May Deep Learning contribute to improve Downscaling techniques?

Peña-Izquierdo J., Gómez Gonzalez C., Marcos R., Pérez-Zanón N.

Barcelona Supercomputing Center, Barcelona, Spain.

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Summary

Downscaling techniques are a common data-driven methodology used to generate high resolution forecasts without the need of running computationally expensive simulations. Climate variables from a low resolution dataset (predictors) are used to train an algorithm with a respective high resolution ground truth (predictand). Under the perfect prognosis approach, both the predictors and the predictand belong to an observational dataset. The algorithm learns finer grain structures not resolved by the coarse grid but present in the high resolution predictand used during training. Once trained, this algorithm can be used to infer fine structures from an independent low resolution numerical simulation. Classical downscaling techniques are usually based on the implementation of multivariate regressions or analogues (Ribalaygua et al. 2013, Maraun et al. 2014, Perez-Zanon et al. 2020). However, impressive recent progress in the field of computer vision through the implementation of deep neural networks has opened a new world of possibilities (Baño-Medina et al. 2019, Leinonen et al. 2020). In this work, we start an initial exploratory analysis to assess the potential of deep learning architectures in generating downscaling products. In particular, we focus on the implementation of encoder-decoder architectures (U-Net) without any physical constraint, in contrast with previous studies (Baño-Medina et al. 2019) that include some type of ad-hoc assumptions. Although imposing some physical constraints may guarantee some known properties of the simulated phenomena, it may also come with downsides effects in the prediction performance due to loss of degrees of freedom. This work aims to pave the road for more advanced approaches capable of competing with the state-of-the-art methods.

Dataset

PREDICTORS
ERA5 daily (1.4ºx1.4º)

Total precipitation
2m temperature
10m u-component of wind
10 v-component of wind
Orography
Total cloud cover
Specific Humidity 700, 850 hPa
Temperature 500 hPa
Geopotential 500, 1000hPa

Downscale

PREDICTAND
ERA5 daily (0.25ºx0.25º)

Total precipitation

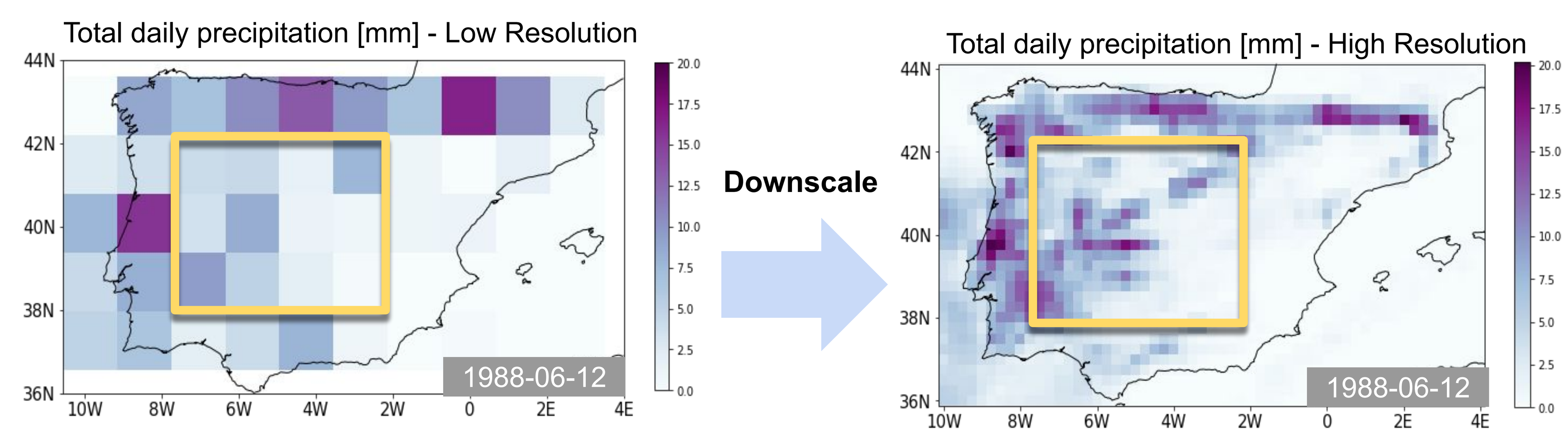


Figure 1. Field for total daily precipitation for a given date (1988-06-12) for the low resolution (left) and high resolution (right) datasets. Yellow squares indicate the area used as case study for the downscaling [8W-2W, 38N 42N].

