EGU21-2451
https://doi.org/10.5194/egusphere-egu21-2451
EGU General Assembly 2021

Towards data-driven estimates of the transient climate response to cumulative CO_2 emissions using interpretable statistical learning methods

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CO_2-induced warming is approximately proportional to the total amount of CO_2 emitted. This emergent property of the climate system, known as the Transient Climate Response to cumulative CO_2 Emissions (TCRE), gave rise to the concept of a remaining carbon budget that specifies a cap on global CO_2 emissions in line with reaching a given temperature target, such as those in the Paris Agreement (e.g., Matthews et al. 2020). However, estimating the policy-relevant TCRE metric directly from the observation-based data products remains challenging due to non-CO_2 forcing and land-use change emissions present in the real-world climate conditions.

Here, we present preliminary results for applying and comparing different statistical learning methods to determine TCRE (and later, remaining carbon budgets) from: (i) climate models' output and (ii) the observational data products. First, we make use of a 'perfect-model' setting, i.e. using output from physics-based climate models (CMIP5 and CMIP6) under historical forcing (treated as pseudo-observations). This output is used to train different statistical-learning models, and to make predictions of TCRE (which are known from climate model simulations under CO_2-only forcing, per experimental design). Next, we use such trained statistical learning models to make TCRE predictions directly from the observation-based data products.

We also explore interpretability of the applied techniques, to determine where the statistical models are learning from, what the regions of importance are, and the key input features and weights. Explainable AI methods (e.g., McGovern et al. 2019; Molnar 2019; Samek et al. 2019) present a promising way forward in linking data-driven statistical and machine learning methods with traditional physical climate sciences, while leveraging from the large amount of data from the observational data products to provide more robust estimates of, often policy relevant, climate metrics.

References:

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