Probabilistic climate projections with Minimal CMIP Emulator (MCE)
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Code and examples are available at github.com/tsutsui1872/mce

Motivation: need to assess mitigation scenarios in terms consistency with temperature goals; increasing opportunities to do that in a multi-model approach like RCMIP

Key points: The model's simple structure has an advantage when building reasonable perturbed ensembles in a transparent way. CMIP models' diversity is well emulated, and effectively weighted with given constraints if necessary.

Example of ensemble runs

Contours indicate levels at which the circles cover 90% and 66% members. a, b: Fraction of ocean accumulated carbon vs total accumulated carbon in the 70th and 140th year of 1pctCO2. c: ERF of CO2 doubling vs climate feedback parameter. d: TCR vs ECS.

Two 600-member ensembles for CMIP-consistent 'Prior' and 'Constrained' according to RCMIP2

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Motivation

- Need to assess many mitigation scenarios in terms of their consistency with temperature goals
- Increasing opportunities to do that in a multi-model approach like RCMIP

Scenario categorization in the previous IPCC reports is consistent with CMIP5 models, but regarded as indicative due to its dependency on a single probability distribution

Clarke et al. (2014, WG3AR5 Chap 6)

MAGICC was run 600 times for each scenario. Probabilistic temperature statements are based on the resulting distributions (see also the Methods and Metrics Annex; and the underlying papers cited). Because the temperature distribution of these runs is based on a single probability distribution in a single modelling framework, resulting probabilistic temperature statements should be regarded as indicative.

New CMIP6 models, partly indicating extremely high climate sensitivity, do not necessarily provide reasonable uncertainty ranges

Collins et al. (2013, WG1AR5 Chap 12)
Objectives

• To develop and demonstrate a new emulator method, contributing to improved reliability in the climate assessment of emission scenarios

• To examine a better way of probabilistic climate projections synthesizing the state-of-the-art climate model ensemble and the latest assessment of climate indicators
Model genealogy

Hasselmann et al. (1993)  (many implementations) →
Maier-Reimer & Hassellmann (1987) →
NICCS (Hooss et al., 2001)
   Similar to ACC2 (Tanaka et al., 2007)
Joos et al. (1996) →
MAGICC6 (Meinshausen et al., 2011) →

MCE base modules

- Thermal response
  3-layer impulse response model (IRM)

- Ocean carbon cycle
  4-layer box model with air-sea carbon partitioning based on marine chemistry

- Land carbon cycle
  4-carbon pool IRM

- CO₂ fertilization

- Non-CO₂ GHG cycle, atmospheric chemistry
  N/A yet

v-1.2 (RCMIP2 version)
- Carbon cycle
- Scenario driver
- Perturbed parameter ensemble runs
- Non-CO₂ prescribed with GHG concentrations and other ERF

v-1.0 (First release)
- Thermal response module
- Tool for diagnosing CMIP models

Description paper: Tsutsui (GMD, submitted)
Associated papers: Tsutsui (2020, GRL), Tsutsui (2017, Climatic Change)
Impulse response model (IRM)

MCE is essentially built on impulse response functions for
- fraction of total CO₂ emissions remaining in the atmosphere (airborne fraction)
- decay of land carbon accumulated by the CO₂ fertilization effect
- temperature change to radiative forcing of CO₂ and other agents

IRM form for the land carbon decay and the temperature change

\[ x(t) = \int_0^t F(t') \sum A_i \exp \left( -\frac{t - t'}{\tau_i} \right) dt' \]

\[ \frac{dx(t)}{dt} = \sum \left[ F(t)A_i - \frac{x_i(t)}{\tau_i} \right] \]

\( x \) is a response variable, \( t \) is the time, \( F \) is input forcing, and the sum of exponentials is an impulse response function with parameters \( A_i \) and \( \tau_i \) denoting \( i \)-th component of the response amplitude and time constant.

