by a negative response R, but both are time-varying. In a stable climate, R balances F. A positive N indicates excess energy storage in the Earth system.

Effective radiative forcing (hereafter "forcing" F) is the sum of instantaneous radiative forcing (initial flux changes after a perturbation in emissions or prescribed concentrations in greenhouse gases or aerosols) and radiative adjustments (radiative flux changes induced by the forcing within the atmosphere but independent of surface temperature; e.g., Sherwood et al. 2015; Smith et al. 2020; Forster et al. 2021; Sherwood et al. 2020). Instantaneous radiative forcing has recently been estimated from observations using radiative kernels (Kramer et al. 2021), but radiative adjustments have to be added to make its use valid in equation (1) and to compare it to other estimates of radiative forcing (see discussion below; Forster et al. 2024). Radiative adjustments rely on climate models and are very uncertain. Here, we directly estimate effective radiative forcing without relying on the concept of radiative adjustments or climate models calculating them.

Estimates of historical forcing are uncertain because it requires the input of external factors such as greenhouse gas concentrations or aerosol emissions and relies on specific implementations of parametrizations that can lead to model biases (Soden et al. 2018; Bellouin et al. 2020; Forster et al. 2021, 2024). Here, we present a new method to quantify effective radiative forcing from the observed surface temperature and radiative imbalance, using a minimal number of assumptions. We combine observations with physically explainable machine learning methods to predict the radiative response to surface warming, from which we subsequently estimate the historical radiative forcing.

1. Convolutional neural network predicts radiative response

The radiation *R* is an aggregate of many processes initiated by the perturbation of a forcing. For example, CO_2 or aerosols change the structure of temperature in the atmosphere and at the surface, and the amount and distribution of water vapour, clouds, snow, sea ice, and vegetation. In turn, all of these factors can change the radiation balance of the Earth, both in the net shortwave solar radiation and the longwave outgoing radiation (Charney et al. 1979; Cess et al. 1990; Roe 2009). Research over the last decade has highlighted that global-mean radiation sensitively depends on the spatial patterns of surface warming, termed the pattern effect (Senior and Mitchell 2000; Andrews et al. 2015; Rugenstein et al. 2023).

We predict *R* from maps of surface temperature (*T*) with a convolutional neural network (CNN; Supporting Information Fig. 1 and Methods). CNNs have recently gained popularity in the geosciences (Reichstein et al. 2019), because they are well-equipped to recognize nonlinear spatial patterns in images (LeCun et al. 2015). It has been shown that CNNs outperform traditional and regularized linear methods in predicting global-mean radiation from spatial variations of *T* caused by internal variability (Rugenstein et al. in review). Here, we train a CNN to recognize the relationship between maps of *T* and the globally averaged *R* caused by internal variability in large initial condition ensembles of four climate models (see Methods). That is, the forced response is removed from all data prior to training by subtracting the ensemble mean, leaving only natural variations in *T* and *R*.

Training on internal variability removes the need to rely on the correct simulation of forcing or forced surface warming in climate models. We only make the assumption that climate models correctly simulate the relationship between the spatial pattern of *T* and global-mean *R* in an unperturbed climate. We do not argue that any individual model is fully correct (Forster et al. 2021; Maher et al. 2023; Myers et al. 2021), but rely on the spread and diversity in the multi-model ensemble to be broad enough to lie *around* the true relationship between *T* and *R* (Olonscheck and Rugenstein 2024).

The CNN replaces the usual approximation that *R* is linearly dependent on global-mean temperature (Gregory et al. 2004; Sherwood et al. 2020), which is unable to explain large variations of radiation in the historical record (Andrews et al. 2015; Gregory et al. 2020; Rugenstein et al. 2023). Instead, the CNN takes into account the spatial pattern effect, along with potential nonlinearities among T and R. The CNN successfully reproduces held-back testing members with high skill (Supporting Information Fig. 3a-b). Moreover, CNNs trained on data from only three models can effectively predict R in the fourth model, indicating that our CNN can make out-of-sample predictions. Importantly, the CNN skilfully predicts the forced response to temperature patterns that have seen strong radiative forcing (Supporting Information Fig. 3c-d). That is, applying the CNN to simulated temperature maps from a warming climate (as opposed to the internal variability the CNN is trained on), we correctly predict a negative trend in R. This is evidence that the CNN is transferable to real-world climate change.

2. Quantifying observed radiative forcing

We estimate the historical forcing with Eq. (1) by quantifying R with our CNN, and subtracting R from the observed N:

First, we apply observed surface warming patterns since 1985 to the CNN (Fig. 1, bottom blue lines). Different observational products result in very similar radiation responses (see Methods). Crucially, these observation-derived temperature maps have not been used to train the CNN, and they include a forced trend. Although the CNN has not been trained on forced climate change, the predicted radiation has a significant negative trend, as it should in a changing climate in which F increases (Raghuraman et al. 2021; Roe 2009; Knutti and Rugenstein 2015).

Second, the radiative imbalance N can be derived from the satellite record (Fig. 1, middle black line). Since 2001, these measurements are considered fairly precise (solid black line, derived from CERES, Loeb et al. (2018)) but N has been reconstructed back to 1985 from older satellite products (dashed black line, DEEP-C, Allan et al. (2014); Liu et al. (2020); Liu and Allan (2022)).

Finally, we quantify the forcing (Fig. 1, top red lines) by subtracting our predicted radiative response from the observed imbalance (i.e., $F = N - R$). This new estimate of F primarily uses observable quantities: the radiative imbalance and surface warming patterns. At the same time, we limit the use of climate model input: the relationship between T and R learned from internal variability only.

