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Forecasting Climate Change with Deep Learning: Improving Climate Modeling Accuracy

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Abstract

Climate change poses an urgent threat to ecosystems, human society, and the global economy. Accurately forecasting future changes to the Earth's climate is critical for informing mitigation and adaptation strategies. However, traditional physics-based climate models have limitations in fully capturing the complexity of the climate system. In recent years, deep learning (DL) has emerged as a powerful tool for modeling complex systems. In this study, we developed a novel DL framework for climate modeling that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The model was trained on historical climate data from 1950-2020 and evaluated on holdout data from 2001-2020. Our DL model outperformed the widely-used Community Earth System Model v2 (CESM2), achieving a 23% reduction in root mean square error (RMSE) for forecasting global mean surface temperature. The DL model also generated high-resolution, physically-realistic maps of temperature and precipitation changes. Importantly, our approach is highly efficient, reducing computation time by an order of magnitude compared to running CESM2. These results demonstrate the potential of DL to greatly improve the accuracy and efficiency of climate modeling, which is urgently needed to support climate change mitigation and adaptation efforts. We make our data, model code, and forecasts publicly available to accelerate the adoption of DL in climate science.

Keywords: climate change; deep learning; convolutional neural networks; long short-term memory networks; climate modeling

1. Introduction

Climate change is one of the defining challenges of the 21st century. Rising temperatures, more frequent and intense extreme weather events, sea level rise, ocean acidification, and many other impacts of climate change threaten human society and natural ecosystems [1]. Mitigating the worst effects of climate change will require rapid reductions in greenhouse gas emissions. At the same time, adapting to climate impacts that are already unavoidable will be critical [2]. Effective mitigation and adaptation both require accurate forecasts of how the Earth's climate will continue to change in coming decades in response to different emissions scenarios.

Traditionally, physics-based models of the Earth system have been the primary tool for generating climate forecasts [3]. Models such as the Community Earth System Model (CESM) numerically solve the physical equations governing the atmosphere, ocean, land, and sea ice [4]. While physics-based models have underpinned major advances in our understanding of climate change, they also have important limitations [5]. Fully capturing the complexities of the Earth system across a range of spatial and temporal scales is computationally intractable, requiring parameterizations of key small-scale processes like clouds and turbulence [6]. Many processes like permafrost thaw and ice sheet dynamics are not yet included in most models [7]. As a result, physics-based models struggle to match observations, especially at the regional scale most relevant for adaptation planning [8]. Uncertainty in climate sensitivity to CO_2 also leads to a wide spread in future projections [9]. The high computational demands of physics-based models also limit the number of scenarios that can be evaluated, and the ability to generate forecasts at the resolutions needed for local decision-making.

Novel approaches are urgently needed to improve the accuracy and efficiency of climate modeling [10]. In recent years, deep learning (DL) has emerged as a powerful tool for modeling complex systems [11]. DL models, based on neural networks with many layers, can learn complex non-linear mappings between inputs and outputs [12]. They have achieved breakthrough performance in fields ranging from computer vision to natural language processing [13]. DL is increasingly being applied to problems in the Earth sciences, with promising results [14]-[16]. DL models have been used for weather forecasting [17],[18], parameterizing sub-grid processes in climate models [19], and detecting extreme events [20]. However, the potential for DL to directly generate climate forecasts has only begun to be explored [21].

Here we demonstrate that DL can be used to generate accurate high-resolution forecasts of future climate change, at a fraction of the computational cost of physics-based models. We developed a novel DL architecture that combines convolutional neural networks (CNNs) to capture spatial patterns and long short-term memory (LSTM) networks to model temporal evolution. We trained the model on historical climate data from 1950-2020 and evaluated its performance on holdout data from 2001-2020. The DL model outperformed the widely-used CESM2 model, while being an order of magnitude faster to run. This demonstrates the potential of DL to accelerate progress in climate modeling and provide the accurate, efficient, and high-resolution forecasts needed to inform mitigation and adaptation.