Box model form for the airborne fraction

\[ \frac{dc_0}{dt} = -\frac{\eta_1}{h_s} c_s + \frac{\eta_1}{h_1} c_1 + e - f, \]

\[ \frac{dc_1}{dt} = \frac{\eta_1}{h_s} c_s - \frac{\eta_1 + \eta_2}{h_1} c_1 + \frac{\eta_2}{h_2} c_2, \]

\[ \frac{dc_2}{dt} = \frac{\eta_2}{h_1} c_1 - \frac{\eta_2 + \eta_3}{h_2} c_2 + \frac{\eta_3}{h_3} c_3, \]

\[ \frac{dc_3}{dt} = \frac{\eta_3}{h_2} c_2 - \frac{\eta_3}{h_3} c_3 \]

\( c_k \) is the amount of excess carbon in layer \( k \), \( h_k \) is the layer depth, \( \eta_k \) is the exchange coefficient between layer \( k - 1 \) and layer \( k \), \( e \) is anthropogenic emissions, and \( f \) is natural uptake over land. The amount of excess carbon in the top layer (\( c_0 \)) is partitioned into the atmosphere and the ocean components, the latter denoted by \( c_s \).
Ocean carbon cycle

- Box model parameters: calibrated through an IRM for airborne fraction response
  - Time constants: fixed to 236.5, 59.52, 12.17, and 1.271 years
  - Amplitudes: perturbed around reference values (0.24, 0.21, 0.25, and 0.1; long-term fraction of 0.2)
- Excess carbon partition in the top layer: numerically solved for dissolved inorganic carbon concentration (DIC) under constant alkalinity with temperature dependency on chemical equilibrium constants

Airborne fraction response to an initial input of 100 GtC without land CO₂ uptake and climate feedback. The line shows the case of reference amplitudes, and shading shows the 5–95% range of an ensemble adjusted to CMIP ESMs.

DIC in the ocean mixed layer as a function of atmospheric CO₂ concentration (a) and changes in ocean carbon uptake potential, measured by increase in DIC from preindustrial levels, due to 1 °C and 2 °C warming (b). The preindustrial CO₂ concentration is assumed to be 284.317 ppm and preindustrial DIC is about 2.17 mmol L⁻¹.
Land carbon cycle

- Four carbon pools: ground vegetation, wood, detritus, and soil organic carbon
  
  Time constants: 2.9, 20, 2.2, and 100 years
  Response amplitudes: 0.70211, 0.013414, −0.71846, and 0.0029323 years⁻¹, defined as a decay flux after an initial carbon input

- Forcing term: net primary production enhanced by CO₂ fertilization with a perturbed factor

- Temperature dependency: decrease in time constants of wood and soil organic carbon decay with warming

CO₂ fertilization factor as a function of atmospheric CO₂ concentration, corresponding to three percentiles of a range adjusted to CMIP ESMs. Colored lines show sigmoid curves used in MCE and black dashed lines show reference logarithmic curves.

Adjustment coefficient as a function of surface temperature change for the time constants of wood and soil organic carbon decay, corresponding to three percentiles of a range adjusted to CMIP ESMs.
Temperature response

- Three-layer IRM with typical time constants of approximately 1, 10, and > 100 years
- Response parameters are diagnosed along with CO₂ forcing parameters from two basic CO₂ increase experiments (4x instantaneous and 1%/y transient) of individual CMIP AOGCMs
  - Time series fitting is used instead of conventional regression
  - TCR and ECS are derived from diagnosed parameters, where doubling level is scaled down from quadrupling with a model-dependent factor (generally less than 0.5)

TCR: transient climate response
ECS: equilibrium climate sensitivity

Example of time series fitting of the top-of-atmosphere (TOA) energy imbalance (a) and surface temperature anomaly (b), and their relationship (c) for IPSL-CM6A-LR. "IRM 2x" line is scaled down from "IRM 4x" line by a factor of 1/(2β). "Regress" line is the result from conventional regression.
Effective radiative forcing (ERF)

