Super-resolution for downscaling climate data

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I. Extended Abstract

A common task in Earth Sciences is to infer climate information at local and regional scales from global climate models. An alternative to running expensive numerical models at high resolution is to use statistical downscaling techniques. Statistical downscaling aims at learning empirical links between the large-scale and local-scale climate, i.e., a mapping from a low-resolution gridded variable to a higher-resolution grid that incorporates observational data.

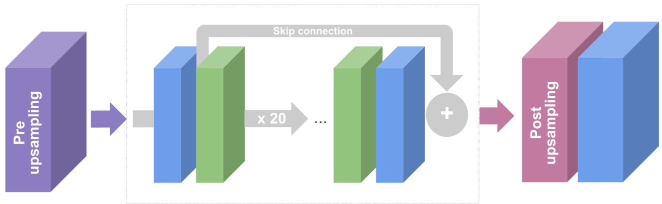
Seasonal climate predictions can forecast the climate variability up to several months ahead and support a wide range of societal activities. The coarse spatial resolution of seasonal forecasts needs to be downscaled or refined to the local scale for specific applications.

In this study, we present super-resolution (SR) techniques for the task of downscaling climate variables with a focus on temperature over Catalonia. Our models are trained using high and medium resolution ($\sim$5 and $\sim$25 km) gridded climate datasets with the ultimate goal of increasing the resolution of coarse resolution ($\sim$100 km) seasonal forecasting systems. Taking the gridded data from $\sim$100 to $\sim$5 km implies a 20x upscaling factor. It is worth pointing out that handling such large upsampling factor is not typical in computer vision, where most applications focus in 4x factors while 16x is considered as extreme SR.

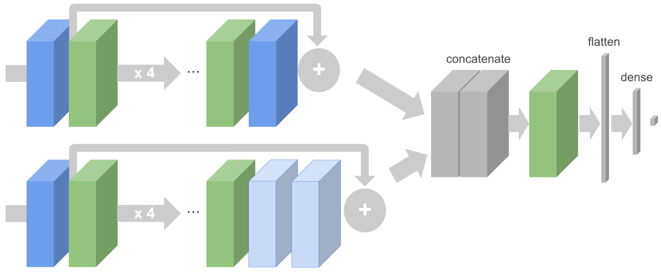
A. *Super-resolution for statistical downscaling*

Statistical downscaling of gridded climate variables is a task closely related to that of SR in computer vision, considering that both aim at learning a mapping between low- and high-resolution images. Unsurprisingly, several deep learning-based approaches have been explored by the climate community in recent years [1], [2].

For this study, we work with data from two reanalysis datasets: ERA5 [3], produced by the European Centre for Medium-range Weather Forecasts (ECMWF), and UERRA MESCAN-SURFEX [4]. ERA5 provides hourly estimates of a large number of atmospheric, land and oceanic climate variables at a resolution of 0.25º ($\sim$25 km). UERRA MESCAN-SURFEX provides temperature, precipitation and wind at a resolution of 0.05º ($\sim$5 km). We focus on temperature at two meters above the ground from both ERA5 and UERRA, selecting the period between 1979 and 2019 at a daily temporal resolution, resulting in about 14k temporal samples. The inference is performed on the ECMWF's seasonal forecast system, SEAS5 [5] to downscale its coarse temperature grids from $\sim$100 to $\sim$5km resolution in a transfer learning fashion.



(a) Supervised ResNet / Generator



(b) Residual discriminator

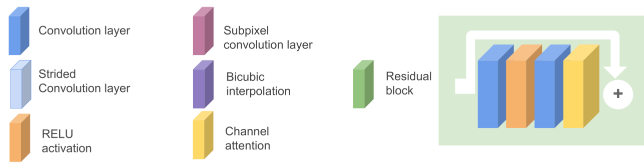


Fig. 1. Panel (a) shows the architecture of our SR CGAN generator, while panel (b) shows the architecture of our SR CGAN discriminator. The architecture of the supervised ResNets is the same of the CGAN generators.

