Collaborative Project

CLIM-RUN

Climate Local Information in the Mediterranean region Responding to User Needs

WP 3 – Observational support and downscaling methods
Task 3.4 Downscaling methods and portal

Statistical downscaling methodologies focused on the case studies needs

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1. Introduction

Global Circulation Models (GCMs) are sophisticated tools based on basic laws of physics to simulate the climate system. In comparison to the first GCMs, the performance of these models has improved over the last decades taking into account different parameterizations and including additional climate components (carbon cycle, aerosols, etc) and atmosphere interactions with land-use and vegetation between others. Despite the increasing ability to successfully model present-day climate, the latest generation of GCMs still has serious difficulties in capturing regional variability details in smaller regions (Räisänen, 2007; Errasti et al., 2011). The coarse resolution of the GCMs to study the regional or local characteristics makes necessary the application of particular regionalization approaches also known as downscaling methods. Different downscaling techniques have therefore been developed as tools for interpolating large-scale information into a local or regional scale (Wilby and Wigley, 1997). Depending on the criterion considered, two general approaches have been developed in downscaling: dynamical and statistical downscaling. On the one hand, dynamical downscaling techniques are based on the integration over a limited area of high spatial resolution regional climate models (RCMs), driven at their boundaries by the outputs from GCMs (Rummukainen, 2010). On the other hand, the statistical downscaling methods are based on a statistical model that takes into account empirical relationships between large (used as predictors) and local scale variables (Zorita and von Storch, 1999). Statistical downscaling is nowadays a sound and mature field that can be applied to outputs from different GCM experiments as long as historical data are available for the region of interest. Another advantage of this approach is the inexpensive computational burden. These two aspects have been considered in the statistical downscaling portal (https://www.meteo.unican.es/downscaling/climrun) developed by the Santander Meteorology group from the University of Cantabria (see the user guide by Gutiérrez et al, 2011 and the deliverable 3.2 from the CLIM-RUN project). The portal has been adapted to the CLIM-RUN project needs and it is currently available for all the partners. This is an interactive user-friendly tool to ease the downscaling process for end users, thus maximizing the exploitation of the available climate projections (see the deliverable 3.2 for more details).

The applications of this statistical downscaling portal are focused on the three main case studies analysed in CLIM-RUN: tourism, energy and wild fire in different areas over the Mediterranean region. In particular the aim of this deliverable is to provide an overview of the statistical downscaling methodologies focused on the case studies needs. To this end, different experiments have been done in the portal for particular predictands related to the case studies and regions of interest for the CLIM-RUN project. The analysis described here in relation to the statistical downscaling methods applied through the portal, the predictors selected, etc, tries to ease the downscaling process for the CLIM-RUN end-users who have to do similar applications for their particular regions and variables of interest. On the other hand, this study also shows the application of the Thin Plate Spline (TPS) interpolation method to the climate variables involved in the Fire Weather Index. In particular it is applied to several hot spots in Greece located in the Peloponnese.

2. Statistical downscaling methodologies focused on the case studies needs

The present deliverable is intended for CLIM-RUN end-users with some basic knowledge on statistical downscaling and focused on the description of some particular examples applied to areas and local variables of interest for the project. In particular, two experiments are described related to two of the case studies analyzed in the project: wild fires and tourism. The first one is analyzed in terms of the climate variables included in commonly used fire risk indices such as temperature, relative humidity, wind velocity and accumulated precipitation. The tourism case study is analyzed through the mean and maximum temperature, mean and minimum relative humidity, precipitation, sunshine hours and wind data used to calculate the Tourism Comfort Index (TCI). This section describes the different experiments performed noting the main aspects of the statistical downscaling process applied mainly through the CLIM-RUN statistical downscaling portal. It should be considered as an overview of the possibilities that the statistical downscaling offers to end users who need local climate information. Note that the experiments described here should be analyzed in more detail considering proper local station data demanded in the statistical downscaling process.

2.1. Wild Fires

One of the objectives in CLIM-RUN is the analysis of the fire risk for regions of interest over the Mediterranean. In particular, the main case study in the project is Greece. The analysis of this issue (among others) is vital for several national parks in the region that were burnt by recurrent wildfires in 1985 and 2000 and for some peri-urban forests of significance for the city population. According to the needs of the local stakeholders the aim of this analysis is to provide climatic indices related to fire risk at local scale and estimations of future changes. This aspect is important to identify fire-prone regions and to assess the potential impacts of climate change on fire activity. The high spatial resolution required for this purpose is in this case provided through statistical downscaling methods. Two different approaches have been considered to this end. The first one is applied through the CLIM-RUN statistical downscaling portal developed by the Santander Meteorology Group (UC). The second one considers the Thin Plate Spline Interpolation method applied by the NOA partner.

2.1.1. Downscaling fire risk indices using the CLIM-RUN statistical downscaling portal

A wide variety of indices related to fire risk assessment can be found in the literature with different formulations and input variables. Some of them use only weather conditions for example the Canadian forest Fire Weather Index (FWI) (Stocks et al., 1989), the Angström index (Willis et al., 2001), the Baumgartner index (Skvarenina et al., 2003) or the Nesterov index (Nesterov, 1949). Table 1 shows the weather variables needed to estimate these indices.