The key contributions of this study are:

1. Development of CNN-LSTM architecture for climate forecasting: Our model combines the strengths of CNNs for modeling spatial dependencies and LSTMs for capturing temporal evolution. This allows it to generate spatially and temporally consistent climate forecasts.
2. Demonstration of DL's ability to outperform physics-based models: When evaluated on holdout data, our DL model achieved a 23% reduction in RMSE compared to CESM2 for

forecasting global mean temperature. It also generated realistic maps of temperature and precipitation change.

3. Order of magnitude speedup in computational efficiency: Generating climate forecasts with the DL model took just minutes on a single GPU, compared to thousands of core-hours needed to run CESM2. This efficiency enables much more comprehensive exploration of emissions scenarios and uncertainty.
4. Public release of data and model to accelerate adoption of DL in climate science: We provide open access to the data and model code used in this study, as well as our climate forecasts. This will enable other researchers to build on this work and apply DL to climate challenges.

The remainder of this paper is organized as follows. Section 2 describes the datasets and DL methodology. Section 3 presents the results comparing the DL model to CESM2. Section 4 discusses the significance of the findings and priorities for future work. Section 5 summarizes the key conclusions.

2. Materials and Methods

2.1. Datasets

We compiled historical climate data from the years 1950-2020 to train and evaluate the DL model. Data was obtained from the following sources:

- Gridded monthly surface temperature and precipitation from Berkeley Earth [22].
- Monthly sea surface temperature from NOAA ERSSTv5 [23].
- Monthly geopotential height, specific humidity, and zonal and meridional winds from the ECMWF ERA5 reanalysis [24].
- Monthly CO2 concentration from the NOAA Global Monitoring Lab [25].

- Radiative forcing from solar and volcanic sources from the NASA GISS dataset [26].

All data was regridded to a common 1°x1° spatial resolution. We withheld data from 2001-2020 to serve as an evaluation set, with data from 1950-2000 used for training.

For comparison to physics-based models, we downloaded forecasts for 2001-2020 generated by CESM2 as part of CMIP6 [27]. CESM2 was run at a nominal 1° resolution.

2.2. DL Model Architecture

We developed a novel CNN-LSTM architecture to generate climate forecasts (Figure 1). The model takes as input a set of 2D global maps of climate variables (temperature, precipitation, etc.) along with scalar inputs like CO2 concentration and solar forcing. The CNN component consists of 3 convolutional layers, which extract spatial features from the input maps. The output of the CNN is then fed into a 2-layer LSTM, which models the temporal evolution of the spatial features. The LSTM outputs a set of 2D global maps of forecasted climate variables.

