Progetto di Interesse NEXTDATA

WP2.5 Archivio di dati numerici e previsionali

Deliverable D2.5b:
Archivio e portale di accesso al software e ai campi di temperatura e precipitazione disaggregati con tecniche di downscaling stocastico.

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1. Introduction

Global and regional climate model (GCMs and RCMs) provide output fields with resolutions (of the order of 100 Km for climate models and down to typically at most 10K m for regional climate models), which are frequently not suitable for several application studies. In particular fine-scale precipitation fields down to 1km resolution may be required to estimate precipitation extremes in mountain areas and in particular in the Alpine region, where frequently small basins need to be considered for hydrological impact studies.

Various techniques exist to downscale large-scale rainfall fields such as those produced by GCMs and RCMs to the high temporal and spatial resolutions required by local impact studies (see Maraun et al. 2010 for a detailed review). In addition to dynamical downscaling techniques, which require expensive dynamical simulations at small scales, statistical and stochastic downscaling techniques have been proven to be particularly effective (Bordoy and Burlando, 2014). In particular stochastic rainfall downscaling, a type of weather generator, uses information directly from the large-scale precipitation to generate an ensemble of possible stochastic realizations of precipitation fields with a realistic spatial and temporal correlation structure and preserving the large-scale properties of the original field (Ferraris et al. 2003). Stochastic downscaling allows to create ensembles of downscaled fields, permitting to gauge the uncertainties in the small scale precipitation fields. Among the available methods, so-called full-field weather generators are generally based upon simple autoregressive models, so-called meta-Gaussian models (Rebora et al. 2006a), or point process models simulating individual rain cells (Rodriguez-Iturbe et al. 1987, 1988), or spatio-temporal implementation of multifractal cascade models (Lovejoy et al. 2006, Deidda 1999, 2000, Lovejoy et al. 1985).

In this project we have used and further developed the Rainfall Downscaling by a Filtered AutoRegressive Model (RainFARM) technique (Rebora et al., 2006a, 2006b), a metagaussian model based on nonlinear filtering of the output of a linear autoregressive process, whose properties are derived from the information available at the large scales. The RainFARM technique was originally developed for the spatial and temporal downscaling of individual precipitation events on the time scales typical of meteorological events (Rebora et al., 2006a, 2006b). Applications have included the analysis of the sensitivity of a distributed hydrological model to the variability of the spatio-temporal rainfall distribution (Gabellani et al., 2007), the estimation of the uncertainty in flood predictions (Rebora et al., 2006a), the assessment of the main uncertainty sources in ensemble precipitation forecasts (von Hardenberg et al., 2007), and the quantification of sampling errors for the verification of meteorological forecasts against rain gauge observations (Brussolo et al., 2008). In 2014, in the framework of the NextData project, the method was further adapted for downscaling of long climate simulations, improving in particular the method by removing artefacts in pure spatial downscaling (please see D'Onofrio et al. 2014 for a detailed description).

An important limitation of the D'Onofrio et al 2014 method is that it does not take into account orographic effects at scales smaller than those resolved by the original precipitation field to downscale. Orographic precipitation mechanisms, such as orographic lifting, play an important role in determining patterns of small-scale precipitation in areas with complex orography (Roe 2005, Smith 2006). As a result the fine-scale distribution of precipitation in the downscaled fields is not conditioned on orography and in particular the long-term climatology at individual grid points may differ significantly from observations. This may make the original downscaling method not suitable for applications particularly in the Alpine region.

A recent improvement of the RainFARM method, developed in the framework of Nextdata and described in detail in Terzago et al. 2018, allows to exploit an existing log-term fine-scale climatology of precipitation to define appropriate weights to allow RainFARM to reproduce a realistic climatology also at small scales. Such an improvement is of importance also in the framework of ecosystem studies and modelling. Such an information on the fine-scale climatological distribution of precipitation may often be available from other sources, such as gridded observational datasets (such as the EURO4M dataset for the Greater Alpine Region) or from globally available estimates, such as WorldCim (Hijmans et al. 2005, 2010). Also non-hydrostatic RCMs, when applied at very fine scales (1-5 km resolution), can capture the main physical mechanisms for orographic precipitation and may lead to a realistic spatial distribution of precipitation amounts on average, albeit often with significant biases in amplitude (Kotlarski et al 2014).

In the following we describe in detail the recently improved RainFARM procedure adapted for areas with complex topography (section 2). Section 3 describes a complementary simple method to downscale temperatures over complex orography using environmental lapse-rates. Section 4 describes the open-source software implementation of these methods developed in the project and the github repository with which it is distributed.