Fire risk indices	**Weather variables used to construct the index**
FWI	Temperature, relative humidity, wind velocity and accumulated precipitation
Angströn	Temperature and relative humidity
Baumgartner	Temperature, relative humidity and precipitation
Nesterov	Temperature, relative humidity and precipitation

Table 1: Fire risk indices.

The formulation of the different indices varies as can be seen in the corresponding references provided, however some of them consider the same weather variables as input data, mainly temperature, relative humidity and precipitation. For this reason, these are the variables that are considered in the downscaling process shown in this deliverable as an example in order to focus the wide range of possibilities to this particular case study.

The FWI is one of the most popular fire danger indicators (Moriondo et al, 2006; Groissman et al, 2007) with two particularities with respect to the other indices. On one hand it considers wind velocity which is a non-standard variable in the downscaling process that in general yields poorer results. On the other hand, the FWI calculation requires the observed variables (temperature, wind speed and relative humidity) at noon (12:00 a.m.) and the total precipitation of the previous day as input data set. In some cases this requirement is not easy to satisfy, since data for that time are not commonly available at local scale. According to our experiments, it is important to note the need of using these climatic variables at the proper time (at noon in this case) to evaluate the FWI. The consideration of daily mean values produces an underestimation of this index and yields erroneous results for percentiles and frequencies over thresholds, (see Herrera et al, 2012 for more details). Related to this point, some experiments have been developed by the NOA partner over Athens using daily values of wind speed, relative humidity and maximum temperature. A constant underestimation of this index was found during the summer season when these values are used, e.g. for Athens, this underestimation is around 30-40%, but sensitivity tests are needed for every region of interest.

According to these considerations, two different approaches were developed for the wild-fire case study. Firstly, we propose a downscaling methodology using as predictands the most common weather variables used in the simplest fire risk indices and, secondly, the study for the particular case of the FWI. In the latter, the most suitable downscaling approach that can be applied over different areas in the Mediterranean basin takes into account the ERA_Interim as predictands which provide data at noon. For this reason, we will use the ERA_Interim reanalysis as pseudo-observations for the examples performed through the statistical downscaling portal. ERA_Interim is the latest global atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) conducted in part to replace ERA-40 reanalysis. Nowadays it covers the period from 1979 to 2011, although it is intended to extend it back to the early part of the twentieth century. ERA_Interim provides a large variety of 3 hourly surface variables, among other variables, at a 1.5º resolution. This reanalysis is derived from successive short-term integrations of a general circulation model that assimilates different kind of data (satellite data and land and sea surface observations). More information about this product can be found in Dee et al (2011).

Three different statistical downscaling methods have been used to generate the climatic variables involved in the fire risk indices using the CLIM-RUN statistical downscaling portal over Greece which is the main domain of interest for the project. Variables are downscaled for the red points of Figure 1, consisting of 27 grid points over land according to ERA_Interim resolution.

Fig.1: Geographical domain for the Greek case study according to ERA_Interim resolution. Red points represent the places were the downscaling is performed.

We applied the analog method and two kinds of linear regression, one based only on 15 PCs (Principal Components) and other based on 15 PCs and the nearest neighbour. Note that the portal offers to the user the possibility to select the desired regression, to change the number of Principal Components or the number of nearest neighbors. According to previous experiments developed by the Santander Meteorology Group (Gutierrez et al 2012 and Herrera et al 2012) we selected these three methods.

The analog method has been applied in many fields such as weather forecasting (Lorenz 1969), paleoclimate (Folland et al., 1990) and short-term climate prediction (van den Dool 1989). In particular it is one of the most popular methods of statistical downscaling (Zorita and von Storch, 1999, Frias et al., 2010). This technique consists of finding the most similar situation to the present one in a pool of historical cases. That situation is chosen as the analog or nearest-neighbour and the subsequent evolution of this analog state is assumed to also occur for the base case. See Figure 2 for a graphical description of this process. In our study the search for the analog is based on finding the past situation that minimizes the Euclidean distance as it is implemented in the statistical downscaling portal. This approach offers clear advantages since it provides physically coherent series for all the meteorological variables driving the different fire risk indices.

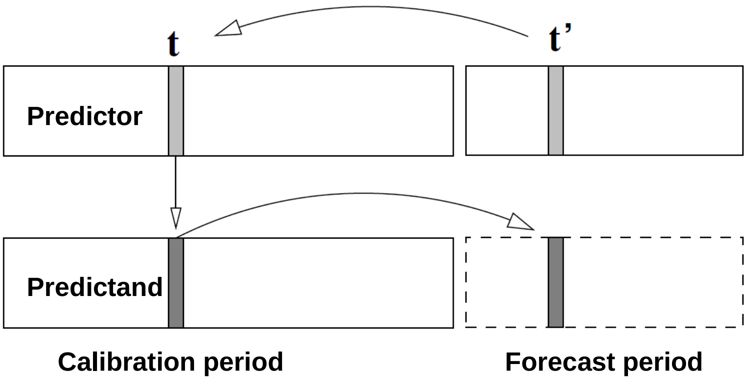


Figure 2: Downscaling analog scheme.

