CSDownscale: an R Package for Statistical Downscaling

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***Abstract*—Downscaling is any procedure to infer high-resolution information from low-resolution variables. Many of these techniques have been defined and applied to climate predictions, which suffer from important biases due to the coarse global grids in which they are delivered.**

To help solve this undesirable issue, the R package resulting from this work provides a set of statistical downscaling methods for climate predictions, ready to be applied to refine the output of climate predictions.

A. *Introduction*

Climate predictions appear helpful in anticipating climate variations and taking timely action to manage their possible effects better. Their applicability in many sectors such as agriculture or renewable energy has increased lately, mirroring their potential value and cost-saving benefits[1]. Climate predictions rely on General Circulation Models (GCMs), which are based on a set of equations representing the dynamics of the atmosphere plus other processes occurring in oceans or the land surface.

These predictions are obtained on a global scale. Therefore, the grids used to compute the model values avoid using fine spatial resolutions in order to reduce computational costs. The downside, however, is that climate values at the fine or local scale are often misrepresented due to biases and drifts produced by the fact that model values represent an average value for a grid cell of thousands of square kilometres[2]. The so-called representativeness errors limit the usage of climate predictions for regional or local applications.

To transfer the coarse-scale information into the fine-scale, downscaling techniques have been introduced into the climate prediction arena. Two types of downscaling techniques do exist. Dynamical downscaling uses a Regional Climate Model, which is coupled to the GCMs, using its output as boundary conditions, to model the fine-scale phenomena that cannot be simulated by the GCMs alone. Although dynamical downscaling may be preferred for some applications, it is known to be computationally expensive[3]. On the other hand, statistical downscaling uses empirical relationships established by the coarse-scale data (predictor) and the fine-scale values (predictand). The statistical downscaling approach (see [4] for a review) is relatively straightforward to implement with climate prediction systems and is computationally cheaper than dynamical downscaling. The present work compiles different statistical downscaling techniques for climate predictions and provides the code using the R programming language.

B. *Statistical downscaling methods*

Table 1 summarises the six statistical downscaling methodologies available in the R package CSDownscale.

TABLE I
STATISTICAL DOWNSCALING METHODS IN CSDOWNSCALE

Method	Definition
Interpolation	Regrid of a coarse-scale grid into a fine-scale grid, or interpolate model data into a point location. Different interpolation methods, based on different mathematical approaches, can be applied: conservative, nearest neighbour, bilinear or bicubic. Does not rely on any data for training.
Interpolation plus bias adjustment	Interpolate model data into a fine-scale grid or point location. Later, a bias adjustment of the interpolated values is performed. Bias adjustment techniques include simple bias correction, calibration or quantile mapping.
Interpolation plus linear regression	Interpolate model data into a fine-scale grid or point location. Later, a linear-regression with the interpolated values is fitted using high-res observations as predictands, and then applied with model data to correct the interpolated values.
Large-scale predictors and local ECVs	Interpolate model data into a fine-scale grid or point location. Later, a linear-regression with large-scale predictors from the same model (e.g. teleconnection indices) is fitted using high-resolution observations as predictands. Finally, the linear-regression is applied with model data to correct the interpolated values.
Stencil	Interpolate model data into a fine-scale grid or point location. Later, a linear-regression with the four (or nine) nearest neighbours is fitted using high-resolution observations as predictands, and then applied with model data to correct the interpolated values.
Logistic regression	Relate ensemble mean anomalies of the large-scale forecasts directly to probabilities of observing above normal/normal/below normal conditions at the local scale using a sigmoid function. It does not produce an ensemble of forecasts but rather their associated probabilities. It is a statistical method with few parameters to train, and only benefits from local information, but it has shown good performance.

C. *Results*

The R package CSDownscale has been applied to actual climate data. Seasonal predictions for surface temperatures in February in the Iberian Peninsula have been downscaled from 1º to ~0.3º of horizontal resolution. The SEAS5 seasonal prediction system (Figure 1 (a)) has a spatial resolution of 1 degree, thus being unable to represent localities and particularities of temperatures in highly heterogeneous areas (e.g. mountainous regions or coastlines).

