pyClim-SDM: a software for statistical downscaling of climate change projections with a graphical user interface.

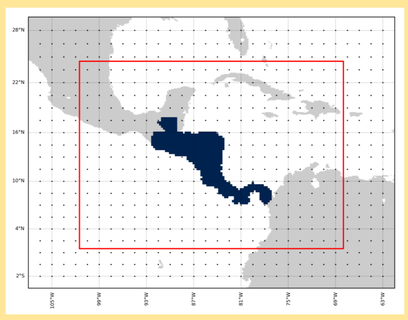
Alfonso Hernanz[1], Carlos Correa[1], Juan Andrés García-Valero[2], Marta Domínguez[1], Esteban Rodríguez-Guisado[1], Ernesto Rodríguez-Camino[1]

1 Spanish Meteorological Agency (AEMET), Madrid, 28040, Spain
2 AEMET, Murcia, 30107, Spain
Correspondence to: Alfonso Hernanz (ahernanzl@aemet.es)

Summary

The climate change impact and adaptation communities need future scenarios with sufficient high resolution, which are usually achieved by applying Statistical Downscaling Models (SDMs) over Global Climate Models. A large variety of SDMs exists, and some can be more suitable than others for each specific purpose. For this reason, it is important to develop tools to facilitate the evaluation and generation of downscaled scenarios following different approaches. We present a python software, pyClim-SDM, freely available at https://github.com/ahernanzl/pyClim-SDM, which allows users to generate their own downscaled scenarios with a very simple and user-friendly graphical interface. This software includes a large collection of *state-of-the-art* methods belonging to different families to downscale daily data of the following surface variables: temperature, precipitation, wind, relative humidity and cloud coverage. Additionally, the software is prepared to be applied over any other user defined target variable. Thus, multivariable indexes can be tackled as target variables themselves, instead of being calculated from the downscaled fundamental variables. With this possibility, potential intervariable inconsistencies are avoided. An application example for a Fire Weather Index, dependent on temperature, wind, humidity and precipitation, is shown.

Data



Predictands: reanalysis ERA5 (Hersbach *et al.*, 2020) of the European Center for Medium-Range Weather Forecasts (ECMWF) with a resolution of 0.25º in Central America.

Predictors: for evaluation, same reanalysis but with a resolution of 1.5º, and for application, seven CMIP6 (Eyring *et al.*, 2016) models interpolated to the same resolution in the domain (23.5ºN, 100.5ºW, 1ºN, 70.5ºW).

Methods

Raw GCMs (RAW):
- **RAW**: nearest neighbor
- **RAW-BIL**: bilinear interpolation

Model Output Statistics (MOS):
- **QM**: empirical Quantile Mapping
- **DQM**: Detrended Quantile Mapping
- **QDM**: Quantile Delta Mapping
- **PSDM**: (Parametric) Scaled Distribution Mapping

Analogs / Weather Typing (ANA):
- **ANA-SYN**: Analog based on synoptic analogy. **1NN**: Nearest analog, **kNN**: k-nearest analogs, **rand**: random analog from Probability Density Function.
- **ANA-LOC**: Same as ANA-SYN but using synoptic+local analogy.
- **ANA-VAR**: Same as ANA-SYN but using the spatial pattern of the target variable itself.

Linear (LIN):
- **MLR**: multiple linear regression. **MLR-ANA**: multiple linear regression based on analogs. **MLR-WT**: multiple linear regression based on weather types.
- **GLM**: Generalized Linear Model. Logistic + MLR (**LIN**), or over transformed data (**EXP** for exponential and **CUB** for cubic regression).

Machine Learning (ML):
- **SVM**: Support Vector Machine.
- **LS-SVM**: Least Square Support Vector Machine.
- **RF**: Random Forest.
- **XGB**: eXtreme Gradient Boost.
- **ANN**: Artificial Neural Networks.
- **CNN**: Convoltional Neural Network.

