Adjustment of ocean carbon sink predictions with an emission-driven Earth system model using deep neural networks

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Motivation

The Global Carbon Budget (GCB, globalcarbonbudget.org) provides annual estimates of the anthropogenic CO_2 emissions and their redistribution among the atmosphere, land, and ocean.

Starting in 2006, GCB annual updates have relied on observation-based products and standalone models of land and ocean.

In 2023, for the first time, the GCB update [1] included estimates and predictions with Earth system models (ESMs), which couple global climate models with an interactive carbon cycle.

Using ESMs has the advantage of tracing back the annual carbon budget to global physical processes [2], thus helping to better inform policy and society on the variable carbon cycle.

Problem statement

Annual-to-decadal (A2D) climate predictions with ESMs drift from the initial model states toward the unconstrained model climatology, leading to forecast errors and biases.

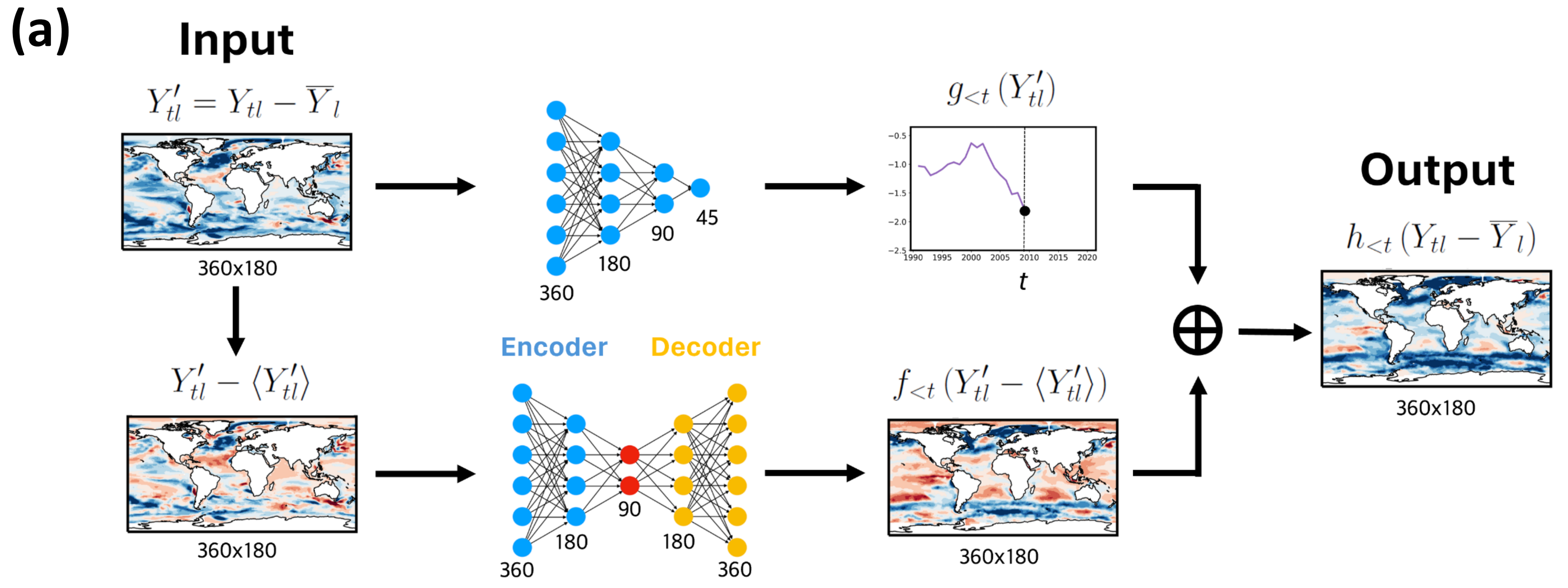
For many applications, A2D forecasts are post-processed to account for such biases [3], typically relying on simple bias and linear trend correction methods [4,5].

We propose a deep learning-based approach to adjust A2D predictions of the global carbon budget, focusing here on the adjustment of atmosphere-ocean carbon flux predictions.