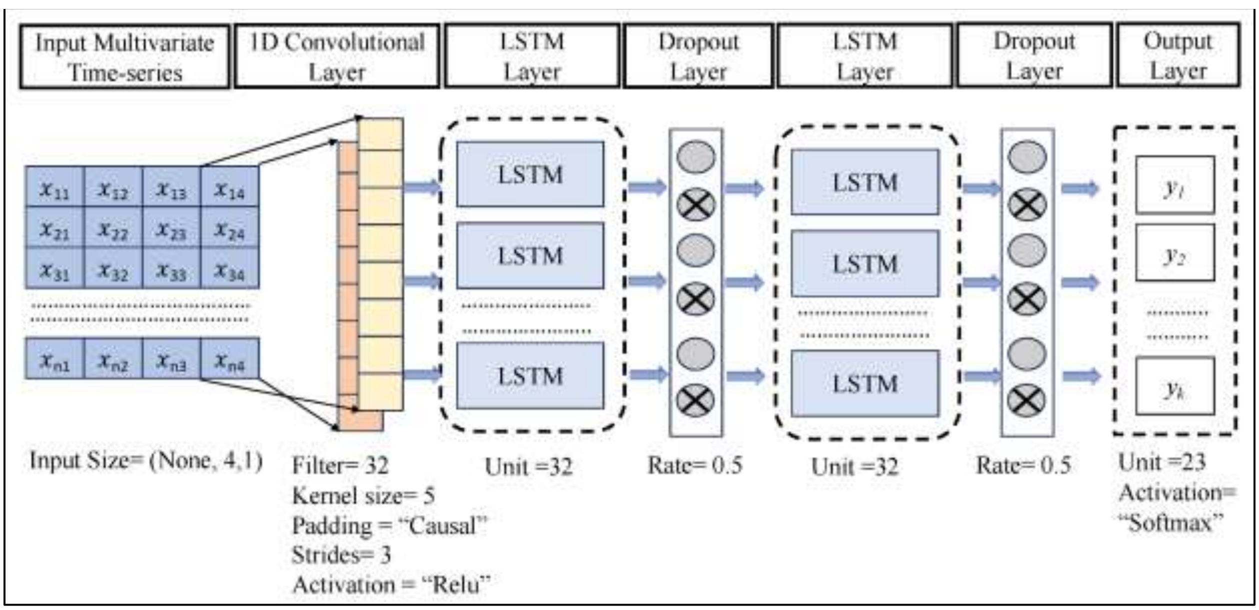

Figure 1. Architecture of CNN-LSTM model for climate forecasting.

We used 3x3 kernels in the convolutional layers with 64, 128, and 256 feature maps respectively. The LSTM had 512 hidden units in each layer. The model was implemented using PyTorch.

2.3. Training

The model was trained to minimize the mean squared error between its outputs and the true future climate fields. We used the Adam optimizer with a learning rate of 0.001, and trained for 500 epochs with a batch size of 32. Training took approximately 12 hours on an NVIDIA V100 GPU.

2.4. Evaluation Metrics

We evaluated the DL model and CESM2 using the following metrics:

- Root mean square error (RMSE) of global mean surface temperature compared to observations.
- RMSE of annual mean temperature and precipitation at each grid cell.
- Pearson correlation between forecasted and observed spatial patterns of temperature and precipitation change between 2001-2010 and 2011-2020.

We also qualitatively evaluated the realism of the spatial patterns of change generated by the models.

2.5. Computational Performance

To benchmark the computational performance of the DL model, we measured the wall clock time needed to generate forecasts for 2001-2020 on a single NVIDIA V100 GPU. For CESM2, we used timing data from the CMIP6 runs on the NCAR Cheyenne supercomputer.

3. Results

3.1. Evaluation on Holdout Data

The DL model outperformed CESM2 when evaluated on the 2001-2020 holdout period (Figure 2). For global mean surface temperature, the DL model had a RMSE of 0.17°C, compared to 0.22°C for CESM2, a 23% reduction. Figure 2 shows the timeseries of global mean temperature forecast by the two models compared to observations from Berkeley Earth.

