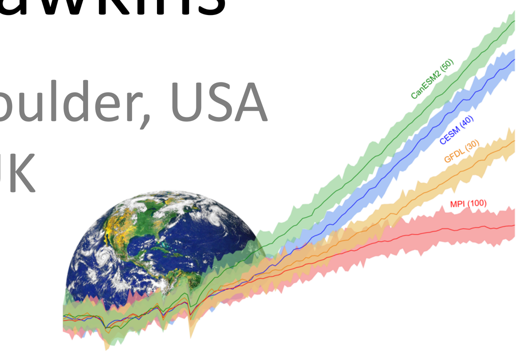
Partitioning climate projection uncertainty with multiple Large Ensembles and CMIP5/6

Flavio Lehner*[1,2], Clara Deser[1], Nicola Maher[3], Jochem Marotzke[3], Erich Fischer[1], Lukas Brunner[1], Reto Knutti[1], and Ed Hawkins[4]

[1]Institute for Atmospheric and Climate Science, ETH Zürich, Zürich, Switzerland [2]Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, USA
[3]Max Planck Institute for Meteorology, Hamburg, Germany [4]National Centre for Atmospheric Science, Dept. of Meteorology, University of Reading, Reading, UK

*flehner@ucar.edu | @ClimateFlavors | Personal website

| Funding & Support: FNSNF Fonds national suisse, Schweizerischer Nationalfonds, Fondo nazionale svizzero, Swiss National Science Foundation, US CLIVAR, ETH zürich, NCAR



How to read this display item

VIDEO PRESENTATION: https://bit.ly/2W9X3Ba

READ SLIDES

Motivation:

Partitioning uncertainty of climate projections is important to better understand them and to evaluate model performance. It requires a clean separation of forced response and internal variability, which has historically been difficult due to the scarcity of large ensemble simulations. With the advent of multiple Single-Model Initial-Condition Large Ensembles (SMILEs) we can scrutinize and overcome previous limitations.

Slide #1 | Main results:

- Forced response and internal variability can now be separated robustly
- Model uncertainty in CMIP6 is larger than in CMIP5, but this is reconciled with a performance-based weighting that down-weighs models that clearly warm too fast

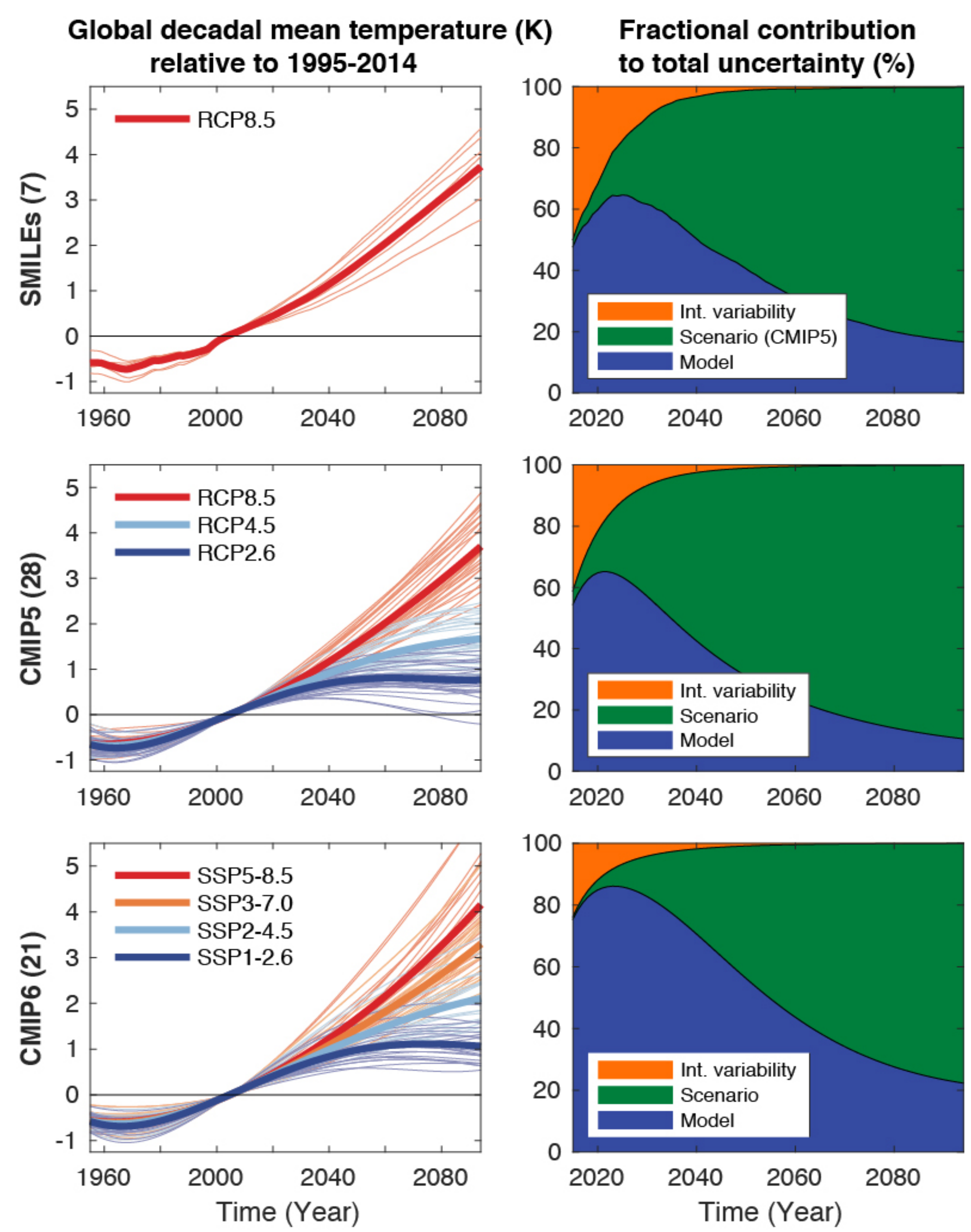
Slide #2-3 | Technical bits:

