Scrubbing Forced and Unforced Variability in CMIP5

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Accuracy of Model Projections During the Hottest Period

Data: Surface air temperature (°C) of the HadCRUT4 dataset and pre-industrial control historical ensembles. Simulations of 14 models from CMIP5 project were inter-prediction onto common grid of 9 x 9°. Each model is constructed based on data availability of HadCRUT4.

Hypothesis:

1. Detection of a pattern of anomalous forcing on annual time scales. Current detection and attribution methods assume that the internal variability does not change. Our study tests this assumption. Previous studies assessed this question using univariate metrics such as the “residual consistency” test (Allen and Tett, 1999). Unfortunately, this metric tests consistency in an aggregate sense, based on a suitably weighted seasonal variability, and so it fails to detect changes in any of the components.

Detection: Anomalies were calculated as anomalies relative to climatology of 1961-1990. A set of models was chosen to represent a range of outcomes. The data were separated into a common control period and a test period, with the latter having a shorter period of anomalies. A linear trend was removed from the test period of each run.

Conclusion:

8 models simulations (blue) are consistent with HadCRUT4 observations (black). 6 model simulations (red) are consistent with HadCRUT4 observations (black). The dominant forced response pattern differs significantly among some models.

References:


Changes in Internal Variability Due to 20th Century Climate Changes

The study investigates the possibility that internal variability and its response to anthropogenic forcing on annual time scales. Current detection and attribution methods assume that the internal variability does not change; our study tests this assumption. Previous studies assessed this question using univariate metrics such as the “residual consistency” test (Allen and Tett, 1999). Unfortunately, this metric tests consistency in an aggregate sense, based on a suitably weighted seasonal variability, and so it fails to detect changes in any of the components.

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Relation Between AMO and AMOC

MOTIVATION: Research suggests that the Atlantic Multi-decadal Oscillation (AMO) is the most predictable mode of temperature variability. This predictability is often attributed to variations in the Atlantic Meridional Overturning Circulation (AMOC). Here we ask the following questions:

1. Is there a relation between the AMOC and AMO?
2. Is the relation consistent across climate models?
3. Is the maximum streamfunction the best variable for assessing the AMOC-AMO relation?

Methodology

DATA: Analysis is performed on 455 years of annual anomalies of sea surface temperature (SST) and Atlantic mass overturning circulation (AMOC) data from the following pre-industrial control runs:

- GFDL-CM3
- MIROC-5
- IPSL-CM5A-LR
- MIROC-ESM
- IPSL-CM5A-LR
- MRI-MRI
- MIROC-ESM-CHEM
- IPSL-CM5A-LR
- MRI-MRI

An index for the Atlantic Multi-decadal Oscillation (AMO) is defined as the area-weighted annual SST over the North Atlantic from 0-40N. The maximum strength of the AMOC is defined as the maximum in the AMOC between 30°N-60°N, and denoted as AMOC. Control runs are split into two parts: a training part (225 years) for building the model and a verification part (225 years) for testing the model.

OPTIMIZATION: The relation between the AMO and AMOC is diagnosed by finding the linear combination of AMO principal components (PCs) that are most highly correlated with AMO in an integral sense (Jia and De sole, 2011). This integral is called Averaged Predictable Time (APT):

\[ \text{APT} = \frac{1}{n} \sum_{i=1}^{n} (\text{AMO}_i \times \text{AMOC}_i) \]

Results

1. AMOC MOST RELATED TO AMO

Only 3 APT are found to be significant across all models. No robust relation was found on decadal-to-multidecadal time scales

2. MODEL COMPARISON

Differences in cross model-AMO-AWO relation are quantified by fitting an empirical model:

\[ \text{AMOC}_i = \theta \times \text{AMO}_i + \epsilon \]

\[ \epsilon \sim N(0, \sigma^2) \]

A Fi-test is used to test equality of all models

3. AMOC and AMOC

- APT patterns have larger correlation with AMO compared to AMOC
- Regressions of APT from AMOC have significant variances with AMO

Future Work

- Extend optimization to include sea level pressure over the North Atlantic
- Construct simple dynamical model to describe AMO-AMOC mechanism
- Attribute differences in AMO variability to differences in regression model and AMOC variability