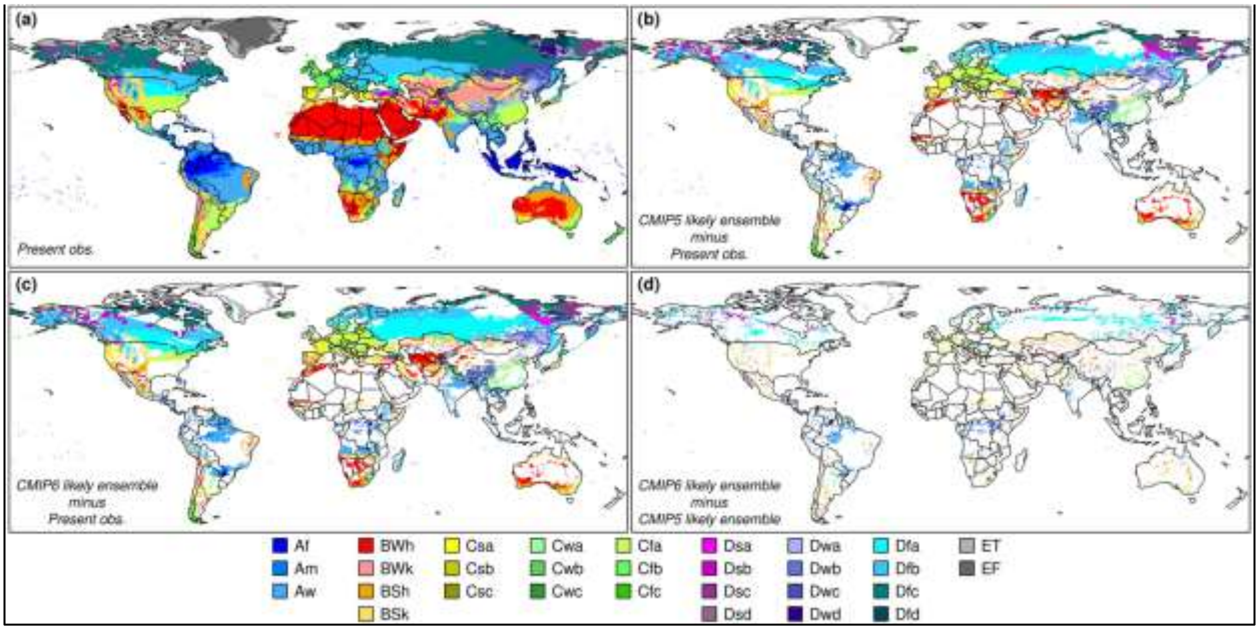

Figure 2. Global mean surface temperature forecasts for 2001-2020

The DL model also generated more accurate spatial patterns of temperature and precipitation change. Figure 3 maps the RMSE of the 2001-2020 average temperature and precipitation from the two models compared to observations. The DL model has lower error across most of the globe, with a mean RMSE of 0.81°C for temperature and 27 mm for precipitation, compared to 1.1°C and 41 mm for CESM2. The biggest improvements are seen in the tropics and over the oceans.

