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Using a Gaussian process emulator to approximate short-term climate response patterns to greenhouse gas and aerosol forcings

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Abstract. We present a Gaussian process emulator for estimating fast surface temperature response patterns to a range of different climate forcing agents, including both long-lived greenhouse gases and short-lived pollutants such as aerosols. This emulator is trained on simulations driven by perturbations to emissions (for short-lived pollutants) and concentrations (for long-lived greenhouse gases) using a full-complexity global climate model and predicts the response in the first five years after the forcing, at a small fraction of the computational cost. We outline the emulator design, including the choice of pollutant perturbations and the input space covered by the training data. We show that the emulator performs well in most regions of the chosen input space, except under very large aerosol perturbations. A global sensitivity analysis is carried out to characterize and understand emission-response relationships for each pollutant. We find similar large-scale patterns of sensitivity to aerosol pollutants released in different regions. Our work demonstrates the potential for rapid climate change projections subject to various climate forcing agents, focusing on the short-term response. This paves the way for the future development of more policy-relevant emulators, that can target decadal and multi-decadal timescales.

1 Introduction

Climate change projections are essential to inform society and policymakers about possible scenario-dependent impacts. To estimate the state of the future climate, we rely on Global Climate Models (GCMs) to run numerical simulations of the Earth system, including atmospheric, oceanic, land and sea-ice components and their interactions. These GCMs project the climate at a time in the future, given the current climate state and an emissions scenario that describes how the emissions/concentrations of greenhouse gases, aerosols and other atmospheric constituents are expected to evolve. Since future emissions are highly uncertain, GCMs must be run for a range of different possible scenarios. The output from a GCM can add to our understanding of the individual and net effects of different anthropogenic forcings on the climate system, which has long been of interest to climate scientists. Furthermore, understanding the climate response to emissions can inform important policy decisions.

The high complexity and computational cost of climate and atmospheric modelling puts a limit on the number and range of climate projection studies that can be carried out. This has led to a recent increase in application of surrogate models that reproduce climate relevant variables given

known inputs, at a much lower cost (Bolton and Zanna, 2019; Castruccio et al., 2014; Kaltenborn et al., 2023; Mansfield et al., 2020; Nowack et al., 2018; Rasp et al., 2018; Ryan et al., 2018; Watson-Parris, 2021; Wild et al., 2020). Here, we use a type of surrogate model called a *Gaussian process (GP) emulator*, which have become popular for aiding atmospheric and climate model development, through sensitivity analyses, uncertainty quantification and calibration (Carslaw et al., 2013b; Lee et al., 2012; Ryan et al., 2018; Salter and Williamson, 2016; Williamson et al., 2015).

Climate model emulators are beginning to emerge with the primary aim of climate change projection. One approach currently gaining traction involves learning an *autoregressive model of the full climate state*, i.e., by predicting all climate variables at one timestep, given all climate variables at the previous timestep (e.g., Boussard et al., 2023; Cachay et al., 2024; Guan et al., 2024; Watt-Meyer et al., 2023, 2025). These require large-scale neural networks to capture all climate model variables and often suffer from instability when implemented over long timescales. These studies are also limited to only exploring a few forcings that have been included during training, such as through sea surface temperature forcing or CO_2 forcing (Watt-Meyer et al., 2025), and are yet to explore a wide range of climate change responses to different scenarios. In contrast, an alternative approach is to directly *learn the climate model response to a change in forcing*, often referred to as "reduced complexity models" (Nicholls et al., 2020). This approach leverages simpler machine learning models to emulate the change in the climate state given a change in forcing, typically focusing on the response to different CO_2 scenarios (Bao et al., 2016; Castruccio et al., 2014; Foley et al., 2016). Most past emulation studies estimate the *global mean* response to forcings over a timeseries (Castruccio et al., 2014; Meinshausen et al., 2011; Smith et al., 2018a), with some extending this to include spatial patterns (Bao et al., 2016; Beusch et al., 2022; Dewey et al., 2025; Nath et al., 2022). The ability to predict climate response to changing forcings with quick, simple models is particularly valuable for policy-makers as they can be embedded within Integrated Assessment Models (IAMs, e.g., Foley et al., 2016) or can inform climate change scenario pathways (e.g., Durack et al., 2025; Forster et al., 2021).

In this paper, we present an emulator based on the HadGEM3 GCM, that predicts the short-term global surface temperature response to a wide range of forcing types, including regional aerosol emissions and global greenhouse gas concentration changes. This is the fast adjustment of the surface temperature in the first 5-years following the perturbation. This fast adjustment emulator predicts the response to an abrupt change in emissions, such as the simulations run in idealized forcing-response studies (e.g., Myhre et al., 2017; Richardson et al., 2019; Stohl et al., 2015; Samset et al., 2018; Smith et al., 2018b). The emulator is designed to predict the entire spatial pattern of the global climate change response, rather than just the global mean, which could prove useful in future policy and impact studies. Our approach lays the foundations for the development of long-term climate response emulators which would be valuable in informing policy. Furthermore, we propose that this type of emulator could be coupled to other emulators designed to predict across different timescales. For instance, it could be combined with the emulator developed in Mansfield et al. (2020), which predicts the long-term temperature response given the short-term temperature response. Additionally, while such a fast-response emulator is not directly applicable for long-term policy design, it can have real-world use for predicting regional and global temperature responses to short-term forcings that are triggered by episodic pollution sources such as wildfires or sudden anthropogenic pollution decreases (e.g. as during the COVID-19 pandemic).

In Sect. 2, we describe the emulator design including the choices of input variables and perturbation ranges. Section 3 considers the performance of the trained emulator on a set of test scenarios, on both regional and spatially resolved scales. In Sect. 4, the emulator is used to carry out a global sensitivity analysis to explore the main effects of each perturbation and the sensitivity of each region to local and remote emission perturbations. Section 5 makes the concluding remarks on the study.

2 Emulator design

2.1 Global climate model configuration

The GP emulator is trained on simulations from the HadGEM3 model, in the third Global Coupled configuration 3.1 (GC3.1) (Williams et al., 2018) which consists of the global atmosphere-land (GA7/GL7.1) (Walters et al., 2019), global ocean (GO6) (Storkey et al., 2018) and sea-ice (GSI8.1) (Ridley et al., 2018). This configuration uses the modal version of the Global Model of Aerosol Processes (GLOMAP-mode), two-moment aerosol microphysics scheme (Mann et al., 2010). The model resolution is 1.25° latitude by 1.875° longitude, giving a grid cell of roughly 208 km by 139 km at the Equator and a total of $144 \times 192 = 27\,648$ grid cells. The same model configuration was employed for historical simulations in Andrews et al. (2020), which formed part of the UK contribution to the sixth Coupled Model Intercomparison Project (CMIP6). "Present-day" conditions are taken from the end of these simulations, and correspond to the year 2014. The present-day simulation was run for 300 years as "spin-up", to reach an approximate equilibrium. The last 40-years of this simulation is treated as a control run and this was then used as the starting point for simulations that serve as training data for the emulator.

