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Climate model emulation in an integrated assessment framework: a case study for mitigation policies in the electricity sector

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Abstract

We present a carbon cycle-climate modelling framework using model emulation, designed for integrated assessment modelling, which introduces a new emulator of the carbon cycle (GENIEem). We demonstrate that GENIEem successfully reproduces the CO_2 concentrations of the Representative Concentration Pathways when forced with the corresponding CO_2 emissions and non-CO_2 forcing. To demonstrate its application as part of the integrated assessment framework, we use GENIEem along with an emulator of the climate (PLASIM-ENTSem) to evaluate global CO_2 concentration levels and spatial temperature and precipitation response patterns resulting from CO_2 emission scenarios. These scenarios are modelled using a macroeconometric model (E3MG) coupled to a model of technology substitution dynamics (FTT:Power), and represent different emissions reduction policies applied solely in the electricity sector, without mitigation in the rest of the economy. The effect of cascading uncertainty is apparent, but despite uncertainties, it is clear that in all scenarios, global mean temperatures in excess of 2 °C above preindustrial levels are projected by the end of the century. Our approach also reveals the diverse temperature and precipitation patterns that could occur regionally in response to the global mean temperatures associated with these scenarios, enabling more robust impacts modelling and emphasising the necessity of focussing on spatial patterns in addition to global mean temperature change.

1 Introduction

Integrated assessment modelling can be used to explore the climatic consequences of particular climate mitigation policy scenarios. However, most integrated assessment models (IAMs) do not directly utilise sophisticated coupled Atmosphere Ocean General Circulation Models, such as those employed in the Coupled Model Intercomparison Project Phase 5 (CMIP5: Friedlingstein et al., 2013), to represent the climate and

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carbon cycle. Due to the large computational resources they require, the direct use of such models within IAMs is not feasible.

Instead, many IAMs have used simple mechanistic models to represent the carbon cycle. One such simplified carbon-cycle/climate model is MAGICC6 (Meinshausen et al., 2011a), which is calibrated against higher complexity models from the Coupled Carbon Cycle Climate Model Intercomparison Project (C4MIP), to emulate the atmospheric CO_2 concentrations of those models. Schaeffer et al. (2013) used MAGICC6 to derive probability distributions for radiative forcing, which drive a simple climate model that projects GCM global mean temperature response by linearly scaling the CO_2 step experiment response of 17 CMIP5 GCM $4\times CO_2$ simulations. Such approaches can be used to generate large ensembles quite quickly; for instance, MAGICC6 has been used to generate a 600-member perturbed parameter ensemble (Schaeffer et al., 2013) of CO_2-equivalent concentration and global-mean surface-air temperature change projections.

It has been suggested that a conceptual advantage of this approach is that the mechanistic model fit adds some confidence when extrapolating beyond the training data (Meinshausen et al., 2011a). A limitation of simplified mechanistic models is that they may contain a high level of parameterization. For example, the Meinshausen et al. (2011a) carbon cycle calibration procedure uses global mean temperature as a proxy for changes in patterns of temperature and precipitation. These drivers of change in the carbon cycle would be explicitly represented in a more sophisticated model.

To represent regionally varying patterns of climatic change, as opposed to global mean temperature change, many IAM studies have used pattern-scaling (e.g. IMAGE: Bouwman et al., 2006). This computationally inexpensive technique linearly relates regional climatic change, derived from stored GCM ensembles such as those generated in CMIP5, to global mean temperature change, simulated using a simplified model, so that the regional response to many emissions scenarios can be computed quickly (e.g. Cabré et al., 2010). Simple pattern scaling assumes that the climate response is spatially invariant (with respect to time and forcing), and therefore cannot

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capture aspects which may be sensitive to the greenhouse gas (GHG) concentration pathway (O'Neill and Oppenheimer, 2004; Tebaldi and Arblaster, 2014). Tebaldi and Arblaster (2014) cite a number of instances where it is liable to break down, in particular for scenarios with strong mitigation or less mean temperature change. Recent advances in pattern-scaling have considered the effects of different forcing components; for example, with the most recent iteration of MAGICC-SCENGEN, the effects of aerosols can be estimated for some climate parameters by generating patterns specific to these emissions[1].

The AOGCM ensembles used in pattern scaling are usually multi-model ensembles (MMEs). Such ensembles consist of simulations from different models, and are neither a systematic nor random sampling of potential future climates (Tebaldi and Knutti, 2007). Similarities between models may lead to a lack of independence amongst ensemble members (Foley et al., 2013), complicating the interpretation of the ensemble as a whole (Knutti et al., 2013).

Perturbed physics ensembles (PPEs) offer a more systematic sampling of potential future climates, but embedding a PPE approach into an IAM framework requires a computationally fast climate model. In this context, statistical emulation of complex models is a useful alternative. For example, Castruccio et al. (2014) constructed a statistical climate model emulator using simulations performed with the Community Climate System Model, version 3 (CCSM3), in which statistical models are fitted to temperature and precipitation for 47 subcontinental-scale regions. Such an approach is suitable for applications requiring annual temperatures of specific regions, but is less appropriate when climate impacts within regions are to be considered. Carslaw et al. (2013) apply a similar approach to the grid-cell level. However, such an approach requires many emulators, and correspondingly, computational resources. Furthermore, the global emulation may not be self-consistent, as the individual emulators do not utilise the correlations between grid cells.

[1] MAGICC/SCENGEN user manual, p. 2: http://www.cgd.ucar.edu/cas/wigley/magicc/UserMan5.3.v2.pdf.