- Bias is sizable when estimating the forced response from insufficient number of ensemble members for small spatial scales or noisy variables
- Models vary a lot in their magnitude of internal variability – need for validation of models' variability
- There are robust forced changes in internal variability
- The full CMIP5 spread is often well-represented by the seven SMILEs

Uncertainty partitioning method

T = total uncertainty = *M+I+S* (*Hawkins&Sutton, 2009, BAMS*)
M = model uncertainty = variance across models' forced response
I = internal variability = variance across time or ensemble members
S = scenario uncertainty = variance across scenarios

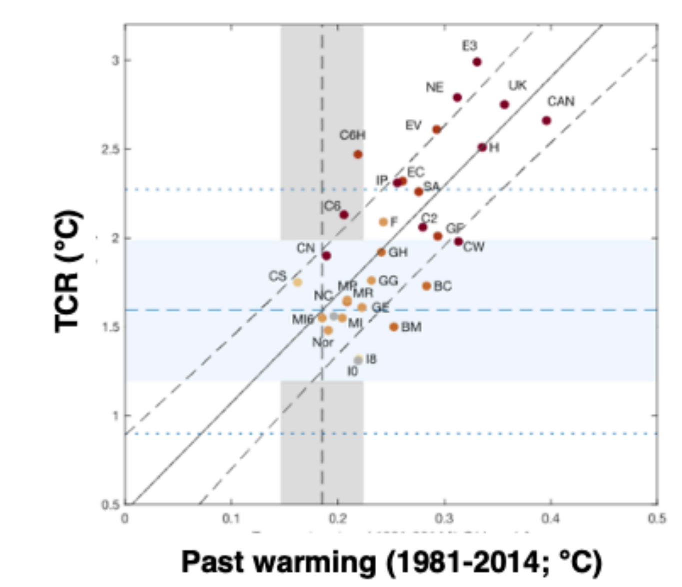
Fractional uncertainties: *M/T, I/T, S/T*



Constraining CMIP5+6 projections

CMIP6 warms more than CMIP5, leading to seemingly larger model uncertainty. Weighting the models by how well they fit the observed 1981-2014 warming (x_{obs}) reduces CMIP6 model uncertainty and brings CMIP5 and CMIP6 into closer agreement.