Our forcing estimate has a significant positive trend of $0.72 \pm 0.20\,\mathrm{Wm^{-2}decade^{-1}}$ (5%-95% confidence range, see Methods) in the period 2001-2023 (Fig. 1, dotted red line). This confirms that the Earth system is experiencing a rapid increase in forcing. We predict a stronger trend in F

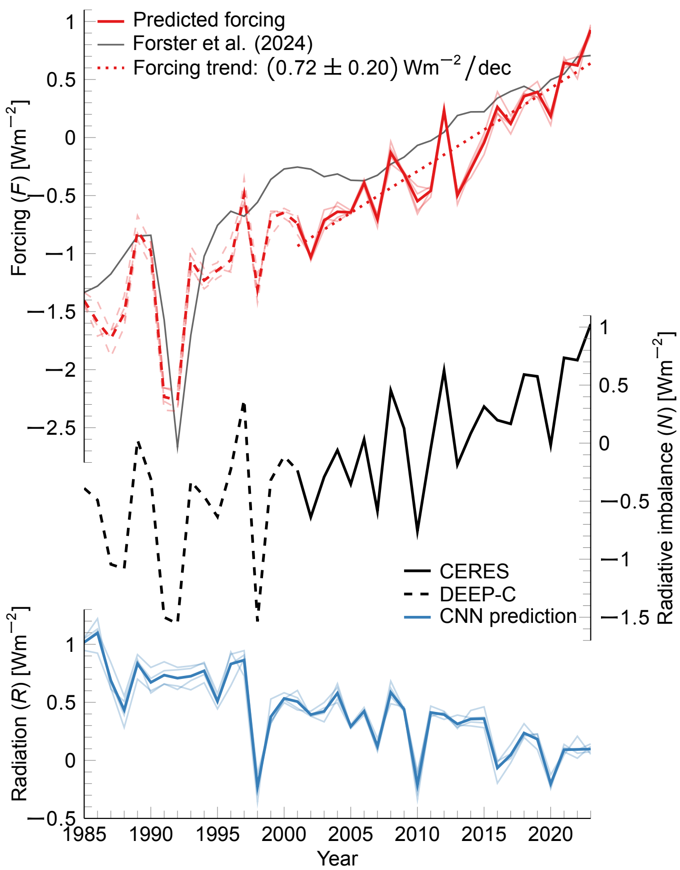

Fig. 1. **Radiative forcing derived from observations.** Bottom panel shows radiation (R, blue) predicted by the convolutional neural network from four observational surface temperature datasets (thin lines; thick line shows the average). Middle panel is the observed radiative imbalance (N, black). Top panel shows the predicted radiative forcing ($F = N - R$, red), and the dotted red line is the best linear fit for 2001-2023. As a comparison, the thin black line shows the radiative forcing from Forster et al. (2024).

than Forster et al. (2024) (top thin black line in Fig. 1, with a trend of $0.52\,\mathrm{Wm^{-2}decade^{-1}}$ in the same period), although it lies within the 5%-95% confidence range.

Contrary to other methods, we can resolve interannual variability of the forcing. For example, we correctly predict a strongly negative forcing in 1991/1992, when natural aerosol emissions peaked due to the 1991 Pinatubo eruption (Minnis et al. 1993; Stenchikov et al. 2009).

Over the last decade, the Earth energy imbalance has steadily increased (Hodnebrog et al. 2024; von Schuckmann et al. 2023; Storto and Yang 2024; Cheng et al. 2024) and may even be accelerating (Forster et al. 2024; Loeb et al. 2024b), most likely due to increased anthropogenic

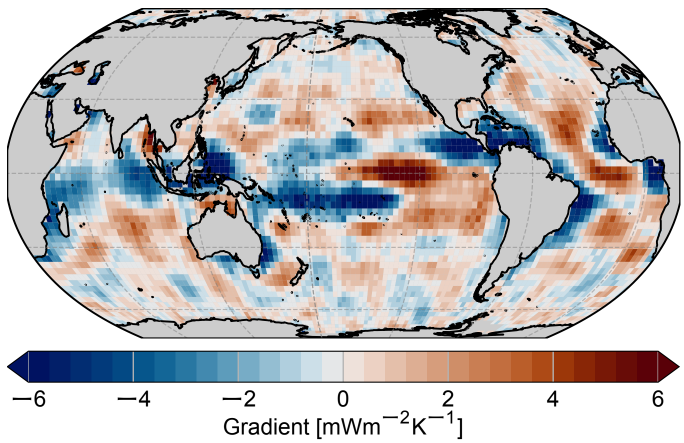

Fig. 2. **Gradient map of the convolutional neural network.** The map shows the derivative of global mean radiation to local surface temperature, and can thus be interpreted as local radiative feedback. Gradient maps are dependent on the input, because the CNN is nonlinear. Gradients with respect to detrended temperature maps from the testing dataset are averaged.

forcing (Raghuraman et al. 2021; Hodnebrog et al. 2024). Our results provide independent evidence that this increasing N is driven by an escalating F. Based on trend analysis, F increased by $0.51 \pm 0.61\,\mathrm{Wm^{-2}}$ from 2001 to 2010, and by $0.80 \pm 0.44\,\mathrm{Wm^{-2}}$ from 2011 to 2020, indicating an acceleration of the forcing. This acceleration could be explained by a reversed aerosol forcing trend (Quaas et al. 2022; Kramer et al. 2021), slowing down the global cooling effect of aerosols.