Before computing any perturbation runs, an additional six 5-year-long control simulations were performed starting from this equilibrium state, giving a total of 70-years

of control simulations. We estimate the control surface temperature, by averaging over all years and all control simulations $\overline{\mathbf{T}}^{\mathrm{CTRL}}$. All perturbation runs are initialized from the same state and also run for 5 years. The well-mixed GHGs are perturbed via their global concentrations, while for the short-lived pollutants we use scaling factors for emissions over broad regions, described further in Sect. 2.2. We define these as inputs to the GCM, denoted $\boldsymbol{x}^{\mathrm{p}}$ for perturbation p. We estimate the perturbation surface temperatures by averaging over the 5 years and we denote this as $f_{\mathrm{GCM}}(\boldsymbol{x}^{\mathrm{p}})$. We define the short-term surface temperature "response" as

$$\boldsymbol{y}^{\mathrm{p}} = f_{\mathrm{GCM}}\left(\boldsymbol{x}^{\mathrm{p}}\right) - \overline{\mathbf{T}}^{\mathrm{CTRL}}. \tag{1}$$

The surface temperature response is defined at every grid cell of the GCM, giving a complete spatial map, i.e., $\boldsymbol{y} = (y_1, y_2, \cdots, y_N)$ for all $N = 27\,648$ grid cells.

2.2 Gaussian process emulator

Our perturbation simulations create $P = 80$ input-output pairs which we call our training data $D = (\boldsymbol{x}, \boldsymbol{y})$. We use a GP emulator to estimate the surface temperature response to a new emissions scenario, $\boldsymbol{x}^*$. The GP provides a probability distribution for each $\boldsymbol{x}^*$, from which we can sample, i.e.,

$$\boldsymbol{y}_{\mathrm{GP}} \sim \mathrm{GP}\left(\boldsymbol{x}^* | D\right). \tag{2}$$

This means we can also estimate the mean μ_{GP} and uncertainty σ^2_{GP} for each $\boldsymbol{x}^*$. Note that there is internal variability overlaying this (i.e., noise), which makes weaker responses more difficult to predict. While we do not attempt to model this noise explicitly, we take advantage of the GP emulator's ability to estimate uncertainty about the prediction and assume that a portion of this uncertainty is due to the internal variability of the GCM. Note that $\boldsymbol{y}$ and $\boldsymbol{y}_{\mathrm{GP}}$ are vectors containing the estimated surface temperature response at each grid cell. Here, we build separate GP emulators for each grid cell. We learn the function, f_{GP}, by training the GP emulator with input-output pairs ($\boldsymbol{x}^{\mathrm{p}}$, $\boldsymbol{y}^{\mathrm{p}}$) obtained from GCM simulations. In the following section, we describe how input values were chosen, including the choice of pollutants that are varied and the range of possible values they can take.

2.3 Choice of inputs and ranges

Due to the high cost of running the GCM, we aim to minimize the number of simulations required to build and test this emulator. This can be done with a careful choice of inputs and a space-filling design of these inputs (Currin et al., 1991). First, we limit the number of possible inputs to the dominant climate forcers. These include well-mixed climate pollutants, specifically the two most important anthropogenic greenhouse gases carbon dioxide (CO_2) and methane (CH_4) (Stocker, 2013). For the short-lived pollutants, we perturb sulfur dioxide – SO_2, the precursor to sulfate aerosol (SO_4) – and biomass burning (BB) carbonaceous aerosols – black carbon (BC) and organic carbon (OC). Sulfate aerosol is chosen because it has a strong cooling impact on the climate, particularly at a regional level, and because its precursor is emitted mostly from fossil fuel burning, making it highly relevant for scenario projection studies (Stocker, 2013). BB OC/BC are chosen as they strongly affect the climate through scattering and absorption of radiation and due to their dominance in the tropics (Boucher et al., 2013; Haywood and Boucher, 2000). In addition, BB is a particularly high source of scenario uncertainty, but has not been studied as extensively as other forcing perturbations (Lasslop et al., 2019; Tosca et al., 2013; Voulgarakis and Field, 2015; Ward et al., 2012). While other pollutants (e.g., NO_x, NMVOCs, OC/BC from other sources) are also relevant for climate change, we keep these fixed at present-day levels because even for large perturbations, the effects are too small to exceed the regional climate noise in any of our simulations and thus are less useful for training the emulator (Aamaas et al., 2019; Baker et al., 2015; ECLIPSE, 2014; Shindell and Faluvegi, 2009; Stohl et al., 2015).

For the greenhouse gases, we apply global perturbations to their concentrations in the GCM as they have long lifetimes and relatively homogeneous spatial forcing. For the short-lived pollutants, we perturb the emissions fields for the GCM. As the region of emission is paramount when considering the effect of short-lived pollutants, these perturbations are made over regional scales. We select broad continental regions in which short-lived emissions are scaled up or down (e.g., $2\times$, $0.5\times$), while keeping the spatial distribution of emissions within each region unchanged.

Following the procedure used in previous studies, we perturb SO_2 in North America, Europe, East Asia and South Asia (the same regions as (Kasoar et al., 2018; Lewinschal et al., 2019; Westervelt et al., 2020)), by scaling the regional present-day distribution of emissions. This approach allows for the entire region to be represented by a single scaling factor, but restricts the emulator to scenarios where the spatial distribution of emissions within each region does not change significantly. In other words, it does not account for the possibility of new emission hotspots within each region. This assumption is made because in these four regions, SO_2 emissions are predicted to decline in the future (Westervelt et al., 2020; Lund et al., 2019).

We further extend our study by perturbing SO_2 in Africa and South America, which currently have low levels of SO_2 relative to the rest of the world but are likely to see increasing emissions in the coming decades, due to changes in land use and industrialization in South America (Popp et al., 2017) and rapid growth of cities in Africa (Liousse et al., 2014). For these regions, the assumption of a constant spatial distribution of emissions may not be valid, as present day SO_2 emissions are low and originate from isolated hotspots (see Fig. S1 in the Supplement). We therefore use the emission distribution from the SSP5 baseline scenario with rapid

Table 1. All input and the ranges used in the emulator, with associated reasoning for maximum value. The minimum values are taken to be pre-industrial concentrations for CO_2 and CH_4 and a scaling factor of zero for all short-lived pollutants.

Input	Range	Reasoning
Global CO_2 concentration	282–834 ppm	SSP3 baseline projection in 2100 (Riahi et al., 2017)
Global CH_4 concentration	248–3238 ppb	SSP3 baseline projection in 2100 (Riahi et al., 2017)
SO_2 over North America	0–3×	Historical data from 1990 (ECLIPSE, 2014)
SO_2 over Europe	0–5×	Historical data from 1990 (ECLIPSE, 2014)
SO_2 over East Asia	0–2×	Historical data from 2005 (ECLIPSE, 2014) and SSP1 projection in 2100 (Riahi et al., 2017)
SO_2 over South Asia	0–3×	ECLIPSE projection in 2030 (ECLIPSE, 2014)
SO_2 over Africa	0–7×	Inventory based projection in 2030 (Liousse et al., 2014)
SO_2 over South America	0–3×	SSP3 baseline projection in 2080 (Riahi et al., 2017)
BB OC/BC over Tropics	0–2×	Estimates of fire activity by 2100 (Pechony and Shindell, 2010)

growth (Riahi et al., 2017) to represent future conditions, while keeping total emissions fixed (Fig. S1).

