Climate Informatics Opportunities for Earth system model evaluation

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20 June 2017
1st Workshop on Environmental Informatic Challenges
Jena, Germany
Outline

1. Introduction
   - Multi-model climate projections
   - How to gain confidence in Earth system models (ESMs)?

2. Overview  Coupled Model Intercomparison Project Phase 6 (CMIP6)

3. Climate Informatics Opportunities for Earth system model evaluation
   - Data Management for efficient & more routine ESM evaluation with observations
   - Data Analysis with data science methods

4. Summary
1. Introduction
Climate projections in the **IPCC Fifth Assessment Report (AR5)** largely based on climate model output coordinated by the World Climate Research Programme (WCRP) **Coupled Model Intercomparison Project Phase 5 (CMIP5)**.

- **The objective of WCRP’s CMIP** is to better understand past, present and future climate change in a multi-model context by defining common experiment protocols, forcings and output.

- **Multi-model mean and spread is commonly used for climate projections**
  1. Spread of model ensemble often used as first-order estimate of projection uncertainty.
  2. Used to determine why similarly forced models produce a range of responses.

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**Distillation of robust information from multi-model output is needed for science and as evidence for policy-making**
Climate Model Projections WG I AR5
- Largely based on Coupled Model Intercomparison Phase 5 (CMIP5) simulations -

Relative to the 1986-2005 average

WG I
Paleoclimate Archives (Chapter 5)
Process Understanding
  Chapter 6: Carbon and other Biogeochemical Cycles
  Chapter 7: Clouds and Aerosols
From Forcing to Attribution of Climate Change
  Chapter 8: Anthropogenic & Natural Radiative Forcing
  Chapter 9: Evaluation of Climate Models
  Chapter 10: Detection and Attribution of Climate Change: from Global to Regional
Future Climate Change and Predictability
  Chapter 11: Near-term Climate Change
  Chapter 12: Long-term Climate Change: Projections, Commitments and Reversibility
Integration
  Chapter 13: Sea Level Change
  Chapter 14: Climate Phenomena and their Relevance for Future Regional Climate Change
Atlas of Global and Regional Climate Projections

Process understanding and projections including uncertainty estimates also relevant for
WG II and III
How do we gain confidence in climate model projections?

- Based on physical understanding of the climate system and its representation in climate models, and
- On a demonstration of how well models represent a wide range of processes and climate characteristics on various spatial and temporal scales

Relative error measures of CMIP5 model performance (normalized by the median error of all model results), based on the global seasonal-cycle climatology (1980–2005)

Climate models have continued to be developed and improved since the AR4.

IPCC AR5 Chapter 9, Fig. 9.7
Equilibrium Climate Sensitivity Remains Uncertain

Defined as the change in global mean surface temperature at equilibrium that is caused by a doubling of the atmospheric CO₂ concentration.

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<thead>
<tr>
<th></th>
<th>TAR</th>
<th>AR4</th>
<th>AR5</th>
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<tbody>
<tr>
<td>ECS</td>
<td>Likely range: 1.5 to 4.5°C</td>
<td>likely range: 2.0 to 4.5°C</td>
<td>likely range: 1.5 to 4.5°C</td>
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<tr>
<td></td>
<td>very unlikely &lt;1.5°C</td>
<td>extremely unlikely &lt;1.0°C</td>
<td>extremely unlikely &lt;1.0°C</td>
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<tr>
<td></td>
<td>—</td>
<td>very unlikely &gt;6.0°C</td>
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<tr>
<td></td>
<td>best estimate about 3°C</td>
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The model spread in ECS ranges from 2.1°C to 4.7°C and is very similar to the assessment in AR4 (IPCC AR5, Chapter 9).

Large Uncertainty Remains in Some Projected Variables

Is the multi-model mean always the best measure?
The spread of an ensemble of models is often used as a first-order estimate of projection uncertainty

– Despite the fact that models differ in terms of resolution, processes and components included, and agreement with observations.
– Despite there is inter-model dependence
2. CMIP6 Organization and Design
CMIP: a More Continuous and Distributed Organization

(1) A handful of common experiments

**DECK (entry card for CMIP)**
For enhanced model evaluation and evaluation consistency

i. AMIP simulation (~1979-2014)
ii. Pre-industrial control simulation
iii. 1%/yr CO₂ increase
iv. Abrupt 4xCO₂ run

**CMIP6 Historical Simulation**
(entry card for CMIP6)
v. Historical simulation using CMIP6 forcings (1850-2014)

(2) **Standardization, coordination, infrastructure, documentation**

DECK (Diagnosis, Evaluation, and Characterization of Klima) & CMIP6 Historical Simulation to be run for each model configuration used in CMIP6-Endorsed MIPs