3. Further evidence supporting our approach

Our method relies on the CNN to learn the correct relationship between radiation and surface temperature patterns. Although machine learning techniques are often regarded as a black box, explainable artificial intelligence (XAI) techniques (Mamalakis et al. 2022) allow us to understand why and how the CNN makes predictions.

Local gradients of the CNN explain the sensitivity of the CNN to local temperature variations and can be interpreted as radiative feedback arising from internal variability. Radiative feedback characterizes how radiation responds to changes in temperature through processes including clouds, sea ice, or water vapor (Roe 2009; Lutsko and Takahashi 2018; Ceppi and Nowack 2021). A local positive feedback indicates that R increases when T in that location increases. This increased incoming radiation can eventually lead to higher global temperature, hence a positive feedback.

Conversely, a negative feedback is stabilizing: increased temperature causes a negative response R, which slows down warming of the planet.

The gradient of the CNN (Fig. 2 and Methods) elucidates the physically meaningful regions used to make predictions. For example, the large amplitude of the gradient in the Tropics reveals that the CNN is most sensitive to temperature changes in these areas. Regions of tropical deep convection, such as the Western Pacific, show strong negative values, interpreted as negative feedbacks. These negative feedbacks are caused by changes in nonlocal lower tropospheric inversion strength, modulating low cloud coverage and hence radiation (Dong et al. 2019; Alessi and Rugenstein 2023; Wood and Bretherton 2006). In contrast, increased temperature in more stable areas (e.g., the subtropical Eastern Pacific) can cause a local decrease in shallow marine clouds and a positive radiative response, as indicated by a strong positive feedback. Importantly, the CNN learns this relationship without explicit knowledge of the underlying physical processes.

We further evaluate the reliability of our approach by using existing climate model simulations. For the climate models used to train the CNN, designated model runs provide an estimate of F (Pincus et al. 2016, Methods), while T and N are available as standard model output. Instead of using observations, here we use the simulated temperature maps to predict R in the climate models (Fig. 3, blue lines). Then, we subtract the simulated N (Fig. 3, middle black lines) from the result to predict F (Fig. 3, red lines). For most models, the CNN is able to reproduce the simulated F (Fig. 3, top black lines) almost perfectly. Note that we perform this test on ensemble members that have not been used to train the CNN. For MPI-ESM, the forcing is underestimated by ~20 % by 2039, due to it simulating a stronger climate scenario (RCP8.5, see methods) compared to the other models (SSP2-4.5).

We are able to correctly predict F in the climate models, even though the CNN was trained on internal variability only. This, combined with the physically meaningful gradient maps (Fig. 2), increases our trust that our CNN learned a credible relationship between T and R and that our estimate of historical F is trustworthy.

4. Implications for past and future climate change

Our approach is independent of previous assessments of the forcing. Forster et al. (2024) (Fig. 1, top thin black line) finds a similar value based on a combination of model simulations and emission