The second method used consists of a linear regression to infer the relationships between predictands and the large scale predictors in particular we selected two linear regression models in these experiments. Firstly, we apply a linear regression with 15 PCs. That is the number of principal components that enter in the regression model. PCs explaining a small portion of variance are frequently considered to be noise and to adversely affect the regression results. Secondly, we apply a linear regression including 15 PCs and the nearest neighbor in the regression model. The consideration of the nearest neighbors takes into account local effects however, it is not recommended to include more than 4 nearest points in order to avoid over-fitting problems. See Gutierrez et al 2012 and references therein for more details about the statistical downscaling methodologies.

There are variables that strongly deviate from normality, including daily precipitation. A solution to this issue may be to transform the non-normal predictand so that the distribution of the transformed variable is approximately normal. This is always possible for a variable with continuous probability density, but it is problematic for daily rainfall, since it generally contains considerable probability mass at zero. Additionally, linear approaches usually suffer from an underestimation of predicted variability, which constitutes a problem in the case of precipitation, typically associated with high levels of variability. To solve these issues, Generalized Linear Models (GLMs, Nelder and Wedderburn, 1972) are available in the portal to downscale precipitation. Essentially, GLMs are an extension of the multiple linear regression that relate the distribution of the predictand to the predictors through a set of coefficients that must be estimated and a mathematical function. The user can also choose the number of PCs and/or nearest neighbors to fit the model. Best results are attained when using a number of PCs between 15 and 30. Problems of numerical instability, due mainly to collinearity, may arise when using too many PCs. Introducing nearest grid points data helps the model to account for local effects, but it is not recommended to use more than 4 points since numerical instabilities due to collinearity may appear.

Several large scale variables have been considered as predictors to train these downscaling approaches. As shown in Table 2 two high levels have been taken into account for some variables to select the best group of predictors. All these variables are well reproduced by most of the GCMs used in the EU-funded ENSEMBLES project (van der Linden and Mitchell, 2009), thus it will be possible to extend the present study using the simulations from these GCMs to assess the future fire

danger impacts. This study considers variables from ERA_Interim reanalysis as predictors for the period 1979-2010.

Predictor	Level	Unit
Temperature (T)	850	K
Surface Temperature (T2m)	surface	K
Relative humidity (R)	850	%
U-wind (U)	850	ms^{-1}
U-wind (U10m)	10 meters	ms^{-1}
V-wind (V)	850	ms^{-1}
V-wind (V10m)	10 meters	ms^{-1}
Sea level pressure (SLP)	surface	Pa

Table 2. Variables considered as predictors in the downscaling approach.

The domain for the particular case of Greece extends from 18.5º to 27.5ºE and from 35º to 42ºN. Figure 3 shows an example about the selection of the domain, dates and predictors as it is performed by the statistical downscaling portal.