Finally, we perturb BB OC/BC in the tropics (between 24° S and 24° N), which covers tropical regions of Africa, South America and South East Asia, where biomass burning due to fires is the largest source of OC/BC (Cachier et al., 1989; Pechony and Shindell, 2010; Tosca et al., 2013; Van der Werf et al., 2003). We perturb OC and BC in the same proportions, assuming that their ratio remains constant, following other studies (Hodnebrog et al., 2016; Tosca et al., 2013). This allows the emulator to be used to explore future scenarios under different levels of tropical biomass burning, whether it be due to anthropogenic suppression/ignition, a consequence of a warmer planet (e.g., alongside increasing GHGs) or under natural variability (Pechony and Shindell, 2010). We note that by using tropics-wide perturbations, the emulator may not capture highly regionalised forcing-response patterns (Westervelt et al., 2020; Williams et al., 2022). However, we do not consider OC/BC on smaller regional scales because previous studies have found that large, unrealistic OC/BC forcings are required to obtain a climate responses that exceeds the internal climate noise (e.g., Myhre et al., 2017; Baker et al., 2015; Stohl et al., 2015).

This gives a total of nine inputs, two of which are the global GHG concentrations and seven of which are regional scaling factors of short-lived pollutant emissions, as shown in Table 1. For each input, we define an input space that encompasses the range of possible scenarios of interest to policy-makers and climate scientists, based on the minimum and maximum plausible values estimated by previous studies, which include projections of the Shared Socioeconomic Pathways (SSPs) (Riahi et al., 2017; van Vuuren et al., 2017) and Evaluating the Climate and air quality Impacts of short-lived pollutants (ECLIPSE) project (Aamaas et al., 2017; Baker et al., 2015; ECLIPSE, 2014; Stohl et al., 2015), as well as other individual studies (Liousse et al., 2014; Pechony and Shindell, 2010). For the greenhouse gases, we take the pre-industrial levels as the minimum value and for the short-lived pollutants we take the minimum value as a scaling factor of zero, representing near-idealized anthropogenic pollution-free conditions. For all forcings, we determined the maximum levels to be the worst-case estimate from both future projections and historical scenarios (up to pre-industrial) in previous studies. Table 1 shows the ranges selected for each input and the reasoning behind the maximum values. Note that these "maximum" scaling factors do not reflect realistic scenarios, but are chosen as an appropriate upper limit for scenarios that one may wish to emulate.

The fact that we apply regional perturbations to the short-lived pollutants inevitably leads to small changes in abundances and weak forcings. This can give weaker grid-scale climate response signals that are difficult to separate from the internal noise (Kasoar et al., 2018; Shawki et al., 2018). For this reason, we extend the input space beyond the ranges described in Table 1 for these forcers, in order to create an emulator that gives less uncertain results. We expect that including simulations with stronger perturbations, which should have larger signal-to-noise ratios, could be beneficial for constraining the emulator prediction to these perturbations. We therefore extend the input space for the short-lived pollutants only so that 75 % of simulations fall within the input range indicated in Table 1 and the remaining 25 % lie outside this but within a range that is double this (see Fig. S2). This makes our emulator more capable of capturing responses to large idealized perturbations in short-lived pollutants, which are common in scientific studies exploring the physical processes linking short-lived pollutant forcing and response (Liu et al., 2018; Myhre et al., 2017; Richardson et al., 2019).

2.4 Design of training data

We design a set of training simulations by selecting combinations of input values that will be inputs to the GCM. The best approach to do this is to generate sets of input values that are space-filling (e.g., Currin et al., 1991; Lee et al., 2016; O'Hagan, 1978; Ryan et al., 2018; Santner et al., 2003; Wild et al., 2020). This minimizes the number of samples needed to cover the input space efficiently, which is particularly important for this study as model simulations are computationally expensive (around 80 node hours per simu-

lation on a Cray XC40; Met Office, 2021). An informal rule of thumb is that the number of runs for training should be around 10 times the number of input dimensions (Loeppky et al., 2009), and this approach has worked well in previous climate model emulators (e.g., Carslaw et al., 2013b; Lee et al., 2012; Ryan et al., 2018). Given the nine inputs of interest in this study and the high computational cost of the simulations, we perform 80 simulations for training. These 80 training points are selected to be space-filling by using a maximin Latin Hypercube Sampler (LHS), which subdivides the input space evenly and samples each partition so that the distance between samples is maximized (e.g., Lee et al., 2011, 2012; Ryan et al., 2018). To generate the samples with the distribution described above, we first sample 80 points using a maximin LHS for values between 0 and 1 for all inputs. For the GHGs, we use a linear transform to scale the input range so that all values fall within the defined bounds. For the short-lived pollutants, we use a linear transform to scale the first 75 % of samples to lie within the ranges defined in Table 1. We then scale the remaining 25 % of samples to fall between 1 and 2× the maximum values in Table 1. This provides us with samples that are further separated for the larger, unrealistic perturbations values, but more closely sampled in the region we are most interested in. The samples are shown in Fig. S2. We also perform an additional 18 simulations for testing, which are sampled separately from the ranges in Table 1 using a standard LHS design.

2.5 Gaussian process emulator details

With the 80 training simulations available, we build an emulator to project the short-term surface temperature response based on the nine inputs that control the CO_2 and CH_4 concentrations and the short-lived emission scaling factors described above (Table 1). Prior to building the emulator, the inputs and outputs are scaled to be centered around 0 with standard deviation of 1. Separate GP emulators are then applied to estimate the surface temperature response for each grid-cell independently. For each grid cell, the GP emulator is

$$f_{\mathrm{GP}}(\boldsymbol{x}) = \mathcal{G}(m(\boldsymbol{x}), K(\boldsymbol{x}, \boldsymbol{x}')) \tag{3}$$

where $m(\boldsymbol{x})$ is the prior mean function and $K(\boldsymbol{x}, \boldsymbol{x}')$ is the prior covariance function or "kernel" that describes the covariance between two inputs, $\boldsymbol{x}$ and $\boldsymbol{x}'$. The choice of $m(\boldsymbol{x})$ and $K(\boldsymbol{x}, \boldsymbol{x}')$ controls the structure of the GP emulator (Rasmussen and Williams, 2006). The prior mean function is often assumed to be zero so that all choices are determined by the covariance function, as done here. The kernel defines the similarity of two inputs $\boldsymbol{x}$ and $\boldsymbol{x}'$ and how this propagates through to the similarity of the outputs $f_{\mathrm{GP}}(\boldsymbol{x})$ and $f_{\mathrm{GP}}(\boldsymbol{x}')$. We use

$$K(\boldsymbol{x}, \boldsymbol{x}') = \sum_{d=1}^{9} \sigma_{\mathrm{Ld}}^2 x_{\mathrm{d}} x'_{\mathrm{d}} + \sigma_{\mathrm{SE}}^2 \exp\left(-\frac{1}{2}\sum_{d=1}^{9} \frac{\left(x_{\mathrm{d}} - x'_{\mathrm{d}}\right)^2}{l_{\mathrm{d}}^2}\right) + \sigma_{\mathrm{W}}^2. \tag{4}$$