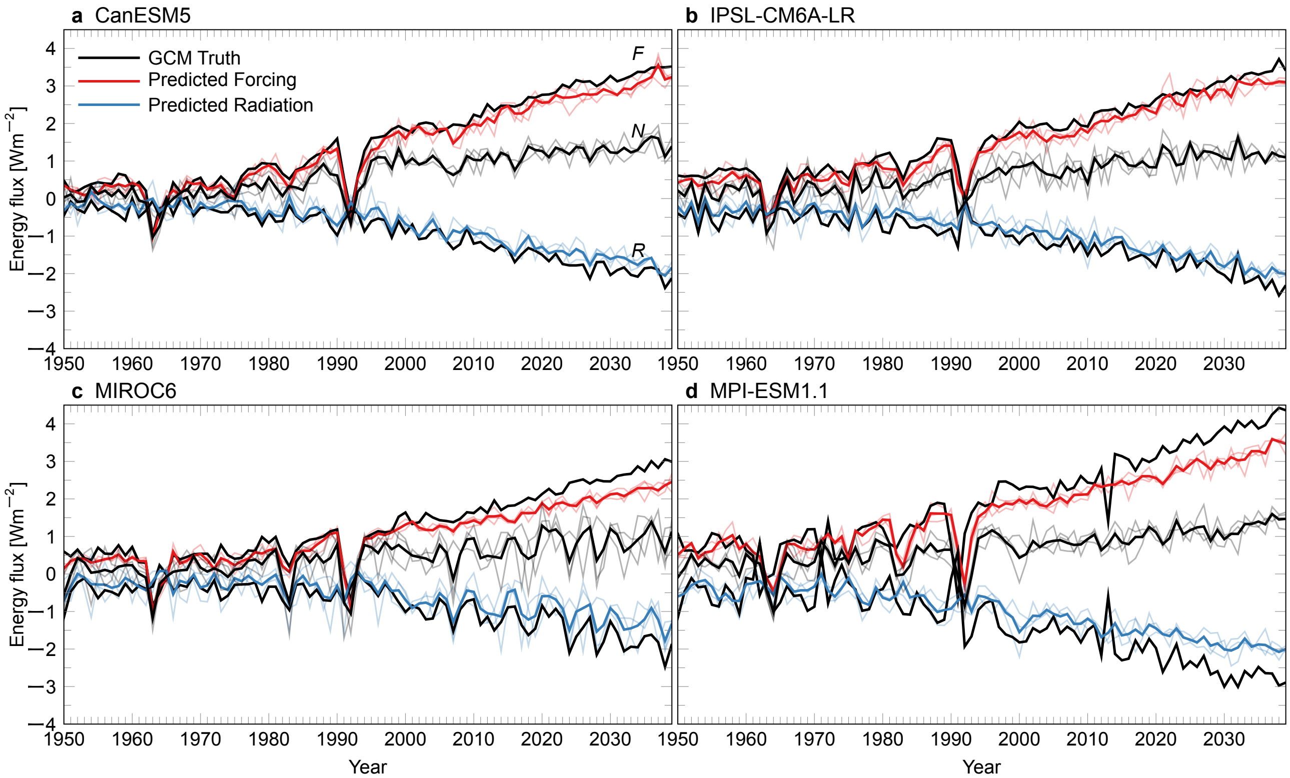

Fig. 3. **Radiative forcing estimated and simulated by four climate models.** Radiative response (R, bottom blue lines) and radiative forcing (F, top red lines) as predicted by the convolutional neural network (CNN) compared to the true model output (black lines). The middle black lines are the radiative imbalance (N) from the climate model, used to predict the forcing ($F = N - R$). Thick lines indicate ensemble averages, thin lines are individual ensemble members.

measurements. Our trend in F is somewhat higher than previous estimates (Bellouin et al. 2020; Raghuraman et al. 2021; Hodnebrog et al. 2024; Forster et al. 2024), but lies within the 5%-95% confidence range of other methods. Most other estimates are restricted to shorter periods and do not include 2023 yet. We highlight that our method allows us to estimate F instantaneously as soon as observations of surface warming (T) and radiative imbalance (N) become available and does not rely on model intercomparison protocols, bottom-up emission estimates, or expert assessments.

a. Stabilizing feedbacks

By construction, our estimate of the forcing trend ($0.72 \pm 0.20\,\mathrm{Wm^{-2}decade^{-1}}$ for 2001-2023) is consistent with stabilizing radiative feedbacks in the last two decades. The CNN predicts a trend in R of $-0.21 \pm 0.10\,\mathrm{W m^{-2} decade^{-1}}$. Reformulating this in terms of radiative feedbacks, i.e. $\lambda = \Delta R/\Delta\bar{T}$ with $\Delta\bar{T} = 0.22\,\mathrm{K/decade}$, we find an effective feedback parameter of $-1\,\mathrm{W m^{-2} K^{-1}}$. Conversely, other current estimates of F imply unrealistic values of R and feedbacks. For example, using the CERES observed N ($0.51 \pm 0.17\,\mathrm{W m^{-2} decade^{-1}}$) and estimated F by Forster et al. (2024) ($0.52\,\mathrm{W m^{-2} decade^{-1}}$) results in an unrealistically low $\Delta R = -0.01\,\mathrm{W m^{-2} decade^{-1}}$, implying a feedback of only $-0.05\,\mathrm{W m^{-2} K^{-1}}$. This feedback estimate suggests that increasing global temperature barely balances the excess forcing and implies that the Earth's temperature would sharply increase if the feedback and forcing trend remain constant. Our estimate is more realistic in terms of physical understanding of radiative feedbacks, which are universally recognized as stabilizing in the global mean for the current climate state and all commonly used future scenarios of climate change (Forster et al. 2021; Lee et al. 2021; Gregory et al. 2004, 2020; Bloch-Johnson et al. 2021; Dessler and Forster 2018; Dessler 2010).

b. Annually resolved drivers of the radiative imbalance

Our approach gives unique insight into annual drivers of the observed radiative imbalance N. According to Eq. (1), N can be influenced by F (a particular forcing) or R (response to the observed warming patterns and radiative feedbacks). As mentioned above, the low N in 1991/1992 is consistent with a negative F from the eruption of Pinatubo (Minnis et al. 1993; Stenchikov et al. 2009), while R remained approximately constant. In contrast, in 2010, the low N occurs in conjunction with an anomalously negative R, which we attribute to high anomalous temperatures in the West Pacific and low temperatures in the East Pacific.

Since 2021, F has increased strongly (Fig. 1). This has been linked to stricter international shipping regulations on aerosol emissions, that went into effect in 2020 (Yuan et al. 2024; Gettelman et al. 2024), although this increase in forcing was counter-acted by the Hunga Tonga-Hunga Ha'apai eruption in 2022 (Schoeberl et al. 2024). The rising F, in combination with a steady trend in R, contributed to an increase in the radiative imbalance in the last three years.

The year 2023 was exceptionally warm (Esper et al. 2024; Min 2024). The causes behind this record are still unknown, and there is disagreement on whether it can be explained by internal variability (Samset et al. 2024; Jiang et al. 2024; Raghuraman et al. 2024) or was due to external forcing (Rantanen and Laaksonen 2024; Gettelman et al. 2024; Min 2024; Kuhlbrodt et al. 2024;

Schoeberl et al. 2024). According to our results, the large N in this year was mostly induced by a large F. In the satellite record, the observed N has never been as high, while R did not decrease enough to balance N. That is, the observed temperature pattern in 2023 did not induce a radiative effect stabilizing enough to counteract the increased F. The continued amplification of the forcing, together with a weak radiative response could explain the remarkably warm 2023.

Eq. (1) does not include the influence of natural variations on N. In principle, also the internal variability of the ocean heat content affects N, independent of F and R (Raghuraman et al. 2021). Therefore, we cannot exclusively attribute changes in N to F and R. However, our method allows for the addition of ocean heat uptake, which could move the understanding of forcing from decadal-long trends towards annual timescales.

c. Outlook

We use the recently demonstrated dependence of global-mean radiation on patterns of surface warming (the pattern effect) to predict effective radiative forcing with a novel framework. Our convolutional neural network allows us to rely on climate models less than traditional methods and predict physically realistic values of R. We confirm the order of magnitude and acceleration of effective forcing, but our estimate lies on the high end of former approaches. Yet, our effective forcing estimate might still be too conservative, because tests in strong climate change scenarios indicate that the CNN slightly underestimates the forcing (e.g., Fig. 3**d**).