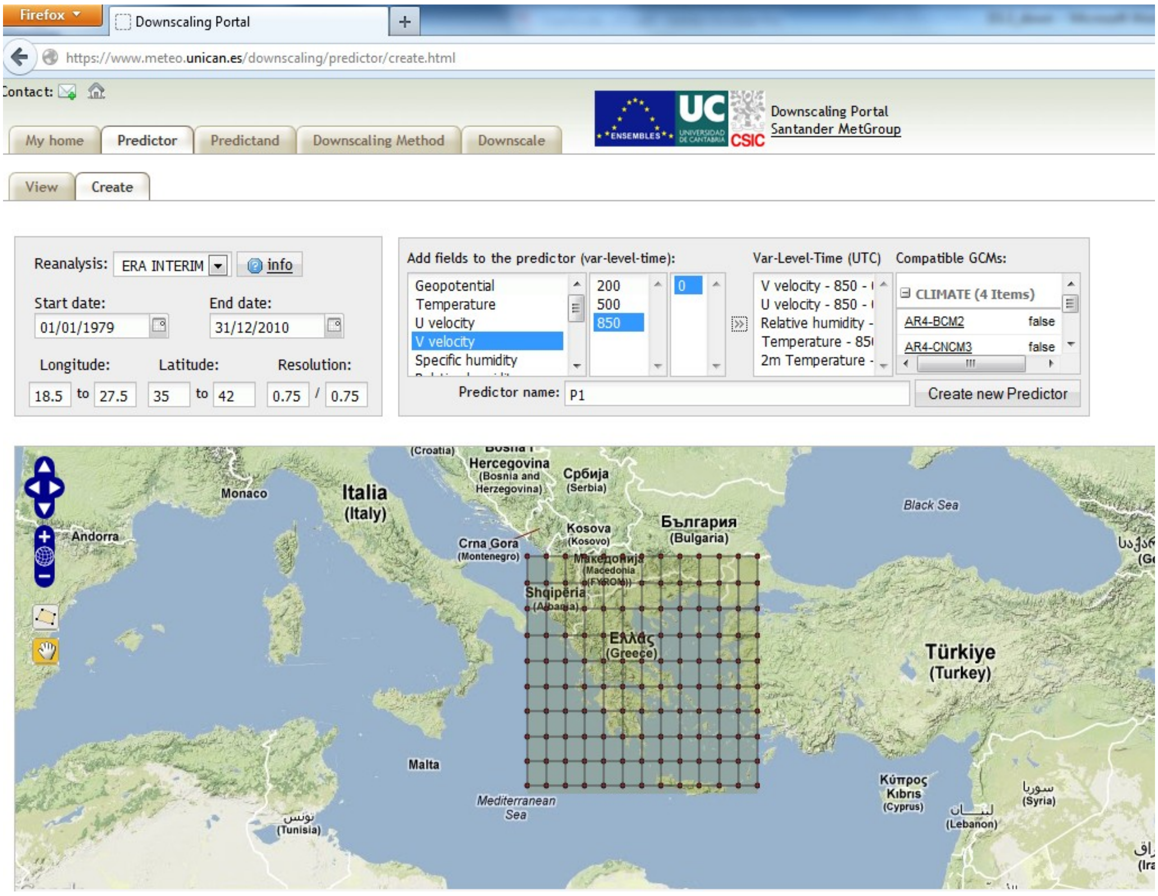


Fig.3: Window of the predictor selection in the statistical downscaling portal.

Five experiments have been carried out in this study selecting a different combination of the predictors shown in Table 2. Table 3 describes the different set of predictors considered according to the acronyms defined in Table 2. Results obtained in previous studies performed in several areas over Europe have been taken into account in the selection of the most suitable combinations (Gutierrez et al 2012 and Herrera et al 2012).

Pattern	Variables					
P1	T2	T850	R850	U850	V850	
P2	T2		R850	U10	V10	
P3	T2	T850	R850	U850	V850	SLP
P4	T2		R850	U10	V10	SLP
P5		T850	R850	U850	V850	SLP

Table 3: Predictor combinations tested for the statistical downscaling methods. Variable names are indicated in Table 2.

2.1.1.1. Angströn, Baumgartner amd Nesterov indices

First, the most common weather variables considered in the simplest fire risk indices (for example Angströn, Baumgartner or Nesterov indices, see Table 1 for more details) are downscaled over Greece to show as an example the process developed. In this case daily mean values of temperature, precipitation and relative humidity have been considered since they are easily available from different stations over the region of interest. The downscaled values over this region can be then used to estimate the fire risk indices.

For all the variables involved in the different fire risk indices, the three downscaling methods mentioned above were applied considering the five predictor combinations shown in Table 3. In order to select the best downscaling method and predictor combination, we present in this section the validation results of the downscaled variables over the red points in Figure 1.

Tables 4 and 5 show the validation results obtained for each predictor combination in columns, and for the downscaled local variables (temperature (T), precipitation (P) and relative humidity(H)), in rows. Results obtained from the three downscaling methods are given in different colours (analog in blue, linear regression with 15 PCs in green and linear regression with 15 PCs + 1 neighbour in orange). The experiments have been applied for the whole period (Table 4) and also for summer (June, July and August) (Table 5) since most of the wild fires take place in this season. Four different scores are calculated: the mean (μ), the standard deviation (σ), the Spearman correlation (r) and the bias (b) for every experiment. The tables show the spatial mean of these scores over the domain. Observation results are also included (column labelled as OBS) which in this case refers to the pseudo-observations we are considering, i.e. ERA_Interim reanalysis.

YEAR	OBS	P1	P2	P3	P4	P5
T (ºC)						
μ	14.27	14.47|14.27|14.27	14.52|14.27|14.27	14.47|14.27|14.27	14.56|14.27|14.27	14.57|14.27|14.27
σ	7.53	7.48|7.41|7.45	7.47|7.43|7.46	7.48|7.42|7.46	7.46|7.43|7.46	7.47|7.33|7.33
r		0.96|0.98|0.99	0.96|0.99|0.99	0.96|0.98|0.99	0.95|0.99|0.99	0.94|0.97|0.97
b		0.20|-0.00|-0.00	0.25|-0.00|0.00	0.20|-0.00|0.00	0.29|-0.00|0.00	0.30|-0.00|-0.00
H (%)						
μ	71.22	71.22|71.22|71.22	71.24|71.22|71.22	71.30|71.22|71.22	71.23|71.22|71.22	71.22|71.22|71.22
σ	12.39	12.33|9.61|10.09	12.30|9.83|9.99	12.29|9.70|10.17	12.27|9.79|10.01	12.30|9.48|9.67
r		0.72|0.77|0.81	0.74|0.79|0.80	0.72|0.78|0.82	0.73|0.78|0.80	0.71|0.75|0.77
b		0.01|0.00|0.00	0.02|0.00|0.00	0.08|0.00|0.00	0.01|0.00|0.00	0.00|0.00|0.00
P (mm)						
μ	1.91	1.81|1.89|1.88	1.69|1.88|1.88	1.81|1.89|1.90	1.77|1.89|1.89	1.79|1.90|1.88
σ	4.68	4.38|4.39|4.42	4.24|4.43|4.50	4.43|4.50|4.61	4.41|4.57|4.61	4.42|4.50|4.53
r		0.44|0.35|0.35	0.45|0.36|0.36	0.44|0.36|0.36	0.45|0.37|0.37	0.44|0.35|0.36
b		-0.10|-0.02|-0.03	-0.22|-0.03|-0.02	-0.10|-0.02|-0.01	-0.14|-0.02|-0.02	-0.12|-0.01|-0.02

Table 4: Validation results (spatial mean values) of the downscaling approach for the three methods (analog in blue, linear regression with 15 PCs in green and linear regression with 15 PCs + 1 neighbour in orange), for the five predictor combinations P1...P5 (Table 3), for daily mean temperature (T, in ºC), daily mean relative humidity (H, in %) and accumulated precipitation in 24h (P, in mm). The scores presented are the mean (μ), standard deviation (σ), Spearman correlation (r) and bias (b).