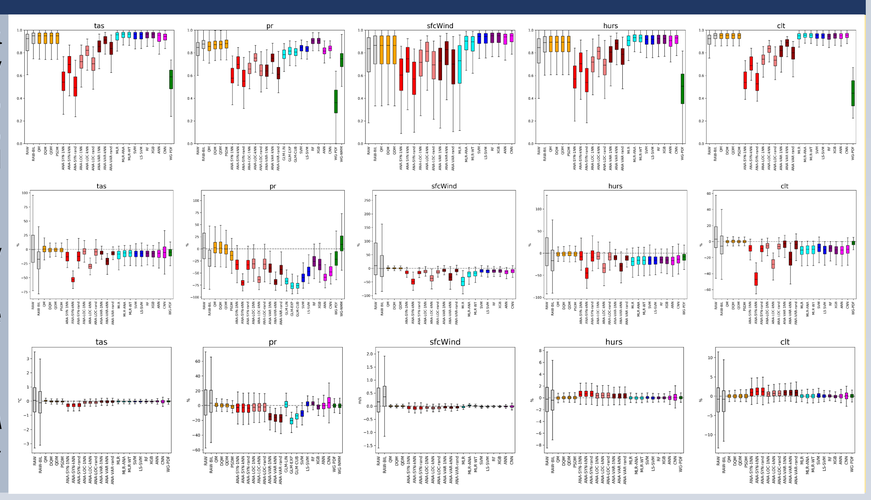
Weather Generators (WG):
- **WG-PDF**: Downscaling parameters of the distributions instead of downscaling daily data.
- **WG-NMM**: Non-homogeneous Markov Model.

Evaluation

Evaluation results in a historical period for daily surface temperature, precipitation, wind speed, relative humidity and cloud cover, are shown:

1. Correlation of daily series.
2. Bias in variance of the daily series.
3. Bias in mean values.

RAW (gray), MOS (orange), ANA (reds), LIN (cyan), ML (blue/purple/pink), WG (green)



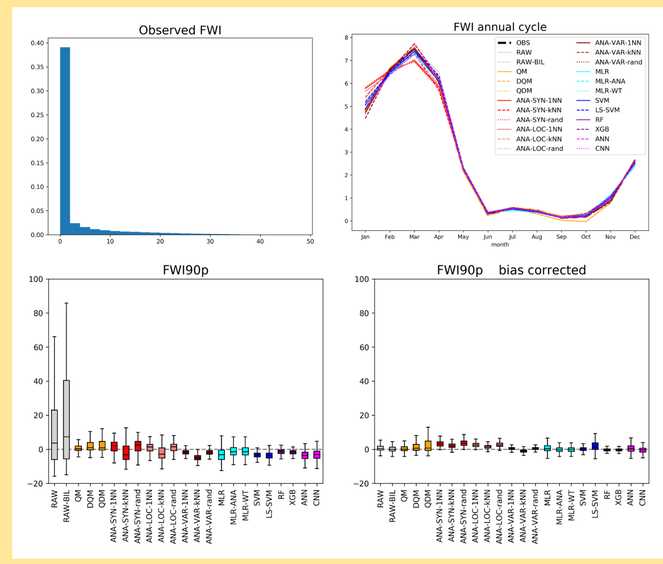
Application:

Fire Weather Index (FWI)

Evaluation

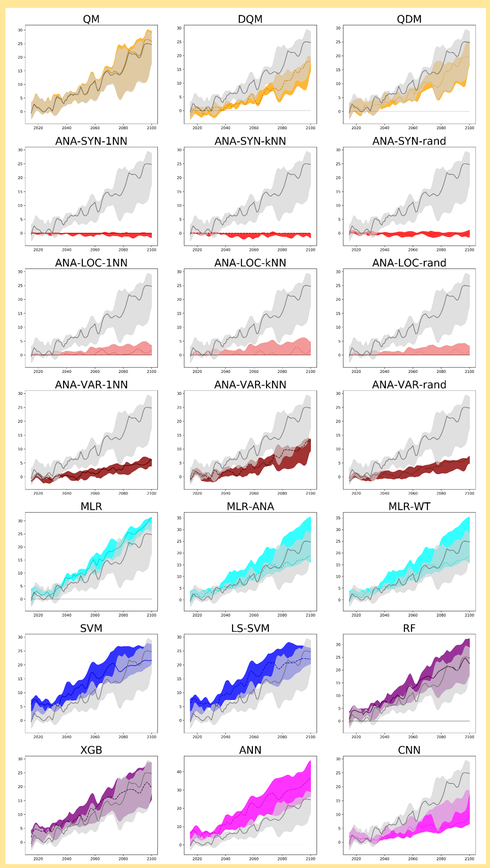
As an application example, the Canadian Fire Weather Index (Van Wagner, 1987), which depends on temperature, precipitation, wind and humidity, has been used.