Eyring et al., Overview CMIP6, GMD, 2016
21 CMIP6-Endorsed MIPs

Eyring et al., Overview CMIP6, GMD, 2016
## CMIP6: Participating Model Groups

<table>
<thead>
<tr>
<th>Institution</th>
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<tr>
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<td>INPE</td>
<td>Brazil</td>
<td>NIMS-KMA</td>
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<td>IPSL</td>
<td>France</td>
<td>NOAA-GFDL</td>
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<td>Germany</td>
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<td>MOHC</td>
<td>UK</td>
<td>THU</td>
<td>China</td>
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<tr>
<td>CSIRO-BOM</td>
<td>Australia</td>
<td>MPI-M</td>
<td>Germany</td>
<td>23</td>
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</tbody>
</table>

### New in CMIP:
- 2 new model groups from Germany (AWI, MESSY-Cons)
- 4 new model groups from China (CAMS, CasESM, NUIST, THU)
- 1 new model group from Brazil (INPE)
- 1 new model group from India (CCCR-IITM)
- 1 new model group from Taiwan, China (TaiESM)
- 1 new model group from USA (DOE)
- 1 new model group from Republic of Korea (NIMS-KMA)
- 1 new model group from South Africa / Australia (CSIR-CSIRO)

⇒ **12 new model groups so far**

* Other models can join providing DECK and historical simulations are submitted

More models (>70) New models > 180 CMIP6 experiments

![CMIP logo]
Models are Increasing in Complexity and Resolution

From AOGCMs to Earth System Models with biogeochemical cycles, from lowres to highres

130 km resolution orography

25 km resolution orography

I. Allows to study processes as horizontal resolution is increased to “weather-resolving” global model resolutions (~25km or finer)

II. Allows to study new physical & biogeochemical processes & feedbacks (e.g., carbon cycle, chemistry, aerosols, ice sheets)

Increase in complexity and resolution
More (and new) models participating in CMIP6

- Increase in data volume (from ~2PB in CMIP5 to ~20-40 PB in CMIP6)
- Archiving, documenting, subsetting, supporting, distributing, and analysing the huge CMIP6 output will challenge the capacity and creativity of the largest data centres and fastest data networks, and the analysis of the data.
Earth System Observations

- Satellite measurements
- Insitu data
- Meteorological reanalyses

The recent progress in climate science is producing an unprecedented amount of data from climate models and observations, giving us a unique opportunity to develop and apply methods for machine learning and data mining.

The increasing desire for operational analysis means that a system has to be set in place that allows for an efficient and comprehensive analysis of the large volume of data from models and observations.
Over the last decades, the magnitude of climate data from satellite sensors and climate models has substantially increased. This is starting to overwhelm the relatively simple tools and methods currently used to analyse the data. It is therefore essential to develop an innovative and efficient computational approach to address these analysis challenges.

This relatively new field is called Climate Informatics and represents a promising and growing path of research, which could contribute to substantially enhance understanding of the Earth system and confidence in future climate projections.

– The complexity and vast amount of Earth system data together with the pressing scientific and societal demand for more accurate climate projections, makes Earth system data an ideal candidate for developing and applying computational intelligent analysis techniques to quickly sort through the data from models and observations.

– New methods of Data Science (e.g., data mining, artificial intelligence, machine learning) could potentially help finding new ways of analysing the data.

– These techniques have been successfully applied in other natural sciences (e.g., biology), yet they are not fully exploited in climate research.

see also Monteleoni et al. (2013)
3. Climate Informatics
Opportunities for Earth system model evaluation

(A) Data Management for efficient and more routine ESM evaluation with observations
How to characterize the wide variety of models in CMIP6?
- Routine Benchmarking and Evaluation Central Part of CMIP6 -

Earth System Model Evaluation Tool (ESMValTool) developed as community tool at DLR-IPA (PI) and many other institutes to produce well-established analyses as soon as CMIP model output is submitted

Similar to Figure 9.7 of AR5

Broad Characterization of Model Behavior (incl. IPCC AR5 Chap 9 & 12 diagnostics in ESMValTool)

Running alongside the ESGF

Link to projections

Similar to Figure 9.24 of AR5

Eyring et al., ESMValTool version 1.0, GMD (2016)
ESMValTool version 1.0 released as open source software

http://www.esmvaltool.org/
Eyring et al., GMD, ESMValTool v1.0, 2016

- Community diagnostics and performance metrics tool for the evaluation of Earth System models
- Open source code based on python, NCL, R etc.
- Standardized model evaluation can be performed against observations, against other models or to compare different versions of the same model
- Many diagnostics and performance metrics covering different aspects of the Earth System (dynamics, radiation, clouds, carbon cycle, chemistry, aerosol, sea-ice, etc.) and their interactions
- Well-established analysis from peer-reviewed literature
- Ensuring traceability and provenance (e.g. input data, metadata, diagnostics (incl. citation), tool version, doi)
- Currently ≈ 80 scientist from >30 institutions part of the development team and > 120 users
- Development in several projects (e.g. APPLICATE, CRESCENDO, C3S-MAGIC, ESA CMUG, PRIMAVERA)
- Rapidly expanding
We argue that the community has reached a critical juncture at which many baseline aspects of ESM evaluation need to be performed much more efficiently.