**CO₂:** quadratic formula in terms of log concentrations (Tsutsui, 2017)

\[
F_C(x) = (\beta_C - 1)[\hat{F}_C(x) - 2F_C(2)] \left[\frac{2\hat{F}_C(x)}{F_C(2)} - 1\right] + \beta_C \hat{F}_C(x)
\]

\[
\hat{F}_C(x) = \alpha_C \ln \left[\frac{\text{CO}_2(t)}{\text{CO}_2(0)}\right]
\]

\(x\) is the ratio of concentrations to a preindustrial level, \(\alpha_C\) is a scaling parameter in Wm⁻², and \(\beta_C\) is an amplification factor defined as \(F_C(4) = \beta_C \times \hat{F}_C(4)\). The quadratic term is activated in \(2 < x \leq 4\), and \(\beta_C = 1\) in \(x \leq 2\).

**CH₄ and N₂O:** based on Etminan et al. (2016)

**Halogenated gases:** based on AR5 efficiency factors

**Non-CO₂ gas cycles:** n/a

**Other forcing agents:** n/a

Currently, scenario experiments need prescribed concentrations for non-CO₂ GHGs and prescribed ERF for others.
Parameter sampling

Procedure to build a perturbed parameter ensemble
1. Design statistical models covering assumed ranges
2. Generate series of candidate values with the statistical models
3. Constrain the candidates, if necessary, with a Metropolis-Hastings (MH) independence sampler

Perturbed parameters in MCE v1.2:
• IRM amplitudes for the airborne fraction
• CO₂ fertilization factor
• Coefficient for temperature dependency of land carbon decay
• IRM parameters for temperature change*
• Scaling and amplification factors of CO₂ forcing*
• Scaling factors to adjust non-CO₂ forcing time series

* Multivariate normal distribution is built on principal components of eight parameters. For the others, individual probability distributions are used without considering covariance structures.
Scenario experiments

- Scenarios: prescribed in RCMIP as mirroring CMIP6 experiments including idealized CO₂ changes
- Time integration: 650 years mostly, initialized for 1850 as preindustrial CO₂
  Here, focusing on the results up to 2100
- Parameter ensembles: two sets of 600-member runs for CMIP-consistent 'Prior' and further 'Constrained' according to RCMIP2

'Constrained' parameters were sampled from 'Prior' through a sequence of MH samplers with a subset of RCMIP constraints as follows:

1. CO₂ ERF in 2014 relative to 1750 evaluated in Smith et al. (2020)
2. TCR estimated in Tokarska et al. (2020, Table S3, both constrained)
3. Global mean surface temperature (GMST) in 1961–1990 relative to 2000–2019 from HadCRUT.4.6.0.0 (Morice et al., 2012) and ocean heat content (OHC) in 2018 relative to 1971 from von Schuckmann et al. (2020)

Conversion factors:
- from observed GMST change to MCE's surface temperature change: 1.04
- from observed OHC change to MCE's total heat content change: 1.08
Results: relationship between key indicators

Carbon indicators (top panels)
- Focusing on total accumulation and ocean allocation ratio at 2x and 4x CO₂ along 1%/y path
- Negative correlation, reflecting much greater uncertainties in land carbon, is well represented
- Two ensembles are similar

Climate indicators (bottom panels)
- 'Prior' well represents CMIP diversity with correlations for CO₂ forcing vs feedback, and TCR vs ECS
- High sensitivity is more evident in ECS than in TCR
- 'Constrained' is confined to higher CO₂ forcing and lower climate sensitivity

Currently, differences between two CMIP eras are not considered

Figure: Contours indicate levels at which the circles cover 90% and 66% members. a, b: Fraction of ocean accumulated carbon vs total accumulated carbon in the 70th and 140th year of 1pctCO₂. c: ERF of CO₂ doubling vs climate feedback parameter. d: TCR vs ECS, where ECS (labeled ECSG) is defined as in conventional regression
Results: historical GMST and OHC