Our work moves towards attribution and increased physical understanding of annual values of the global-mean radiative imbalance. Combining our approach with in-situ ocean heat uptake estimates could strengthen and formalize this annual attribution. Our framework could be used to predict radiative imbalance into the future, because surface warming and radiative forcing are – in principle, partially – predictable.

Materials and Methods

Convolutional neural network

The convolutional neural network (CNN) consists of a series of convolutional, max pooling, and fully connected layers (Supporting Information Fig. 1). The input data (yearly surface temperature maps) is passed through a convolutional layer with 32 kernels of size 3×3, a max pooling layer with a 2×2 kernel, a second convolutional layer (32 kernels, size 3×3), and another max pooling layer (2×2 kernel). The output from the second max pooling layer is flattened and connected to two fully connected layers, with 32 and 16 nodes, before being compared to the output (global mean radiation). Every layer uses a ELU activation function, except for the last dense layer, which uses a linear one. We have tested different CNN architectures (Supporting Information Fig. 2 and Tab. 1) and chose the setup that performed best (lowest mean squared error) on the testing output data.

Because the CNN depicts a nonlinear function, its gradient is state dependent. To compute the gradient map in Fig. 2, derivatives with respect to local temperature are evaluated with the testing dataset (internal variability in the climate models, see below) and averaged over all years and ensemble members. Gradient maps averaged over members from individual climate models look similar to the one shown in Fig. 2, indicating that the average gradient in Fig. 2 is a good representation of all models. We use the CNN trained on four climate models simultaneously, under the assumption that, combined, they display enough variability to encompass observed variations of R with T.

Global climate model data

The CNN is trained on four different large ensemble climate models: CanESM5 (Swart et al. 2019), IPSL-CM6A-LR (Boucher et al. 2020), MIROC6 (Tatebe et al. 2019), and MPI-ESM1.1 (Maher et al. 2019). These models were selected based on two criteria: (1) they have at least 25 ensemble members; and (2) they contributed to the Radiative Forcing Model Intercomparison Project (RFMIP, Pincus et al. 2016), which provides dedicated simulations to quantify the radiative forcing (used as perfect model testbed in Fig. 3 and to compute the internal variability of R for training the CNN).

The input training data are maps of annual surface temperature (T). The output training data is global-mean radiation R, computed by subtracting the forcing F from the net radiative imbalance

N. We define a downward flux at the top of the atmosphere as positive. The forcing F is computed from a dedicated model run and is the same for all ensemble members, but model-dependent (Pincus et al. 2016). N is available as standard model output as the sum of incoming shortwave, outgoing shortwave, and outgoing longwave. CanESM5, IPSL-CM6A-LR, and MIROC6 simulate the historical forcing from 1870-2014 and the Shared Socio-economic Pathway 2-4.5 (SSP2-4.5) for following years. MPI-ESM1.1 simulates historical forcing from 1870-2004 followed by the representative concentration pathway 8.5 (RCP8.5). We apply a land mask to the surface temperature, such that we can use observed sea surface temperature datasets (see below). However, using a CNN trained on surface temperature over both land and ocean does not significantly alter our results.

We use annual means from 1870 to 2039 (the longest period of overlap across the model data) and scale to the resolution of CanESM5 ($\sim 2.8°$) using a bilinear regridder with period boundary conditions. We use 25 ensemble members from each model, of which 19 are used for training, 3 for validation, and 3 for testing. In total, we train on $19 \times 4 = 76$ ensemble members over a period of 169 years, evenly distributed over the four models. In order to use a minimal amount of information from climate models, T and R are detrended by removing the ensemble mean (at every grid point, for each model separately), effectively removing the forcing (Suarez-Gutierrez et al. 2021). Hence, any climate change information is removed, except for the indirect effect of the forcing on internal variability. Only this detrended data is used to train the CNN, and thus the CNN has never seen a forced response during training.

Observational data

When estimating the forcing (Fig. 1), we use temperature data from four different observational/reanalysis datasets: the European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5, Hersbach et al. 2020, 2023), COBE2 (Hirahara et al. 2014), NOAAGlobalTemp 6.0.0 (Huang et al. 2022, 2024), and The Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST-1.1, Rayner et al. 2003). All data are interpolated to the same grid as the CNN input data ($\sim 2.8°$) using a bilinear scheme with periodic boundary conditions. Note that NOAAGlobalTemp has a native grid of 5°, and thus had to be downscaled, while the other datasets have a smaller native grid. After regridding, the largest overlap of land areas across datasets is used as a land mask and applied to all training, validation, and testing data.

The observational datasets (apart from ERA5) report sea surface temperature (SST), and not near-surface air temperature (TAS), on which the CNN is trained. For ERA5, we compare CNN predictions based on SST and TAS and find similar values of the radiation (Supporting Information Fig. 4**a**, TAS is used in the main text). The forcing trend predicted from SST is slightly lower than the one predicted from TAS, but is not significantly different (Supporting Information Fig. 4**b**).