- Dataset used in this study is the ERA5 reanalysis [Hersbach et al. 2020] with a daily temporal resolution from 1979 to 2018.
- Eleven predictors are selected from an interpolated (1.4ºx1.4º) version of ERA5
- Predictand is the daily precipitation from the original ERA5 dataset (0.25ºx0.25º).
- All variables are deseasonalized and normalized within the range [0,1]

Model

- Deep Learning computer vision architectures are mainly composed by convolutional layers
- A modified version of the U-net convolutional neural network [Ronneberger et al. 2015] is implemented.
- Advantage of this architecture is the use of skip connections [yellow arrows] that preserve information of different semantic levels.
- Model input is the bilinear interpolation of the low resolution predictors into the high resolution grid of the predictand

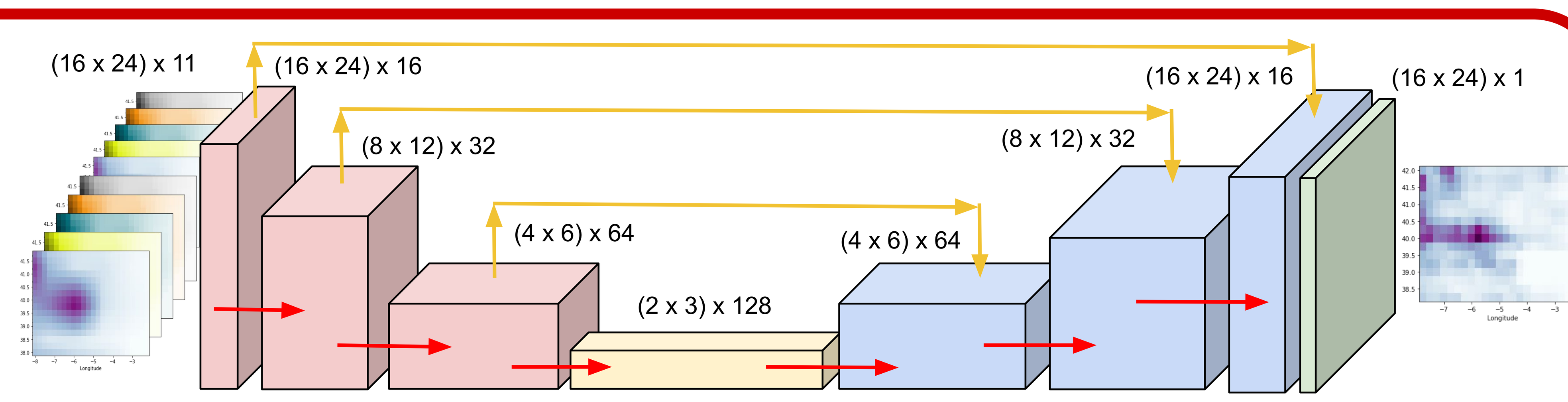
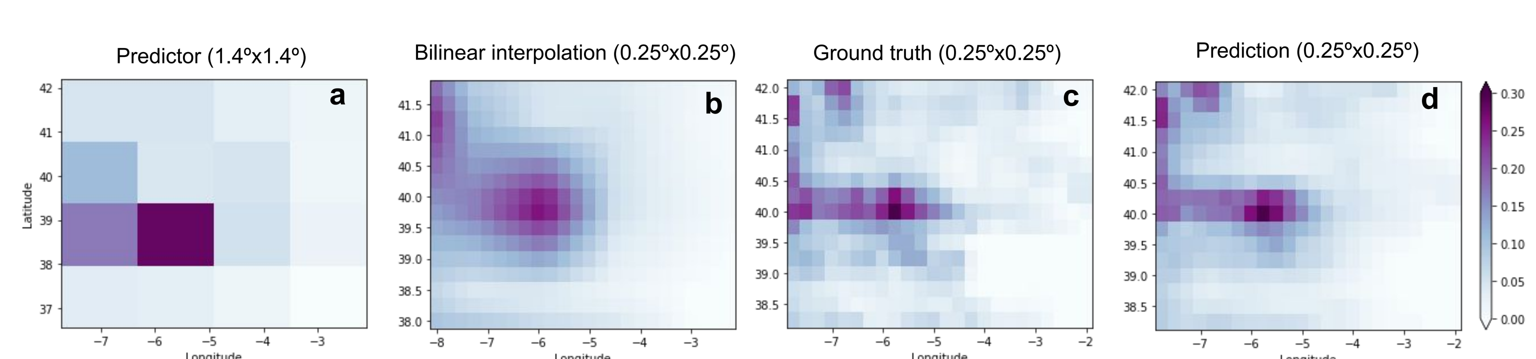
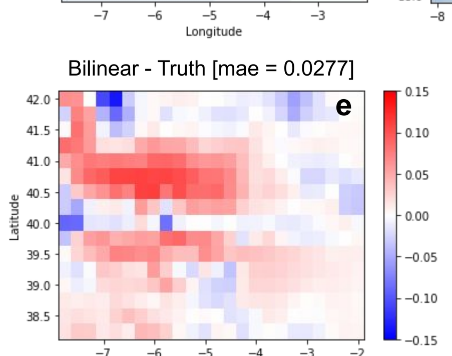