2. *The RainFARM stochastic precipitation downscaling method with fine-scale weights for complex orography*

In the following we describe only the recent modifications applied to the D'Onofrio et al. 2014 version of the RainFARM procedure. We refer to that paper for a detailed description of the adaptation of RainFARM for climate applications and to Rebora et al. 2006a for a detailed description of the original procedure. The extension to take into account a fine-scale climatology described in the following is explored in more detail in Terzago et al. 2018. That paper also contains a validation of the modification, by applying the method in a perfect-case experiment and in a more realistic case comparing E-OBS downscaled precipitation with a dense network of raingauge measurements in the Swiss Alps.

The RainFARM method downscales a large-scale spatio-temporal precipitation field $P(X,Y,t)$, which is considered reliable at scales larger than a reliability scale L_o (which often may coincide with the spatial resolution of the field). In the following we will use large-caps coordinates (X,Y) to indicate fields defined on a coarse grid and small-caps coordinates (x,y) to indicate fields on a fine grid.

From the large-scale field to downscale, the method generates a fine-scale field $\tilde{r}(x,y,t)$ at a desired fine-scale resolution by extrapolation of its large-scale power spectrum to the unresolved smaller scales, using the same spectral slope in a log-log plot as the large-scale field, choosing random Fourier phases at small scales and finally using an inverse Fourier transform to return to physical space. Since this procedure by itself would create fields with an unrealistic, almost Gaussian, amplitude distribution, a final nonlinear (exponential) transformation is applied to the resulting field in physical space (von Hardenberg et al. 2003).

In the final step of the procedure, $\tilde{r}(x,y,t)$ is further adjusted to guarantee that when coarse-grained (aggregated) at the large reliability scales, it reproduces exactly the original field to downscale $P(X,Y,t)$:

$$r(x,y,t) = \frac{\tilde{r}(x,y,t)\langle P(x,y,t)\rangle_{L_o}}{\langle \tilde{r}(x,y,t)\rangle_{L_o}}, \tag{1}$$

where the operator $\langle\cdot\rangle_{L_o}$ indicates aggregation (averaging) at scale L_o. This aggregation can consist either in simple averaging over boxes of side L_o, or it could consist in using a smooth operator, such as averaging over a moving circular window with diameter L_o:

$$\langle a(x,y)\rangle_{L_o} = \int_\Omega K(x-x', y-y') \cdot a(x', y')\mathrm{d}x'\mathrm{d}y' \tag{2}$$

where Ω is the entire domain of interest and $K(x\text{-}x',y\text{-}y')=\theta[L_o^2/4 - (x\text{-}x')^2 - (y\text{-}y')^2]$ is a kernel representing a circular homogeneous patch of diameter L_o, with $\theta[..]$ the Heaviside step function. When the aggregation operator is applied to a large-scale field, the same approach is used, but the field is considered constant over boxes of size L_o, that is the value of a large scale field $A(x,y)$ at a fine-scale point (x,y) is considered to be that at the closest large-scale point $A(X,Y)$, where (X,Y) is the closest large-scale coordinate point. All cases discussed in this work use this smooth approach for the aggregation operator in eq. (1).

We assume that a reference precipitation climatology field $c(x,y)$ at fine spatial scales is available. This could be obtained from long-term time averages of gridded observational datasets of precipitation, radar or satellite observations or from numerical simulations with high-resolution models. This reference climatology is used only to derive local weights used to modify the spatial distribution of precipitation, but the absolute value of precipitation itself is not considered, so that possible large-scale biases in the reference climatology are not introduced in the downscaling chain and do not affect the results.

The spatial pattern of precipitation is translated into a map of weights that is used to correct the spatial pattern of the downscaled precipitation fields as follows:

$$w(x,y) = c(x,y)/\langle c(x,y)\rangle_{L_o}, \tag{3}$$

that is, we divide each value $c(x,y)$ by its local average at scale L_o. Notice that the weights aggegated at scale L_o average to 1. When the spatial average of $c(x,y)$ is 0 (as may happen in arid areas), the weights are all set to 1. If a box-averaging is used for aggregation, the resulting weights field reflects the average climatological distribution in space, inside each cell of size L_o of the climatological precipitation in the reference dataset. In case a smooth moving-window averaging is used for aggregation this is true only in an averaged sense.
In general, if the climatology needs to be reproduced at a monthly time-scale, this method can be applied separately for each month, computing separately monthly weights $w_i(x,y)$ from Eq. (3), where $c_i(x,y)$ is the long-term monthly average of the original reference precipitation dataset for month i, with $i=1,..,12$.