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In this paper, we demonstrate how model emulation using singular vector decomposition (SVD) can be used within an IAM framework to generate perturbed physics ensembles, systematically capturing uncertainty in the future climate state while also providing insight into regional climate change. We introduce the GENIEem-PLASIM-ENTSem (GPem) climate-carbon cycle emulator, which consists of a statistical climate model emulator, PLASIM-ENTSem, to represent climate dynamics (Holden et al., 2014a), and a new carbon cycle emulator GENIEem. Compared to a simple mechanistic model, the purely statistical GENIEem does not impose a predefined functional structure, allowing the emulator to capture more of the behaviour of the underlying simulator, and notably providing a representation of the parametric uncertainty of the simulator. Although parametric uncertainty of MAGICC itself can be investigated (Meinshausen et al., 2009), this is distinct from representing the parametric uncertainties and associated non-linear feedbacks in the underlying simulator. Similarly, compared to pattern-scaling, the more complex statistical approach used in PLASIM-ENTSem enables a representation of spatial uncertainties due to parametric uncertainties in the underlying model. The use of SVD to decompose spatial patterns of climate parameters makes PLASIM-ENTSem computationally efficient, compared to techniques in which statistical relationships are developed for each grid-cell.

We demonstrate how these emulators can be applied in an IAM framework to resolve the regional environmental impacts associated with policy scenarios by coupling GPem to FTT:Power-E3MG, a non-equilibrium economic model with a technology diffusion component. Our work builds on that of Labriet et al. (2013) and Joshi et al. (2015) who also derived IAMs from economic and energy technology system models coupled to PLASIM-ENTSem.

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2 The GENIEem carbon cycle model emulator

The carbon cycle model emulator GENIEem is an emulator of the GENIE-1 ESM (Holden et al., 2013a) (i.e. a statistical model that approximately reproduces selected outputs from the full GENIE-1 simulator). The emulator takes a time series of anthropogenic CO_2 emissions and non-CO_2 radiative forcing as inputs and provides a time series of atmospheric CO_2 concentration as output. Uncertainty in the carbon cycle is captured by emulating 86 possible futures, each with a different set of GENIE-1 parameter inputs. The 86 parameter sets cover a wide range of values, reflecting a large assumed structural uncertainty.

2.1 GENIE-1 description

The full GENIE-1 simulator comprises the 3-D frictional geostrophic ocean model GOLDSTEIN (Edwards and Marsh, 2005) coupled to a 2-D Energy Moisture Balance Atmosphere based on that of Fanning and Weaver (1996) and Weaver et al. (2001), and a thermodynamic-dynamic sea-ice model based on Semtner (1976) and Hibler (1979). Ocean biogeochemistry is modelled with BIOGEM (Ridgwell et al., 2007), coupled to the sediment model SEDGEM (Ridgwell and Hargreaves, 2007). GENIE-1 is run at 36×36 spatial resolution ($\approx 10^\circ \times 5^\circ$ on average) with a ≈ 1 day atmospheric time step, and 16 depth levels in the ocean. Vegetation is simulated with ENTSML (Holden et al., 2013a), a dynamic model of terrestrial carbon and land use change (LUC) based on the single plant functional type model ENTS (Williamson et al., 2006). ENTSML takes time-varying fields of LUC as inputs. Each simulation used to build the emulator is a transient simulation from AD 850 through to 2105. Historical forcing (AD 850–2005), including changing land use, is prescribed as described in Eby et al. (2013). Future forcing (2005–2105) is defined by a CO_2 emissions time series and a non-CO_2 radiative forcing time series, both represented by polynomials (see Sect. 2.3). The LUC mask is held fixed from 2005, as capturing LUC-climate-carbon feedbacks in the emulator would require high dimensional inputs, a significantly more complex ensemble design

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and emulation challenge. The future forcing due to LUC is instead subsumed into the CO_2 emissions (LUC emissions) and non-CO_2 radiative forcing (LUC albedo).

The configuration is the same as that applied in the Earth system model of intermediate complexity (EMIC) intercomparison project (Zickfeld et al., 2013). Due to its reduced complexity, GENIE-1 is a good choice for performing the many simulations required to build an emulator.

2.2 GENIE-1 parameter set selection

Construction of GENIEem is summarised in (Fig. 1). To build the carbon cycle emulator, a subset of the 471-member emulator filtered plausibility-constrained parameter sets described in Holden et al. (2013b) is used. Each of these 471 parameter sets was previously applied to a CO_2 emissions-forced transient historical simulation (850 to 2005 AD). They comprise experiments 1 and 2 of Holden et al. (2013a). In addition to emissions forcing, these simulations were forced by non-CO_2 trace gases, LUC, anthropogenic aerosols, volcanic aerosols, orbital change and solar variability, as described in Eby et al. (2013).

The 471 parameter sets are constrained to be plausible in the preindustrial state by design (Holden et al., 2013b). However, they are not constrained to be plausible in the present day as neither the anthropogenic carbon sinks nor the LUC emissions are calibrated. Additionally, these 471 parameter sets are known to contain members that display numerical instabilities (Holden et al., 2013a).

In order to identify useful parameter sets, we apply a filter to this transient historical ensemble. A parameter set is accepted as plausible if the difference between simulated and observed atmospheric CO_2 concentration lies within an acceptable range at each of five time points, 1620, 1770, 1850, 1970 and 2005 AD:

$$|CO_2(t) - CO_2{}^*(t)| < \sqrt{\epsilon_0^2 + \epsilon_t^2} \tag{1}$$

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where $CO_2(t)$ and $CO_2^*(t)$ are simulated and observed atmospheric CO_2 concentration, evaluated at each time slice t, and the acceptable errors ϵ_0 and ϵ_t relate to the preindustrial spin-up state and to the transient change. The time points span the preindustrial period and are not associated with volcanic eruptions as these can lead to an unrealistic carbon-cycle response in GENIE due to the single layer soil module (Holden et al., 2013a).

The ϵ_0 term dominates the acceptable error during the preindustrial era and is designed to reject any simulations that exhibit numerical instability. It is set equal to 2 standard deviations (9 ppm) of the 471-member spin-up ensemble. The ϵ_t term is given by $0.22 \times (CO_2{}^*(t) - 280)$ ppm. This term dominates the acceptable error in the postindustrial era and is designed to reject simulations that exhibit an unreasonable strength for the CO_2 sink. It approximately limits the range of acceptable uncertainty to the inter-model variance of the multi-model C4MIP ensemble (Friedlingstein et al., 2006), assuming that the range of simulated CO_2 change across the C4MIP ensemble scales linearly with simulated CO_2 change relative to preindustrial (280 ppm). Eighty-six parameter sets satisfied this constraint at all 5 time points.