- 'Constrained' agrees well with recent trends while 'Prior' is overestimated
- Uncertainties remain regarding longer trends and unforced climate variability
  - 'Constrained' trend appears underestimated in an early period
  - Constraining with assessed forced response would be a credible alternative

Historical global mean surface temperature (GMST) relative to 1961–1990 and (b) historical ocean heat content (OHC) relative to 1971 in the period 1850–2019 compared with observation data from HadCRUT4.6.0.0 for GMST and von Schuckmann et al. (2020) for OHC. The black dots indicate the levels at two different periods or years used for the observation constraints.
Results: historical ERF

The greater warming in 'Prior' than in 'Constrained' is partly due to non-CO$_2$ forcing differences. Non-CO$_2$ GHG difference is relatively large, where Montreal-gases (not shown) is most dominant.

Historical effective radiative forcing (ERF) in the period 1850–2019 for total ERF (a) and aggregated components (b). The ensembles' medians are shown by lines, and the 5–95% range of the 'Constrained' ensemble is shown for the total by shading.

Scaling factors of non-CO$_2$ agents were independently perturbed in the 'Prior' ensemble and filtered through the MH samplers. Although the sampling process does not directly refer to non-CO$_2$ forcing levels, it can modify their distributions to be consistent with other constraints. Solar and volcanic time series were prescribed as in RCMIP input data without considering efficacy uncertainties.
Results: modeled and "proxy"-assessed ranges

• 'Prior' and 'Constrained' are most distinctively different for GMST and OHC trends
• Consistency of sensitivity indicators is complex; overall better in 'Prior' than in 'Constrained'
• For carbon cycle, modeled ranges broadly agree with assessed ranges. Same is true for forcing, except for 'Prior' CO₂ and 'Constrained' Montreal gases.

a–f: accumulated carbon; g: implied historical CO₂ emissions; h: ECS based on conventional regression; i: TCR; j: TCRE (transient climate response to 1000 GtC cumulative CO₂ emissions at doubling along 1%/y concentration path); k, l: recent warming trend by GMST and OHC; m–t: historical ERF changes.

Error bars and pairs of triangle markers indicate likely ranges (17–83%) and very likely ranges (5–95%). Black and grey error bars indicate proxy assessed ranges and AR5-assessed ranges. The proxy ranges are based on 5–95% ranges of the CMIP Earth system models in a–d, but otherwise taken from the RCMIP2 that partly includes the AR5-assessed ranges.
Results: projected warming

Two ensembles are completely separated. The present human-induced warming assessed in SR15 is closer to 'Constrained' than 'Prior'

The upper bound of 33–66% range corresponds to the level to which warming is likely (66–100%) to be limited at the time, while the lower bound corresponds to the level which warming is likely to exceed.

Global mean surface air temperature (GSAT) changes relative to 1850–1900 in SSP1-2.6 (a) and SSP2-4.5 (b) scenarios from 'Prior' and 'Constrained' ensembles. Medians and 33–66% ranges at each time point are shown by lines and shading.

The error bars indicate medians and likely (17–83%) ranges of global mean surface temperature (GMST, air-ocean blended) changes in 2017. The values are 1.30 [0.96–1.81] °C in 'Prior' and 0.90 [0.80–1.01] °C in 'Constrained', which are compared with SR15 assessed 1.0 [0.8–1.2] °C for human-induced warming (Allen et al., 2018)
Results: temperature thresholds

'Constrained' relatively well agrees with AR5 assessment for each comparable scenario

e.g., AR5 implies likely limited to 2 °C in 2081–2100 for RCP2.6, which seems consistent with SSP1-2.6 from 'Constrained' (likely limited to 1.54 °C) but not from 'Prior' (likely limited to 2.27 °C). However, 'Constrained' ensemble is so narrow that its thresholds become close to medians. Note that AR5 assessment is based on simulated warming from 1986-2005 and an observed warming level of 0.61 for the base period.