The weights are then applied to the fine-scale fields produced by the RainFARM procedure:

$$\tilde{r}(x,y,t) \rightarrow \tilde{r}(x,y,t) \cdot w(x,y) \tag{4}$$

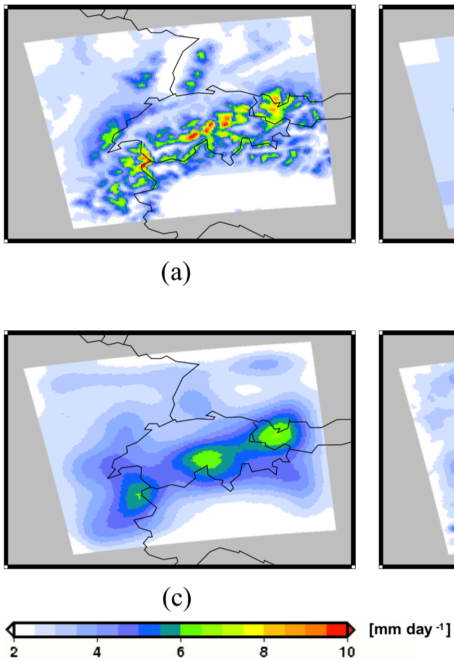

Fig. 1: (a) Precipitation climatology (1980-2008) from high-resolution WRF simulations; (b) climatology of the WRF fields upscaled to 64 km resolution; (c) climatology of the upscaled fields downscaled with the original RainFARM procedure; (d) climatology of the upscaled fields downscaled with the modified RainFARM procedure. (Figure adapted form Terzago et al. 2018)

generating a new field where precipitation is reduced or intensified according to the weights obtained from the long-term climatology. As a last step, the final amplitude adjustment to conserve average precipitation at scale L_o, i.e. Eq. (1), is again applied to $\tilde{r}(x, y, t)$.

The resulting fine-scale field $r(x,y,t)$ still coincides exactly with the large-scale field $P(X,Y,t)$ when both are aggregated at the confidence scale L_o, but its long-term time averaged climatology will reflect on average the small-scale spatial distribution of the reference dataset $c(x,y)$.
Notice that the weights in Eq. (3) only use the local distribution of precipitation, but are not sensitive to possible large-scale biases in the precipitation climatology.
The effectiveness of the procedure is demonstrated in fig. 1 for a "perfect-model" experiment case (where we know what we should achieve). Panel 1a shows the long-term climatology over the Western Alps from high-resolution (4 km) simulations with the WRF regional climate model, in the period 1980-2008. The high-resolution daily WRF fields have been upscaled (aggregated by box-averaging) to 64 km resolution and their climatological mean is shown in fig. 2b. Downscaling these coarse-scale fields with the original RainFARM procedure provides daily fields with a long-term climatology which is very different (and smoother) than the original fine-scale climatology (see fig. 1c). Using the new improved procedure recovers almost exactly the correct long-term climatology (see fig. 1d).

The complete algorithm has been implemented into a software package in the Julia language (https://julialang.org), including command-line tools to perform the downscaling and to compute orographic weights, and a corresponding library of Julia functions, described in section 4.

3. Temperature downscaling

In order to downscale surface temperatures (daily minimum, daily maximum and instantaneous and average values) we implemented a very simple method based on a correction of the coarse-scale field using an environmental lapse rate (such as those tabled by Rolland et al. 2003 for the Alpine Region).
In order to compute the correction, an available fine-scale orography is first smoothed by a smoothing kernel operator as in eq. 2 with a chosen radius (half a large-scale grid spacing by default). A prescribed lapse rate is multiplied with the anomaly of the fine-scale orography compared to this smoothed version, to obtain a fine-scale temperature correction field. We add this correction to an interpolated version of the large-scale temperature field obtained using a nearest-neighbour approach, followed again by application of a smoothing kernel as in eq. 2 (we found this approach to be more consistent and giving better results than using a linear interpolation scheme for temperature).
Also this procedure has been implemented in the Julia language package described in section 4.

4. The RainFARM library and tools in Julia language

The procedures described in the previous sections have been implemented in the RainFARM.jl package available in the github repository at https://github.com/jhardenberg/RainFARM.jl (von Hardenberg 2018). The package is written in the open-source language Julia (https://julialang.org), a new and powerful language which is open-source, extremely fast and easy to use, which allowed to create a particularly efficient version of the RainFARM tool, capable of efficiently creating large ensembles of downscaled stochastic fields. The package contains both a Julia library of functions (fully documented at https://jhardenberg.github.io/RainFARM.jl/dev/) and a command-line interface (CLI) with commands allowing to downscale precipitation and temperature and to compute the weights necessary for orographic downscaling. In the following we report only on the available CLI commands, while we refer to the full online documentation for the library functions.
The library is distributed with an open-source license (the Apache license), it has been widely tested, and is currently still under continuous development. The package has been registered as an official Julia package.