This describes an additive kernel consisting of three components. The first term represents a non-stationary linear kernel which learns independent hyperparameters, σ_{Ld}^2, for each input parameter, d (known as Automatic Relevance Determination, ARD), which represent the rate of change of the output for each input parameter. This captures the first-order linear relationships between emission perturbations and temperature response, while the remaining terms aim to capture the local variability (Craig et al., 1996; Edwards et al., 2019; Vernon et al., 2010). The second term is a squared exponential kernel which also uses ARD to learns independent lengthscales l_{d} for each input parameter, d. These lengthscales describe how rapidly the output changes with respect to varying input parameters. The hyperparameter σ_{SE}^2 is a scale that describes the total amount of variation in the output (Rasmussen and Williams, 2006). The last term is a white noise kernel which represents the internal variability of the GCM, assumed to be constant σ_{W}^2, for all predictions. We explored both fixing σ_{W}^2 at the internal variability derived from the GCM (described further below and used throughout the paper unless stated otherwise), and allowing σ_{W}^2 to be learned as an additional hyperparameter (described in Sect. 3.3). We chose this kernel function because of its interpretability, however, we found the emulator to be robust to a range of kernel choices (Fig. S3). We learn all kernel hyperparameters through maximum likelihood estimation, using the python library, GPy (GPy, 2012). Here, we use independent emulators for each of the 27 648 grid cells, however, we also found similar results with GP emulators applied to the top principal components, a dimension reduction technique that also enforces spatial correlations between grid-cells (e.g., Salter et al., 2019; Salter and Williamson, 2022; Wilkinson, 2010). We also tested different methods such as random forests but we did not find improvements in performance, so we focus only on GP emulators here.

In this study, we consider two types of uncertainty. Firstly, we view the uncertainty associated with the chaotic nature of the Earth system, the aleatoric uncertainty (Shepherd, et al., 2018), as a limitation of the GCM prediction, and secondly, we diagnose the uncertainty due to the emulator prediction being an approximation of the GCM at new unseen scenarios not within the training set (which we call the predictive uncertainty). As a GP emulator is a Bayesian method and predicts a distribution of responses, the latter is a natural output of each prediction. Note that we do not consider the uncertainty caused by the difference in the GCM predictions and the truth, i.e., epistemic uncertainty or model inadequacy/discrepancy.

The uncertainty due the chaotic nature of the GCM is the internal variability, σ_{GCM}, and is estimated as the standard deviation between as many 5-year control runs as available. We have available 8 segments from one long, 40-year control run after equilibrium had been reached in the spin-up simulation, and 6 independent 5-year control runs that branched off from this. Ideally, all control runs would be strictly in-

dependent but the 8 segments of the longer control run are included to improve the sample size for estimating the standard deviation. The standard deviation across the 14 control runs is calculated for each grid point independently, giving a map of uncertainty associated with the internal noise. This is an uncertainty associated with any prediction from the GCM, and is partly due to the limited number of years we have averaged over. We expect this to be present for any prediction and therefore, we include this as a fixed noise term in our emulator, by setting $\sigma_W^2 = \sigma_{GCM}^2$ for the white noise covariance function of the GP emulator. When the emulator predicts the temperature response at new unseen input values, there is also predictive uncertainty provided by the GP emulator, which we label σ_{GP}. Note that this comes from the other covariance functions and is dependent on the inputs, x. The total uncertainty arising from both the GCM internal variability and the GP emulator prediction is denoted σ_{total} and these are related via $\sigma_{total}^2 = \sigma_{GCM}^2 + \sigma_{GP}^2$, discussed later in Sect. 3.3.

3 Emulator performance

To test the performance of the emulator, we predict the output for 18 test simulations that have not been used for emulator training, where the input values have been generated with a Latin Hypercube Sampler, with a uniform distribution across all input ranges of interest (Table 1).

3.1 Global response predictions

Figure 1 shows an example of typical emulator performance, with the input values shown along the top panel, relative to the baseline, minimum and maximum possible values. Note that these perturbations are not intended to be realistic perturbations over a five-year period, but rather they estimate the short-term response to abrupt perturbations, which at this stage would be used for scientific experimentation, with the view to develop the ideas further in the future for more direct policy relevance. The maps show, from top to bottom, the GCM output for the test scenario, y_{test}, the GP prediction, y_{pred}, and the absolute errors, $|y_{pred} - y_{test}|$, with the stippling indicating regions where this exceeds 1 SD predicted by the GP emulator. These examples are representative of the test simulations which are presented in Fig. S4. Most test simulations are reasonably well predicted by the emulator and show patterns of warming or cooling generally in the correct spatial location. The absolute differences are generally larger at high latitudes, particularly around the Arctic, Greenland and Northern Europe, for instance, in Fig. 1a where the emulator does not capture the cooling over Europe due to the strong SO_2 Europe perturbation. Although the magnitude of σ_{total} is slightly larger in these regions than in the tropics, the stippling where $|y_{pred} - y_{test}| > \sigma_{total}$ is more prominent in these high latitude areas, indicating that prediction is poorer there compared to other regions worldwide. These regions are highly correlated with the regions that experienced larger errors in our previous emulation study that found these to be areas that experience both increased sensitivity to forcings and increased variability (Mansfield et al., 2020). Statistically, we would expect $\sim 32\,\%$ of predicted points to fall outside the 1σ prediction level, which is generally the case across all test scenarios, with the exception of Fig. S4k. However, the predicted points that fall outside this accuracy threshold have a specific regional pattern and occur more often in the Northern Hemisphere, rather than being distributed randomly across the globe.

For the test scenario in Fig. S4k, the emulator predicts the correct sign of response in most regions, but the prediction is too weak in magnitude compared to the GCM. We believe this to be because the inputs are all strongly positive relative to present-day levels meaning this scenario falls close to the corner of the input space, where there are fewer training data points to constrain the prediction. The emulator overestimates the cooling effect of strong aerosol perturbations, highlighting that caution should be taken when interpreting emulator predictions on very strong aerosol perturbation scenarios. Future studies may wish to refine the accuracy of the emulator in this region of the input space, by running additional training simulations with even stronger aerosol perturbations. The remainder of this study does not focus on the strong aerosol perturbation regime since we consider more realistic emission perturbations. Overall, however, the test simulations indicate that the GP emulator can predict the response to a range of scenarios under these nine inputs. Based on all 18 test simulations, 76.1 % of grid points are predicted to within 1σ of the true response and 95.0 % are predicted to within 2σ, which is roughly in line with expectations, assuming a Gaussian distribution of responses.