2.3 GENIE-1 ensemble design

These 86 parameter sets from the full GENIE-1 simulator were used to generate an ensemble of future simulations (2005 to 2105) forced with time-varying CO_2 emissions and non-CO_2 radiative forcing. Each simulation was continued from its respective transient historical simulation. Radiative forcing was applied as a globally uniform modification to outgoing long-wave radiation to capture the combined effects of non-CO_2 trace gases, aerosols and LUC on global temperature. The LUC mask was fixed at the 2005 distribution, but effects of future land use changes are accounted for, albeit approximately, in the applied radiative forcing and emissions anomalies.

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To capture the range of possible future forcing we followed the approach of Holden and Edwards (2010). The CO_2 emissions profile is represented as:

$$E = E_0 + 0.5E_1(t+1) + E_2(2t^2 - 2) + E_3(4t^3 - 4t) \tag{2}$$

where t is time, normalised onto the range −1 to 1 (2005 to 2105). The coefficient ranges were chosen to span the Representative Concentration Pathway (RCP; Van Vuuren et al., 2011) emission scenarios (Moss et al., 2010): $E_1 = -30$ to $30\,\mathrm{GtC\,yr^{-1}}$, $E_2 = -15$ to $15\,\mathrm{GtC\,yr^{-1}}$, $E_3 = -15$ to $15\,\mathrm{GtC\,yr^{-1}}$. The 2005 emissions $E_0 = 9.166\,\mathrm{GtC\,yr^{-1}}$. Note that Eq. (2) is strictly a linear combination of Chebyshev polynomials such that the first two terms give the linear increase in emissions; we refer to the coefficients henceforth as "Chebyshev coefficents".

The non-CO_2 radiative forcing profile is also represented by a linear combination of modified Chebyshev polynomials:

$$R = R_0 + 0.5R_1(t+1) + R_2(2t^2 - 2) + R_3(4t^3 - 4t) \tag{3}$$

These Chebyshev coefficients are varied in the ranges $R_1 = -10$ to $10\,\mathrm{W\,m^{-2}}$, $R_2 = -5$ to $15\,\mathrm{W\,m^{-2}}$, $R_3 = -5$ to $5\,\mathrm{W\,m^{-2}}$. The 2005 non-CO_2 radiative forcing $R_0 = 0.619\,\mathrm{W\,m^{-2}}$.

The 86 parameter sets were reproduced three times, and combined with different future emissions profiles to produce a 258-member ensemble. To achieve this, the six coefficients were varied over the above ranges to create a 258-member Maximin Latin Hypercube design, using the maximinLHS function of the lhs package in R (R Development Core Team, 2015). 257 simulations completed successfully; in the remaining simulation, input parameters led to an unphysical state and ultimately, numerical instability.

2.4 Construction of GENIEem

The emulation approach closely follows the dimension reduction methodology detailed in Holden et al. (2014a). We have an ensemble of 257 transient simulations of

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the coupled climate-carbon system, incorporating both parametric uncertainty (28 parameters) and forcing uncertainty (6 modified Chebyshev coefficients). For coupling applications we require an emulator that will generate the annually resolved evolution of CO_2 concentration through time (2006 to 2105). The simulation outputs were combined into a (100 × 257) matrix **Y**, and SVD was performed on the matrix

$$\mathbf{Y} = \mathbf{L}\mathbf{D}\mathbf{R}^{\mathrm{T}} \tag{4}$$

where **L** is the (100 × 257) matrix of left singular vectors ("components"), **D** is the 257 × 257 diagonal matrix of the square roots of the eigenvalues and **R** is the 257 × 257 matrix of right singular vectors ("component scores").

We retain the first four components, which together explain more than 99.9 % of the ensemble variance. Each individual simulated time series can thus be well approximated as a linear combination of the first four components, scaled by their respective scores. Each set of scores consists of a vector of coefficients, representing the projection of each simulation onto the respective component. As each simulated time series is a function of the input parameters, so are the coefficients that comprise the scores. So each component score can be viewed, and hence emulated, as a scalar function of the input parameters to the simulator.

Emulators of the first four component scores were derived as functions of the 28 model parameters and the 6 concentration profile coefficients. These emulators were built in R (R Development Core Team, 2015), using the stepAIC function (Venables and Ripley, 2002). For each emulator, we first built a linear model from all 34 inputs allowing only terms that satisfy the Bayes Information Criterion (BIC). BIC-constrained stepwise addition of quadratic and cross terms was then performed, allowing only inputs present in the linear model.

While the variance in emulator output is dominated by the Chebyshev forcing coefficients, uncertainty for a given forcing scenario is generated through emulator dependencies on GENIE-1 parameters. The most important of these is the CO_2 fertilisation parameter, k_{14}, describing the uncertain response of photosynthesis to

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changing CO_2 concentrations. To use the emulator, we constrain k_{14} using the calibration of Holden et al. (2013a), to better quantify the uncertainty associated with the terrestrial sink. We approximate the prior as a normal distribution with mean 500 ppm and standard deviation 150 ppm, following the base posterior of Holden et al. (2013a). We sampled values at random from this distribution and replaced the k_{14} values in the 86-member training parameter set. Then, to generate a perturbed parameter ensemble of emulated futures, the emulation is performed for each of the resulting 86 parameter sets.

2.5 Validation of GENIEem

To validate the emulator, we apply leave-one-out cross-validation, which involves rebuilding the emulator 257 times with a different simulation omitted and comparing the omitted simulation with its emulation. The proportion of variance V_T explained by the emulator under cross-validation is given by:

$$V_T = 1 - \sum_{n=1}^{257}\sum_{t=1}^{100}(S_n,t - E_n,t)^2 \Bigg/ \sum_{n=1}^{257}\sum_{t=1}^{100}(S_n,t - \bar{S}_t)^2 \tag{5}$$

where $S_{(n,t)}$ is the simulated CO_2 concentration at time t in left-out ensemble member n, $E_{(n,t)}$ the corresponding emulated output and $\bar{S}_t$ is the ensemble mean output at time t. V_T measures the degree to which individual emulations can be regarded as accurate (Holden et al., 2014a).