JJA	OBS	P1	P2	P3	P4	P5
T (ºC)						
μ	23.43	23.30|23.17|23.22	23.32|23.25|23.26	23.33|23.19|23.24	23.40|23.25|23.26	23.29|22.97|22.97
σ	2.61	2.76|2.76|2.80	2.73|2.66|2.74	2.71|2.73|2.77	2.68|2.64|2.73	2.76|2.96|2.96
r		0.82|0.90|0.93	0.78|0.90|0.92	0.82|0.90|0.92	0.77|0.90|0.92	0.78|0.88|0.88
b		-0.13|-0.26|-0.21	-0.12|-0.19|-0.18	-0.10|-0.24|-0.20	-0.04|-0.19|-0.18	-0.14|-0.46|-0.46
H (%)						
μ	60.21	60.91|61.82|61.55	70.90|61.56|61.52	60.81|61.57|61.36	60.72|61.51|61.33	61.03|62.07|62.04
σ	9.71	9.85|5.16|5.80	9.81|5.27|5.67	9.75|5.34|5.87	9.78|5.28|5.78	9.77|5.47|5.49
r		0.60|0.65|0.72	0.61|0.68|0.73	0.56|0.65|0.72	0.61|0.67|0.72	0.58|0.63|0.65
b		0.70|1.61|1.34	0.69|1.35|1.31	0.68|1.36|1.15	0.51|1.30|1.12	0.82|1.86|1.83
P (mm)						
μ	0.90	0.89|0.87|0.85	0.85|0.85|0.86	0.89|0.90|0.90	0.88|0.90|0.89	0.87|0.92|0.89
σ	2.37	2.29|2.33|2.27	2.26|2.27|2.34	2.44|2.45|2.42	2.33|2.42|2.40	2.43|2.46|2.38
r		0.30|0.18|0.18	0.31|0.18|0.18	0.29|0.19|0.18	0.30|0.18|0.18	0.28|0.18|0.19
b		-0.01|-0.03|-0.05	-0.05|-0.05|-0.04	-0.01|0.00|0.00	-0.02|0.00|-0.00	-0.03|0.02|-0.01

Table 5: As in Table 4, but for summer (JJA).

Results from the validation considering the whole period (Table 4) show the best results for the temperature which presents the highest correlation with the observed values and low bias. Good skill is also found for the humidity, with high correlation and low bias. As expected, lower skill was found for the precipitation, with weaker correlations and large dispersion. In the case of temperature and humidity the linear regression method (15 PCs + 1 neighbor) slightly improves the results. For precipitation, the non-linear method based on analogs presents the highest correlations. Note also that the this downscaling method in general presents the highest bias. With regard to the choice of the best predictor combination, we can not elucidate which one is the best, since results are very similar. In particular, the P1 and P2 combinations present similar results to those for P3 and P4 respectively in the case of temperature, since they only differ in the SLP.

In summer (Table 5), the conclusions are roughly the same, but lower correlation coefficients and higher biases are obtained in some cases for this season. The low skill for precipitation could limit the performance of the predicted fire risk indices in this season.

The same approach has been applied over the Iberian Peninsula which is also a region of interest for the wild fire case study and Tunisia which is considered in the tourism case study and it is here studied as an example of the downscaling application in a region with different climate conditions. Figure 4 shows the geographical domains considered in each case. The downscaling methods described above are also here applied to the meteorological variables related to the simplest fire risk indices (tables not shown). As obtained for Greece, the best skill is found for temperature with correlation values around 0.95 for the whole period and 0.88 for summer. Temperature and humidity presents the best results for the two methods based on linear regression (correlation around 0.7). Lower skill is obtained for precipitation, especially for Tunisia, with the analog method being the best approach for this variable. In general, the analog method presents higher bias than those based on linear regression. As mentioned above, results for summer present lower skill than for the annual study. No clear difference was found for the five sets of predictors considered. Only the case of Tunisia presents slightly better results considering P2 and P4 as predictors for the estimation of the relative humidity.