3.2 Regional mean response predictions

We have also assessed the response for each region by taking broad averages over areas of interest. The response predicted by the GP emulator is plotted against the true GCM response for all test scenarios in Fig. 2 where the error bars indicate the 1σ uncertainty levels. A perfect prediction would correspond to the $y = x$ line (black dashed line), a coefficient of determination $R^2 = 1$ and a mean absolute difference (MAD) equal to zero. Most regional mean predictions fall very close to this line, or within 1σ from it. The exception to this is the outlier with a positive true response of around 1 °C in most regions, that is strongly underestimated, which corresponds to the test scenario in Fig. S4k. Other than this scenario, the majority of responses are well predicted and cover a fairly broad range of responses including both cooling and warming of up to 1–2 °C (R^2 values are all above 0.87). These plots also highlight the increased uncertainty associated with some regions, namely North America and Europe, in comparison to the tropical regions such as South Asia, South America and

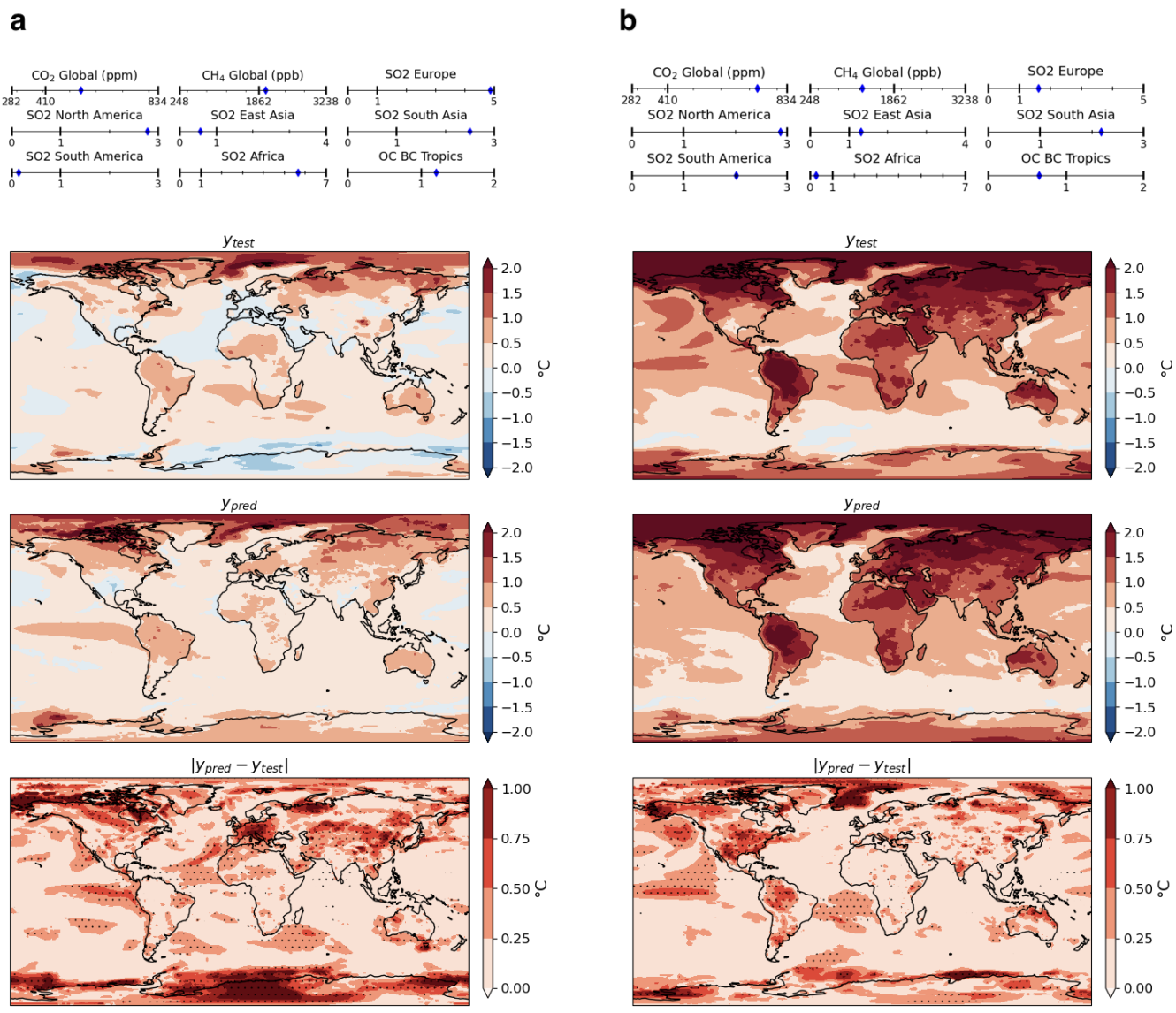


Figure 1. Two example test scenarios, where top panel shows inputs values, as well as the baseline, minimum and maximum possible values. The maps show, from top to bottom, the GCM output for the test scenario, y_{test} the GP prediction, y_{pred} and the absolute errors, $|y_{\text{pred}} - y_{\text{test}}|$, where in the latter the stippling indicates regions where this absolute error exceeds 1 SD predicted by the GP emulator, $|y_{\text{pred}} - y_{\text{test}}| > \sigma_{\text{total}}$.

Africa. As well has exhibiting increased uncertainties, these regions also show a wider range of temperature responses in the test data. This leads to slightly higher absolute errors (increased MAD values) in these regions, but overall each prediction is still close to the ground truth (GCM), as highlighted by the high R^2 values. This gives confidence to the use of an emulator in this way for quick predictions, for instance in policy-relevant studies.

3.3 Internal variability

We used the internal variability of the GCM as a fixed component of uncertainty when building the emulator where $\sigma^2_{\text{W}} = \sigma^2_{\text{GCM}}$, in order to view it as a form of aleatoric uncertainty, in other words, caused by the unpredictability of the system and intrinsic to any GCM prediction. The internal variability is calculated over 14 control simulations of 5-year segments, and is shown in Fig. S5a. The GP emulator provides an additional predictive uncertainty when predicting new scenarios, but this uncertainty is generally much smaller than the internal variability (Fig. S5b). For comparison, we built an alternative version of the GP emulator, where rather than fixing the internal variability based on the GCM internal variability, $\sigma^2_{\text{W}} = \sigma^2_{\text{GCM}}$, we treat the white noise covariance σ^2_{W}, as an additional hyperparameter to be optimized. This emulator performs virtually identically and reproduces almost exactly the same distribution of total un-