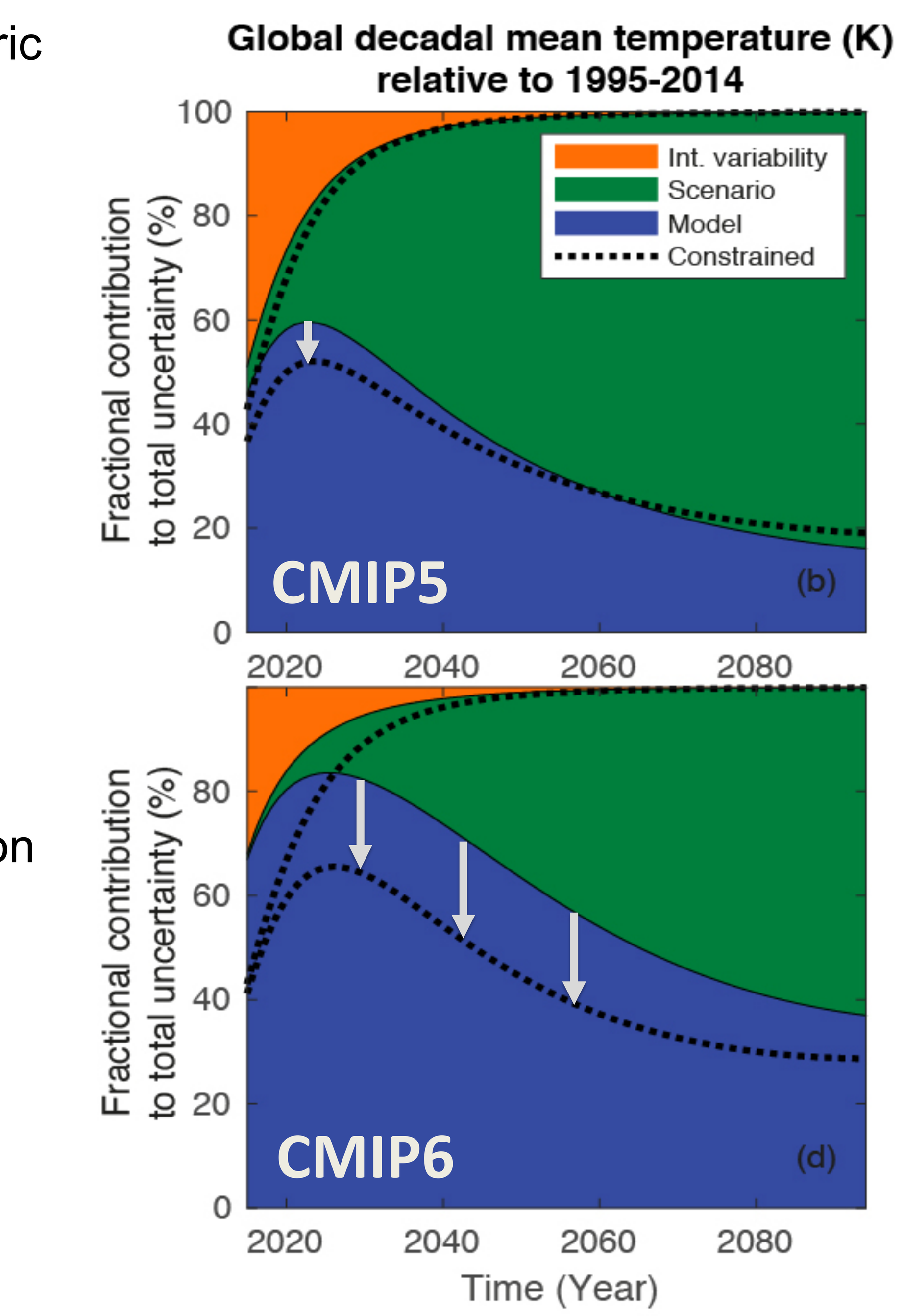
Models with too much historic warming show higher TCR.



An observational constraint is possible, as in Hawkins&Sutton (2009), by developing relative model weights W_m:

$$w_m = \frac{1}{x_{obs} + |x_m - x_{obs}|}$$

$$W_m = \frac{w_m}{\sum_m w_m}$$



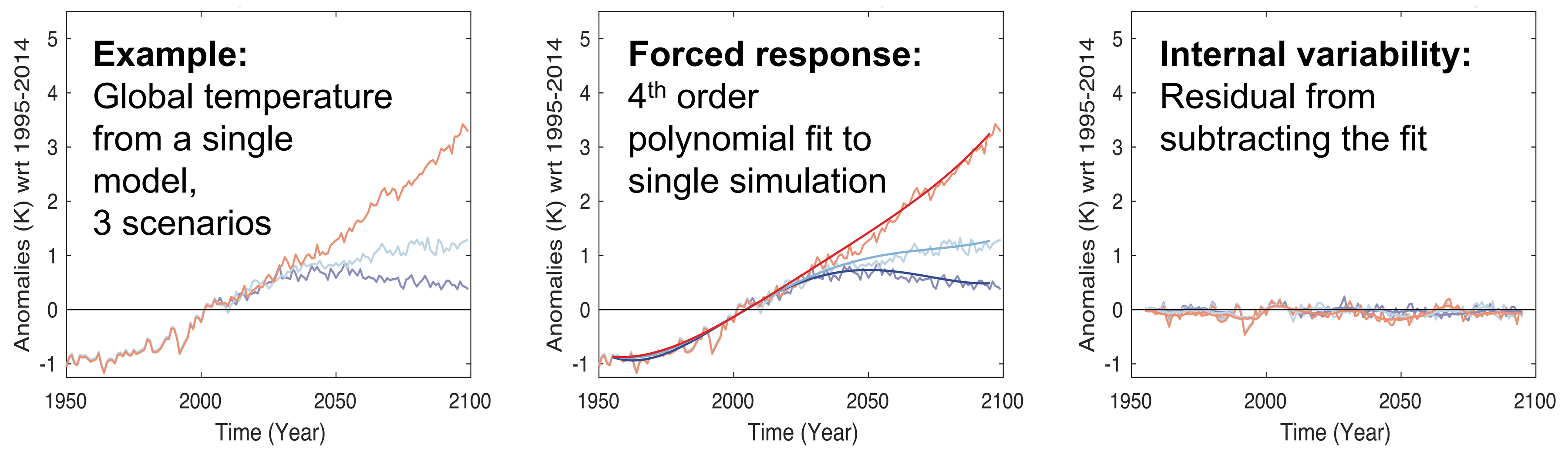
Data and References

All Large Ensemble data is freely available from Multi-Model Large Ensemble Archive (MMLEA)

