Uncertainties in multi-model assessments of future climate

Lukas Brunner (ETH Zurich) | Virtual EC-Earth meeting | November 16th 2021

With contributions from Reto Knutti, Ruth Lorenz, Angeline G. Pendergrass, Flavio Lehner, Anna L. Merrifield and many others

A very brief history of model comparison

- 1996/1997: CMIP1 and CMIP2 compare the ability of coupled climate models to simulate stable and warming climate Meehl et al. (1997), Meehl et al. (2000)
- 2005: CMIP3 provides historical and future scenario runs Meehl et al. (2005)
- Early 2000s: Increasing number of studies using properties emerging from multi-model comparisons Knutti et al. (2002), Stott and Kettleborough (2002), Tebaldi et al (2005), Furrer et al. (2007), Tebaldi and Knutti (2007), Meehl et al. (2007)
- 2010: **CMIP5** includes about 50 models, specialized MIPs, prediction experiments Taylor et al. (2012)
- 2020: With **CMIP6** the most comprehensive comparison so far starts becoming available Eyring et al (2016)



An output-based view on ~25 years of model development

Generalized model-observations distances

- model performance reduced to only 2 variables
 - 20-year climatology of temperature (1981-1999)*
 - 20-year climatology of precipitation (1981-1999)*
- difference to ERA5 on a grid cell level (2.5°x2.5°)
 - global mean bias removed before difference
- Area-weighted root-mean-squared distance

*last 20 years of pre-industrial control for CMIP2

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EC-Earth in CMIP 5 & 6

- One of the best models in CMIP5
- Distance to observations stayed about the same from CMIP 6 to 5
 → average model in CMIP6
- very large 20-year internal variability
 - mainly due to temperature in high northern latitudes
 - similar for 50- and 165-year internal variability
- → Oscillation between low/high AMOC with a period of about 200 years. Döscher et al. (2021, in press)

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Model development & dependence

- The CMIPs try to collect as many models as possible ('ensembles of opportunity') Tebaldi and Knutti (2007)
 - Models that share components or ideas \bigcirc
 - Models that have been branched from each other \bigcirc
 - Different versions of the same model 0
- Giving each model one vote when **assessing** future climate does not account for this model dependence
- Strategies beyond such a 'model democracy'
 - Model independence weighting Sanderson et al. (2015) 0
 - Institutional democracy Leduc et al. (2016) 0
 - Pooling models by components Maher et al. (2021) Ο



Figure: Development and dependencies for several climate models. Edwards (2010)



An output-based view on model dependence

Generalized model-model distances visualized as a tree based on hierarchical clustering

- same setup as for observation distances
 - climatology of temperature and precipitation
 - bias-corrected global fields
- models with know and clear connections are labeled in the same color
- CMIP6 models (**bold font**) and selected CMIP5 models (normal font)
 - NCAR/CESM, HadGEM, and EC-Earth families

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Uncertainty in multi-model projections of future change

3 main sources are typically considered Hawkins and Sutton (2009)

- **Scenario uncertainty** representing different socio-economic and technological developments
- **Model uncertainty** based on structural differences between models in a multi-model ensemble
- Internal variability due to the chaotic behavior of the climate system



1960 1980 2000 2020 2040 2060 2080







Figure: Global mean, annual mean temperature change based on 39 CMIP6 models. The dashed brown lines indicate the 90% model range. Adapted from IPCC AR6



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Figure: Global mean, annual mean temperature change based on 39 CMIP6 models. The dashed brown lines indicate the 90% model range which is interpreted as the 66% (likely) uncertainty range. Adapted from IPCC AR6 The **actual uncertainty might be larger** than the raw model uncertainty

• There might be processes not covered by any model IPCC AR5, IPCC AR6





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- There might be processes not covered by any model IPCC AR5, IPCC AR6
- The models are not independent from each other

The **actual uncertainty might be smaller** than the raw model uncertainty

• Not all models are equally 'fit for **purpose'** Sanderson et al. (2015), Herger et al. (2018)



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Weighting models by independence and performance



Knutti et al. (2017)

- w_i : weight for model i
- D_i: generalised distance of model i to observations (performance diagnostics)
- σ_{D} : performance shape parameter
- M: number of models
- S_{ij} : generalised distance between model pair (independence diagnostics)
- σ_s : independence shape parameter