Data

- **CanESM5 decadal predictions [6,7]:**
  - Specified CO_2 emissions [8,9]: historical (1850-2014) and SSP2-4.5 scenario (2015-now)
  - 10 ensemble members initialized separately on January 1 for every year in 1981-present
  - The carbon cycle is initialized indirectly through the effect of the model ocean and atmospheric states in the nudged runs used to initialized the forecasts
- **Observation-based data**: MPI-SOMFFN [10] available from 1982 to 2021

Methods: deep learning-based adjustment



(b)

ANN operator

Forecast climatology over time $<t$

Adjusted forecast $\boxed{\hat{Y}_{tl} = h_{<t}(Y_{tl} - \overline{Y}_l) + \overline{X}_l}$ Obs climatology over time $<t$

Forecast at initial year t and lead month l

Rationale: **Bias corrected forecast** $\hat{Y}_{tl} = \underbrace{Y_{tl} - \overline{Y}_l}_{} + \overline{X}_l$

$Y'_{tl} = \langle Y'_{tl} \rangle + Y'_{tl} - \langle Y'_{tl} \rangle$ **Field decomposition**

Global average — Anomaly pattern

Fig 1. (a) Architecture of the decoupled artificial neural network (ANN) used to adjust the forecast. The ANN inputs the anomaly forecast at initial year *t* and lead month *l*. Anomalies are relative to the climatology over the training period, given by all times before *t* and *l* with observations. The upper branch adjusts the globally averaged anomaly. The lower branch adjusts the anomaly pattern from the global average. The output is the sum of the two, giving the adjusted forecast anomaly. **(b) The adjusted forecast is the sum of the adjusted anomaly and the observed climatology.** The approach is like a bias correction, except that the ANN adjusts the forecast anomalies. The field decomposition allows to treat the global average and the anomaly pattern separately, with each branch targeting a different metric and using a different loss function.

Results

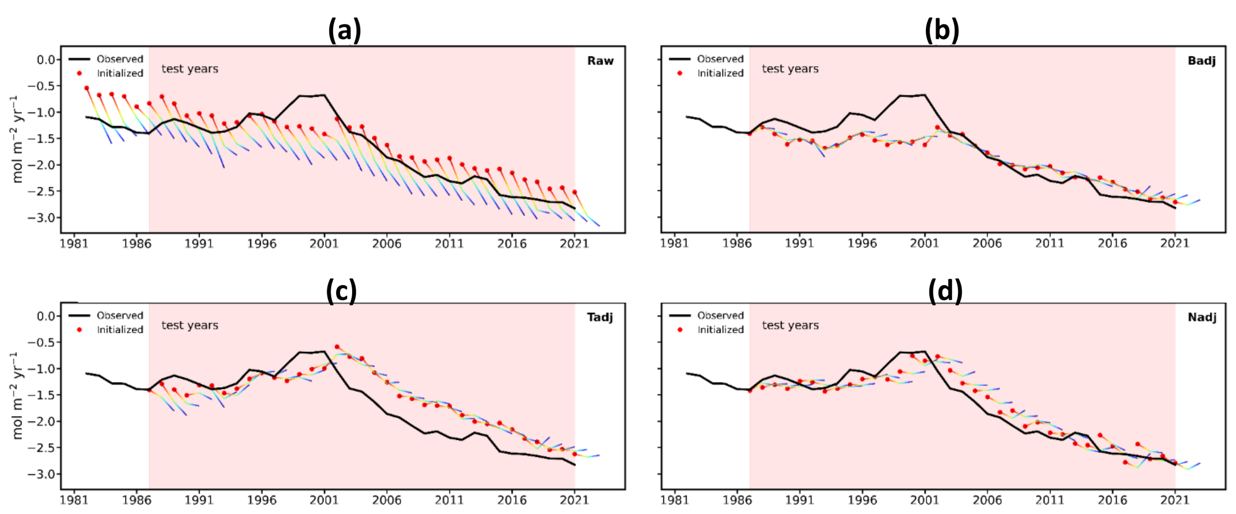


Fig 2. Global air-sea carbon flux for observations (black) and **(a)** raw, **(b)** bias adjusted, **(c)** linear-trend adjusted and **(d)** ANN adjusted forecasts. Dots indicate Year 1 forecasts and colors subsequent years. Light red band indicates test period. For a given test year, the training period comprises all previous years with available observations, with a 5-year partial validation period for hyper-parameter tuning.