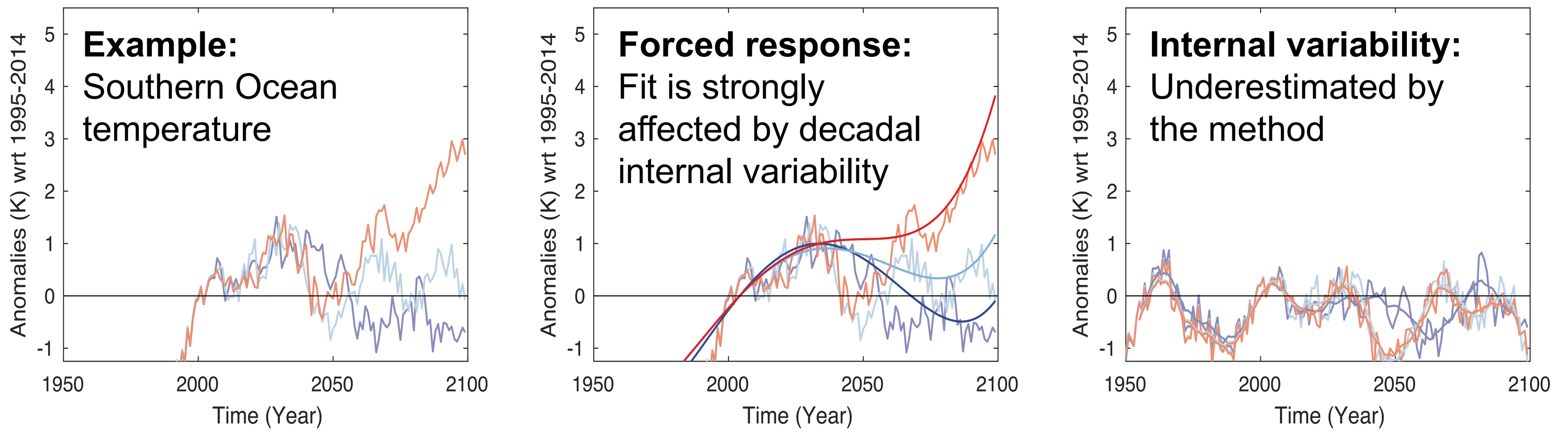
Lehner et al., 2020, *Earth System Dynamics*
Deser et al., 2020, *Nature Climate Change*

SMILE community website

What we used to do (Hawkins&Sutton 2009)



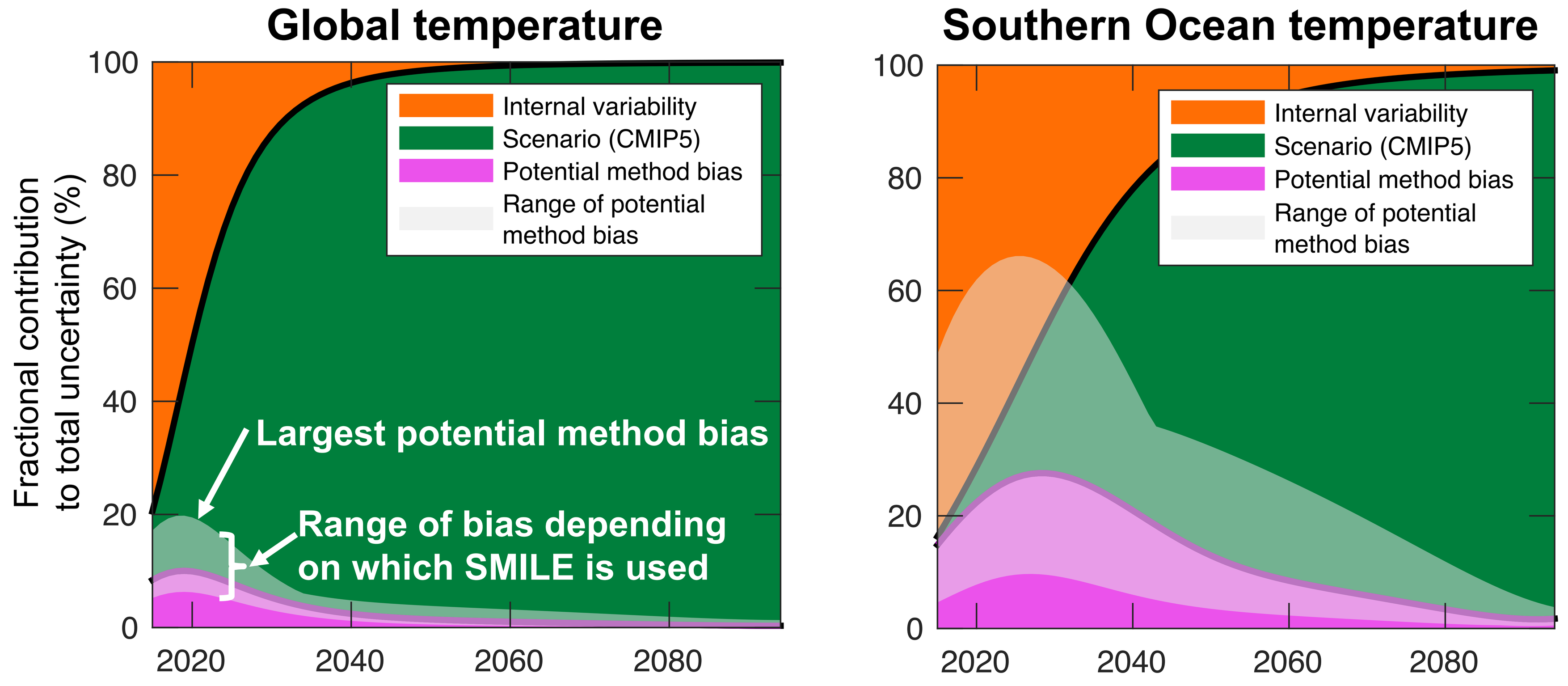
Estimate forced response via a statistical fit, treat residual as internal variability. This works well for time series that are naturally smooth due to spatial averaging, like global mean temperature (**above**). It works less well at regional scales or for noisy variables, like Southern Ocean temperature (**below**). This potential method bias can affect the uncertainty partitioning, as internal variability gets erroneously partitioned towards model uncertainty, and vice versa.



