Climate data processing with GIS support: description of Bias Correction and Temporal Downscaling tools implemented in Clime software

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SUMMARY Although Regional Climate Models (RCMs) are powerful tools for describing small scale climate conditions, their direct use in impact studies is still challenging since they are commonly biased. According to scientific literature, the most adopted method to provide 'corrected' climate scenarios, consists in the application of different post-processing techniques in cascade to Regional Climate Models. Furthermore, another critical issue of impact studies is the need of precipitation at sub-daily scale, since hydrogeological instability is often caused by rainfall of high intensity but short duration. However precipitation time series are usually available only on daily scale, so there is the need to disaggregate these series. In literature different stochastic rainfall disaggregation models have been developed, that, starting from precipitation data at daily scale, provide series of precipitation at sub-daily scale.

In order to handle these problems, REMHI (Regional Models and Geo-Hydrological Impacts) Division of CMCC has implemented different bias correction techniques, based on linear scaling and quantile mapping approaches, both for temperature and precipitation data and a temporal downscaling tool for precipitation data. All these tools have been integrated in *Clime*, a software for climate data analysis developed by the REMHI Division. This work represents a complete guide to these Bias Correction and Temporal Downscaling tools.

Keywords: Bias Correction; Climate Data Analysis; Linear Scaling; Quantile Mapping; Temporal Downscaling; Disaggregation; Climate Data Processing in GIS Enviroment; Software *Clime*

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INTRODUCTION

This report is the deliverable P17 of GEMINA WP A.2.2 'High resolution regional scenarios'. In the framework of this WP, CMCC REMHI Division (Regional Models and Geo-Hydrological Impacts) has developed *Clime*, a GIS software for climate data analysis [3]. *Clime* is the result of a close collaboration of REMHI division with impact communities, with the main goal to grant the use of climate data also to users with little experience in this field. The main goal of this research activity is to correctly link impact and climate models, through the realization of an integrated system able to combine, in appropriate way, high-resolution regional climate scenarios, impact models and statistical downscaling techniques.

Unfortunately the direct use of state-of-the-art RCM data in impact studies is still challenging due to two main problems: model biases and poor predictability on sub-daily time scale. In order to overcome these issues, the need arises to post-process RCM outputs using statistical techniques, providing information usable for impact studies.

The potential effects of Climate Changes (CC) on the hydrological cycle (HC) and especially on weather-induced geo-hydrological hazards (strictly linked to HC) have raised an increasing interest in recent years [21] [5] [17] [4] [6].

To this aim, a proper reproduction of observed hydrological conditions ('minimum requirement' according to [20]) through a correct estimate of the components of water/energy budgets and of weather forcing is needed. Such estimates, that should be provided by fully physically based climate simulation chain formed by General Circulation Model (GCM) dynamically downscaled through Regional Climate Model (RCM), have often proven to be affected by biases making them not suitable for a direct application to studies on weather-induced geo-

hydrological hazards.

Although the RCM model is able to capture the basic climatic features, some biases may still exist, especially concerning precipitation. The reason for such biases include systematic model errors caused by imperfect conceptualization, discretization and spatial averaging within grid cells. This makes the use of RCM simulations as direct input data for hydrological impact studies more complicated. So, since the impact of climate change on water resources is usually assessed at the locale scale, the common state of art approach is to post-process the RCM simulation output to produce reliable estimates of local scale climate.

Different bias correction methods may be used to solve the various problems present in the raw RCM model results.

Simulated precipitation statistics are generally affected by a positive bias in the number of wet days, due to an excessive number of drizzle days, a bias in the mean, the standard deviaton, and the inability to reproduce extreme events.

Several bias correction methods have been developed to downscale climate variables from climate models. These methods range from simple scaling approaches to rather sophisticated methods, for example quantile mapping.

Most methods are able to correct the daily mean values, but only higher-skill approaches such as distribution mapping are also capable of correcting other statistical properties.

Furthermore, another critical issue of impact studies is the fact that geo hydrological impacts are often regulated by sub-daily dynamics (for instance in the case of rainfall-induced shallow landslide), and state-of-the-art climate models do not show good predictability on this time scale. Shallow-landslides (SL) induced by heavy precipitations represent remarkable hazards able to cause huge damages and casualties. A proper assessment about how frequency and magnitude of such events could

change under the effect of Climate Changes (CC) is crucial for the development of future territorial planning (such as early warning systems). However the current constraints of climate modeling prevent an adequate representation of sub daily precipitation patterns, necessary to assess their potential contribution to landslide triggering processes.

To overcome these limitations, a new methodology is proposed [1] [18]: daily precipitation outputs on 24 and 48 hours, provided by high resolution climate simulations [2] bias corrected by means quantile mapping [19], are adopted for a stochastic disaggregation approach combining Random Parameter Bartlett-Lewis (RPBL) original model [11] [12] with his gamma modified version provided by HYETOS [9].

Several methods of post-processing for bias correction and temporal downscaling have been implemented and integrated in *Clime* software, with the aim to make an impact user able to use "corrected" climate data to perform impact studies. Specifically, this work is a description and assessment of the bias correction and temporal downscaling methods implemented in *Clime*.