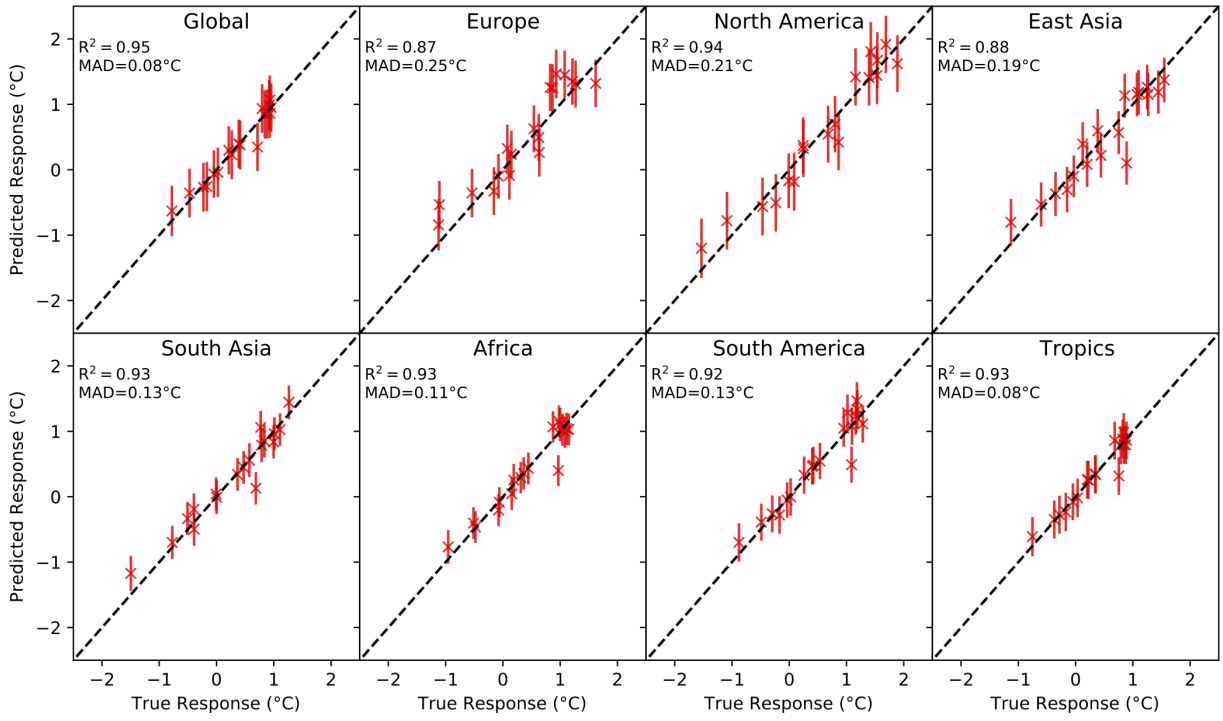


Figure 2. Regional mean predicted responses of test simulations against true GCM response, where error bars represent 1σ uncertainty level of Gaussian process prediction, for the main regions of interest, including the global mean. The coefficient of determination R^2 and the mean absolute difference (MAD) is also shown for each region.

certainty (Fig. S5c and d). This result is encouraging, as it suggests that even without providing the GCM internal variability, the GP emulator is able to learn it as a form of uncertainty. This suggests that the accuracy of the emulator is limited primarily by GCM internal variability when predicting the short-term surface temperature response.

4 Global sensitivity analysis

The climate modelling community has benefited from a wide range of GP emulation studies concerned with uncertainty quantification and sensitivity analysis, which aim to characterize the uncertainty on the outputs and identify where it arises from. Due to the high computational cost of GCM simulations, GP emulators have been utilized to diagnose uncertainties and sensitivities in a wide range of GCM components and settings, including atmospheric chemistry models (Beddows et al., 2017; Lee et al., 2012; Stell et al., 2021; Wild et al., 2020), sea-ice models (Edwards et al., 2019; Urrego-Blanco et al., 2016), climate-vegetation models (Bounceur et al., 2015), convection parameterizations (Souza et al., 2020), and atmospheric gravity waves (King et al., 2024). The inputs to these are typically climate model parameters that are not known perfectly, where gaining an understanding of how sensitive the outputs are to each input parameter is beneficial for model development and calibration. In this study, the inputs are emission perturbations and we are primarily interested in exploring patterns of potential future climate responses to a range of scenarios. Sensitivity analysis can be used to deepen our understanding of the sensitivity of climate across all world regions to different competing emissions. In particular, we carry out a global sensitivity analysis, which quantifies sensitivities to each input averaging over the effects of all other inputs (Saltelli et al., 2019; Saltelli and Annoni, 2010).

4.1 Main effects

Firstly, we explore the "main effect" of each pollutant, meaning the effect of each pollutant on the output independent of all other pollutants. This is done by using the emulator to predict surface temperatures across the full range of possible input values for the pollutant of interest, while randomly sampling all other inputs repeatedly. This generates a set of many independent realizations, where here we use 200 realizations for our sensitivity analysis. We average over all realizations to find the main effect attributed to the pollutant of interest. Here, we wish to assess the main effect of the pollutants relative to the present-day climate and therefore we sample all other inputs from independent normal distributions, centered at present day levels with standard deviations set to $1/4\times$ the input range presented in Table 1.

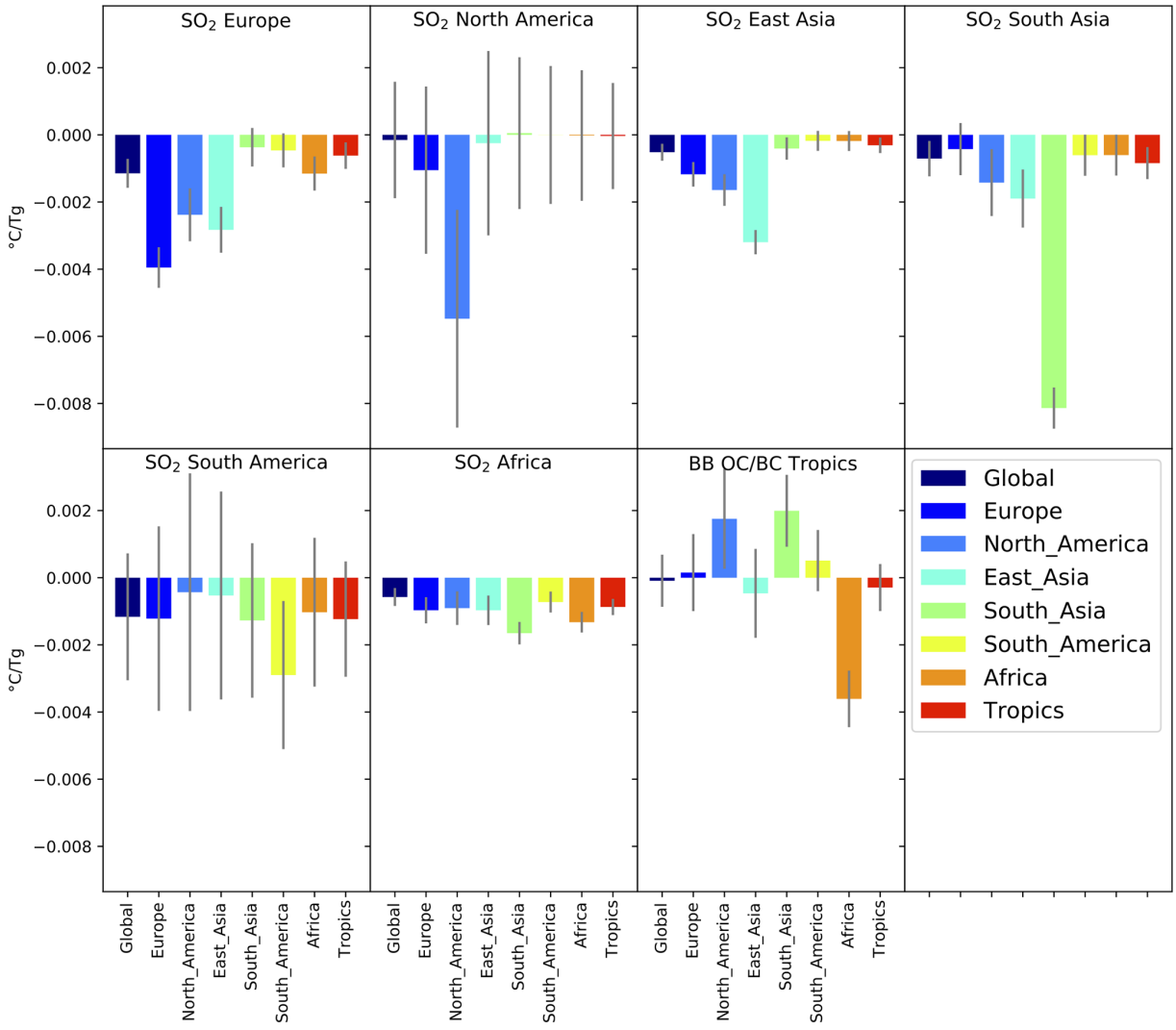


Figure 3. The expected change in temperature (°C) for every 1 Tg increase of each aerosol pollutant in each response region. The values are estimated from the gradients of the lines of each plot in Fig. S6, based on the linear relationships found between the response in °C and the aerosol emission perturbation. The error bars represent 1σ uncertainty estimated by 200 different realizations.