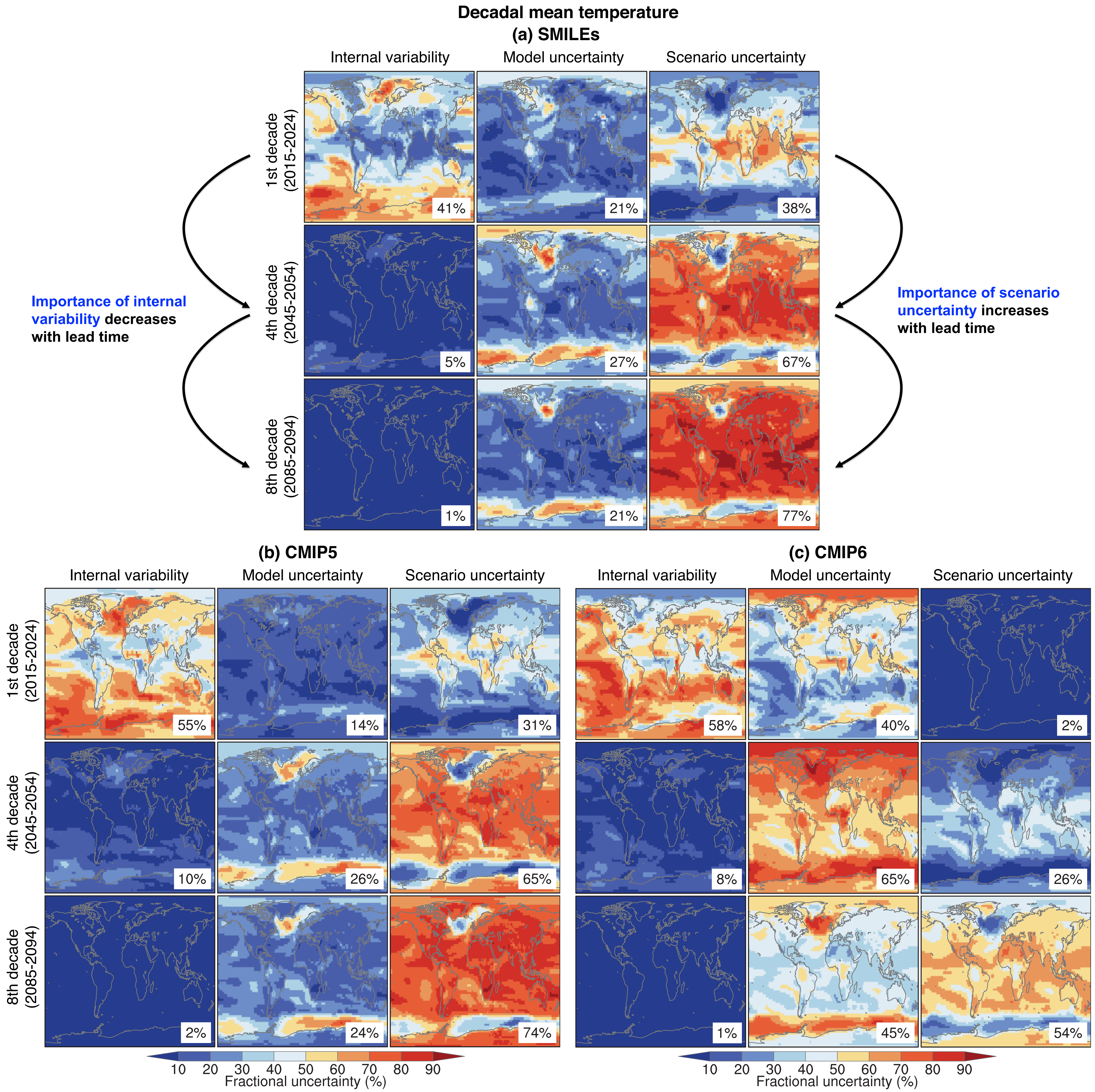
What we can do now (Lehner et al. 2020)