B. *Methods*

Four different deep learning-based methods were implemented for downscaling temperature gridded fields: ResNet-INT, ResNet-SPC, and their conditional adversarial counterparts, CGAN ResNet-INT and CGAN ResNet-SPC. The ResNet-SPC is based on the EDSR [6] SR model, with residual blocks using skip connections and without batch-normalization. On the panel (a) of Fig. 1, we show the architecture of our ResNets. These networks share the main section, inside the dotted-line box, composed of convolutional layers and a stack of twenty residual blocks. The ResNet-INT, short for residual neural network with pre-upsampling via bicubic interpolation, is a model that learns an end-to-end mapping from interpolated LR images to HR images. HR UERRA/ERA5 images are downsampled by a given factor to create LR counterparts. These are then upsampled to match the size of the HR image before entering the network. The ResNet-SPC works in a post-upsampling framework using subpixel convolution layers [6]. This model learns a mapping from LR to HR images, of different sizes, in low-dimensional space and

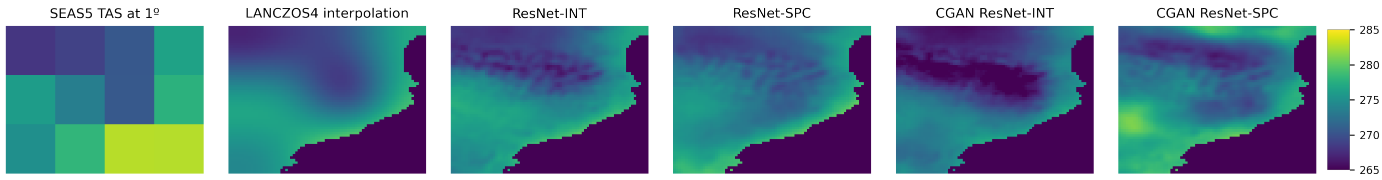


Fig. 2. Comparison of the SR models proposed in this study with respect to a LANCZOS4 interpolation for a single SEAS5 temperature grid.

requiring less computations.

Our CGAN ResNet-INT and CGAN ResNet-SPC are Conditional Generative Adversarial Networks (CGAN) [7] that use either the ResNet-INT or ResNet-SPC as generators. GANs are generative models that rely on a generator that learns to generate new (HR) images (from a LR counterpart), and a discriminator that learns to distinguish synthetic (HR) images from reference (HR) images. CGANs are supervised GANs that are trained with paired samples. We concatenate to all our input samples a topographical map and a land-ocean binary mask, as proposed in [1]. The addition of these fields, as image channels, improves the reconstruction of high-frequency details while downscaling the temperature fields.

To achieve a 20x upscaling factor, our models are composed of a stack of two networks, each one trained separately: LR to MR (4x, using ERA5) and MR to HR (5x, using UERRA). The inference is performed progressively. We tested training single models to jump from LR to HR resolution directly but the results were poor in general. All the networks were trained with sixty-four filters per layer and convolution kernels of size 3x3. The supervised ResNets and the CGAN ResNets were trained for 180 and 60 epochs respectively using the Adam optimizer. The supervised ResNet optimize a mean absolute error (MAE) loss function. A holdout of eight years was used for testing the performance of the trained models. During training, a validation dataset was used to monitor the behavior of the loss function and avoid overfitting.

C. Results

Figure 2 shows a side-by-side comparison of the four different SR algorithms developed for downscaling SEAS5 temperature from its native 1° to the 0.05° resolution. This temperature grid corresponds to a single date and a single SEAS5 ensemble member. Table I summarizes the performance of each model in terms of the spatial RMSE and Pearson correlation. These metrics are computed per each pair of images: the model prediction and its reference from the holdout UERRA dataset. Based on these metrics and on visual inspection, we argue that the CGAN ResNet-SPC stands out at recovering high-frequency details while downscaling SEAS5 grids not seen during training. Additionally, we have compared our results with those of a traditional technique for statistical downscaling, the KNN-based analogs method. This method delivers higher RMSE and lower correlation, but is on par with the deep learning-based models in terms of the ranked probability skill score, a metric used for validating seasonal forecasts.

TABLE I. VALIDATION METRICS FOR EACH SR METHOD

CNN model	MSE	Pearson correlation
ResNet-INT	0.6379	0.9865
ResNet-SPC	0.5153	0.9912
CGAN R-INT	0.6472	0.9860
CGAN R-SPC	**0.4960**	**0.9917**

D. Summary

In this study, we developed SR models for the task of downscaling temperature fields and showed their superior performance with respect to a LANCZOS4 interpolation baseline. We thoroughly tested different architecture choices, such as the type of upsampling or the training strategy (adversarial vs non-adversarial). In the future, we will perform more rigurous ablation studies for tuning these networks and explore tailored loss functions (beyond MAE and reconstructive losses) for improving the skill of the seasonal forecasts.

II. Acknowledgments

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