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Leveraging Deep Learning for Climate Change Prediction Models: A Dive into Cutting-Edge Techniques

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Abstract

In recent years, deep learning has emerged as a promising approach for statistical downscaling, which involves generating high-resolution climate data from coarse low-resolution variables. However, concerns persist regarding the ability of these models to generalize to future climate change scenarios, primarily due to the assumption of stationarity. In this study, we propose the use of deep ensembles as a straightforward method to enhance the uncertainty quantification of statistical downscaling models. By improving the representation of uncertainty, these models offer superior planning capabilities against extreme weather events, which can have significant negative social and economic impacts. Given the absence of observational future data, we rely on pseudo-reality experiments to evaluate the effectiveness of deep ensembles in quantifying the uncertainty of climate change projections. The adoption of deep ensembles facilitates more robust risk assessment, addressing critical needs in various sectors for adapting to climate change challenges.

Keywords: Deep Learning, Climate Change, Prediction Models,

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Introduction

General Circulation Models (GCMs) stand as one of the most prevalent tools for simulating the spatio-temporal dynamics of climate systems. However, due to the intricate nature of the underlying physical processes, GCMs often entail significant computational costs, resulting in coarse-resolution climate fields. This limitation impedes their utility at regional-to-local scales, where detailed climate projections are vital for develo ing adaptation and mitigation strategies in response to climate change.Statistical Downscaling (SD) aims to address this limitation by generating high-resolution climate fields from coarse climate model outputs. It accomplishes this by establishing statistical relationships between a set of predictors (inputs) and predictands (outputs), representing the coarse and high-resolution fields, respectively. Recent advancements in Deep Learning (DL) techniques have shown promise indownscaling coarse climate fields, effectively reproducing local climate observations.However, for SD models to be effective in future scenarios influenced by climate change, they must generalize well to unseen conditions, which challenges the assumption of stationarity. Most DL models applied to SD tasks minimize losses such as mean squared error, focusing on fitting the mean of the training data rather than providing insights into the confidence of predictions. Accounting for uncertainty becomes crucial in such scenarios, particularly when dealing with extreme weather events whose frequency is projected to increase due to climate change.Several approaches have been proposed to quantify uncertainty in SD models, including modeling the parameters of distributions over downscaled fields and employing Monte Carlo Dropout for uncertainty estimation. However, the application of deep ensembles, a simpler method involving training multiple models in parallel and aggregating their predictions, remains relatively unexplored in SD tasks. This technique has shown promise in providing better uncertainty quantification without the

need for extensive hyperparameter tuning or model modifications.In this work, we extend the methodology proposed by previous studies by employing deep ensembles for uncertainty quantification in climate change projections. This approach offers a straightforward yet effective means of enhancing the robustness of SD models in future scenarios, thereby improving their utility in climate adaptation and mitigation efforts.