Figure 2. Schematic description of the implemented version of the Unet. Each block includes a convolution layer together with a 2D maxpooling (2D upsampling) layer for the different encoder (decoder) steps

Results

- The bilinear interpolation of the total precipitation field from the low resolution to the high resolution is used as benchmark, [Figure 3].
- Training / validation set is randomly sampled from the total number of daily samples in the dataset (14610 images) with a ratio of 80 / 20% respectively.
- A validation set of unseen data by the model is used for validation [Figure 3 and 4]
- Our model outperforms the benchmark by a significant amount in most cases.





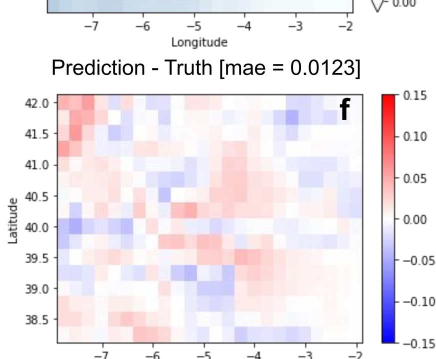


Figure 3. A sample downscale prediction is shown here. Low resolution predictors (a) are interpolated to the high resolution grid (b). Model trained with the ground truth (c) produces images with finer scale (d). Mean Absolute Error (mae) for the bilinear interpolation (e) and for our model (f) shows reduction in error up to 50%.