To quantify the potential method bias in Hawkins&Sutton (2009), we repeat their approach, but with a Single-Model Initial-Condition Large Ensemble (SMILE). We treat each ensemble member from a SMILE as if it were a different model. Then we calculate "model uncertainty" *M* (see slide #1). It should be zero, since all ensemble members are actually from the same model. The degree to which this *M* is not zero tells us about the method bias.

We can see that the potential bias is small for something like global temperature, but can be significant for Southern Ocean temperature (**below**). To partition uncertainty robustly at regional scales, we need SMILEs.

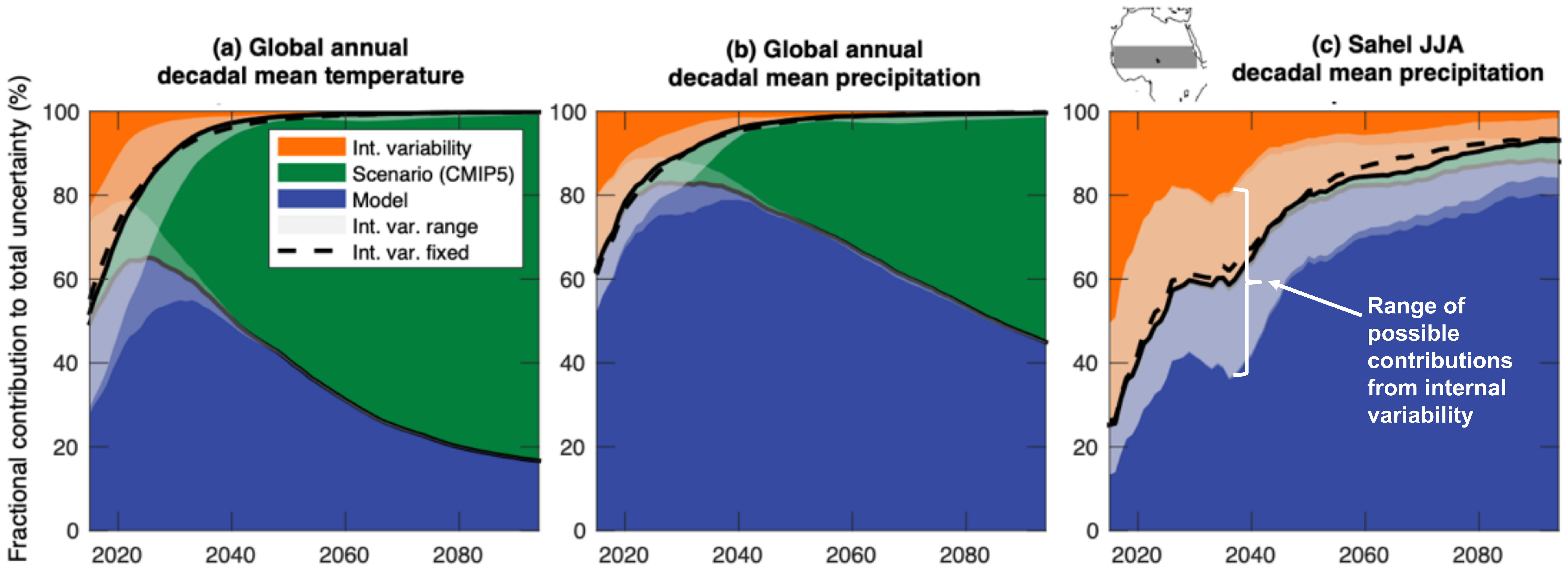


Spatial patterns in SMILEs, CMIP5 and CMIP6



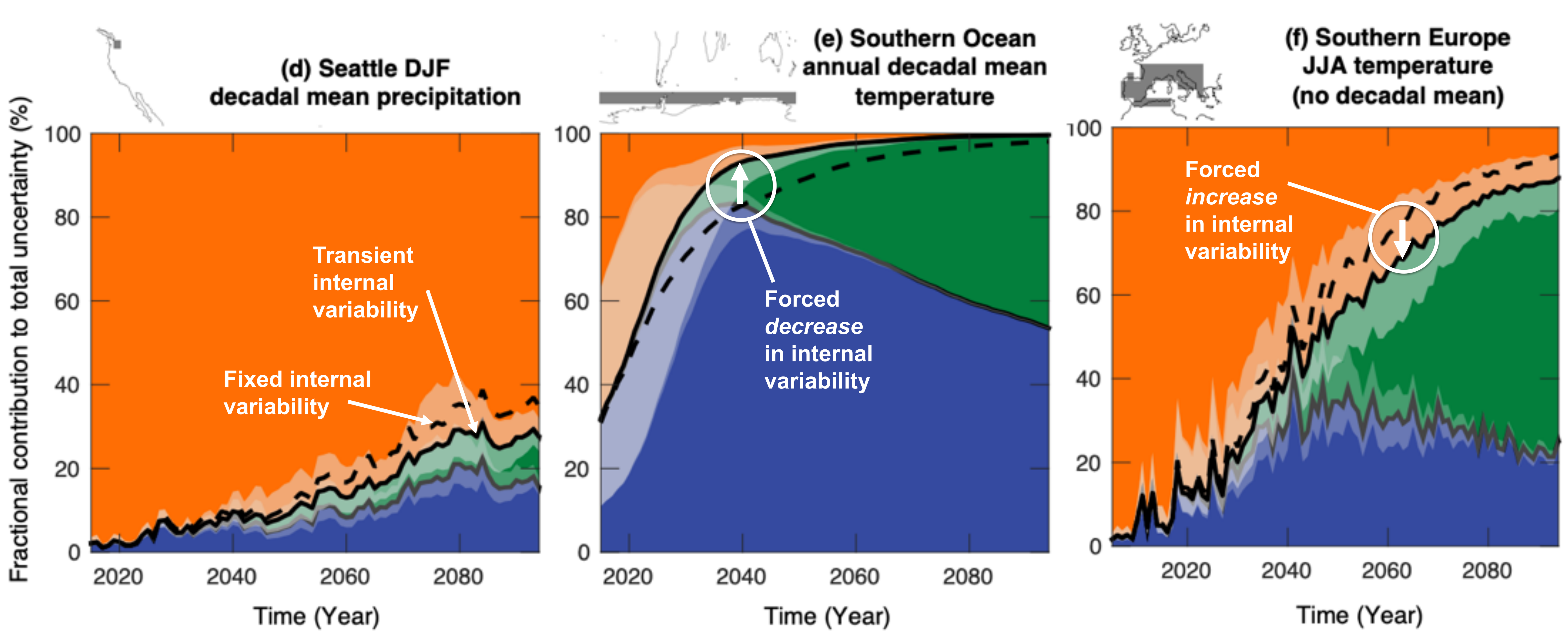