The mean behavior of each pollutant perturbation is calculated by averaging over the 200 different realizations and can be found in Fig. S6 for each key region. The main effects of CO_2 are much stronger in all regions than the other pollutants. As expected, local aerosol perturbations give rise to stronger responses in the region of emission (particularly SO_2 released over Europe, East Asia and South Asia), and often the second most important contributor is an emission perturbation in an area that is closer to the area examined than others (e.g., Africa is sensitive to SO_2 from Europe, also noted in Dong et al., 2014; South Asia is influenced by East Asia, also see Shawki et al., 2018). Additionally, remote regions show reduced response, often near zero. We find that the main effect is approximately linear for all pollutants, both GHGs and aerosols, over the ranges explored here, which is intuitive under small forcing perturbations (Boer and Yu, 2003; Gregory et al., 2004; Hansen et al., 1997, 2005; Collins et al., 2013; Richardson et al., 2019),. However, we would expect to see non-linearities in the response when extending to larger forcing perturbations due to the saturation of aerosol-cloud interactions (Carslaw et al., 2013a; Kasoar et al., 2018), as discussed further in Sect. S1 in the Supplement. This likely explains the overestimation of cooling due to strong aerosol perturbations in test scenario in Fig. S4k.

Figure 3 summarizes the main effect per unit Tg of emissions for the aerosol perturbations, in each emission region, estimated as the gradients in the main effects plots (Fig. S6), with the error bars representing the 1 SD uncertainty propagated from the main effects. These demonstrate similar patterns to previous studies that explore the temperature change per unit Tg emissions, following an abrupt emission perturbation (Aamaas et al., 2017; Collins et al., 2013; Shindell

and Faluvegi, 2009). For instance, both Aamaas et al. (2017) and Kasoar et al. (2018) find European SO_2 perturbations to consistently produce larger responses per unit Tg than East Asian SO_2. Shindell and Faluvegi (2009) also find that broad latitudinal SO_2 perturbations in the tropics give fairly similar responses globally, while Northern hemispheric perturbations responses are much stronger in the latitude band of emission relative to other regions. Figure 3 shows consistencies with this as the Northern hemispheric perturbations show much stronger regional effects in other Northern hemispheric response regions while tropical perturbations (SO_2 Africa, South Asia, and South America) show more evenly distributed responses after accounting for the localized effect. Note that here we focus only on the 5-year response, rather than 20 years or longer explored in other studies and also that we average over the effect of other pollutants, in contrast to previous studies that keep them fixed at present-day levels based on simulations where one pollutant at a time is varied (Aamaas et al., 2017; Collins et al., 2013; Shindell and Faluvegi, 2009). This is also one of the first studies to explore the response to regional tropical perturbations (e.g., Wells et al., 2023; Westervelt et al., 2020) as well as extra-tropical (e.g., Persad and Caldeira, 2018; Westervelt et al., 2020), rather than broad latitudinal perturbations (e.g., Aamaas et al., 2017; Collins et al., 2013; Joshi et al., 2003; Shindell and Faluvegi, 2009; Shindell, 2012). The main effects of the OC/BC tropical perturbation show more diversity between regions. There are local decreases in temperature over Africa, where the majority of the BB emissions are released. This is because, although the absorbing effect of BC aerosol increases temperatures globally (e.g., North America, South Asia), it reduces incident radiation to the surface, which is combined with the cooling effect of scattering from OC (Wells et al., 2023).

4.2 Sensitivity indices

We have also carried out a variance-based global sensitivity analysis, by estimating how much of the variance in the output can be attributed to the variance in the inputs via the Sobol method (Saltelli et al., 2008, 2010). This can be calculated for each output variable at each grid point. Figure 4a shows the global and regional means of first order sensitivity indices for CO_2, CH_4 and aerosols, with a more detailed breakdown for each aerosol pollutant in Fig. 4b. Firstly, the variance due to the CO_2 concentration is responsible for the majority of the variance in the emulator ($\sim 90\,\%$) across all regions, which is not surprising given the wide input ranges covered by the emulator based on the high uncertainty of future CO_2 emissions. The aerosol contributions appear small relative to these large perturbations, and we expect this reflects the weaker range of aerosol perturbations in comparison to the large CO_2perturbations. The first order sensitivity indices to CO_2, CH_4 and the aerosols sum to one almost exactly, leaving $< 10^{-4}$ down to higher order terms, indicating that there are only relatively weak interactions between the effects of the different inputs, described further in Sect. S2. Figure 5 shows the sensitivity analyses for each grid-point, highlighting a fairly homogeneous spatial response for the greenhouse gases, but inhomogeneous spatial responses for the aerosol pollutants. Aside from the strong localized effect, the patterns of sensitivity to SO_2 from Europe and East Asia are remarkably similar; reminiscent of results from Kasoar et al. (2018), where removal of SO_2 from different Northern Hemisphere regions gave similar temperature response patterns. Additionally, the perturbations in tropical regions (SO_2 from South America, Africa and South Asia and OC/BC from the Tropics) give rise to similar distributions of sensitivity indices, with enhanced sensitivity over the tropical Atlantic and Pacific oceans. This mirrors the enhanced temperature sensitivities over the Northern hemispheric oceans due to the Northern hemispheric perturbations, an indication that the climate response is projected onto existing modes, in line with previous studies (Corti et al., 1999; Kasoar et al., 2018; Palmer, 1999; Ring and Plumb, 2008; Shindell et al., 1999).

5 Conclusions

We have presented a new Gaussian process emulator that estimates the *global pattern of short-term response* to a sudden change in emissions based on a carefully designed set of training data from the HadGEM3 coupled climate model. This emulator has the ability to predict the spatial pattern of responses, rather than just the global mean responses as previous studies have done (e.g., Castruccio et al., 2014; Meinshausen et al., 2011; Smith et al., 2018a). It predicts the short-term temperature response to a range of global and regional perturbations that include both long-lived greenhouse gases and short-lived aerosol pollutants.