For the observed radiative imbalance N, we use satellite observations from CERES-EBAF4.2 (Loeb et al. 2018; NASA/LARC/SD/ASDC 2023). Yearly averages from 2001-2023 are computed from monthly data of globally-averaged net top of the atmosphere radiative fluxes. From 1985-2000, we use a reconstruction (DEEP-C, Allan et al. 2014; Liu et al. 2020) based on older satellite observations and model simulations. Note that the reconstruction before 2001 uses models and reanalyses, and is therefore less reliable than the direct observations derived from CERES (Raghuraman et al. 2019, 2023; Loeb et al. 2024a).

Trend analysis

Trends are calculated from yearly averages using ordinary least squares. We include predictions from all four temperature datasets in the calculation of the overall trend. We compare the overall trend with the trend of individual observational datasets and find similar results (within 5-95% confidence bounds). For the individual datasets, we find a trend in F of $0.69 \pm 0.21\,\mathrm{Wm^{-2}decade^{-1}}$ (ERA5), $0.70 \pm 0.21\,\mathrm{Wm^{-2}decade^{-1}}$ (COBE2), $0.76 \pm 0.20\,\mathrm{Wm^{-2}decade^{-1}}$ (NOAAGlobalTemp), and $0.70 \pm 0.19\,\mathrm{Wm^{-2}decade^{-1}}$ (HadISST-1.1).

We estimate the uncertainty in the trend of F by combining the uncertainties in the trends in N and R. Raghuraman et al. (2021) estimated the 95% confidence range of the trend in N to be $0.20\,\mathrm{Wm^{-2}decade^{-1}}$, which encompasses different observational uncertainties (see also Loeb et al. 2021, 2022; Hodnebrog et al. 2024). Assuming a normal distribution, this converts to a standard error of $\sigma_N = 0.10\,\mathrm{Wm^{-2}decade^{-1}}$. The standard error of the trend in R is computed for every observational dataset separately, and the mean is taken over all four datasets, that is, $\sigma_R^2 = \sum_{j=1}^{5} \sigma_j^2/5$. The uncertainty in the trend in R does not include any uncertainty introduced by the CNN. Finally, the standard error of the trend in F is estimated to be $\sigma_F = \sqrt{\sigma_N^2 + \sigma_R^2}$, and converted to a 5-95% confidence range by assuming the trend slope follows a t-distribution with 21 degrees of freedom.

Data availability

All climate model data is standard CMIP model output, and is made freely available by the Earth System Grid Federation (ESGF) at https://esgf-node.llnl.gov/. Observational temperature data is available from https://doi.org/10.24381/cds.adbb2d47 (ERA5), https://psl.noaa.gov/data/gridded/data.cobe2.html (COBE2), https://www.ncei.noaa.gov/products/land-based-station/noaa-global-temp (NOAAGlobalTemp), and https://www.metoffice.gov.uk/hadobs/hadisst/ (HadISST-1.1). The observed radiative imbalance can be downloaded at https://ceres.larc.nasa.gov/data/ (CERES-EBAF4.2) and https://researchdata.reading.ac.uk/347/ (DEEP-C).

Code availability

All reported results were analyzed using Python-3.10, and the CNNs were trained using Tensorflow-2.15. All code will be made available at the time of acceptance of the manuscript.