The observed air-sea global carbon flux has a marked nonlinear trend. ANN-based post-processing corrects for the global bias, the overall trend, and variations above the trend, outperforming the benchmarks.

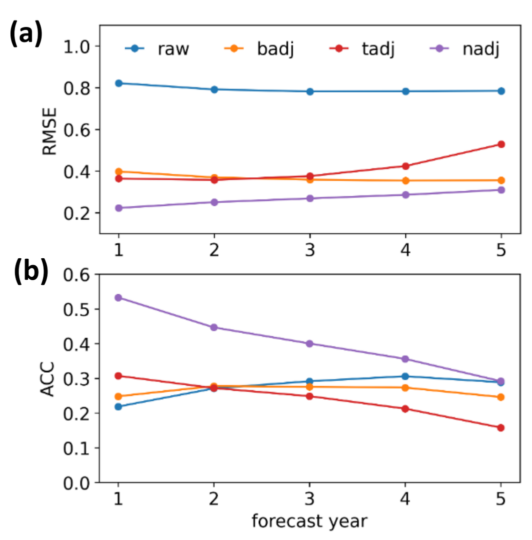


Fig 3. Globally averaged **(a)** root mean square error (RMSE) and **(b)** anomaly correlation coefficient (ACC) for the raw and adjusted forecasts over the 1991-2020 hindcast period as a function of forecast year. Values are global averages of RMSE or ACC at each ocean grid cell computed from annual raw or adjusted forecasts against the observational data.

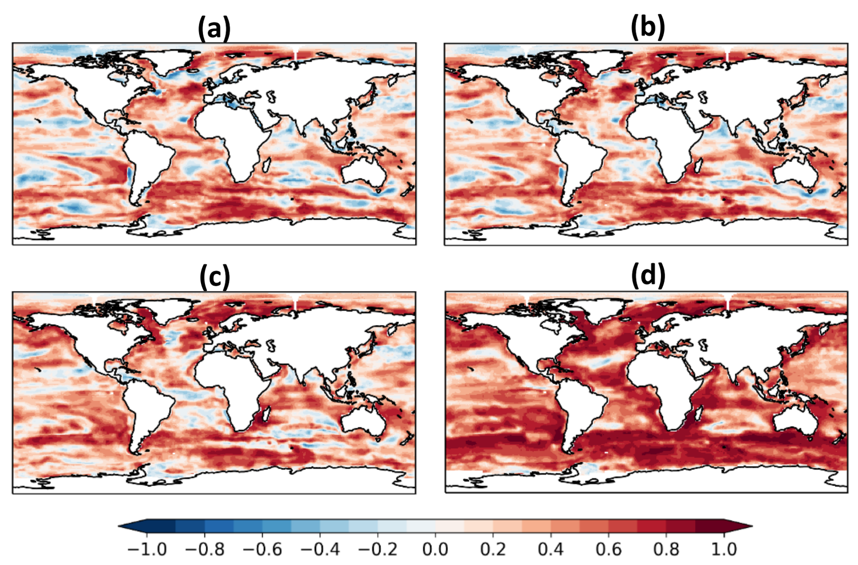


Fig 4. Geographic distribution of ACC for Year 1 **(a)** raw, **(b)** bias adjusted, **(c)** linear-trend adjusted and **(d)** ANN adjusted forecasts in 1991-2020. Global averages are shown in Fig. 3b.

ANN adjusted forecasts markedly outperform the benchmarks, notably in the Southern Ocean (SO). The SO is a highly active region of the carbon sink [11], which is responsible for about 40% of the anthropogenic CO_2 global oceanic uptake [12].

Conclusions

- ANN-based corrections of annual-to-decadal air-sea carbon flux predictions outperform bias and trend correction methods for all forecast years examined
- The ANN model corrects for the ocean carbon sink response to the slow-varying atmospheric CO_2 concentration forcing better than the alternative, as implied by the adjusted global mean time series (ts)
- The simple Autoencoder used to correct the anomaly patterns largely improves the forecasts, but other image-processing methods could be used. Similarly for correction of the global mean ts
- Forecast skill improvement deteriorates with lead times due to the smaller size of the training sample
- Future work includes applications of this methodology to other emission-driven ESMs models contributing to the GCB annual updates and to the uncertainty quantification of the corrected forecasts

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