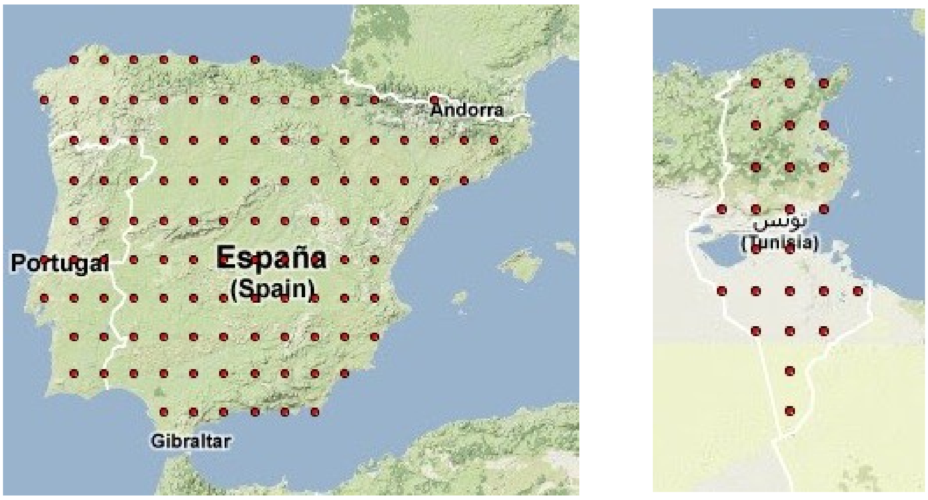


Fig.4: Geographical domains for the Iberian Peninsula (left) and Tunisia (right) according to ERA_Interim resolution. Red points represent the places were the downscaling is performed.

2.1.1.2. Fire Weather Index

The FWI is one of the most popular fire danger indicators with a more complete and complicate formulation than the indices mentioned above. This index provides an estimation of the fire danger throughout an area taking into account the effects of fuel moisture and wind on fire behaviour. In particular it is composed of six standard components. Three of them are known as “fuel moisture codes” and model daily changes in the moisture content of forest fuels with different drying rates depending on the nature of these materials: the fine fuel moisture code (FFMC), the duff moisture code (DMC), and the drought code (DC). The next two components are related to fuel consumption and fire spread: the build-up index (BUI) and the initial spread index (ISI) which rise as the fire danger increases. Finally, the FWI is a numerical rating of fire intensity that combines the Initial Spread Index and the Buildup Index. See van Wagner and Pickett (1985) for more details about the equations to compute the FWI that can be applied to the downscaled local variables.

The FWI is dependent on weather only and its estimation is based on data of temperature (T), relative humidity (H), wind velocity (W) and accumulated precipitation (P) all for noon. As explained above, observations at noon were not available at this stage for the region of interest over Greece, so in order to show the downscaling process through the CLIM-RUN statistical downscaling portal in this area, data from the ERA_Interim at noon were considered here as predictands (pseudo-observations) in stead of station data. Although this approach does not provide the expected spatial resolution for this kind of application, the study by Bedia et al (2012) has shown that ERA_Interim is the best reanalysis for the FWI estimation.

In order to obtain the FWI at local scale the three statistical downscaling methods have been performed for the climatic variables involved in this index over the three different domains considered in the Mediterranean basin: Greece, Spain and Tunisia. The five sets of predictors shown in Table 3 have also been used to train the downscaling methods. Validation results for these four variables are shown in Table 6 for the whole period and in Table 7 for summer.

YEAR	OBS	P1	P2	P3	P4	P5
T (12H)						
μ	18.63	18.93|18.63|18.63	18.96|18.63|18.63	18.92|18.63|18.63	19.03|18.63|18.63	19.02|18.63|18.63
σ	8.43	8.35|8.19|8.21	8.32|8.21|8.21	8.35|8.21|8.22	8.33|8.21|8.21	8.34|8.14|8.16
r		0.94|0.97|0.97	0.94|0.97|0.97	0.94|0.97|0.97	0.94|0.97|0.97	0.93|0.97|0.97
b		0.3|-0.00|0.00	0.36|0.00|0.00	0.29|0.00|-0.00	0.39|0.00|0.00	0.38|-0.00|0.00
H (12H)						
μ	55.30	54.92|55.30|55.30	54.91|55.30|55.30	55.03|55.31|55.30	54.94|55.30|55.30	54.96|55.30|55.30
σ	17.06	16.86|13.27|13.55	16.76|13.55|13.61	16.90|13.28|13.59	16.80|13.52|13.59	16.89|13.01|13.25
r		0.69|0.77|0.79	0.71|0.79|0.79	0.69|0.77|0.79	0.70|0.79|0.79	0.68|0.75|0.77
b		-0.38|0.00|-0.00	-0.39|0.00|0.00	-0.27|0.00|0.00	-0.36|0.00|0.00	-0.34|0.00|0.00
W (12H)						
μ	3.35	3.24|3.35|3.35	3.23|3.35|3.35	3.24|3.35|3.35	3.24|3.35|3.35	3.24|3.35|3.35
σ	1.75	1.68|0.81|0.92	1.68|0.85|0.89	1.69|0.86|0.96	1.69|0.86|0.91	1.70|0.88|0.93
r		0.49|0.42|0.48	0.50|0.45|0.47	0.51|0.45|0.51	0.51|0.45|0.48	0.51|0.46|0.49
b		-0.11|-0.00|-0.00	-0.12|-0.00|-0.00	-0.11|-0.00|-0.00	-0.11|-0.00|-0.00	-0.11|-0.00|-0.00

P						
µ	1.91	1.81|1.89|1.88	1.69|1.88|1.88	1.81|1.89|1.90	1.77|1.89|1.89	1.79|1.90|1.88
σ	4.68	4.38|4.39|4.42	4.24|4.43|4.50	4.43|4.50|4.61	4.41|4.57|4.61	4.42|4.50|4.53
r		0.44|0.35|0.35	0.45|0.36|0.36	0.44|0.36|0.36	0.45|0.37|0.37	0.44|0.35|0.36
b		-0.10|-0.02|-0.03	-0.22|-0.03|-0.02	-0.10|-0.02|-0.01	-0.14|-0.02|-0.02	-0.12|-0.01|-0.02

Table 6: As in Table 4 but for the variables involved in the FWI.