The cross-validated root mean square error of the emulator is given by:

$$\mathrm{RMSE} = \sqrt{\sum_{n=1}^{257}\sum_{t=1}^{100}\frac{(S_n,t - E_n,t)^2}{25\,700}} \tag{6}$$

The proportion of variance explained by the emulator under cross-validation is found to be 96.8 %, and the cross-validated root mean square error of the emulator is

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34 ppm. The ensemble distribution of cross-validated emulator error does not exhibit any significant trends as a function of the forcing, being approximately distributed about zero, independently of the final CO_2 concentration. This suggests that the emulator errors are likely dominated by describing parametric uncertainty with low order polynomials, and so would be randomly distributed across a perturbed parameter emulated ensemble. To test this we performed a simulation ensemble forced by RCP 8.5. The simulated ensemble mean of 2100 $CO_2 = 1040 \pm 99$ ppm. This compares to the emulated ensemble mean of 1032 ± 79 ppm with the same forcing. The emulator explains 74 % of the variance in 2100 CO_2 across the RCP 8.5 simulation ensemble, demonstrating that the parametric uncertainty is reasonably well approximated.

2.6 Evaluation of GENIEem using RCPs

To further evaluate the emulator's performance, we consider GENIEem's response to forcing by RCPs. For each RCP, CO_2 emissions, non-CO_2 radiative forcing and CO_2 concentrations are provided by Meinshausen et al. (2011b).[2] GENIEem is run using Chebyshev coefficients derived by fitting Eqs. (1) and (2) to RCP CO_2 emissions and non-CO_2 radiative forcing data. Emulated CO_2 concentrations are compared to the CO_2 concentrations corresponding to that RCP in the RCP Database. For RCP 8.5, we also compare the emulator range with the CMIP5 ensemble range of CO_2 concentrations for that RCP.

GENIEem median CO_2 concentrations are generally well centred on the RCPs (Fig. 2). The RCP profiles were derived assuming carbon cycle rates that were calibrated to the median of the C4MIP models. This good agreement is therefore not imposed, but is desirable as it suggests that the ensemble of GENIE-1 parameter sets is not significantly biased with respect to C4MIP. The full range of 2105 emulated CO_2 concentrations under RCP 8.5 forcing is 806 to 1076 ppm. When forced with the same RCP, 11 CMIP5 models simulate a range of 795 to 1145 ppm by 2100 (Friedlingstein

[2]Data available via the RCP Database at http://tntcat.iiasa.ac.at:8787/RcpDb.

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et al., 2013), demonstrating that the emulator can reproduce existing estimates of the carbon cycle uncertainty. In a related analysis, the ensemble mean and variance were shown to be easier to emulate than individual simulations (Holden et al., 2014a). The emulator's capacity to capture the CMIP5 simulation ensemble suggests that this is also the case here.

For RCP 2.6, the difference between the RCP value and the emulator median reaches about 15 ppm. One possible explanation for this is the formulation of land use change. When land use is changed in GENIE, soil carbon evolves dynamically to a new equilibrium. Therefore, although the LUC mask is held fixed after the transient AD 850–2005 spin-up, there are ongoing land-atmosphere fluxes in the future (2005–2105) due to historical LUC. Since the RCP emissions data used to force GENIEem already include the contribution from soil carbon fluxes, the inconsistency of approaches is liable to lead to a net additional forcing while the historical contribution decays. These residual emissions would be most significant in RCP 2.6 because other emissions are lowest in this scenario, potentially contributing to the excess concentrations in the emulation of RCP 2.6. This difference could be reduced by using a more sophisticated treatment of the forcing inputs that separated fossil fuel and land use carbon emissions, with land use emissions calculated from spatially explicit scenarios based on above-ground carbon change, as in Houghton (2008).

3 Application of GPem in an IAM framework

To demonstrate the utility of emulation within an integrated assessment framework, we describe how GENIEem, along with PLASIM-ENTSem has been used to explore the climate change implications of four of the policy scenarios for the electricity sector, as presented in Mercure et al. (2014). GPem is coupled to FTT:Power-E3MG, which combines a technology diffusion model with a non-equilibrium economic model. Mercure et al. (2014) emphasises the policy instruments that can be applied to decarbonisation of the global energy sector, and analysis of climate impacts is limited

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to mean surface temperature anomalies. Here, we extend that work to illustrate the regional patterns of climate variability associated with different policy scenarios, and discuss these results in the context of "dangerous climate change" (Jarvis et al., 2012).

3.1 The climate model emulator: PLASIM-ENTSem

PLASIM-ENTSem is an emulator of the GCM PLASIM-ENTS; both simulator and emulator are described by Holden et al. (2014a). The GCM consists of a climate model, PLASIM (Fraedrich, 2012), coupled to a simple surface and vegetation model, ENTS (Williamson et al., 2006), which represents vegetation and soil carbon through a single plant functional type. PLASIM has a heat-flux corrected slab ocean and a mixed-layer of a given depth, and a 3-D dynamic atmosphere, run at T21 $\sim 5^{\circ}$ resolution. It utilises primitive equations for vorticity, divergence, temperature and the logarithm of surface pressure, solved via the spectral transform method, and contains parameterizations for long and short-wave radiation, interactive clouds, moist and dry convection, large-scale precipitation, boundary layer fluxes of latent and sensible heat and vertical and horizontal diffusion. It accounts for water vapour, carbon dioxide and ozone.

As an emulator of PLASIM-ENTS, PLASIM-ENTSem emulates mean fields of change for surface air temperature and precipitation well, while emulations of precipitation underestimate simulated ensemble variability, explaining ~ 60 to 80 % of the variance in precipitation (compared to ~ 95 % for surface air temperature) (Holden et al., 2014a).

3.2 Policy scenarios and emissions profiles

FTT:Power is a simulation model of the global power sector (Mercure, 2012), which has been coupled to a dynamic simulation model of the global economy, E3MG (Mercure et al., 2014)[3]. These models are described in greater detail in the Supplement of this

[3]http://www.4cmr.group.cam.ac.uk/research/FTT/fttviewer

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paper. Policies within the electricity sector drive the uptake or phasing out of types of generators, leading to different CO_2 emission profiles (Fig. 3).