List of the main available CLI commands:

- **`rfarm.jl`** : Precipitation downscaling using RainFARM.
  Creates NENS realizations, downscaling INFILE, increasing spatial resolution by a factor NF. The slope is computed automatically unless specified. Weights can be created with `rfweights.jl`

  Usage:
  ```
  rfarm.jl [-s SLOPE] [-e NENS] [-n NF] [-r REGION] [-w WEIGHTS] [-o OUTFILE]
           [-v VARNAME] [-g] [-c] [-k KMIN] [-h] infile
  ```

  Positional arguments:
  ```
    infile                      The input file to downscale
  ```

  Optional arguments:
  ```
    -s, --slope SLOPE           spatial spectral slope (type: Float64, default: 0.0)
    -e, --nens NENS             number of ensemble members (type: Int64, default: 1)
    -n, --nf NF                 subdivisions for downscaling (type: Int64, default: 2)
    -r, -R, --region REGION     Indices for region to cutout
                                imin/imax/jmin/jmax (default: "0/0/0/0")
    -w, --weights, --weight WEIGHTS
                                Weights file (default: "")
    -o, --outfile, --out OUTFILE
                                Output filename radix (default: "rainfarm")
    -v, --varname VARNAME       Input variable name (default: "")
    -g, --global                conserve precipitation over full domain
    -c, --conv                  conserve precipitation using convolution
    -k, --kmin KMIN             Minimum wavenumber (type: Int64, default: 1)
    -h, --help                  show this help message and exit
  ```

- **`rfweights.jl`** : Tool to create "orographic" weights for RainFARM downscaling starting from an available fine-scale climatology.

  Usage:
  ```
  rfweights.jl [-n NF] [-w WEIGHTS] [-v VARNAME] [-p PASS2] [-i INWEIGHT]
               [-c] [--version] [-h] orofile reffile
  ```

  Positional arguments:
  ```
    orofile                     The input file to use for orography
    reffile                     A reference file (e.g. the file to downscale)
  ```

  Optional arguments:
  ```
    -n, --nf NF                 Subdivisions for downscaling (type: Int64, default: 2)
    -w, -o, --weights, --weight, --outfile, --out WEIGHTS
                                Output weights filename (default:"weights.nc")
    -v, --varname VARNAME       Input variable name (in orofile) (default: "")
    -p, --pass2 PASS2           Previous rainfarm output for 2-pass weighting (default: "")
    -i, --inweight INWEIGHT     Previous weights file to correct for 2-pass (default: "")
    -c, --conv                  conserve precipitation using convolution
    --version                   show version information and exit
    -h, --help                  show this help message and exit
  ```

- **`rfslope.jl`** : Estimate spatial spectral slopes for RainFARM downscaling

  Usage:
  ```
  rfslope.jl [-v VARNAME] [-o OUTFILE] [-k KMIN] [-h] infile
  ```

  Positional arguments:

`infile`	The input file to downscale

  Optional arguments:

`-v, --varname VARNAME`	Input variable name (default: "")
`-o, --outfile, --out OUTFILE`	Output filename for spectrum (default: "")
`-k, --kmin KMIN`	Minimum wavenumber (type: Int64, default: 1)
`-h, --help`	show this help message and exit

- **`rftemp.jl`** : Tool to perform downscaling of temperature fields using an environmental lapse rate

  Usage:
  ```
  rftemp.jl [-r RADIUS] [-l LAPSE] [-v VARNAME] [-b COORD COORD COORD COORD]
            [-o OROCOARSE][--version] [-h] orofile infile outfile
  ```

  Positional arguments:

`orofile`	The input file to use for orography
`infile`	The file to downscale
`outfile`	The output file name

  Optional arguments:

`-r, --radius RADIUS`	Smoothing radius (in grid units) (type: Float64, default: 0.0)
`-l, --lapse LAPSE`	Lapse rate [K/km] (type: Float64, default: 6.5)
`-v, --varname VARNAME`	Input variable name (in orofile) (default: "")
`-b, --coord, --box COORD COORD COORD COORD`	Coordinates of box in which to downscale [lon1 lon2 lat1 lat2] (type: Float64, default: [7.0, 7.65, 45.35, 45.75])
`-o, --orocoarse OROCOARSE`	Coarse orography of original data (default: "")
`--version`	show version information and exit
`-h, --help`	show this help message and exit

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