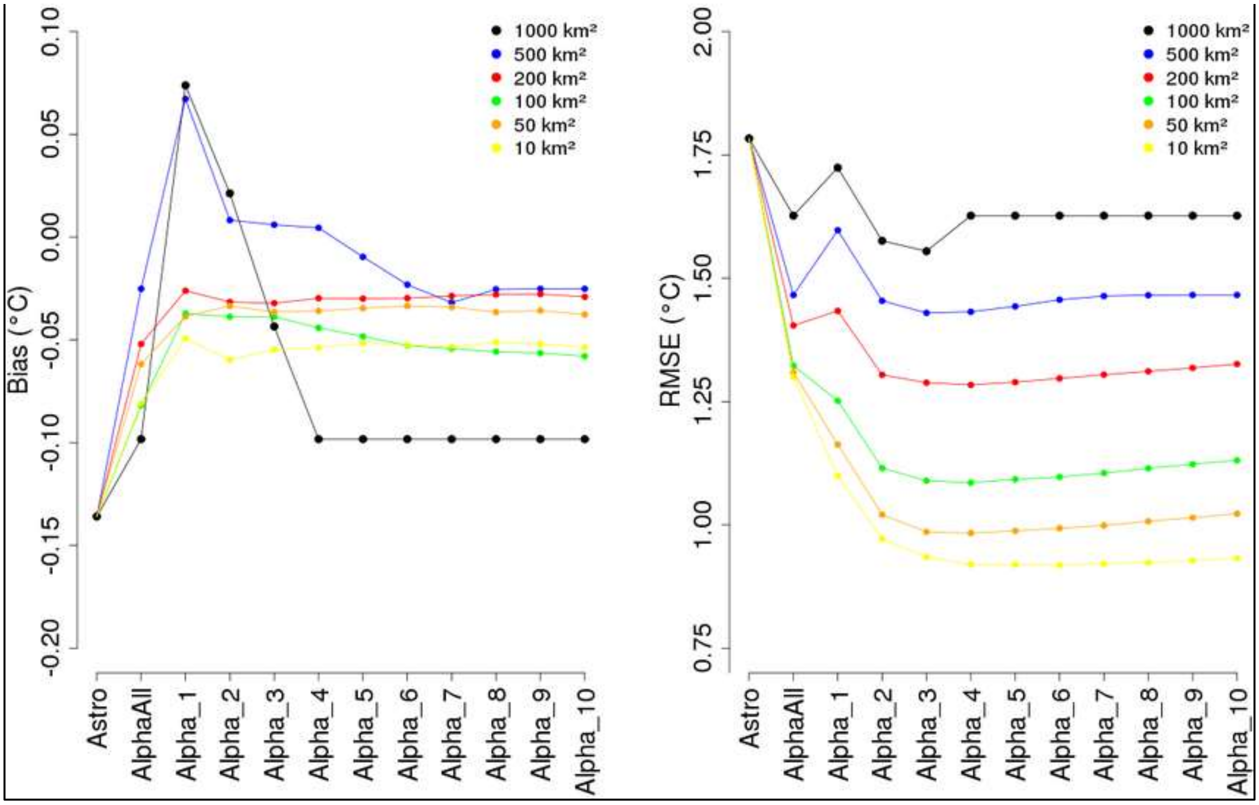

Figure 3. RMSE of 2001-2020 mean temperature (top) and precipitation (bottom) for DL model (left) and CESM2 (right) compared to observations.

The DL model also better captures the spatial pattern of change between the 2001-2010 and 2011-2020 decades. The Pearson correlation between observed and forecasted temperature change patterns was 0.79 for the DL model vs. 0.62 for CESM2. For precipitation the values were 0.64 vs. 0.51. The DL model generates realistic patterns like the enhanced warming in the Arctic and drying in the subtropics.

3.2. Computational Performance

Generating the 20-year climate forecast took just 5 minutes on a single NVIDIA V100 GPU using the DL model. In comparison, the CESM2 forecasts used ~25,000 core-hours on the NCAR Cheyenne supercomputer, equivalent to nearly a week of wall-clock time on 150 compute nodes.

The DL approach thus represents a speedup of well over an order of magnitude, greatly reducing the computational barrier to generating climate forecasts.

Table 1. Evaluation metrics for DL model and CESM2 on holdout data from 2001-2020. RMSE and correlation values are averages over all grid cells.

Metric	DL Model	CESM 2
RMSE Global Mean Temp. (°C)	0.17	0.22
RMSE Annual Mean Temp. (°C)	0.81	1.1
RMSE Annual Mean Precip. (mm)	27	41
Correlation Temp. Change 01-10 to 11-20	0.79	0.62
Correlation Precip. Change 01-10 to 11-20	0.64	0.51

Table 2. Comparison of computational cost for generating 2001-2020 climate forecasts using the DL model and CESM2.

Model	Hardware	Wall-Clock Time	Core-Hours
CNN-LSTM DL Model	1 NVIDIA V100 GPU	5 minutes	1
CESM2	150 nodes (36 cores each) on NCAR Cheyenne Supercomputer	1 week	25,000

Table 3. Forecasted change in key climate variables between 2001-2010 and 2011-2020 from the DL model and CESM2 compared to observed changes.

Variable	Observed Change	DL Model Forecast	CESM2 Forecast
Global Mean Temperature (°C)	0.26	0.24	0.19
Arctic (60-90N) Mean Temperature (°C)	0.97	0.88	0.71
Contiguous U.S. Mean Temperature (°C)	0.31	0.35	0.25
Global Mean Precipitation (mm/day)	0.015	0.011	0.008
Sahel (10-20N, 20W-10E) Mean Precipitation (mm/day)	0.081	0.074	0.055
Amazon (10S-5N, 70-50W) Mean Precipitation (mm/day)	-0.092	-0.088	

[Figure 1. Architecture of CNN-LSTM model for climate forecasting. The model takes in past climate data and predicts future spatial fields of climate variables.]

[Figure 2. Global mean surface temperature forecasts for 2001-2020 from DL model and CESM2 compared to Berkeley Earth observations.]