BIAS CORRECTION METHODS IMPLEMENTED IN *CLIME*

The bias correction methods most adopted in scientific literature have been implemented in software *Clime*. These are:

- Linear Scaling (LS): based on monthly correction values calculated as the differences between observed and simulated data.

- Quantile Mapping (QM): based on the idea to correct on monthly basis the PDF of the RCM to agree with the observed PDF.

Linear-scaling is the simplest approach. In the case of precipitation it consists in scaling the model rainfall data using a corrective factor calculated as the ratio of observed and simulated monthly mean precipitation data (Equation 1).

$$P^*(d) = P(d) \cdot \frac{\mu_m(P_{obs}(d))}{\mu_m(P_{rcm}(d))} \qquad (1)$$

where, for the day d, P^* is the corrected value, $P(d)$ is the original daily precipitation value from the RCM, $\mu_m(P_{obs}(d))$ is the observed monthly average for the month m, and $\mu_m(P_{rcm}(d))$ is the simulated monthly average.

Whereas model temperature data are corrected using an additive term based on the difference of observed and simulated monthly mean (Equation 2).

$$T^*(d) = T(d) + \mu_m(T_{obs}(d)) - \mu_m(T_{rcm}(d)) \quad (2)$$

where, for the day d, T^* is the corrected value, $T(d)$ is the original daily temperature value from the RCM, $\mu_m(T_{obs}(d))$ is the observed monthly average for the month m, and $\mu_m(T_{rcm}(d))$ is the simulated monthly average [16].

Quantile mapping correction aims to correct the probability distribution function (PDF) of the modeled data to properly fit with the observed PDF, through statistical transformations. The idea is to calculate the corrected variable P^* as a function of the original simulated variable P using a transfer function calculated forcing the equality between the CDF (cumulative distribution function F) of the observed and simulated variables [13]:

$$F_{rcm}(P_{rcm}) = F_{obs}(P_{obs}) \qquad (3)$$

where F_{rcm} and F_{obs} are, respectively, the CDF of simulated and observed precipitation. So the corrected value of precipitation is obtained

using the following equation:

$$P^*(d) = F_{obs}^{-1}(F_{rcm}(P(d))) \qquad (4)$$

The different quantile mapping methods implemented for post-processing RCM output are classified below [7].

- Distribution derived transformations: using theoretical distributions to solve Equation 4. In this study, F is a mixture of the Bernoulli and the Gamma distribution, where the Bernoulli distibution is used to model the probability of precipitation occurence and the Gamma distribution used to model precipitation intensities. Further mixtures are the Bernoulli-Weibull, the Bernoulli-Lognormal and the Bernoulli-Exponential distributions. The parameters of the distributions are estimated by maximum likelihood methods for both observed and modeled data independently.

- Parametric transformations: using parametric transformations (Equation 5-9) below to solve Equation 4.

$$\hat{P}^* = bP \qquad (5)$$

$$\hat{P}^* = a + bP \qquad (6)$$

$$\hat{P}^* = bP^c \qquad (7)$$

$$\hat{P}^* = b(P - x)^c \qquad (8)$$

$$\hat{P}^* = (a + bP)(1 - e^{-\frac{(P-x)}{\tau}}) \qquad (9)$$

where,$\hat{P}^*$ indicates the best estimate of P^* and a,b,c,x and τ are free parameters that are subject to calibration.

- Non parametric transformations:

  - using the empirical CDF of observed and modelled values. The empirical CDFs are approximated using tables of empirical percentiles [1]. Values between the percentiles are approximated using linear interpolation.
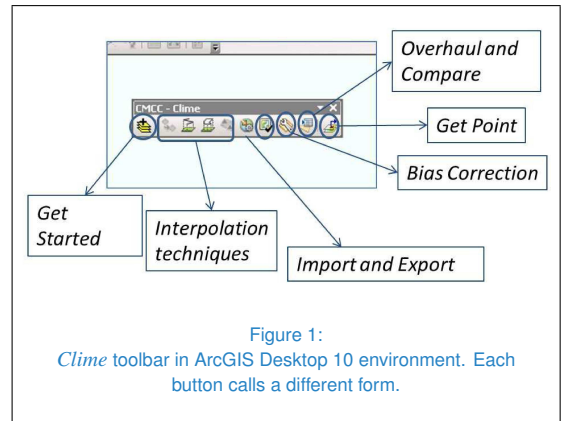
  - Using non-parametric regression (e.g. cubic smoothing spline).

BIAS CORRECTION TOOL IN *CLIME*

Clime allows the user to run Bias Correction processes on any test layer from the database and create a table containing all bias corrected results (they are saved into the database where station data is stored).

All bias correction processes are run by *Clime* software [3] through a set of functions written in R language and bundled in package qmap, currently available on Comprehensive R Archive Network (http://www.cran.r-project.org/).

The bias correction process can be started by clicking on the button **Bias Correction tool** in the multiple buttons bar shown in Figure 1.The panel shown in Figure 2 will appear.

Figure 1:
Clime toolbar in ArcGIS Desktop 10 environment. Each button calls a different form.