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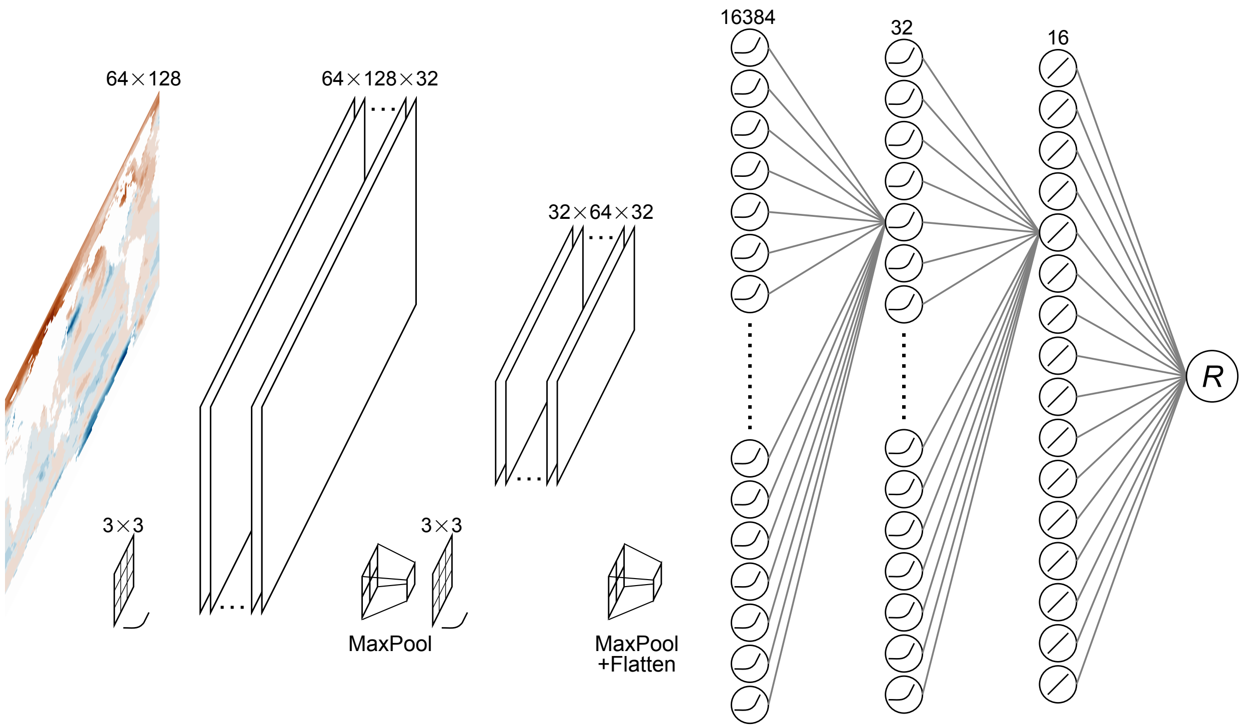
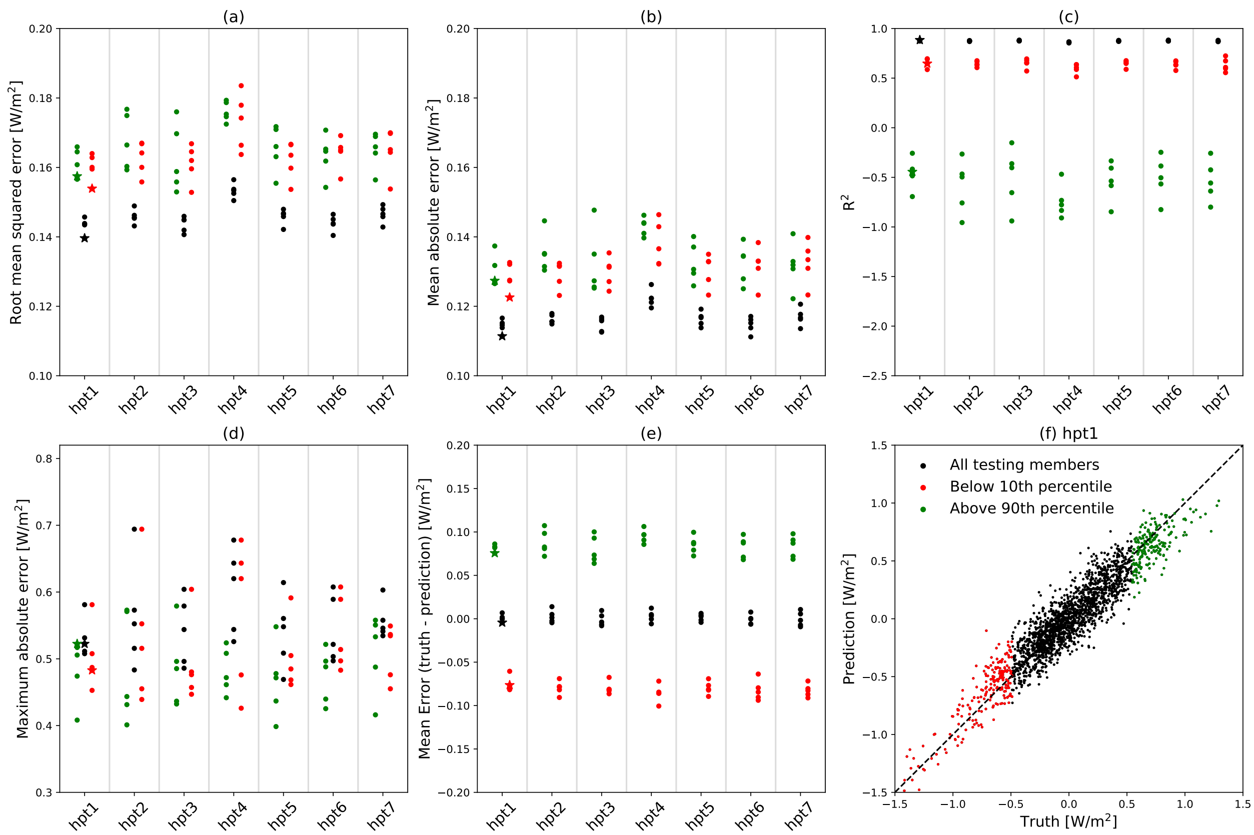
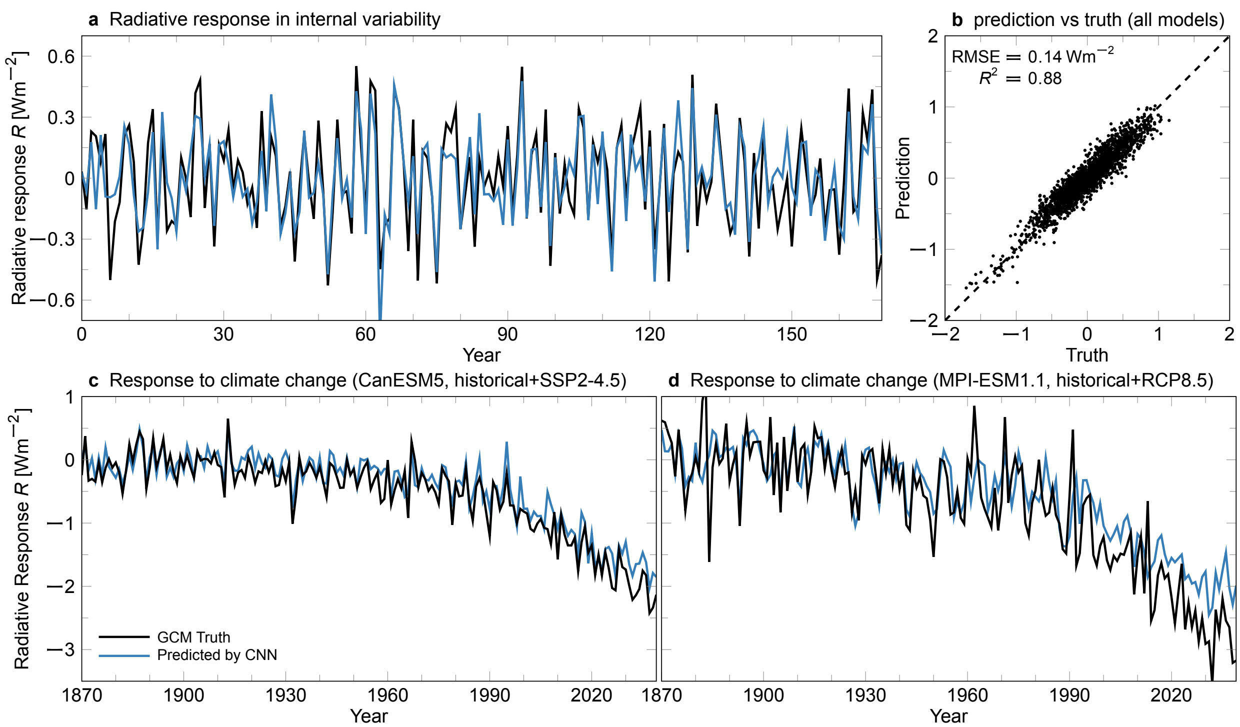
Supporting Information