[Figure 3. RMSE of 2001-2020 mean temperature (top) and precipitation (bottom) for DL model (left) and CESM2 (right) compared to observations.]

[Figure 4. Observed (left) and forecasted (right) change in temperature (top) and precipitation (bottom) between 2001-2010 and 2011-2020 for DL model (middle) and CESM2 (right). Stippling indicates changes that are not statistically significant at the 95% level.]

4. Discussion

The results presented here demonstrate the potential for DL to greatly improve the accuracy and computational efficiency of climate modeling. Our CNN-LSTM model, trained solely on historical data, was able to outperform the state-of-the-art CESM2 physics-based model at a fraction of the computational cost when evaluated on recent observations. This shows the power of DL to extract patterns from climate data and use them to make skillful predictions.

The DL approach has several key advantages over traditional physics-based modeling. First, by learning directly from observations, DL models avoid the need for parameterizations of unresolved processes, a key source of uncertainty in physics-based models [5]. Second, DL models can learn complex, non-linear relationships between climate variables that may be difficult to capture in simplified physical equations [13]. Third, the computational efficiency of DL enables a much more comprehensive exploration of future scenarios and uncertainties [19]. The speedup of over an order of magnitude demonstrated here could allow DL models to be run at much higher spatial resolutions than are currently feasible for physics-based models.

However, DL also has important limitations and challenges that must be addressed. DL models can only learn from the data they are trained on, so their accuracy depends on having a representative set of historical observations that captures the relevant physical processes [11]. For climate modeling, this means DL may have limited skill in predicting the effects of future climate forcing that is outside the range of historical variability, such as high emissions scenarios [28]. DL models can also be less interpretable than physics-based models, making it more challenging to understand the reasoning behind their predictions [29]. Finally, DL models do not conserve physical quantities like energy and mass, which could lead to unrealistic long-term forecasts if not addressed [30]. Careful evaluation of DL forecasts in the context of physical understanding remains essential.

There are several key priorities for further improving DL-based climate forecasting. Expanding the climate variables and timescales used for training could help capture additional relevant processes. Novel physics-constrained DL architectures are being developed to improve consistency with physical understanding [30],[31]. Quantifying uncertainties in DL forecasts, for example due to internal variability and interpolation errors, is also critical [32],[33]. Finally, exploring hybrid approaches that combine the strengths of DL and physics-based modeling is a promising direction [34].

This study serves as a proof-of-concept for the application of DL to climate forecasting. We focused on a single, relatively simple architecture trained on a limited set of variables over a few decades. The results show the promise of the approach, but much work remains to build operational DL climate forecasting systems and fully quantify their skill across different metrics, timescales, and scenarios. By making our data and model publicly available, we hope to accelerate progress towards this goal and enable the climate modeling community to harness the power of DL. Improving the accuracy of climate forecasts is critical for informing adaptation decisions and assessing the impacts of different emissions pathways. DL can play a key role in providing the robust, high-resolution projections needed to support effective climate change mitigation and adaptation.

5. Conclusions

Deep learning represents a powerful new approach for climate modeling that can greatly improve the accuracy and efficiency of climate forecasts compared to traditional physics-based models. Our CNN-LSTM model, trained on historical climate data from 1950-2000, significantly outperformed the CESM2 model when evaluated on holdout data from 2001-2020 while running over an order of magnitude faster. The DL model skillfully forecast the spatial and temporal patterns of temperature and precipitation change. This demonstrates the potential for DL to provide higher-resolution and more comprehensive climate projections to inform adaptation decisions.

However, important challenges remain, including improving the physical realism and interpretability of DL models. Future work expanding the training data, model architectures, and evaluation is needed to further establish the skill of DL climate forecasts across a range of conditions. The public release of our data and model aims to accelerate this research and the adoption of DL in climate science. As climate change accelerates, the continuous improvement of our ability to forecast future impacts is critical for effectively confronting this urgent challenge.

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