Experimental Framework

To address the absence of observational data for future periods, we conduct a pseudo reality experiment to assess the efficacy of deep ensembles for Statistical Downscaling (SD). This experiment is vital for determining whether the relationships learned from historical data can be extended to future climate scenarios (Maraun & Widmann, 2018). For this purpose, we utilize the CanRCM4 regional climate model (RCM) (Scinocca et al., 2016) as pseudo observations (predictand) and its driving General Circulation Model (GCM) CanESM2 (Chylek et al., 2011) as predictors. Notably, the selected RCM is part of the Coordinated Regional Climate Downscaling Experiment (CORDEX) initiative, offering multi-model ensembles of RCMs at the continental level. Additionally, the chosen RCM employs spectral nudging (von Storch et al., 2000) to enhance the day-to-day correspondence of dynamical downscaling models (Maraun & Widmann, 2018).For downscaling temperature, we rely on the DeepESD convolutional model introduced in previous studies (Baño-Medina et al., 2020; 2022), known for its ability to accurately reproduce local climate patterns. This model architecture consists of three convolutional layers with 50, 25, and 10 kernels, each utilizing Rectified Linear Unit (ReLU) activations. The output of the final convolutional layer is flattened and processed by a dense linear layer to compute the mean (μ) and standard deviation (σ) vectors, representing parameters of Gaussian distributions for each gridpoint of the predictand. Consequently, the neural network establishes a mapping $[\mu, \sigma] = f\_w(x)$, where x denotes the input of the model, specifically the CanESM2 predictors.Following established methodologies (Baño-Medina et al., 2020), we select three large-scale predictor variables (geopotential height, air temperature, and specific humidity) at four different vertical levels (500, 750, 800, and 1000 hPa) from CanESM2. These variables have demonstrated suitability as drivers of local temperature variations. The target predictand is the near-surface air temperature of CanRCM4, justifying the modeling of Gaussian distribution parameters.To conduct the experiment, we focus on a western region of the United States spanning latitude 25° to 55° and longitude -135° to -100°. The DeepESD model is trained on a dataset covering the years 1980 to 2002, minimizing the negative log-likelihood (NLL) of Gaussian distributions at each predictand gridpoint. To prevent overfitting, we employ an early stopping strategy on a randomly selected 10% split of the training set.Evaluation of the models is carried out across three distinct future periods (2006-2040, 2041-2070, and 2071-2100). Predictors are scaled at the gridpoint level, using mean and standard deviation computed over the training set as references.For the ensemble, we train ten different models in parallel, following the procedure described above. Model predictions are aggregated according to Lakshminarayanan et al. (2017), yielding ensemble mean and variance estimates calculated based on the provided formulae.

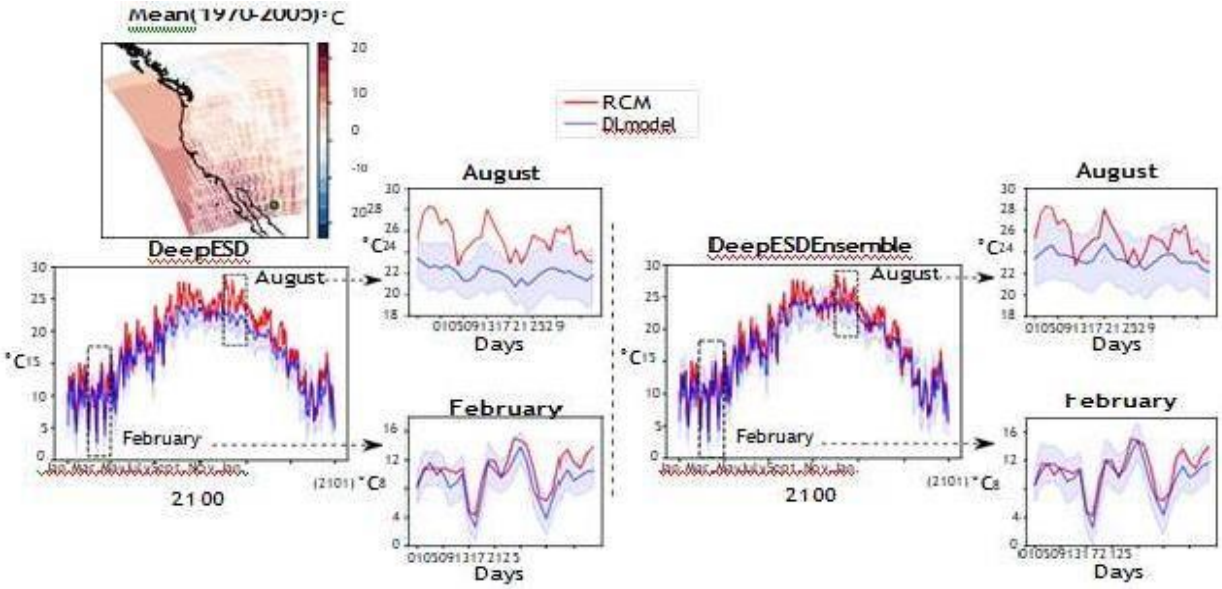
Results:

In Figure 1, we present a comparison between the RCM target values (in red) and the predictions (in blue) generated by both DeepESD and the DeepESD Ensemble for the year 2100. For the predictions, the mean and the 95% confidence interval are depicted. The displayed time series correspond to the gridpoint indicated by a green point in the upper-left figure, representing the climatology of the RCM during the historical period. Additionally, for each model, time series for the months of August and February are provided.