Spatial patterns and fractions for uncertainty partitioning of temperature look similar between the SMILEs and CMIP5. The story is different for precipitation (see the paper). Generally, CMIP6 shows larger model uncertainty than CMIP5 (as discussed also on slide #1), which can also be seen by the global averages of each map given in the bottom-right corners.

Model differences in internal variability



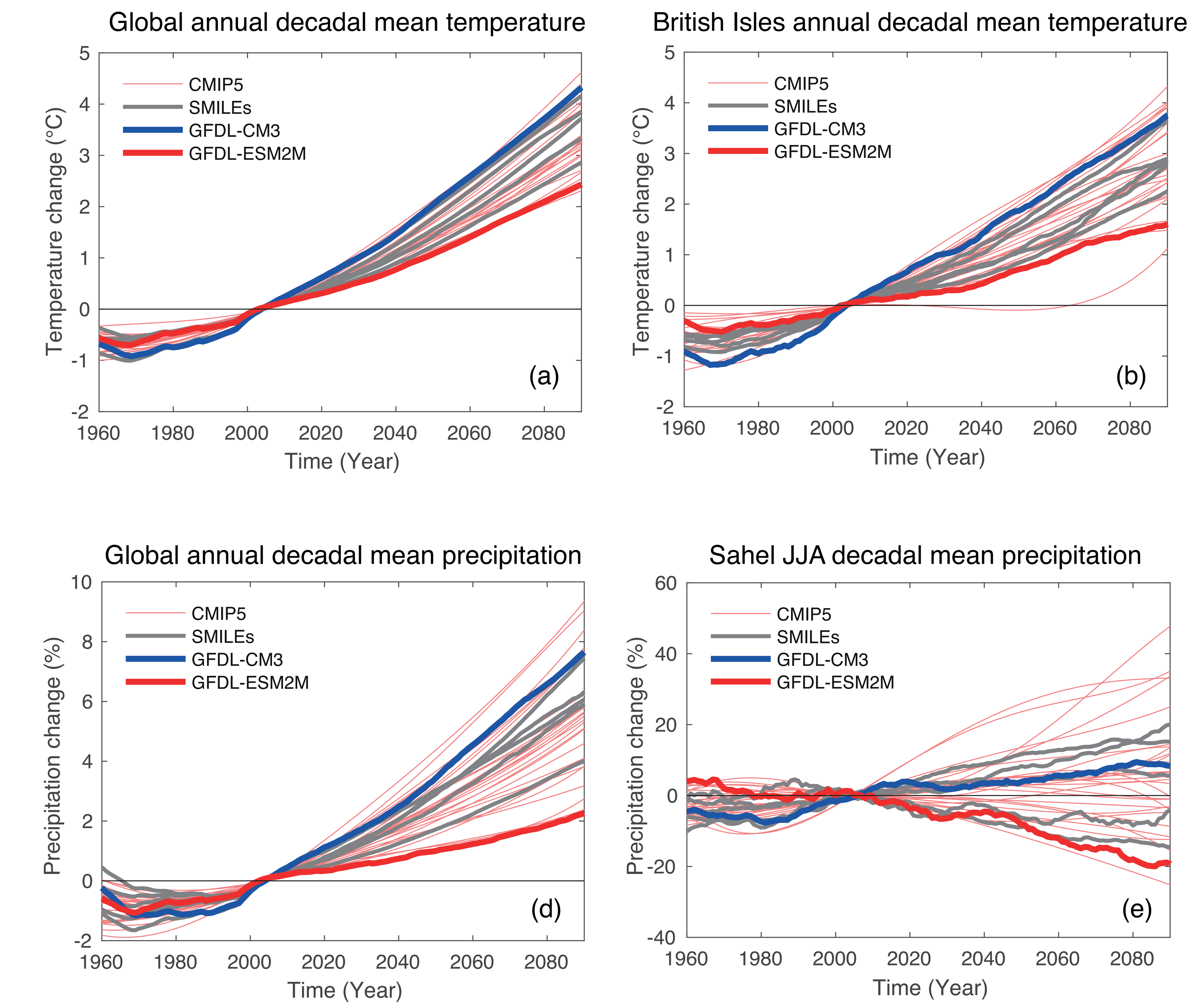
With SMILEs we can now estimate a model's internal variability robustly. Models show substantial differences in their magnitude of internal variability and thus also in how much internal variability contributes to the total uncertainty in climate projections (white shading, **above**). For example, for Sahel monsoonal precipitation, models show large differences in internal variability magnitude on decadal scales – need for observational constraint of models' internal variability.