The general process consists in comparing **Observation Grid** and **Model Grid (Calibration)** within **Calibration Period** over the selected domain, in order to create a correction mask, which is applied to **Model Grid (Correction)** within the **Correction Period**, and evaluate a corrected grid whose values are saved into an **Output Table**. First, it is necessary to select
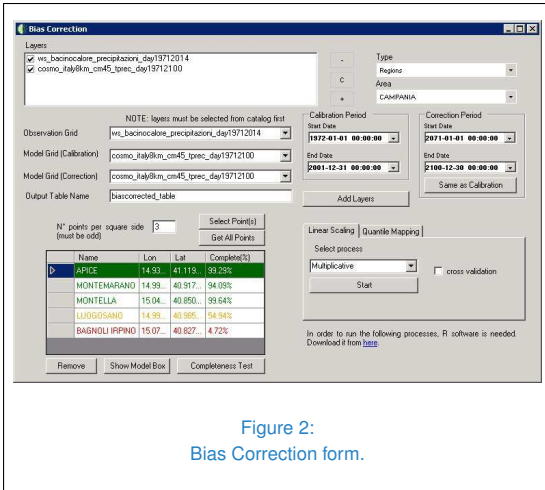
Figure 2:
Bias Correction form.

all desired reference station points from **Observation Grid**: with **Add Layers**, both observation and model grids appear on the screen, then, through the **Select Point(s)** menu; then, it is possible to select the whole set of observation points on the map (**Get All Points**), or picking them one by one (**Select Point(s)**). In the latter case, the **Get a Point** function from *Clime* toolbar enables user to choose a given point by mouse click (Figure 3), whose position is registered and used to evaluate the nearest point relative to every grid under exam (**<<Set Nearest>>**). It is also possible to check how many
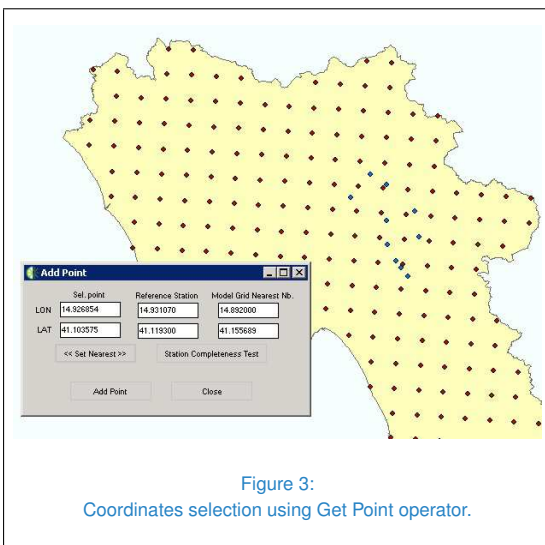

Figure 3:
Coordinates selection using Get Point operator.

values are actually available for the selected point within the chosen period (**Station Completeness Test**) before confirming the choice with **Add Point** (it can be also performed afterwards through **Completeness Test** button in the main menu); it is suggested to discard any point with completeness rate below 75%, since it could lead to poor correction performances. This last action can be repeated for each point you want to select clicking on **Add Point**.Back to **Bias Correction** menu, all selected points will appear in an editable list, including station IDs and completeness test results (if performed): depending on this value, points are written in green (>75%), yellow (50%-75%) or red (<50%).

Since the process takes into account other points surrounding the reference ones within a square neighbourhood, the user must determine the size of such area (by default, it is a square with a 5points side),which can be displayed for each single point with **Show Model Box**. Finally, it is possible to choose the algorithm to use for the bias correction (Linear Scaling and Quantile Mapping, each one with its own settings). As shown on Figure 2, for Linear Scaling two distinct algorithms are available to evaluate and apply a correction mask: Multiplicative (Equation 1) and Additive (Equation 2).

The mask is a gridded layer evaluated from the means of **Observation Grid** and **Model Grid (Calibration)**, each related to a single month of the year, collected over the entire time period. In this way, every value of **Model Grid (Correction)** is subject to a correction depending on its position and the month it belongs to, in order to obtain a table of corrected values. Output is generated on a square grid of the same dimension and position of the one defined as the reference station neighbourhood. **Open Menu** displays **Quantile Mapping Menu**, where user can select all methods he wishes to be performed before starting bias correction

process (**Start Correction**) as shown in Figure 4;**Wet Day Correction** is automatically enabled when dealing with precipitation data, but it can be suppressed if desired.
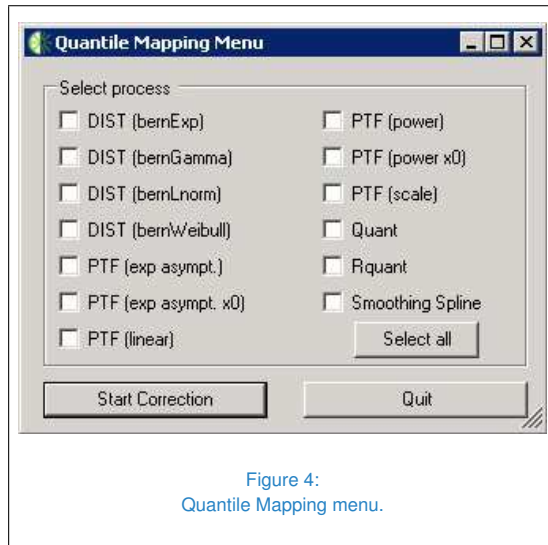

Figure 4:
Quantile Mapping menu.