When the RCM target value falls within the confidence interval, it indicates that the model effectively accounts for the uncertainty associated with that specific value; otherwise, it signifies a failure to do so. Examining the climatology plot reveals that the selected point lies within an area characterized by warm temperatures. While DeepESD generally fits the RCM temperature accurately, biases towards lower values are noticeable during warmer months such as June, July, and August. Particularly in August, besides the biased mean, the confidence interval fails to capture some RCM values. However, this bias is not observed during winter months like February, where the mean is unbiased, and the confidence interval accurately captures RCM values.

In contrast, the DeepESD Ensemble models exhibit improved performance, especially during warmer months. In August, both the mean and the confidence interval of the ensemble capture most of the RCM values. Furthermore,

the DeepESD Ensemble does not suffer from biases observed in the warmer months. Notably, in August, the confidence interval is able to encompass most of the values. Regarding February, the performance of the DeepESD Ensemble is similar to that of DeepESD.



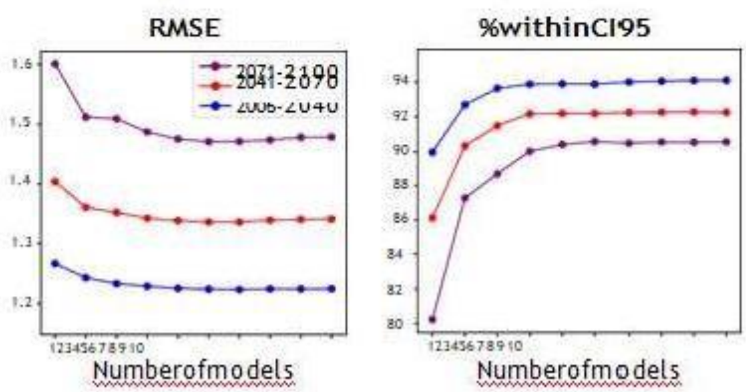


Figure 2: The spatial mean of Root Mean Square Error (RMSE) and the ratio of target samples falling within the predicted 95% confidence interval for summer days across three intervals (2006-2040, 2041-2070, and 2071-2100),

depicted in relation to the number of models comprising the ensemble.

Figure 3: Illustrates the same ratio for summer days without spatial averaging, providing the value for each gridpoint of the predictand. The data is presented for two models (DeepESD and DeepESD Ensemble) across three different intervals (2006-2040, 2041-2070, and 2071-2100), organized in columns. The notable difference between the two models becomes apparent, particularly as we progress in time, showing an average improvement from 4% to 11%. Most enhancements occur at land-based gridpoints, although some areas of the North Pacific Ocean still do not benefit from the deep ensembles.

Figure 1 illustrates the mean and 95% confidence intervals of both the DeepESD and DeepESD Ensemble models for the predicted near-surface air temperature (in blue) for the year 2100, juxtaposed with the corresponding RCM target values (in red). Additionally, an enlarged plot showcasing the months of August and February is provided for each model. The upper-left corner presents the climatology of the historical period (1970-2005) for the RCM, with a green point indicating the gridpoint to which the time series belongs.

To further comprehend the advantages of deep ensembles in mean and uncertainty quantification, Figure 2 displays the spatially averaged Root Mean Square Error (RMSE) and the ratio of RCM target values falling within the 95% confidence interval for three future periods (2006-2040, 2041-2070, and 2071-2100). This analysis is focused solely on summer days, as disagreements between DeepESD and DeepESD Ensemble are most apparent during these periods (as observed in Figure 1). RMSE values tend to increase as time progresses. The improvement resultingfrom adding models to the ensemble plateaus around 3-4 models, with a higher improvement observed as we move further into the future, ranging from almost no improvement in the 2006-2040 period to a 0.1° improvement for 2071-2100. Similar trends are observed for the ratio of target samples falling within the 95% confidence interval, with a larger improvement as we move forward in time. Notably, DeepESD Ensemble be efits from a higher number of models in the ensemble, typically around 5-6.