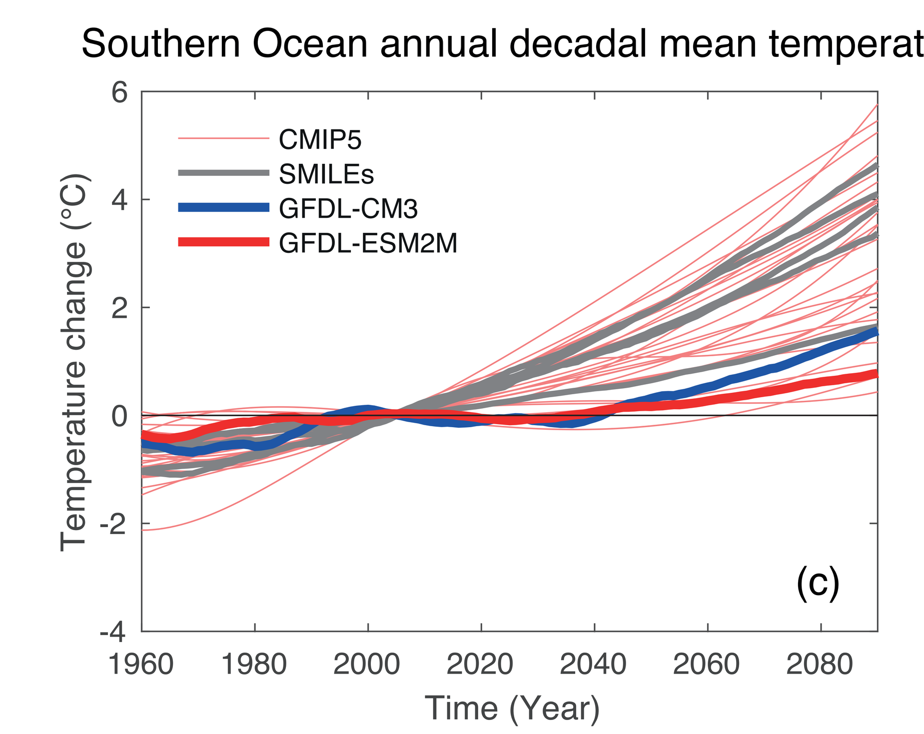
Forced changes of internal variability



Internal variability can be estimated for each point in time by calculating the variance across ensemble members of a SMILE. This way, forced changes in variability can be detected against an assumption of historically fixed variability (compare dashed and solid black line, **left**). We detect robust changes in variability of grid point precipitation, as well as interannual to decadal temperature.

How representative are the SMILEs of CMIP5?





The seven SMILEs available on the Multi-Model Large Ensemble Archive (MMLEA) happen to be a good representation of the CMIP5 archive (here 28 models).

This makes the SMILEs useful for interpreting uncertainty partitioning with CMIP5. Similar analysis for CMIP6 is forthcoming.

Data and References

All Large Ensemble data is freely available from Multi-Model Large Ensemble Archive (MMLEA)

Lehner et al., 2020, *Earth System Dynamics*
Deser et al., 2020, *Nature Climate Change*

SMILE community website

