# Deep learning-based bias adjustment of decadal climate predictions

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## Abstract

Decadal climate predictions are key to inform adaptation strategies in a warming climate. Coupled climate models used for decadal predictions are, however, imperfect representations of the climate system causing forecast biases. Biases can also result from a poor model initialization that, when combined with forecast drift, can produce errors depending non-linearly on lead time. We propose a deep learning-based bias correction approach for post-processing gridded forecasts to enhance the accuracy of decadal climate predictions.

## 1 Motivation and problem statement

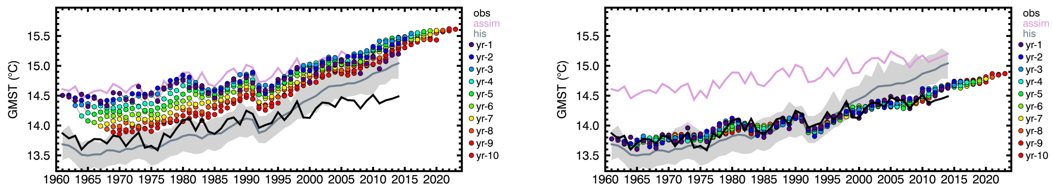
Decadal or near-term climate prediction refers to climate forecasts on the range of a year to a decade. Unlike climate projections, which simulate the climate response to external forcing such as changes in greenhouse gas concentrations and aerosols, decadal predictions also simulate the climate response to unforced variations such as El Niño-Southern Oscillation (ENSO) and other modes of internal climate variability. As part of the Wold Climate Research Program (WCRP), the Decadal Climate Prediction Project (DCPP) [1] offers quasi-real-time decadal forecasts for potential users, whereas the World Meteorological Organization (WMO) Global Annual to Decadal Climate Update (GADCU) is produced annually to inform society on the state of the climate for the next 5 years [2].

Decadal forecasts typically drift from their observation-based initial conditions toward the unconstrained model climatology, which may be far from observations. Consequently, operational decadal predictions often require some form of data post-processing to attain skill. This is often done using simple linear methods. Given the importance of climate predictions for informed adaptation strategies, the exploration of novel post-processing methods to correct forecast bias and drift is an important step to improve adaptation. We propose a deep learning model as a data post-processing tool for gridded climate predictions to enhance forecast skill.

## 2 Background and previous work

While many studies describe adjustments of weather and subseasonal-to-seasonal (S2S) forecasts, there is limited work devoted to adjustments of decadal predictions, partly due to their relatively recent use, unique long-time range, drifts, and potential for erroneous trends. A simple approach is climatological bias correction, for which the difference between the modeled and observed clima-

Tackling Climate Change with Machine Learning: workshop at NeurIPS 2022.




(a) (b)

Figure 1: Annual averaged a) raw and b) trend corrected ensemble mean decadal forecasts (colored dots) of global mean surface temperature initialized from 1961 to 2015 obtained with CanESM5. Forecast years go from 1 (violet dots) to 10 (red dots). Also shown are the observation-based estimates (black curve), the ensemble mean assimilation runs used to initialize the forecasts (magenta curve), the ensemble mean historical simulations (gray curve), and the ensemble spread of historical simulations as a measure of uncertainty resulting from internal variability (gray band).

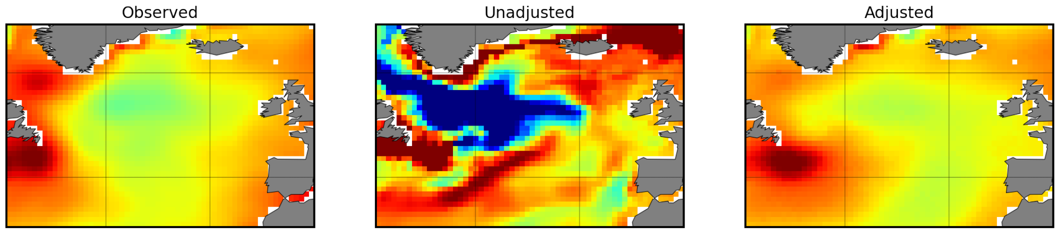
tologies, taken over a common period, is removed from the forecast [1]. While this basic approach can provide substantial skill improvements compared to raw predictions, it is insufficient to correct erroneous variability and trends. For climate variables such as temperature that exhibit strong long-term changes, trend corrections depending on lead time are often used [3], whereas for variables with a small signal-to-noise ratio such as precipitation [4], a variance adjustment may be required [5]. Other bias-correction methods include the use of linear dependence of the drift on the observed initial conditions [6], the use of polynomial representations of the forecast drift and ensemble variability [7], and a dynamic modeling of the drift [8]. Despite these efforts, a comprehensive method for decadal forecast adjustment is lacking, as the accuracy of the above methods typically depend on climate variables, skill measure, initial conditions, and lead time.