The resulting, increasingly systematic characterization of models will, compared with early phases of CMIP, more quickly and openly identify strengths & weaknesses of the simulations.

This activity also aims to assist modelling groups in improving their models.

Running alongside the ESGF, as soon as the output is published.

Eyring et al., ESD (2016)
Envisioned ESMValTool Workflow for routine evaluation at the ESGF (CMIP6-DICAD)

Step-wise access:
1. ESMValTool core team
2. Modelling groups
3. Public

Modified from: Eyring et al., ESMValTool v1.0, GMD, 2016
Reproducibility & Provenance of evaluation results

**Namelist**
Evaluation analysis is controlled by the namelist file that defines the internal workflow for the desired analysis.

It defines:
- **Input datasets** (observations, models)
- **Regridding** operation (if needed)
- Set of **diagnostics**
- Misc. (output formats, output folder, etc…)

**Output files (NetCDF, png)**
Contain meta data from input files and meta data generated by ESMValTool

**Observational data**
- Well defined processing chain
- creation of metadata

**Logfile**
At each execution of the tool a log file is automatically created

The log file contains:
- The list of **all input data** which have been used (version, data source, etc.)
- The list of **variables** that have been processed
- The list of **diagnostics** that have been applied
- The list of **authors and contributors** to the given diagnostic, together with the relevant references and projects
- Software **version** of ESMValTool that was used
3. Climate Informatics
Opportunities for Earth system model evaluation

(B) Data Analysis with data science methods
Promising Examples Climate Informatics Analysis

1. Emergent constraints
   - Emergent constraints between observable aspects of variability and Earth system sensitivities offer the possibility to reduce uncertainties in climate projections.
   - Finding such correlations is a challenge and data mining could help identifying a comprehensive list of strong correlations that could used as starting point for further analysis.

2. Improving multi-model ensembles of climate projections

3. Anomaly detection for abrupt climate change and extreme events

4. Multivariate process evaluation
   - Model evaluation approaches are often limited to the performance assessments of multiple single variables but to identify specific events requires looking across variables in space and time.
   - New algorithms could help in clustering and detecting such patterns and climate networks constructed from observations might help identifying dependencies between climate variables and processes.

*For further examples, see also Monteleoni et al. (2013)*
Example 1: Emergent Constraints 
Uncertainties in Projections of Future Climate

1. Internal Variability
   - Due to the chaotic nature of climate system
   - Noise of climate record is constant with time

2. Emission Uncertainty
   - Dominant uncertainty for long term projections estimated as mean of different scenarios
   - Varying greenhouse gas emissions
   - Land use change

3. Climate Response Uncertainty
   - Models are build on same principles but parametrizations are needed
   - Increases when process become more relevant
   - Decreases with model improvements and observational constraints
Emergent Constraints (ECs)

- **ECs** are a relationship across an ensemble of models, between some aspect of Earth system sensitivity and an observable trend or variation in the current climate
  - Emergent relationship because it emerges from the ensemble of ESMs.
  - Constraint because it enables an observation to constrain the estimate of the Earth System sensitivity in the real world.
  - The goal is to find a observable physical explanation to constrain the unobservable Earth system sensitivity

**Quantity of interest:** sensitivity or future projection → Not observable

**Constraint** quantity of interest

**Observational Constraint**
Emergent Constraints: Carbon Cycle Feedbacks

Change land carbon uptake: $\Delta C_{\text{Land}} \text{ [GtC]} =$

Plants take up CO$_2$ via photosynthesis when they grow, so CO$_2$ is removed from the atmosphere and is stored as organic carbon in the plants. This flux is the Gross Primary Productivity (GPP).

Climate warming reduces the efficiency of CO$_2$ absorption by the land and ocean => more emitted carbon stays in the atmosphere leading to additional warming.

-44±14 GtC/K (constrained)
49±40 GtC/K (unconstrained)

Wenzel et al., JGR, 2014
Cox et al., 2013

$\beta$ : Carbon cycle - CO$_2$ concentration Feedback – Negative Feedback

$\gamma$ : Carbon cycle - Climate Feedback – Positive Feedback
Projected land photosynthesis constrained by changes in the seasonal cycle of atmospheric CO₂

Why should we care?