Here we consider four scenarios, a subset of the ten scenarios explored in Mercure et al. (2014). Scenario (i) is the no-climate-policy baseline. Scenario (ii) introduces carbon pricing, which rises to 200–400 USD (2008)/t CO_2. Scenario (iii) explores the use of carbon pricing, along with technology subsidies and feed-in tariffs in the developed world only. Finally, scenario (iv) uses carbon pricing, along with technology subsidies and feed-in tariffs to incentivise decarbonisation, and also includes regulations to ban the construction of new coal power plants in China if not equipped with Carbon Capture and Storage; this policy set decarbonises the global electricity sector by 90 % (relative to 1990 emissions) by 2050.

3.3 Coupling procedure

As FTT:Power-E3MG runs until 2050, emissions for 2050–2105 are estimated using a linear best-fit trend, except in the case of successful mitigation scenarios, where such an approach could lead to implausible emissions reductions by 2105. In these scenarios, the emissions in $\mathrm{Pg\,C\,y^{-1}}$ reached in 2050 were assumed to remain constant beyond 2050 (i.e. in these scenarios, it is assumed that by 2050, the energy sector has decarbonised as much as can be incentivised under the specified policies).

Chebyshev coefficients are calculated to provide least squares fits to each emissions profile produced by FTT:Power-E3MG. If we conservatively assume that any error in emissions due to differences between the FTT:Power-E3MG emissions profile and the corresponding Chebyshev curve has an infinite lifetime in the atmosphere, the accumulated error does not exceed 4.5 ppm in any scenario over the period 2005 to 2105, well within the 5th to 95th percentiles of GENIEem.

As FTT:Power-E3MG does not simulate non-CO_2 radiative forcing, we select the RCP that best matches the CO_2 concentrations associated with the baseline scenario (RCP 8.5) and force GENIEem with the non-CO_2 radiative forcing associated with that RCP. The RCP 8.5 non-CO_2 radiative forcing was applied to all scenarios as the

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RCPs lack a suitable analog to the CO_2 concentrations associated with the power sector mitigation scenarios examined in this work. Values for Chebyshev coeficients are calculated and these three coefficients, together with the three CO_2 emissions coefficients, are the inputs to GENIEem.

This approach maintains comparability across the different scenarios, although we expect some small reductions in CH_4 and N_2O in the mitigation scenarios, due to a reduction in leaks of these GHGs from drilling. Representations of these GHGs in FTT:Power-E3MG are not sufficiently detailed to provide forcing data for GPem, but reductions in fuel use-related CH_4 and N_2O emissions of around 10 to 15 % by 2050 in the mitigation scenario can be inferred. After 2050, we expect a stabilisation at this new level, as the sectors involved have decarbonised by 90 %, producing a reduction in forcing of roughly 0.1 $W m^{-2}$ (relative to total forcing of 7.3 to 8.3 $W m^{-2}$ in the baseline and 5.3 to 6.2 $W m^{-2}$ in the mitigation scenario, accounting for carbon cycle uncertainty). This small reduction in forcing is well within the uncertainty bounds of GENIEem.

Climate-carbon feedbacks are emulated entirely within GENIEem. No climate information is passed from PLASIMem to GENIEem. PLASIM-ENTSem takes inputs of both actual CO_2 (for CO_2 fertilization) and equivalent CO_2 (for radiative forcing). Chebyshev coefficients are calculated to provide least squares fits to the median, and 5th percentiles and 95th percentiles of the GENIEem ensemble CO_2 concentrations; these coefficients, therefore, correspond to actual CO_2 concentrations. Chebyshev coefficients for equivalent CO_2 are also calculated, corresponding to combined CO_2 and non-CO_2 forcings. To determine these coefficients for equivalent CO_2, the median and 5th percentiles and 95th percentiles of the GENIEem ensemble CO_2 concentrations are converted to radiative forcing following:

$$\Delta F = 5.35 \ln(CO_2/280)\, W m^{-2} \tag{7}$$

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RCP 8.5 non-CO_2 forcing is added to this time series to give total radiative forcing, which is converted to equivalent CO_2 using the previous relationship. Chebyshev coefficients for equivalent CO_2 are fitted to the resulting time series.

Thus, PLASIM-ENTSem is forced with three sets of six coefficients (three actual CO_2 and three equivalent CO_2 each for the median, 5th percentile and 95th percentile of the GENIEem ensemble).

We calculate the median warming of the PLASIM-ENTSem ensemble based on the 5th and 95th percentiles of the GENIEem ensemble. These bounds, therefore, illustrate parametric uncertainty of the carbon cycle model alone.

We also calculate the median, 5th percentile and 95th percentile of warming of the PLASIM-ENTSem ensemble from the median GENIEem ensemble output. These bounds reflect parametric uncertainty in the climate model alone.

Finally, we calculate the 5th percentile of warming from the PLASIM-ENTSem ensemble based on the 5th percentile of CO_2 concentration from the GENIEem ensemble, and the 95th percentile of warming from the PLASIM-ENTSem ensemble based on the 95th percentile of CO_2 concentration from the GENIEem ensemble. This third set of bounds reflects warming uncertainty due to parametric uncertainty in the climate model and the carbon cycle model, computed under the assumption that GENIEem and PLASIM-ENTSem projections are perfectly correlated, i.e. that states exhibiting the greatest CO_2 concentration in GENIEem correspond to states exhibiting greatest warming in PLASIM-ENTSem. Many carbon cycle processes are affected directly by changes in temperature, or by variables which covary with temperature (Willeit et al., 2014), so while such a correlation is not absolute, there is a motivation for this approach.