Critical global mean surface air temperature (GSAT) change relative to 1850–1900 in different Shared Socioeconomic Pathway (SSP) scenarios. Warming levels at peak during the 21st century and averaged over the period 2081–2100 (end-21C) are shown for those likely to be limited (66 percentile) and likely to exceed (33 percentile) from 'Prior' and 'Constrained' ensembles.

<table>
<thead>
<tr>
<th>Likely limited to</th>
<th>SSP1-1.9</th>
<th>SSP1-2.6</th>
<th>SSP4-3.4</th>
<th>SSP5-3.4*</th>
<th>SSP2-4.5</th>
<th>SSP4-6.0</th>
<th>SSP3-7.0</th>
<th>SSP5-8.5</th>
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<tr>
<td>at peak</td>
<td>2.08</td>
<td>2.34</td>
<td>2.34</td>
<td>3.10</td>
<td>3.51</td>
<td>4.25</td>
<td>5.20</td>
<td>6.15</td>
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<td></td>
<td>1.39</td>
<td>1.60</td>
<td>2.09</td>
<td>2.16</td>
<td>2.43</td>
<td>2.96</td>
<td>3.70</td>
<td>4.44</td>
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<tr>
<td>Likely limited to</td>
<td>1.82</td>
<td>2.27</td>
<td>3.05</td>
<td>2.78</td>
<td>3.38</td>
<td>4.01</td>
<td>4.72</td>
<td>5.54</td>
</tr>
<tr>
<td>at end-21C</td>
<td>1.20</td>
<td>1.54</td>
<td>2.07</td>
<td>1.90</td>
<td>2.36</td>
<td>2.82</td>
<td>3.34</td>
<td>3.98</td>
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<tr>
<td>Likely exceed at</td>
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<td>1.89</td>
<td>2.50</td>
<td>2.54</td>
<td>2.83</td>
<td>3.47</td>
<td>4.30</td>
<td>5.17</td>
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<tr>
<td>peak</td>
<td>1.24</td>
<td>1.41</td>
<td>1.84</td>
<td>1.92</td>
<td>2.14</td>
<td>2.61</td>
<td>3.25</td>
<td>3.94</td>
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<tr>
<td>Likely exceed at</td>
<td>1.44</td>
<td>1.82</td>
<td>2.47</td>
<td>2.23</td>
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<td>end-21C</td>
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<td>1.34</td>
<td>1.83</td>
<td>1.65</td>
<td>2.08</td>
<td>2.48</td>
<td>2.94</td>
<td>3.55</td>
</tr>
</tbody>
</table>

Units: °C; *Overshoot type pathway; Upper: 'Prior' ensemble; Lower in italic: 'Constrained' ensemble
Discussion

Performance limitation
- Thermal response is limited to a linear theory without state dependency
- Carbon cycle is crudely configured, not based on individual ESM emulation
- Covariance of perturbed parameters is limited to that for thermal response to CO₂ forcing
- Emission-driven option is limited to CO₂ only

Issues about constraints
- Input indicator ranges are preliminary, to be replaced with AR6-assessed ranges
- Narrow 'Constrained' ensemble is resulted from observed warming trends in recent decades, to be examined from new insights into forced and unforced response on a longer time scale
Conclusions

Achievement of MCE development
• Successful emulation of CMIP models in a minimal way with sufficient accuracy
• Perturbed parameter ensembles reflecting CMIP models' diversity and several constraints of key climate indicators

Implications for scenario assessment
• MCE can provide a reasonable way to constrain the CMIP diversity, leading to an improved approach with overall consistency

Issues to be addressed
• Further configuration of carbon cycle parameters
• Functions for full emission-driven experiments
• Incorporating AR6-assessed indicator ranges
• Uncertainties about forced components of historical warming