At the end of process, the generated output table contains every single-method corrected data, plus input model spatial means and observations, which can be visualized in catalog interface: in order to give a clear idea, each corrected output is displayed with its relative table name followed by correction method in brackets (e.g. **output corrected table (rquant)**, referring to R-Quant correction), while observation and model uncorrected data are respectively identified with ”(obs)“ and ”(mod)“ suffixes (observations data is available as output only if calibration and correction periods coincide). The geographical position of each output is the same of its related station point.

STATISTICAL ANALYSIS OF BIAS CORRECTED DATA IN *CLIME*

Once all bias corrected data are created, user can handle them through **Overhaul & Compare** form (Figure 5) that is selectable from

Clime toolbar. After selecting all desired tables from catalog menu (station, model and bias corrected), they can visualized on ArcMap display by clicking **Add Layer(s)**. By choosing **On Point** spatial selection, it is possible to decide on which single point to execute every ongoing process: with **Get Point** function, it takes to mouse click on any desired point on the map, then confirm the choice with <<Set Nearest>>. In this way, the closest point of each chosen layer will be taken into account for all further analysis (in this case, only 1 point per square grid is needed). As shown in Figure 5, it is also possible to choose a **Time domain** (with season filter, if desired).In this work, the bias corrected data were analysed with **Seasonal Cycles** function (Figure 5), available through **Overahaul & Compare** form in **Plots->General** tabpage.

It is also possible to display extremes (min/max) and standard deviation by properly checking the boxes below **Plot** button before running the process. Bias corrected data were also processed in order to produce climatic signal. Such analysis can be performed by *Clime* from **Plots->Anomalies tabpage**, by adding to its list (lower half of the **Overhaul & Compare** form) all data relative to correction period, which time interval is defined right below, while the main list (upper half) must contain calibration data to set as **Reference Layer** (Figure 6). Although the software automatically adjusts its setting to evaluate differences of monthly means for temperatures and ratios of monthly sums for precipitations, user can change these settings at will. Finally, the output is displayed into a chart and can be saved as a bitmap image or an Excel table.

EVALUATION OF THE SUITABILITY OF BIAS CORRECTION METHODS IN *CLIME*

To evaluate the suitability of the different statistical transformations implemented in *Clime*, the
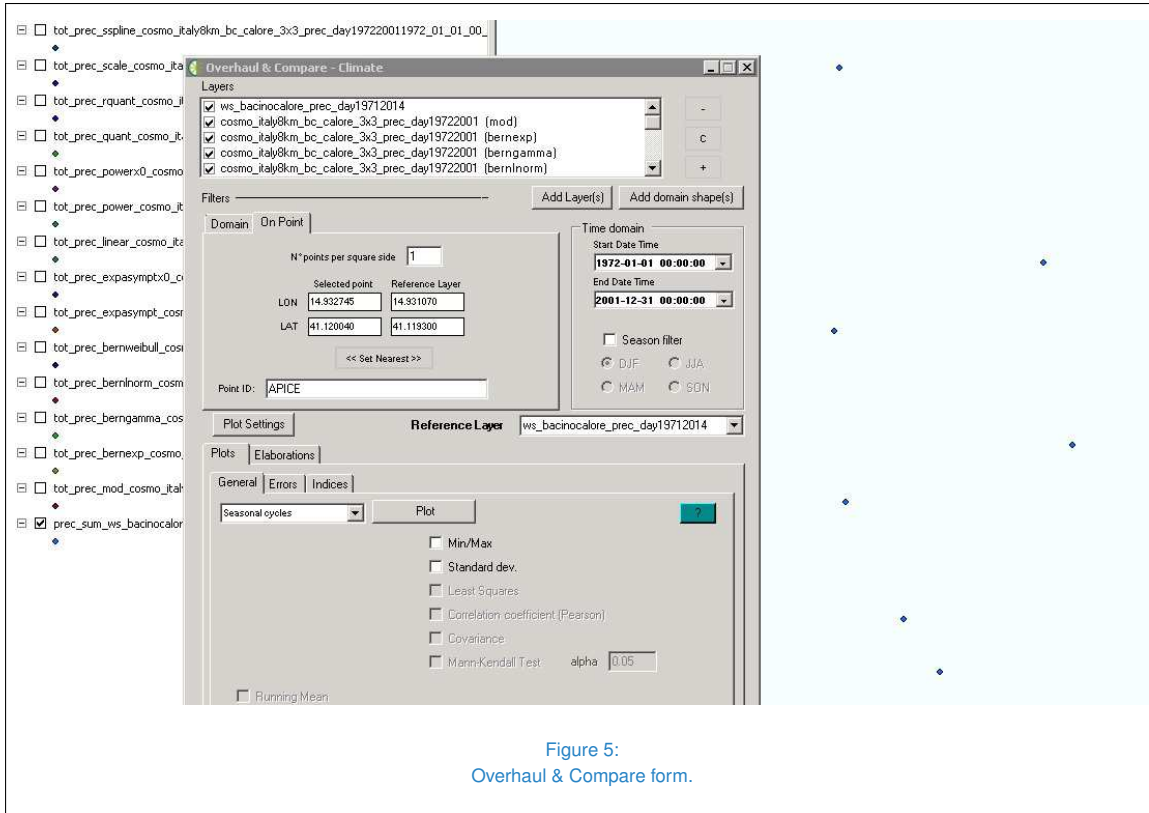
Figure 5:
Overhaul & Compare form.

following example is reported.