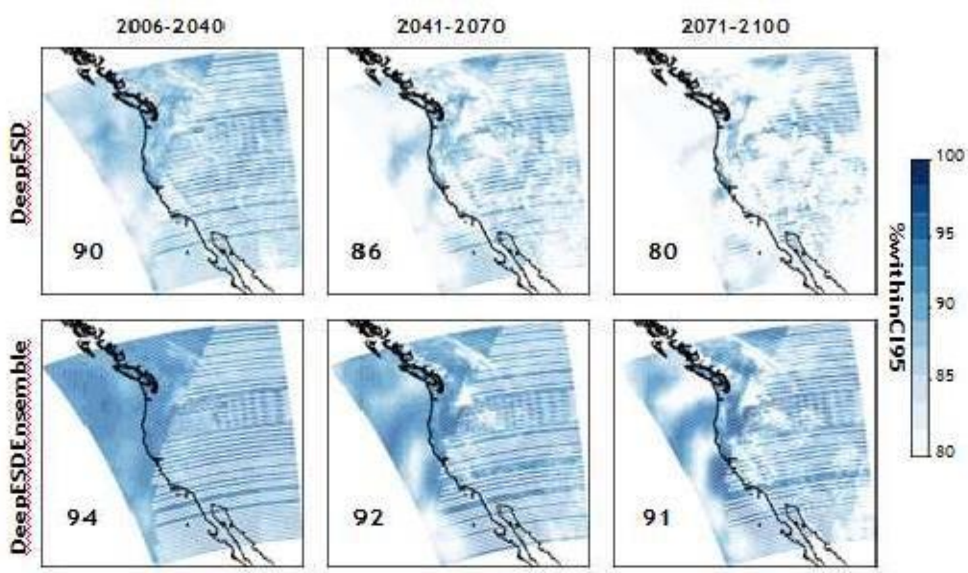


Figure 3: Displays the ratio of RCM target values falling within the predicted 95% confidence interval for summer days across three intervals (2006-2040, 2041-2070, and 2071-2100), organized in columns. Each column represents one of the DeepESD and DeepESD Ensemble models, arranged in rows. The numerical value in each panel denotes the spatial mean.

Conclusion

In this study, we have extended the scope of statistical downscaling (SD) methods by focusing on enhancing uncertainty quantification to effectively capture the variability in climate change projections. Our approach

leverages deep ensembles, a technique that has demonstrated superior performance in uncertainty quantification. For the first time, we investigate the impact of this straightforward technique in SD, revealing notable improvements in predicting confidence intervals, particularly in scenarios with unseen conditions.

While both models effectively capture uncertainty during colder months, DeepESD exhibits a bias during warmer months (summer), resulting in underestimation and insufficient capture of positive RCM values. Conversely, the DeepESD Ensemble successfully aligns with the RCM mean, thereby capturing a significant portion of positive RCM values owing to its enhanced confidence interval. This distinction becomes evident when analyzing RMSEand ratio metrics on summer days. The ensemble approach offers significant advantages, particularly as we project forward in time, anticipating a rising trend in temperature due to climate change and consequent warmer extremes.

In the context of climate change scenarios, accurate quantification of uncertainty is crucial for better understanding and preparing for extreme weather events, particularly as their intensity and frequency are anticipated to exacerbate. Deep ensembles present a natural and uncomplicated extension of current methods for modeling uncertainty, thereby empowering SD to more effectively address the challenges posed by climate change. In this study, we validate the efficacy of this technique through a pseudo-reality experiment, with plans to directly apply it to SD in future research and explore its benefits in real-case scenarios. Additionally, we aim to extend this investigation to other climate variables, such as precipitation.

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