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4 Results

4.1 GPem mean warming under policy scenarios

We applied GPem to determine the atmospheric CO_2 concentrations and mean global temperature anomalies associated with different mitigation policiies applicable to the energy sector. Due to the effect of non-CO_2 radiative forcing on climate, combined with remaining CO_2 emissions, CO_2 concentrations continue to increase in mitigation scenarios (Fig. 4). Figure 4 also illustrates the temperature anomalies associated with each of the scenarios. Modelled anomalies are relative to the model baseline, 1995–2005. Therefore historical warming, estimated at $\approx 0.6\,^{\circ}$C in 2000 (IPCC, 2013) is added to give anomalies relative to the preindustrial period. While there is no scenario in which temperature stabilises by 2100, in scenario (iv), the rate of warming remains roughly constant, while in scenario (i), the rate of warming appears to increase towards the later half of this century. The effect of cascading uncertainty is apparent (Jones, 2000; Foley, 2010), leading to large uncertainty bounds for temperature projections.

4.2 GPem regional climate under policy scenarios

Figure 5 illustrates the 2095–2105 December–February and June–August warming anomalies associated with scenario (i) and (iv), presenting the median and 5th/95th percentiles of the PLASIM-ENTSem ensemble outputs calculated independently at each grid point. These emulated ensembles are forced with GENIEem median CO_2 concentrations for the respective scenario, giving an indication of the range of PLASIM-ENTSem parametric uncertainty associated with the projection. It is evident that the warming associated with the baseline scenario would be partially offset under the mitigation sceanrio. However, certain hotspots of warming are apparent even under the 5th percentile projection. In both scenarios, there is cooling in south-east Asia in summer, which likely arises due to a strengthening of the monsoon in PLASIM-

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ENTSem. However, Holden et al. (2014a) note that this signal may not be robust as the model lacks aerosol forcing.

Figure 6 illustrates the mean 2095–2105 December–February and June–August precipitation patterns associated with scenario (i) and (iv), along with the proportion of ensemble members simulating increased precipitation in each case. Generally, areas that experience a significant increase/decrease in precipitation under scenario (iv) (i.e. larger than $\pm 1\,\text{mm}\,\text{day}^{-1}$) experience even greater extremes under scenario (i), which can be attributed to strengthened Hadley circulation in a warmer world. Plotting the proportion of ensemble members that project increasing precipitation shows that in most regions of the world, there is high agreement between ensemble members on the direction of change for precipitation.

Precipitation patterns are similar for the two scenarios presented ($r = 0.99$), suggesting that a simple pattern scaling approach would have sufficed in the particular example considered here, at least for estimation of the ensemble mean field. However, Tebaldi and Arblaster (2014) considered correlations between the averaged precipitation anomaly fields (2090–1990) of the CMIP5 multi-model ensemble when forced with different RCPs; the lowest correlation (0.85) was between ensembles forced with RCP 2.6 and RCP 8.5, while a correlation of 0.97 was found between RCP 4.5 and RCP 8.5. Applying our emulation framework yielded correlations of: 0.89–0.93 (RCP 2.6, RCP 8.5) and 0.97–0.98 (RCP 4.5, RCP 8.5), depending on season. This comparison demonstrates that the emulation framework captures non-linear feedback strengths that are comparable to those found in a high-complexity high-resolution multi-model ensemble and, furthermore, that the assumptions of pattern scaling are especially likely to break down when applied to strong mitigation scenarios.

5 Conclusions

We have described and validated a new carbon cycle model emulator, GENIEem, and applied it along with PLASIM-ENTSem to demonstrate the utility of statistical model

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emulation in an IAM setting. The climate-carbon cycle emulator GPem was used to examine atmospheric CO_2 concentration, mean global temperature anomalies, and spatial temperature and precipitation response patterns resulting from CO_2 emission scenarios associated with various mitigation scenarios for the electricity sector.

Even the most successful mitigation strategy considered here results in warming of above 3.5 °C by 2100, a level of warming which Parry et al. (2009) notes could result in substantial harmful impacts, including risks of water shortage and coastal flooding. As such, in a context where the global electricity sector is decarbonised by 90 %, further emissions reductions must be achieved in other sectors (e.g. transport and industry) to enable CO_2 concentrations to remain below 450 ppm, and correspondingly, global warming below 2 °C (Meinshausen et al., 2009).

The 2 °C warming threshold is often a focal point of climate mitigation policy and scholarship, and is indeed useful as a guiding principle (e.g. Den Elzen and Meinshausen, 2006; Oberthür and Roche Kelly, 2008; Shindell et al., 2012). However, it is also vital to consider the complex temperature and precipitation patterns that could occur, lest a focus on the global mean temperature result in regional climate impacts being overlooked. Furthermore, consideration must be given to how to adapt to diverse regional climate change, should this target not be met (Parry et al., 2009). Applying the GPem framework yields a more systematic representation of uncertainty in future regional climate states, when compared the pattern-scaling approaches that are based on "ensembles of opportunity" (Stone et al., 2007).

While uncertainty associated with carbon cycle and climate modelling in this framework are accounted for through the use of ensembles, it is still possible that the actual future climate state may fall outside the simulated range. Uncertainty associated with emissions profiles is more difficult to quantify as these depend, ultimately, on human decision-making. Therefore many policy contexts should be modelled in order to find out which ones effectively lead to desired outcomes.