Input model data, covering $1971 - 2100$ period and with 0.0715 resolution (about 8km), are provided by regional climate model COSMO - CLM [14] driven by CMCC-CM global model [15]; starting from year 2006, IPCC RCP4.5 and RCP8.5 scenarios [10] are applied. Observed series have been collected from Hydrological Yearbooks (Part I) of Campania region for the $1971-1994$ period, and extended to 2014 thanks to data made available (upon request) by the regional Civil Protection.

On reference time period $1972 - 2001$, the precipitation seasonal cycles values of observed, modeled and modeled data bias corrected with different methods are displayed for Apice, Montella and Montemarano station (Figure 7).
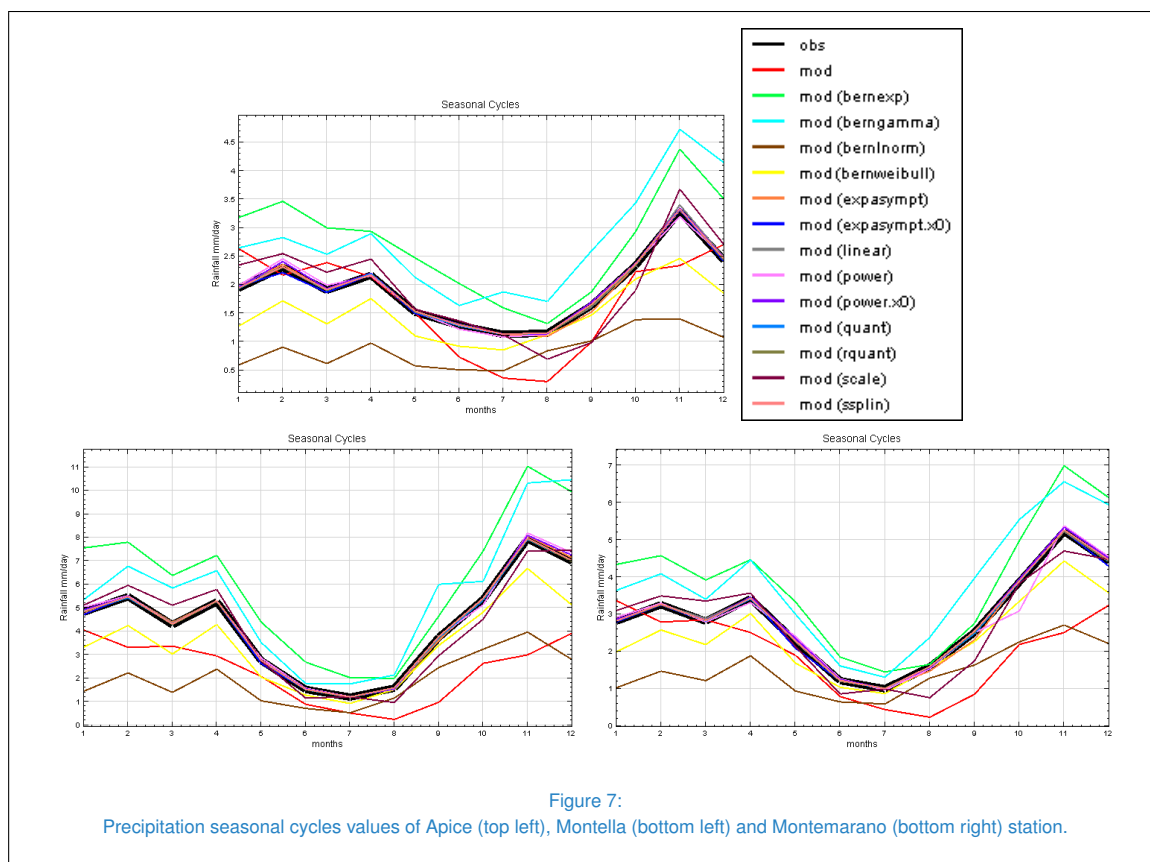
The quantitative comparison between the precipitation seasonal cycles of observed and modeled data allows us to substantiate a re-markable underestimation of modeled data except for the first half of the year, mainly failing to reproduce, for all three stations, the observed autumn peak.

Conversely, the most of the statistical methods induce a more appropriate reproduction for precipitation seasonal cycles values. Nevertheless, it is clear to observe from charts that not all methods perform equally well. In particular, methods adopting distribution derived transformation (bernexp, berngamma, bernlnorm and bernweibul methods) do not achieve adequate corrections, especially during wet seasons.

In [7], similar findings are justifyed recalling the theoretical assumptions of approach under which modeled and observed parameters of the distributions are identified separately not guaranteeing a proper transformation.

Finally, by virtue of their high flexibility, parametric transformations (scale, linear, power,

Figure 7:
Precipitation seasonal cycles values of Apice (top left), Montella (bottom left) and Montemarano (bottom right) station.

power.x0, expasympt and expasympt.x0 methods) and non parametric transformations (quant, rquant and ssplin methods) show the best performances in reducing errors with small deviations. On reference time period $1972 - 2001$, the temperature seasonal cycles values of observed, modeled and modeled bias corrected data (methods are the same used for precipitation, except for the ones that feature theoretical distributions) are displayed for Montella station (Figure 8).