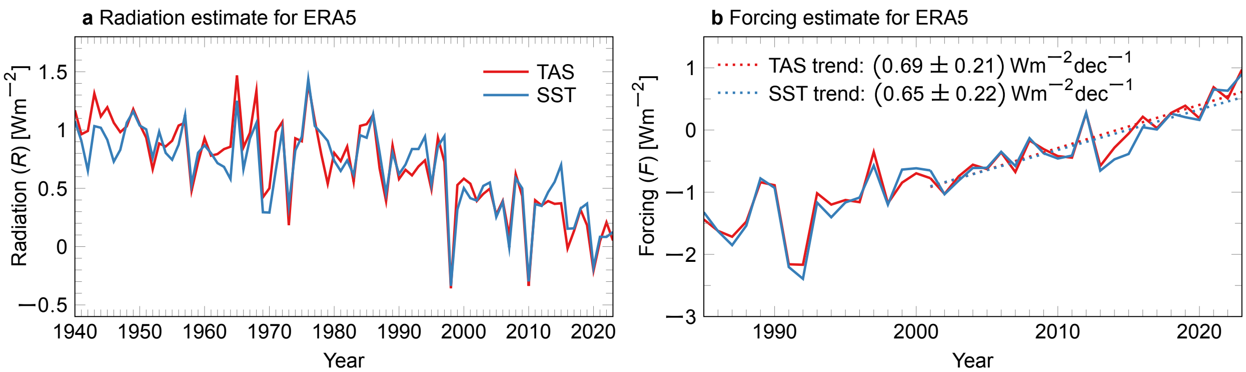
Supporting Information Fig. 1. **Schematic of the architecture of the CNN used.** The input maps (surface temperature) are passed through two convolutional layers, each with 32 kernels of size 3×3 and followed by a max pooling layer and a ReLu activation function. The result is flattened and passed through two additional fully connected layers with 32 and 16 neurons, again with a ReLu activation function. The final result is a single number estimating the global-mean radiative response R.



Supporting Information Fig. 2. **Hyperparameter testing for different CNN architectures.** The x-axis labels are defined in Supporting Information Tab. 1, and each dot represents a different random initialization of the CNN before training. For each trained CNN, we compute the (a) root mean squared error, (b) mean absolute error, (c) R^2 value, (d) maximum absolute error , and (e) mean error (truth-prediction). Panel (f) reports the truth versus prediction of all years in the testing dataset. Black dots represent all years, while red and green dots show only those in the lower and upper 10th percentiles, to examine how well the CNN performs on the extremes. The CNN used in the main text is highlighted by a star.



Supporting Information Fig. 3. **Verification of the CNN.** Panel (a) shows the truth (black) and predictions (blue) for a single ensemble member in the testing dataset, for internal variability of the temperature and radiative response. Panel (b) shows the true versus the predicted radiative response for all years in the testing dataset; the CNN explains 85 % of the variance across all testing members. Panels (c) and (d) show the CNN applied to an out-of-sample member that experiences forced climate change for two different models used in training. Even though the CNN has never seen climate change during training, it can predict the response to forcing well.



Supporting Information Fig. 4. **Comparison of near-surface temperature (TAS) and sea surface temperature (SST) as input for the convolutional neural network**. Panel (a) shows the predicted radiation (R) and (b) shows the predicted forcing ($F = N - R$). Dotted lines in (b) are forcing trends in 2001-2023. We use ERA5 data and our CNN from the main text. Both predictions are very similar; therefore, we expect only minor differences when using observational datasets of SST compared to TAS.

Supporting Information Table 1. **Hyperparameters used in testing different CNN architectures in Supporting Information Fig. 2.** All CNNs use a similar architecture as shown in Supporting Information Fig. 1, but we change the number of convolutional layers/kernels, kernel size, and amount of dense layers/nodes. The set of hyperparameters used in the main text is hpt1.

	Convolutional layers	Kernel size	Dense layers
hpt1	[32, 32]	3×3	[32, 16]
hpt2	[32, 32]	5×5	[32, 16]
hpt3	[64, 64]	3×3	[32, 16]
hpt4	[32, 32, 32]	3×3	[32, 16]
hpt5	[16, 16]	3×3	[32, 16]
hpt6	[32, 32]	3×3	[16, 16]
hpt7	[32, 32]	3×3	[8, 8, 16]

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