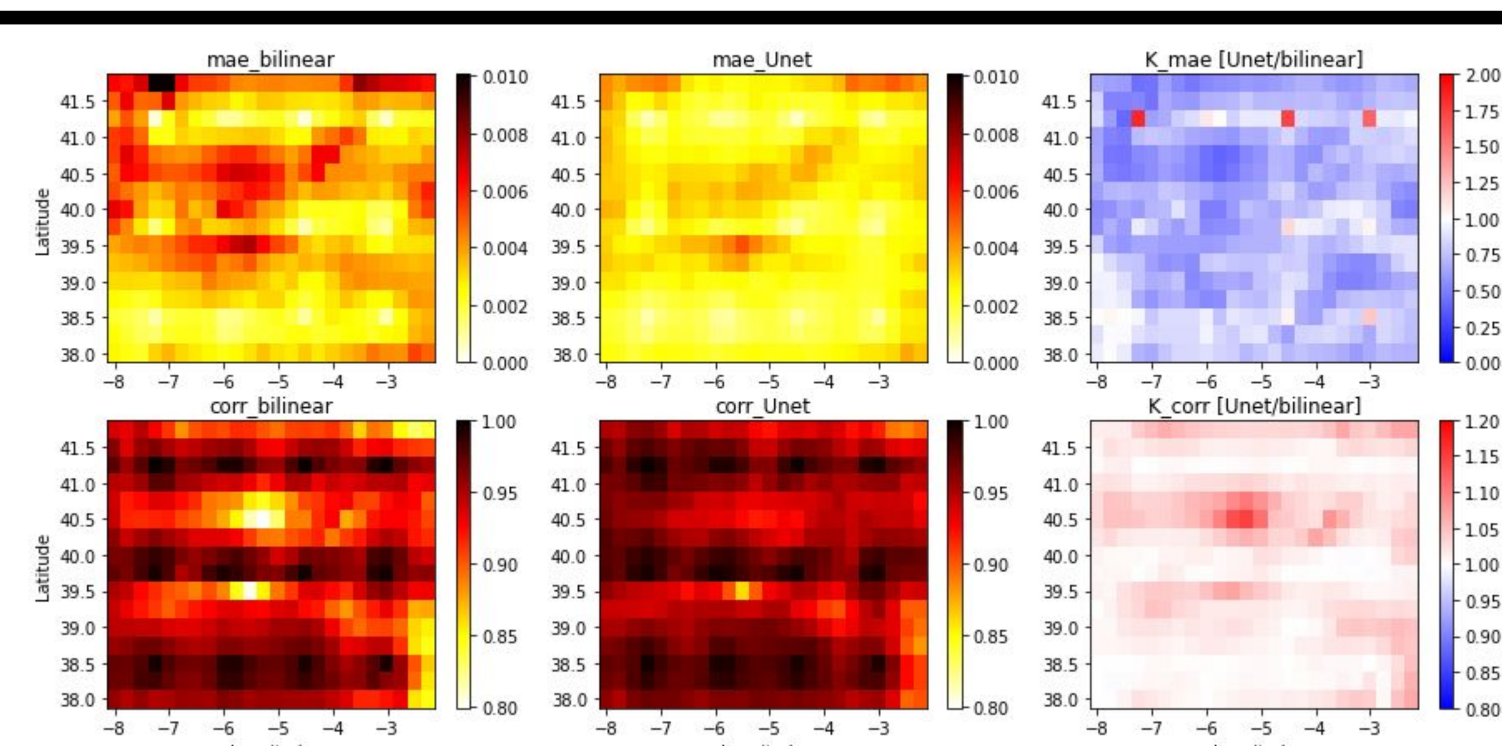


Figure 4. Mean values for Mean Absolute Error [mae] and Correlation [corr] obtained from the validation set for the benchmark (bilinear interpolation) and for our model (Unet) for the area of study. The ratio between metrics values from our model and from the benchmark are shown in the right column; Values smaller / larger than 1 indicates a reduction / increase by our model. For mae a reduction is desired while for corr an increase is expected.

- Average values for the Mean Absolute Error and the Correlation [Figure 4] obtained from the unseen validation data show overall good performance of our model in the area of study.
- Mean Absolute Error is reduced in average a 31% compared with the benchmark. There is certain spatial variability with local regions showing values of reduction around 50%.
- Correlation is also improved with our model although since the benchmark is an interpolation of the ground truth, the base correlation values were already very high. Still an average improvement of the 5% is obtained.

Conclusions

- Our exploratory analysis reveals than even simple convolutional neural networks architectures are able to provide significant improvements (around a 30% reduction in error) from a basic benchmark.
- According to this preliminary test study, adding complexity to the model does not provide better results. This is likely explained by the “limited” number of training sample (~13.000). More complex models are able to extract more complex patterns but they have the requirement of training with much larger number of samples.
- An alternative solution to this limitation is the use of a larger domain. While this does not directly increase the number of samples, it provides more information in general to the model (more pixels). Simultaneously this can be used for extracting more subtle features that our small domain does not provide.
- Another very promising alternative would be the use of generative models (Leinonen et al. 2020). Generative models have the ability to learn the statistical distribution of high level features which is used in turn to generate plausible prediction small scale features. This methodology would also allow the generation of ensemble of predictions which would provide a convenient probability distribution prediction.

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