Like precipitation, the quantitative comparison between the temperature seasonal cycles values of observed and modeled data allows us to substantiate a remarkable underestimation of modeled data, this time without any exception. As shown in Figure 8, statistical methods induce a more appropriate reproduction for temperature seasonal cycles values with the excep-

tion of power.x0 and scale methods. A proper evaluation of the effects of CC on the hydrological cycle require to deal with the following issue: the persistence of the climatic signal, estimated on physical basis by regional climate models after the application of bias correction. Figure 9 displays the ratio between seasonal cycles of cumulative precipitation values estimated by raw RCM and adopting in cascade bias correction approach for $2011 - 2041$ under RCP4.5-8.5 and calibration period $1972 - 2001$. Broadly, both scenarios are characterized by an average decrease of precipitation values and roughly coincident with cold/wet season in RCP4.5 scenario and with hot season in RCP8.5 scenario; the statistical transformations reported below (Figure 9) satisfactorily reproduce the seasonal pattern estimated by RCM; nevertheless, the berngamma method
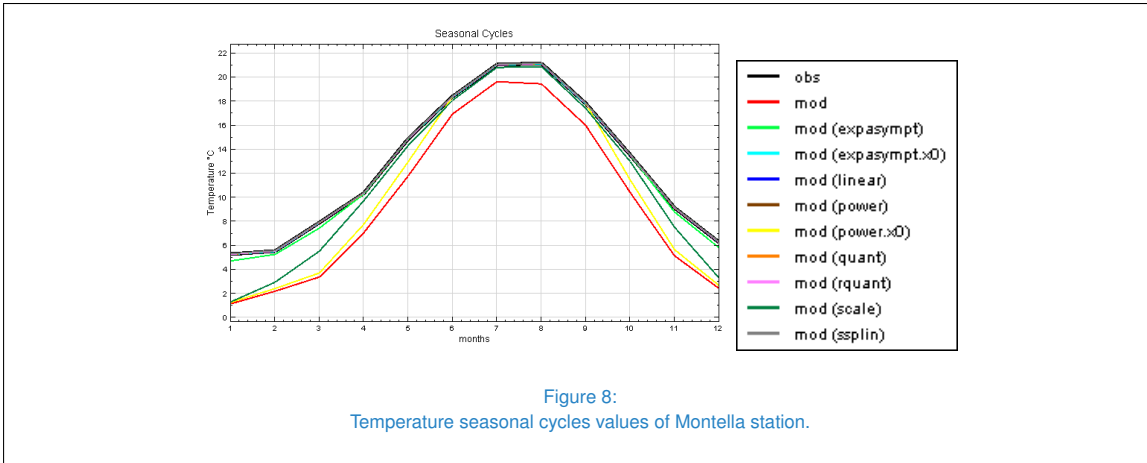
Figure 8:
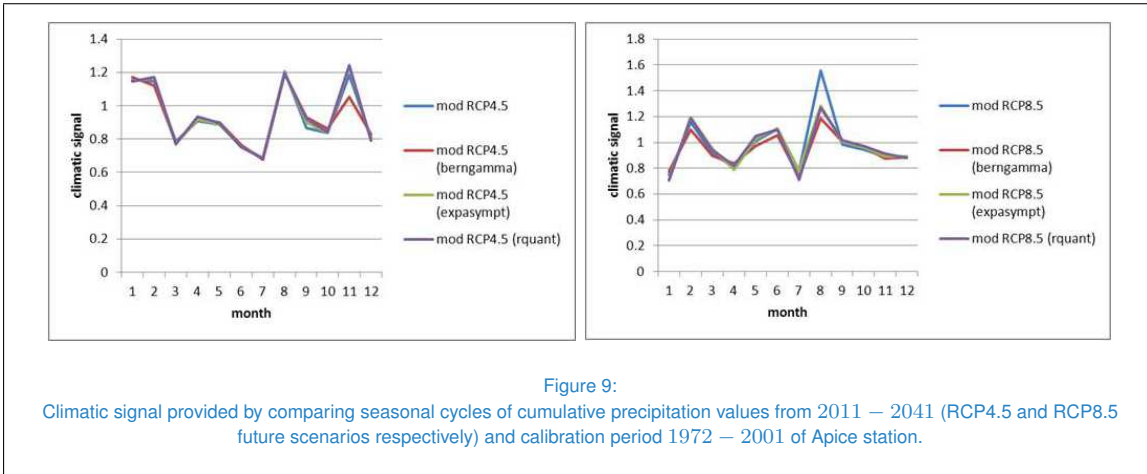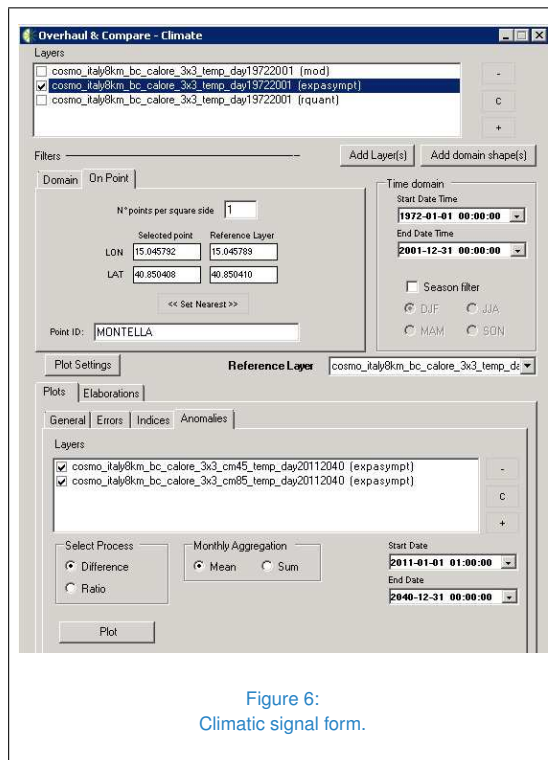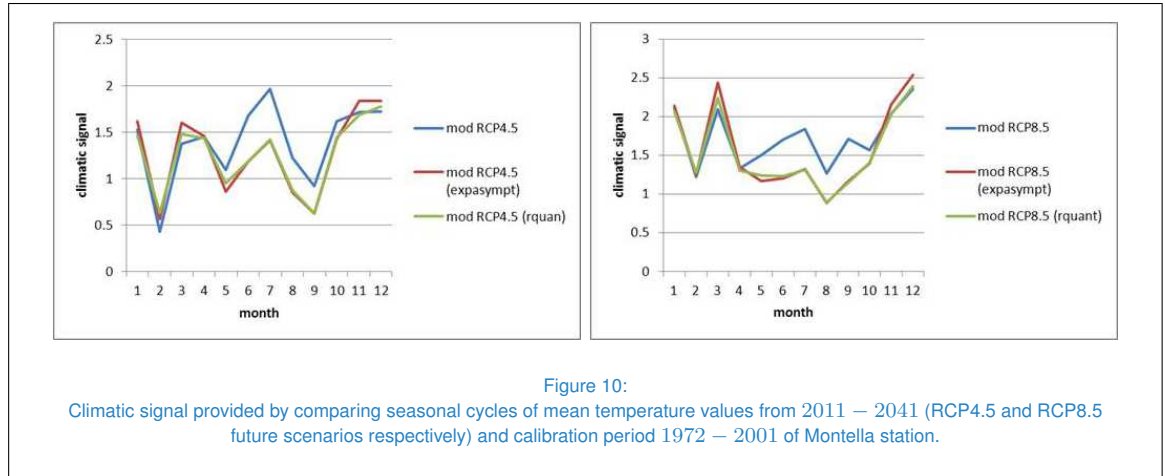Temperature seasonal cycles values of Montella station.