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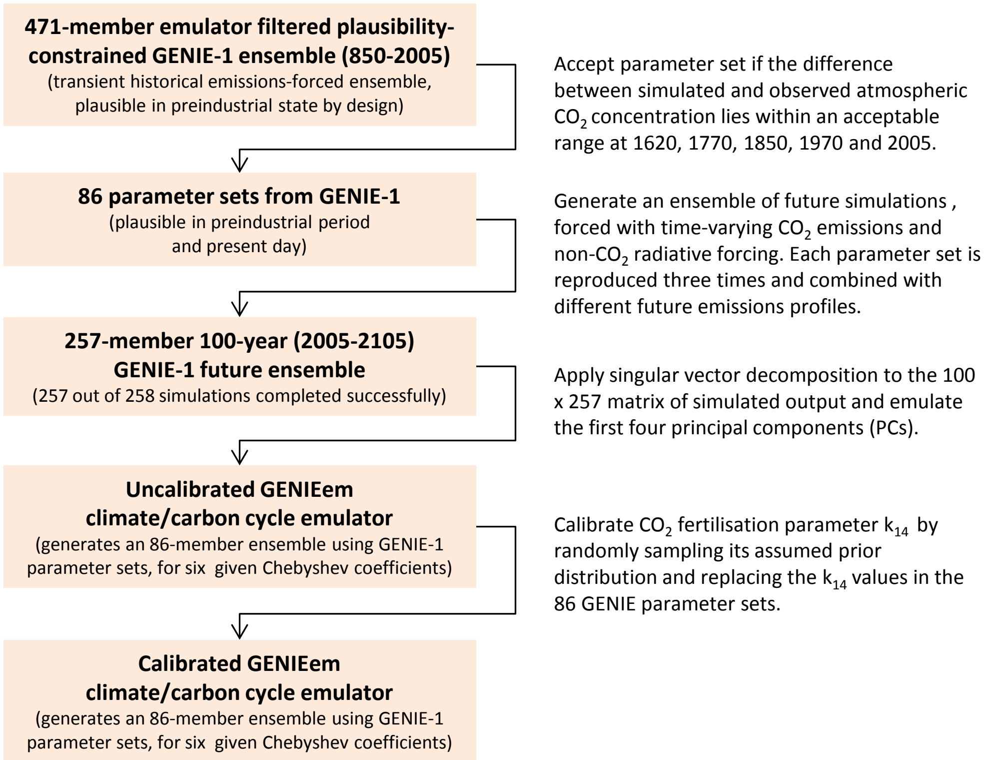

Figure 1. Schematic describing the construction of GENIEem.

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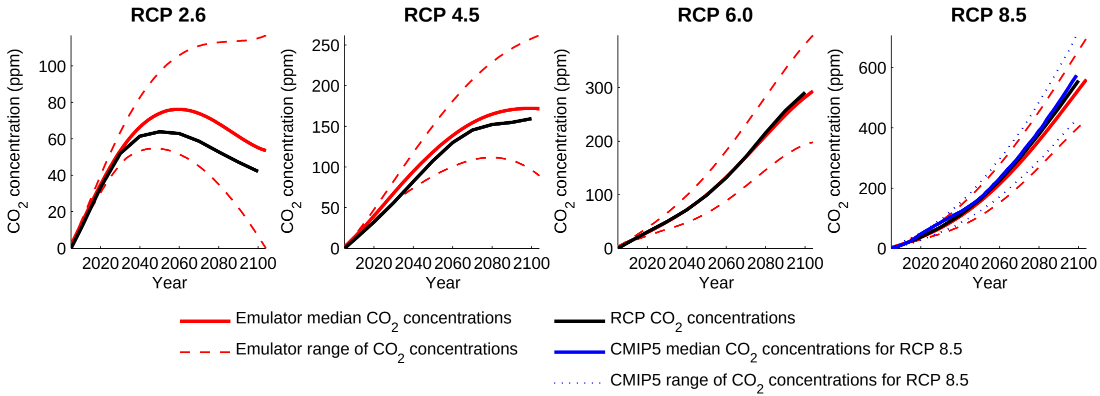

Figure 2. Carbon cycle emulator output compared with RCP data, for the four RCPs 2.6, 4.5, 6.0 and 8.5. Anomalies are relative to 2005. For RCP 8.5, CMIP5 data is presented as a reference.

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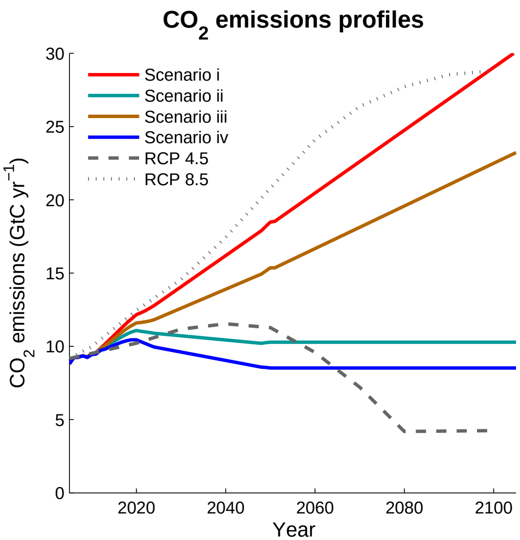

Figure 3. CO_2 emissions associated with four different electricity sector-only policy scenarios. CO_2 emissions associated with two RCPs are shown for reference. (Note that the RCP scenarios cover all sectors and land use.)

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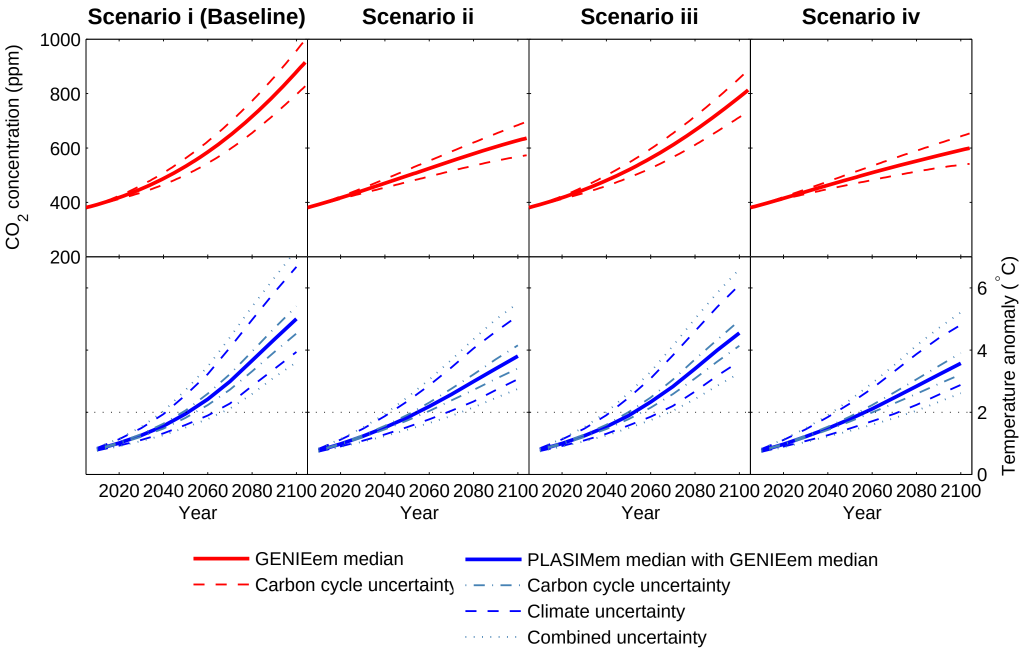