As an example, Figure 1 shows raw and trend adjusted ensemble mean decadal forecasts of global mean air surface temperature obtained with version 5 of the Canadian Earth system model (CanESM5-DP) [9]. Also shown are the ERA5 [10] observation-based estimates, the ensemble mean of the constrained runs used to initialize the forecasts, and the ensemble mean of the unconstrained historical simulations. The latter reproduces the forced warming, but cannot reproduce the observed internal variability, thus highlighting the need for decadal predictions. The initial conditions are warmer than observed, leading to raw forecasts that have significant initial biases, and drift towards the unconstrained historical simulations. These biases are improved with climatological and linear trend correction, but all errors cannot be resolved with these simple methods.

While machine learning and deep learning have been used for forecast adjustment, most research focuses on synoptic and subseasonal predictions. Approaches include the use of Kalman filters to adjust air quality forecasts [11], random forests for wind forecast adjustment [12], and weather and seasonal climate forecast adjustment [13]. An early approach using neural networks (NNs) for post-processing ARPS temperature forecasts is given in [14]. Rasp and Lerch [15] propose a NN to adjust ECMWF ensemble weather forecasts using a distributional regression architecture able to predict outputs with heteroscedastic variance. Kim et al. [16] use a long short term memory (LSTM) network with a single hidden layer for Madden-Julian Oscillation (MJO) forecast adjustment, reducing multi-model forecast errors up to 90%. Convolutional neural networks (CNNs) have been used in several works to correct gridded weather forecasts [17–20]. Lerch and Polsterer [21] combine a CNN with an autoencoder for ECMWF ensemble weather forecast adjustment. A generative model approach to bias correction of climate forecasts using a generative adversarial network (GAN) is described by François et al. [22].

## 3 Data

We use the 40-member ensemble of gridded global temperature and precipitation decadal predictions from CanESM5 contributing to the DCPP endorsed by phase 6 of the Coupled Model Intercomparison Project [CMIP6, 23]. The data includes retrospective forecasts initialized annually in 1960-2019 [24] and quasi-real-time forecasts initialized in 2020-2021 [25]. For forecast adjustment, we use several gridded observation-based products including air temperature reanalyses and station-based products examined in [26], and the Global Precipitation Climatology Project GPCP2.3 product [27]. When




(a) (b) (c)

Figure 2: January sea surface temperature anomalies in the sub-polar North Atlantic from a) observation-based ERSSTv5 [32], and CanESM5-DP based b) raw and c) NN-based adjusted forecasts at 12-month lead averaged over the 2006–2018 test period. Anomalies are taken from temperature averaged over the training period, and range from below -1°C (dark blue) to above 1°C (dark red).

possible, we use a blend of multiple observation-based products to reduce potential uncorrelated random errors that can degrade forecast skill regardless of model biases [26].

## 4 Technical approach and methodology

A convolutional architecture will be used to preserve spatial dependencies in the data. To consider temporal correlations, we combine this approach with a sequential neural network architecture, such as recurrent neural networks (RNN) [28]. We further plan to test other sequential architectures like self-attention [29] and 1D CNNs [30]. The model input are raw, uncorrected retrospective forecasts. The objective of the model is to learn and correct the systematic forecast errors using observational data, and output the adjusted forecasts. This trained model will then be used to adjust forecasts for future years. As a baseline, we will use corrections with linear models, which are currently employed to adjust operational decadal forecasts. Forecast adjustment can either be based on lead time or on forecast initialization year. Previous studies focus on correction methods with models that depend on lead time, however we will explore a model that learns from the forecast drift along the lead time dimension. This way, lead-time dependent bias patterns could be exploited during model training. Forecast bias correction can either be applied to every single ensemble member or the ensemble mean. We will explore both options, although recent research suggests that correcting the forecast ensemble mean may be preferable, since the noise component in the single members may obscure the forecasts systematic errors to be learned by the network [16].

## 5 Expected outcome and impact

Our main objective and expected outcome is two-fold, (1) to improve accuracy of operational decadal predictions, and (2) to gain further understanding of climate model biases for research and model development. We will train our model with retrospective forecasts contributing to the DCPP Component A, and use the trained network to improve the quasi-real-time predictions contributing to DCPP Component B. We will first focus on CanESM5-DP, which is known to have strong biases in the subpolar North Atlantic region severely limiting its forecast skill [31]. We anticipate significant improvements over this region, as suggested by Figure 2 showing preliminary results of adjusted temperature anomalies obtained with a simple dense feed-forward NN. The adjusted temperature and precipitation forecasts will be shared on a publicly accessed repository for dissemination and future use. We plan to extend our work to other coupled models contributing to DCPP, and also to those participating in the WMO-GADCU [2] that do not contribute to the DCPP. We also intend to include other key climate variables in our study, such as sea level pressure, and hydroclimatic variables such as soil moisture and snow water equivalent. Because operational near-term climate predictions inform current adaptation strategies to increase resilience in a warming climate, we expect more accurate decadal forecasts to have a significant impact on society and climate-sensitive socioeconomic sectors.

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