Figure 9:
Climatic signal provided by comparing seasonal cycles of cumulative precipitation values from $2011 - 2041$ (RCP4.5 and RCP8.5 future scenarios respectively) and calibration period $1972 - 2001$ of Apice station.

shows the worst performances (probably because of above recalled constraints). Figure 10 shows the difference between seasonal cycles of mean temperature values estimated by raw RCM and adopting in cascade bias correction approach for $2011-2041$ under RCP4.5-8.5 and calibration period $1972 - 2001$.

Broadly, both scenarios and bias correction methods reported below (Figure 10) are characterized by an average increase of temperature values and roughly coincident with cold/wet seasons (Jan-Apr and Nov-Dec),while they are affected by an average decrease for the rest of the year.

TEMPORAL DOWNSCALING TOOL IN *CLIME*

Temporal Downscaling implemented in *Clime* uses the disaggregation model that combines a modified version of the Bartlett-Lewis Rectangular Pulse stochastic rainfall model (Random Parameter BartlettLewis Rectangular Pulse RPBLRP) with a suitable rainfall disaggregation technique. The latter implements an empirical correction procedure called proportional adjusting procedure. This model requires the identification of a set of parameters that allow to reproduce, as well as possible, the statistical properties of the observed precipitation. The identification is formulated as a global op-

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Figure 10:
Climatic signal provided by comparing seasonal cycles of mean temperature values from $2011 - 2041$ (RCP4.5 and RCP8.5 future scenarios respectively) and calibration period $1972 - 2001$ of Montella station.

Figure 6:
Climatic signal form.

timization problem. For more information from the theoretical point of view refer to the work [18], in which is also reported an example.

Clime allows the user to run a temporal downscaling (disaggregation) process on any daily rainfall data from the database and save output data into an excel file with **nsetpar** (Figure

11) sets of Bartlett-Lewis (BL) parameters, plus multiple text files containing all disaggregated results, and store them into a folder selected by him.

All processes involved in Temporal Downscaling are provided by using the package HyetosR, an updated version of the software Hyetos, developed in R programming environment (http://cran.rproject .org).

In order to run Temporal Downscaling, the first step is the selection of a desired reference station point by choosing **On Point** spatial selection, then, with **Get Point** function, it is possible to click on the desired point on the map and confirm the choice with **<<Set Nearest>>**. Such process is run within a single season, so user has to select it from **Seasons** menu (DJF/MAM/JJA/SON), whereas **All** button will trigger four distinct instances of the process, one for every season.