JJA	OBS	P1	P2	P3	P4	P5
T (12H)						
µ	28.45	28.44|28.40|28.41	28.47|28.45|28.45	28.46|28.39|28.40	28.53|28.44|28.42	28.43|28.17|28.16
σ	3.41	3.45|3.40|3.39	3.40|3.27|3.29	3.40|3.31|3.29	3.37|3.23|3.24	3.44|3.53|3.45
r		0.79|0.87|0.88	0.77|0.87|0.88	0.79|0.88|0.88	0.75|0.87|0.88	0.77|0.87|0.87
b		-0.01|-0.05|-0.04	0.02|-0.00|-0.00	0.01|-0.06|-0.06	0.07|-0.01|-0.03	-0.02|-0.28|-0.29
H (12H)						
µ	42.83	43.01|43.12|42.94	42.94|42.96|42.95	42.91|42.97|42.83	42.90|42.94|42.88	43.09|43.56|43.54
σ	11.55	11.42|7.17|7.35	11.33|7.09|7.19	11.31|7.18|7.29	11.35|7.07|7.21	11.35|7.42|7.22
r		0.54|0.63|0.65	0.56|0.65|0.66	0.53|0.62|0.66	0.55|0.64|0.66	0.53|0.61|0.62
b		0.18|0.29|0.12	0.12|0.13|0.13	0.08|0.15|0.00	0.07|0.11|0.05	0.27|0.73|0.71
W (12H)						
µ	3.15	3.03|3.03|3.05	3.02|3.07|3.08	3.03|3.08|3.09	3.05|3.09|3.12	3.02|3.05|3.04
σ	1.55	1.49|0.65|0.74	1.48|0.70|0.73	1.50|0.61|0.71	1.50|0.66|0.71	1.49|0.64|0.71
r		0.54|0.42|0.46	0.51|0.47|0.49	0.54|0.43|0.48	0.50|0.46|0.48	0.54|0.44|0.47
b		-0.11|-0.12|-0.10	-0.13|-0.08|-0.07	-0.12|-0.07|-0.05	-0.10|-0.06|-0.03	-0.13|-0.10|-0.11
P						
µ	0.90	0.89|0.87|0.85	0.85|0.85|0.86	0.89|0.90|0.90	0.88|0.90|0.89	0.87|0.92|0.89
σ	2.37	2.29|2.33|2.27	2.26|2.27|2.34	2.44|2.45|2.42	2.33|2.42|2.40	2.43|2.46|2.38
r		0.30|0.18|0.18	0.31|0.18|0.18	0.29|0.19|0.18	0.30|0.18|0.18	0.28|0.18|0.19
b		-0.01|-0.03|-0.05	-0.05|-0.05|-0.04	-0.01|0.00|0.00	-0.02|0.00|-0.00	-0.03|0.02|-0.01

Table 7: As in Table 6, but for summer.

Results from the validation show the best results for the temperature with high correlations with the observed daily series and a low bias. The downscaling of humidity also attained a good skill, with high correlations and low bias. Again the best skill for these variables is found for the regression models, especially with 15 PCs+1 neighbor. Lower skill was found for precipitation and wind, with weaker correlations and large dispersion, especially for precipitation. The worse results obtained for precipitation and wind probably limit the performance of the predicted FWI series. This shortcoming would be reduced in other fire risk indices that do not include wind in their definition. The best method for these two variables is the analog method, although similar skill is found by using the linear regression with 15 PCs + 1 neighbor for wind. As shown in Table 6, it is difficult to select the best combination of predictors since the results obtained for the different statistics are quite similar. As explained before the selection of these sets has also the advantage that all the variables are generally found in all GCMs, whereas some other predictors may not be so common. Then, all relevant variables used in the FWI can be projected into future climate conditions using

the best statistical downscaling approach selected.

Similar conclusions are found for summer (Table 7). In particular for this season, the skill of temperature, humidity and precipitation decreases, whereas no significant differences are found for wind.

Results over Spain and Tunisia (Tables not shown) also present higher correlation values for the temperature at noon and lower values for wind and especially for precipitation in Tunisia. The regression models used show the best skill for temperature and relative humidity at noon while the analog method works better for precipitation and wind. The five sets of predictors present similar results in both regions. It is expected that a specific study using local station data could reveal significant differences among the set of predictors. As for the other studies, lower skill is found for summer.