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Effect of weighting global mean temperature from CMIP6



Figure: Global mean, annual mean temperature change (relative to 1995-2014) from 33 CMIP6. Brunner et al. (2020a)



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Effect of weighting global mean temperature from CMIP6



Figure: Weighted global mean, annual mean temperature change (relative to 1995-2014) from 33 CMIP6 models. Brunner et al. (2020a)

- The weighted distribution shows reduced mean warming from CMIP6 models consistent with other recent studies
 - Nijsse et al. (2020)
 - Tokarska et al. (2020)
 - Ribes et al. (2021)

• Reduction of uncertainty by 10%-20% for the likely range due to a constraining of the upper percentiles



Skill and reliability of weighting: model-as-truth testing

- Comparable to a **cross-validation** in statistics (also termed **perfect model test** or using models as **pseudo-observations**)
- **Caveat:** Can not account for processes not included in any of the models
- Model weighting is perfectly reliable by construction
- Projection **skill increases by 10%-20%** in the median depending on SSP and time period



Figure: Continuous ranked probability skill score (CRPSS) for CMIP6 relative to the unweighted ensemble using perfect models from CMIP5. Brunner et al. (2020a)



Consistency of weighting: comparison to other methods

For climate models CMIP provides a **coordinated framework** for comparison. This does not exist for constraining methods. **Differences in the results might have nothing to do with the methods**:

- variable (temperature vs precip)
- region (global vs Europe)
- season and time period
- models included
- uncertainties included



Figures: Comparing (top) methods and (right) apples and oranges right: CC-BY M. Johnson





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A coordinated framework for method comparison

We brought together **8 groups** working on constraining and developed a **level playing field for method comparison**

- **2 conditions** for participation:
- 1. quantify uncertainty in future projections
- 2. able to handle common settings

			European Climate Predict	
Institution name	Method acronym	Method name	References	
ETH Zurich (Switzerland)	ClimWIP	Climate Model Weighting by Independence and Performance	Knutti et al. (2017b); Lorenz et al. (2018); Brunner et al. (2019) ^a	
International Centre for Theoretical Physics (Italy)	REA	Reliability ensemble averaging	Giorgi and Mearns (2002, 2003) ^b	
University of Edinburgh (United Kingdom)	ASK	Allen-Stott-Kettleborough	Allen et al. (2000); Stott and Kettleborough (2002); Kettleborough et al. (2007)	
Centre National de Recherches Météorologiques (France)	HistC	Historically constrained probabilistic projections	Ribes et al. (2020, manus now: KCC to Sci. Adv.) ^c	
Met Office (United Kingdom)	UKCP	U.K. Climate Projections (UKCP) Bayesian probabilistic projections method	Sexton et al. (2012); Harris et al. (2013); Sexton and Harris (2015); Murphy et al. (2018)	
University of Oxford (United Kingdom)	CALL	Calibrated large ensemble projections	O'Reilly et al. (2020)	
Royal Netherlands Meteorological Institute (Netherlands)	BNV^*	Bootstrapped from natural variability	See the online supplemental material	
Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (Italy)	ENA [*]	Ensemble analysis of probability distributions	See the online supplemental material	

^a Source code available online (https://github.com/lukasbrunner/ClimWIP).

^b Source code available online (http://doi.org/10.5281/zenodo.3890966).

^c Method tool available online (https://saidqasmi.shinyapps.io/bayesian).

Table: Participating institutions, methods, andreferences. Brunner et al. (2020b)



Comparing constrained European temperature change

- Trade-off between number of methods and the fairness of the comparison
- Fairest comparison:
 4/8 methods could participate
- All methods narrow the uncertainty range
- All methods agree on slightly less warming

 \rightarrow not all cases look that nice



Figure: Unconstrained (light) and constrained (dark) Central European summer temperature change (2041-60 relative to 1995-2014) from CMIP5. Brunner et al. (2020b)



Summary and conclusions

- CMIP multi-model ensembles allow a consistent comparison of models
- The use of such multi-model ensembles leads to **model uncertainty**
- To better quantify model uncertainty methods have been developed to account, e.g., for past model performance
- Model-as-truth tests can be important to verify the skill of such methods
- A framework for a consistent comparison of constraining methods can help to check consistency between them









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Thank you!

Question?



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