The temporal downscaling process can be started by clicking on the button **Start** available through **Overahaul & Compare** form in **Plots->Temporal Downscaling** tabpage, as shown in Figure 11.

Although input parameters (**nsetpar**, **n**, **m**, **maxeval**, **beta**, **ftol**, **ratio**, **pmut**, **maxclimbs**, **DistAllowed**) (for a better explanation see [18]) have default values, they are fully customisable. Fur-

thermore, clicking on **Set par. range** button, it is possible to modify the BL parameters range (**xmin**, **xmax**, **xlow**, **xup**) (Figure 12).

The first stage of process consists in identifying a set of BL parameters of the stochastic disaggregation rainfall model through EAS(Evolutionary Annealing Simplex) algorithm [18] that allow to reproduce, as well as possible, the statistical properties of the seasonal precipitations within the selected **Time Domain**, then it runs a stochastic disaggregation rainfall model, which combines BL model with disaggregation technique. In this way, the selected set of BL parameters is used to disaggregate the daily precipitation series into hourly scale.

Actually, EAS is executed a number of times defined by user through **nsetpar**, each producing a set of BL model parameters, which are all saved into an Excel file (e.g. test24-48_SON_setpar.xlsx): they can be selected and used as inputs to run directly stochastic disaggregation rainfall model(**Disag.Simul.**).

In both cases, output text files are:

Figure 11:
Temporal Downscaling form.

- '*DisagSimul_input.txt*':= seasonal rainfall daily values.

- '*DisagSimul_output.txt*':= overall report of DisagSimul function (Disaggregate Daily Rainfall Into Hourly Rainfall with daily input) [8].

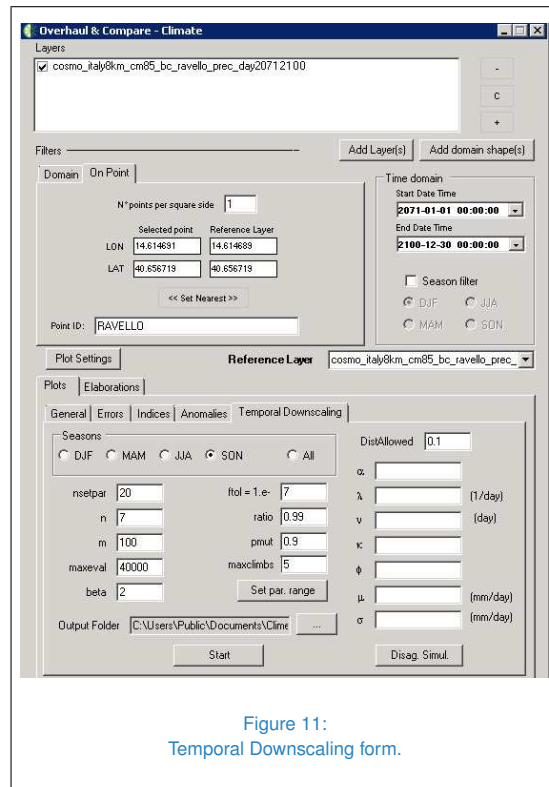- '*DisaggregatedHourlyData.txt*':= seasonal rainfall disaggregated hourly values.

Figure 12:
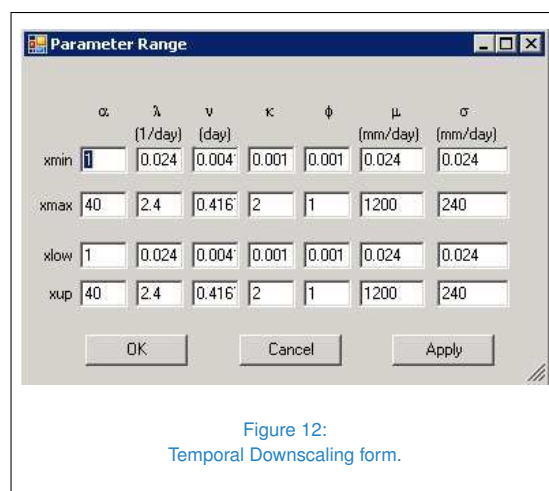Temporal Downscaling form.

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CONCLUSIONS

This work investigates the applicability of spatial and temporal downscaling techniques implemented in software *Clime*. Specificaly two different statistical post-processing methods have been implemented to perform spatial downscaling: linear scaling and quantile mapping, while stochastic models have been used for the disaggregation of precipitation time series on subdaily scale.

All procedures described in this work can be carried out by a wide range of users since *Clime* includes a database that provides a large amount of possible input data that does not need to be pre-processed. In addition, the data obtained with its bias correction are saved permanently in the database and can be furtherly analyzed with the various functions provided by the software.

The validation against the observed data shows that the most of post-processed values clearly outperform the uncalibrated RCM outputs. In most of the cases better performances are achieved using the quantile mapping method. These techniques are applied to future RCM scenarios in order to evaluate the consistency between direct model and post-processed climatic signals. Results show that dynamical model outputs and statistical ones tend to produce similar climatic signals, which indicates the capability of these post-processing techniques to leave such index almost unaltered.

These results suggest that the proposed hybrid downscaling techniques may be very useful tools for climate change impact studies, where users require high-resolution data where systematic errors are reduced.

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