- Photosynthesis is the ultimate source of energy for life on Earth.
- Vegetation and soil are currently slowing down global warming by absorbing about 20% of our CO₂ emissions. This land carbon sink is believed to be in part due to increases in photosynthesis.
- But how will photosynthesis change?
- Climate-carbon models agree that elevated atmospheric CO₂ concentrations will enhance terrestrial GPP but the magnitude of this CO₂ fertilization effect varies.

The unknown:

CO₂ Fertilization of Photosynthesis

Here: relative change in high-latitude (60-90°N) GPP due to a doubling of atmospheric CO₂ in the 1%BGC simulations

20% to 60% projected increase of GPP due to doubling of CO₂

The Observations: Increasing Seasonal Amplitude of Atmospheric CO$_2$

- CO$_2$ concentrations measured for many decades on Hawaii and Alaska show characteristic cycles, with lower values in the **summer** when strong photosynthesis causes plants to absorb CO$_2$, and higher values in the **winter** when photosynthesis stops.

- The peak-to-trough amplitude of the seasonal cycle therefore depends on the strength of the summer photosynthesis and the duration of the growing season.

But what does this mean for the future?
Comparison of CO$_2$ seasonal amplitudes against annual mean CO2 for CMIP5 historical simulations and observations at BRW

Observations

Doubling CO₂ concentration (alone) will lead to an increase in land photosynthesis of about a third. More than the sum of the parts!

Emergent Constraints on CO₂ Fertilization

Point Barrow (BRW: 71.3° N, 156.6° W, Alaska (high-latitude))

Compatible CO₂ Emissions

- Large uncertainty in CO₂ emissions compatible with a given climate target.
- Budget for the 2°C target is about 700 GtC to 1300 GtC.
- Given ~550 GtC emitted so far, that’s 15 to 75 years of current anthrop. CO₂ emissions.

Next to work on: Development of data mining methods

- Automate the process of identifying current climate quantities with skill at predicting individual feedbacks, ECS and transient climate response to emissions (TCRE).
Example 2: Weighted sea-ice projections based on model-performance and interdependence

Observations
Mean and 5-95% range for
No weighting (black line, grey band)
Weighting (red line and band)

Diagnostics included in this example:
1. None (unweighted)
2. Climatological mean (1980-2013) Sep sea ice extent,
3. Sep sea ice extent trend 1980-2013,
5. Interannual variability of monthly surface temperature,
6. All diagnostics 2-5

Development of machine learning techniques for model weighting
Are there weighting strategies that maximize predictive skill?

Knutti et al., GRL, 2017
Example 3: Maximally Divergent Intervals:
Detection of Anomalies in Multivariate Time-Series Data

\[ KL(p_1, p_\Omega) = \int p_1(x) \log \left( \frac{p_1(x)}{p_\Omega(x)} \right) dx \]

- Maximizing Kullback-Leibler divergence
- Example: Detection of hurricanes
- Cooperation in EU-H2020 Project BACI (FSU, MPI-BGC)

Rodner et al., Anomaly Detection Workshop (2016)
New Group *Climate Informatics* at the DLR Data Science Institute in Jena

- In cooperation with **DLR Institute of Atmospheric Physics** (Eyring), the official external collaboration partner of the group **FSU Computer Vision** (Denzler), and the **MPI Department of Biogeochemical Integration** (Reichstein).

- Development of innovative and highly efficient data science methods for Earth system data analysis.

- Focus of research group on three broad scientific themes:
  - Basic research on graphical models
  - **Data management for an efficient data analysis**: Development of innovative and highly efficient methods for data processing to be implemented in the ESMValTool.
  - **Data analyses**: Development of innovative and highly efficient data science methods for data analysis for the extraction of space-time characteristics in massive geoscientific data from Earth system models and observations; subsequent implementation in the ESMValTool.
Summary

➢ **Climate Informatics**
  - is a challenging and promising research field where little has been done so far and where a concentrated effort will have a high impact both to advance science and to address topics of critical importance for the society.
  - It bridges the gap between data and understanding through a strong collaboration between climate scientists with machine learning, data mining, and statistics researcher (see also Monteleoni et al., 2013).

➢ **New methods of Data Science**, such as data mining, artificial intelligence and machine learning techniques could potentially help finding new ways of analysing Earth system data and helping to ensure that results are robust.

➢ **The newly-developed data science methods** will be included in the ESMValTool so open a broad opportunity for other applications that analyze Earth observations or models (or both).

➢ **Efficiently provide a number of derived products such as for example:**
  - Multi-model means (operational service)
  - Evaluation of individual or multiple models with observations
  - Multiple observational datasets