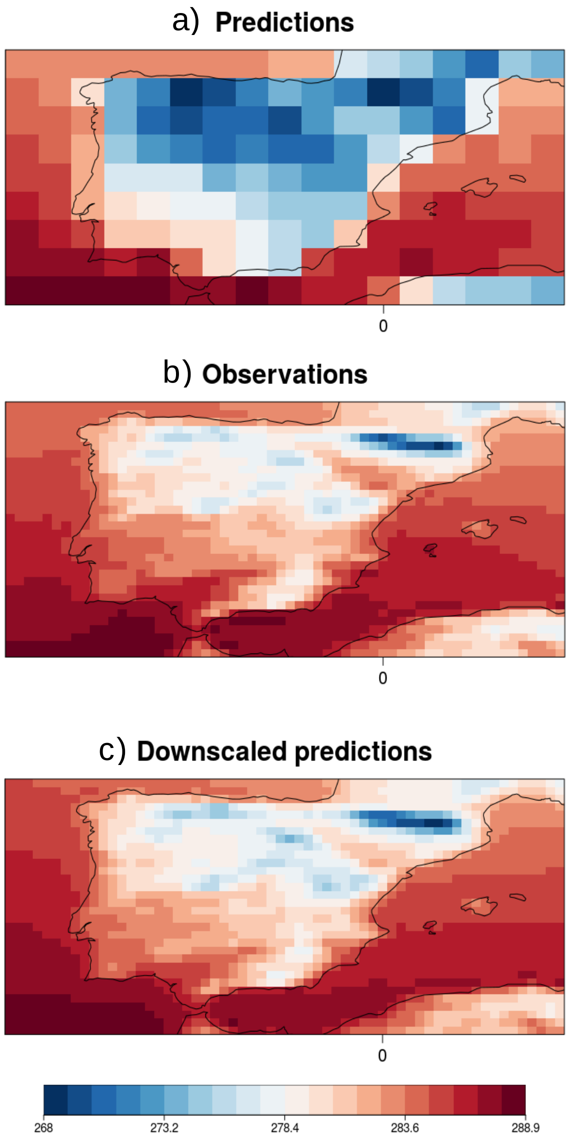

Fig. 1 a) SEAS5 seasonal prediction for surface temperature in its original grid, b) ERA5 observations for the same variable in the high-resolution grid and c) downscaled seasonal predictions to the high-resolution grid using the Analogs method. Lead month is zero and the represented month is February 2000. Temperatures are measured in Kelvin (K).

These differences are especially noticeable after comparing the observed temperatures for that particular month (Figure 1 (b)). Predicted values appear systematically underestimated all over the Iberian Peninsula. Moreover, mountainous regions and coastlines features are not properly represented in the prediction field due to representativity issues.

The downscaled seasonal prediction (Figure 1 (c)) appears to reproduce the local singularities: temperatures are systematically lower in mountainous ranges (e.g. Pyrenees) and higher within the valleys (e.g. Ebro river valley). The discontinuity in the temperature values expected along the coastlines is also noticeable.

D. Conclusions

Statistical downscaling is a cheap and efficient tool to generate seasonal predictions at a fine scale. Different methodologies are available in CSDownscale, allowing for rapid comparison of the strengths and weaknesses between methods.

The applicability of CSDownscale is not restricted to the climate field, but other sectors like agriculture or renewable energy may benefit from analyses using CSDownscale. The wind power industry, for example, may benefit from downscaled seasonal predictions at the wind farm scale and advance the amount of renewable generation.

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Author biography

Jaume Ramon holds a PhD in Physics since January 2022, entirely developed at the Earth Sciences department of the Barcelona Supercomputing Center. He is currently a post-doc researcher at the same institution, where he works hard to improve the quality of seasonal predictions. He also does his best at writing clean and efficient code. A lover of gardening and passionate about board games.