The observed FWI histogram shows how this variable has a non Gaussian distribution with most data close to zero. The annual cycle for FWI averaged in the whole region shows a clear seasonality, which accompanies the precipitation cycle (not shown). The interest of the study should be in capturing the higher values of FWI, so it will be focused on the tail of the distribution and during the dry season (from January to April). In order to study the FWI extremes, the number of days over its 90th percentile (FWI90p) in a reference period has been chosen. All SDMs capture this index with good accuracy, greatly improving results from a simple interpolation. And when a bias correction is applied, both RAW and SDMs improve their results reaching very low biases in FWI90p during the dry season.



Histogram of observed FWI (top-left), annual cycle of observed and downscaled FWI (top-right), bias for the number of days over the 90th percentile of FWI in the dry season by SDMs (bottom-left) and SDMs bias corrected using QM by seasons (bottom-right).

Trends



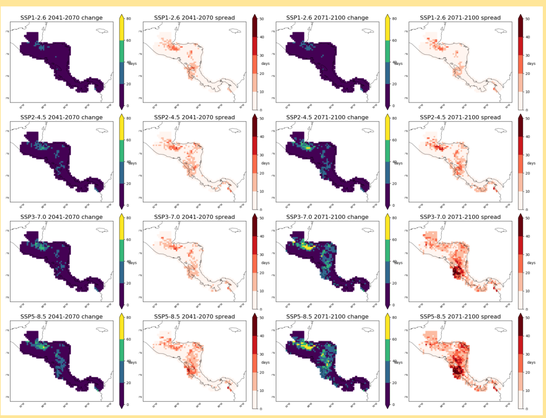
SDMs are calibrated and evaluated in a historical period, but then they are applied over future projections, usually under different climatic conditions. The historical evaluation does not guarantee that SDMs will behave as expected in the future for different reasons: the predictors/predictand relationships might change in the future or some methods might behave wrongly out of the observed range. For this reason, SDMs must be also evaluated in the future, and the analysis here included focuses on the preservation of GCMs trends by SDMs. Trends by raw GCMs and SDMs must be compared over large areas, because they operate in different spatial scales. When comparing trends given by raw GCMs under SSP5-8.5 with trends given by bias corrected SDMs, remarkable differences arise among different methods. Some of them intensify the increase projected by GCMs, while others reveal themselves unable to simulate the signal of change at all.

Change in the number of days over the 90th percentile (days) of FWI under SSP5-8.5, spatially averaged, by RAW (gray) and each SDM bias corrected using QM by season. The shaded area expands from the 25th to the 75th percentiles, and the line represents the median of the multi model ensemble.

Projections

Focusing on one method, XGB bias corrected using QM by seasons, the signal of change in FWI90p given by the multimodel ensemble mean under different emission scenarios and for two temporal horizons is shown. The spatial pattern and the intensity of the change is consistent among scenarios and temporal horizons, with larger increases in the most emissive scenarios and to the end of the century. Additionally, the spread given by the multimodel interquartile range indicates the robustness in the projected change. Some areas show important uncertainties, with spread of the same order than the signal of change itself.

It should be noticed that, although the increase in some regions is extremely high (up to 80 days), the 90th percentile of FWI is not really high, so these projections are not necessarily a sign of high risk of fire.



Change in the number of days over the 90th percentile (days) in the dry season, given by the multimodel ensemble, and ensemble spread. The downscaling method applied is XGB, bias corrected using QM by season. SSP1-2.6 (first row), SSP2-4.5 (second row), SSP3-7.0 (third row) and SSP5-8.5 (fourth row). Changes correspond to 2041-2070 (columns 1 and 2) and 2071-2100 (columns 3 and 4) with respect to the reference period (1979-2005).

References:

- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, Geosci. Model Dev., 9, 1937-1958, https://doi.org/10.5194/gmd-9-1937-2016
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