The main source of uncertainty in the emulator predictions is the internal variability of the GCM. Since this is also a source of uncertainty in GCM runs on the same timescales, the choice of simulating climate response with an emulator is a sensible one. Naturally, one of the next steps would be to reduce this uncertainty, for example, simulations could be averaged over longer timescales (e.g., 10 or 20 years) to reduce the effect of year-to-year fluctuations, although this would require a substantial increase in runtime per simulation. Emulator prediction uncertainty could also be targeted by increasing the size of the training dataset. In addition, we assumed here that the internal variability is constant under different scenarios. In future work, it would be interesting to explore how well this assumption holds by estimating the internal variability for each training simulation independently, for example, by performing an ensemble of simulations each seeded with different initial conditions, for all 80 training simulations. Another extension of this work could involve building an additional GP emulator that explicitly models

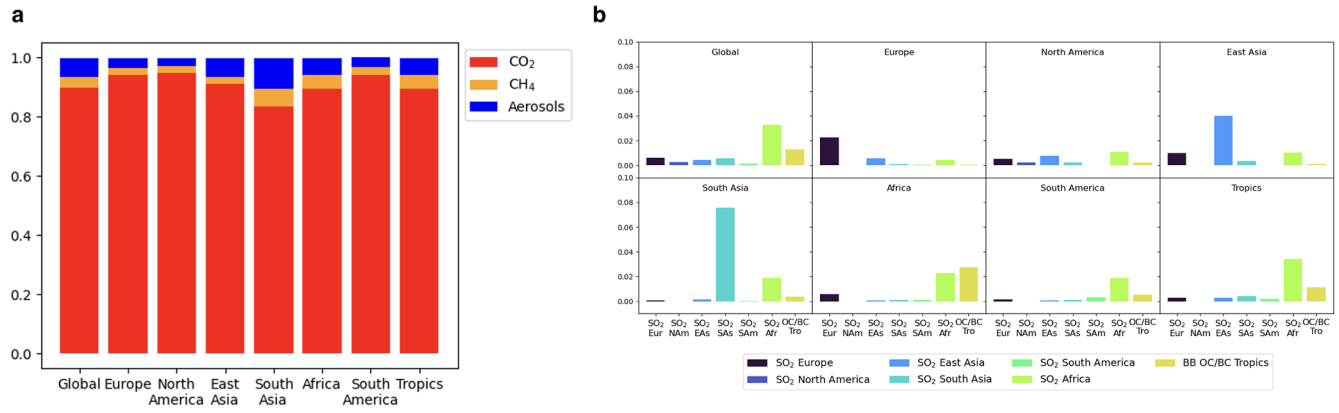


Figure 4. Regional mean first order sensitivity indices **(a)** for CO_2, CH_4 and all aerosols in each region and **(b)** breakdown of the aerosol sensitivity indices: the regional SO_2 perturbations and the tropical biomass burning aerosols (OC/BC).

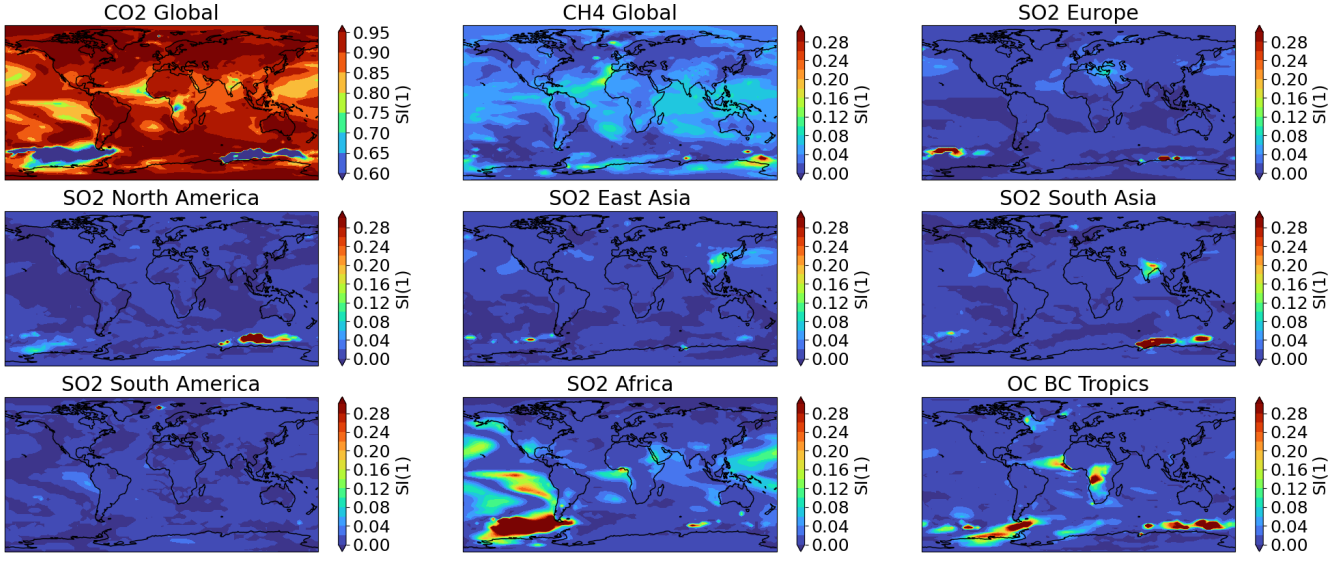


Figure 5. Global maps of first order sensitivity indices, SI(1), for each pollutant perturbation to emulator, where SI(1) is the fraction of contribution to the total sensitivity for each pollutant. Note the different color bar ranges on each subfigure.

the internal variability (heteroscedasticity, e.g., Andrianakis et al., 2017; Binois et al., 2018; Gramacy, 2020). Another approach to reducing uncertainties could be develop multivariate GP emulators, which account for the spatial structure and may be able to share information between neighbouring grid cells (e.g., Conti and O'Hagan, 2010; Gu et al., 2019; Gu and Berger, 2016; Higdon et al., 2008; Rougier, 2009; Rougier et al., 2009).

The overarching goal of this study was to identify a framework for policy-relevant emulators. We made several choices when designing the training and test dataset using GCM simulations, from which future studies can learn. For instance, we chose a maximin Latin hypercube design to sample uniformly across the distribution of each parameter. We extended the parameter space for the aerosol forcings beyond their feasible ranges to account for the weaker aerosol signals compared to the greenhouse gas forcings. Still, we found that many simulations are dominated by the response to greenhouse gas forcings. Future studies may wish to compare the emulator performance under different ratios of extended parameters to realistic parameters. Alternative designs, such as selecting some simulations with restricted greenhouse gas perturbations, which lead to stronger aerosol signals could potentially improve performance in this range. Furthermore, Bayesian optimization techniques could be used to directly identify new parameter choices for additional GCM simulations that would reduce emulator error or uncertainty (Shahriari et al., 2016).

We also identify the opportunity of coupling this fast adjustment emulator with a long-term response emulator, such as that presented in Mansfield et al. (2020), which could lead to full long-term climate projections. Similarly, we see

scope to extend on our work by generating similar emulators from the output of other GCMs, for example to characterize inter-model uncertainty in the relationships derived here. Finally, additional forcings, such as those from separate biomass burning aerosol components, ozone precursors and/or natural aerosols, could also be included in such an emulator. We thus highlight Gaussian process emulators as a useful method to accelerate and understand regional climate change projections under varying anthropogenic emissions scenarios, including not only responses to GHG forcings but also, importantly, to short-lived forcing agents such as aerosols.

Code and data availability. Data was produced using HadGEM3, developed by the UK Met Office. Code and data used to train the emulator and produce all plots for this manuscript are available at https://doi.org/10.5281/zenodo.17814595 (Mansfield, 2025).

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Author contributions. Conceptualisation: AV, PJN, LAM. Supervision: AV, PJN. Formal analysis: LAM, PJN, AV. Software: LAM, Validation: LAM, PJN, EMR, OW, AV. Methodology: LAM, PJN, EMR, OW, AV. Writing (original draft): LAM. Writing (review and editing): LAM, PJN, EMR, OW, AV.

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

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