Figure 4. Top: median CO_2 concentrations for scenarios (i) (baseline), (ii), (iii) and (iv), simulated by GENIEem, with uncertainty bounds (GENIEem 5th/95th percentile). Bottom: median temperature anomalies relative to preindustrial conditions for scenarios*a* (baseline), *d*, (i) and *j*, simulated by PLASIM-ENTSem using median GENIEem CO_2 concentrations. Uncertainty bounds are based on carbon cycle uncertainty (PLASIMem median with GENIEem 5th/95th percentile), climate uncertainty (PLASIMem 5th/95th percentile with GENIEem median), and combined uncertainty (PLASIMem 5th/95th percentile with GENIEem 5th/95th percentile). The 2 °C target, described as "the maximum allowable warming to avoid dangerous anthropogenic interference in the climate" (e.g Randalls, 2010), is also illustrated by the grey dashed line.

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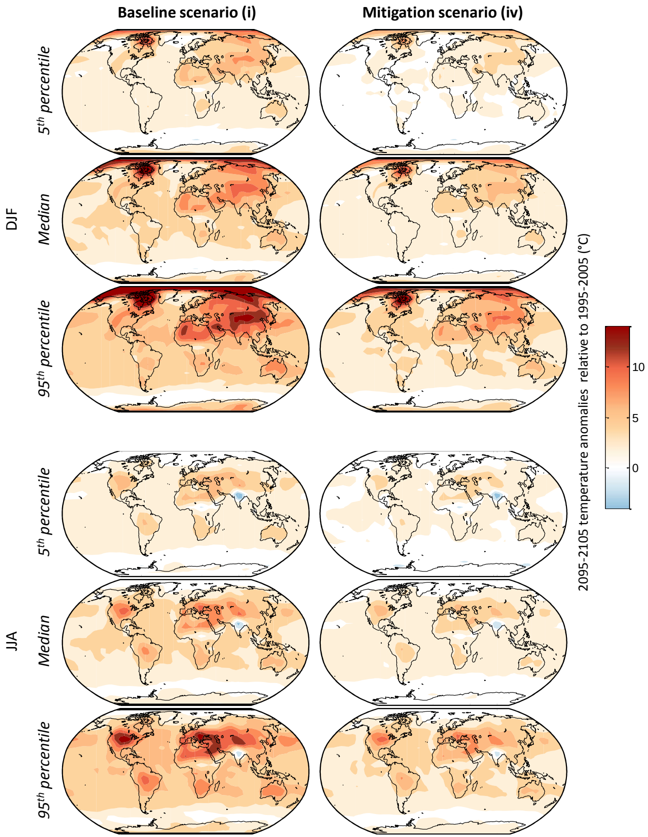

Figure 5. 2095–2105 temperature anomalies relative to 1995–2005 for DJF and JJA under the baseline scenario (i) (right) and the mitigation scenario (iv) (left). The 5th, 50th and 95th percentile of the PLASIM-ENTSem ensemble are calculated independently at each grid point. The PLASIM-ENTSem ensembles are forced with GENIEem median CO_2 concentrations for that scenario.

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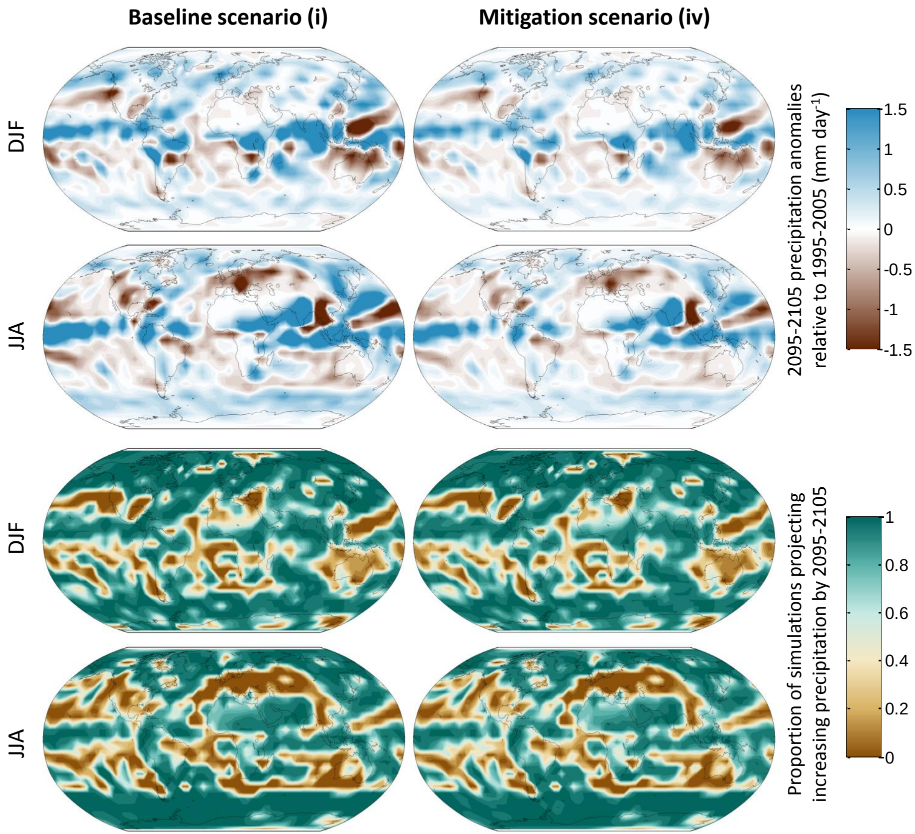

Figure 6. 2095–2105 precipitation anomalies (ensemble means) relative to 1995–2005 under the baseline scenario (i), and the mitigation scenario (iv) (top) and proportion of ensemble members simulating increased precipitation (bottom).

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