2.1.2. Downscaling FWI using Thin Plate Spline (TPS) interpolation method

2.1.2.1. TPS Description

Spline interpolation was initially developed primarily in geophysical science (Wahba and Wendelberger 1980; Wahba 1990), and its application to climate analysis was later implemented by Hutchinson (1991). It is a stochastic method that creates a surface which passes through the control points and has the least possible change in slope at all points. In other words, TPS fit the control points with a minimum curvature surface. In the present study, a three-dimensional (3D) interpolation method of position and elevation was used based on the TPS interpolation as proposed by Hutchinson (1998), who investigated the climatic dependence on topography and showed that there is a small but significant elevation effect on the daily climate data. Hence, a method was developed to compute a trivariate function which incorporates the covariable elevation into bivariate TPS. The method's key features are its robustness and operational simplicity, and therefore, it is often employed to spatially interpolate climatic data (Zheng and Basher 1995; Price et al. 2000; Hong et al. 2005; McKenney et al. 2006; Tait et al. 2006).

The interpolation function at altitude h, latitude φ, and longitude θ is defined as:

$$\mathbf{F\ (\theta,\varphi,h)=c_o+c_1\theta+c_2\varphi+c_3h+\Sigma c_{i+4}\, d\ ln(d\ )}$$

where the distance is $\mathbf{d\ =(\theta-\theta_i)^2+(\varphi-\varphi_i)^2}$ and θ_i, φ_i are the coordinates of input points. The coefficients c_i are determined using the input points (θ_i,φ_i,h_i): $F(\theta_i,\varphi_i,h_i)$ = climatic output of regional models and conditions of orthogonality.

An evaluation of the TPS method using ERA-40 temperature and precipitation data, as well as a comparison with observations over the Balkan Peninsula and Greece, has already been performed by Kostopoulou et al. (2010). The TPS method was proved to reproduce reasonably well the temperature data. In contrast, the model exhibited lower skill in reproducing precipitation. The method succeeded to represent the seasonal cycle of precipitation; however, an overall underestimation of the precipitation amounts appeared in high elevation sites.

2.1.2.2. Methodology and Results

Thin plate spline-3D interpolation has been used to interpolate RACMO2-KNMI simulated data from a grid of 25km into a finer one of 5km spatial resolution.

As mentioned above, since topography is a factor that strongly influences climatic variables, altitudinal data are incorporated into the interpolation procedure as a third spatial covariate using a digital elevation model (DEM) developed at the National Oceanic and Atmospheric Administration's National Geophysical Data Center , available at a 30-arcseconds (approximately 1 km) resolution (http://www.ngdc.noaa.gov/mgg/topo/globe.html).

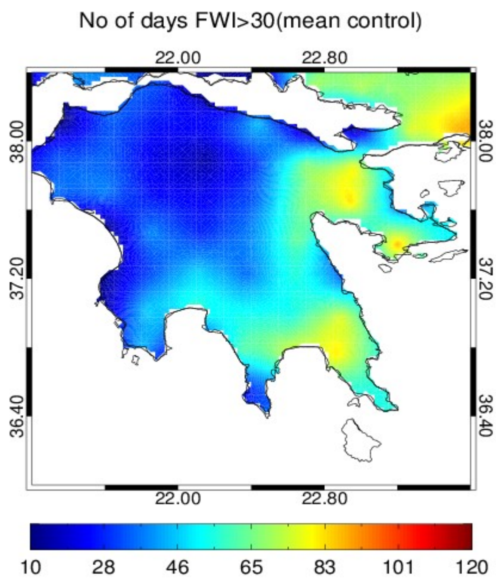
TPS downscaling method was applied to several hot spots in Greece located in the Peloponnese, which was affected greatly by the 2007 devastating fires.

The regional climate model data available for the calculation of FWI (daily maximum temperature, 24h precipitation, daily wind speed and relative humidity) were first downscaled using the TPS method and then the FWI values were calculated using the downscaled variables. The FWI values were also computed using the original meteorological data and a comparison with the downscaled results was made.

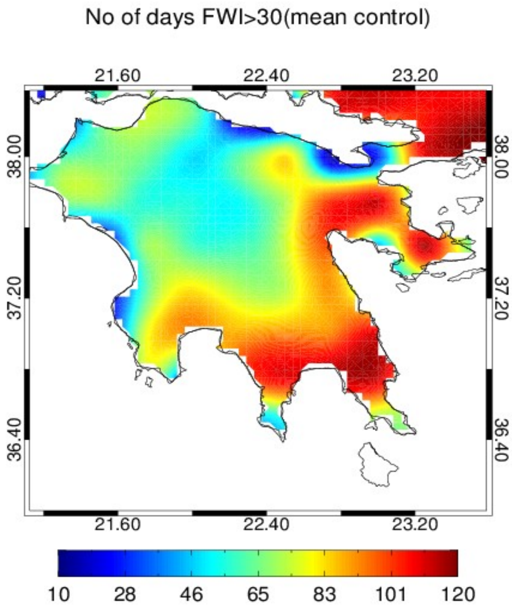
In Figure 5 the number of days with FWI>30 for the control period (1961-1990) and the differences between control and the future period 2021-2050 are illustrated (rows), both for the downscaled and the original results (columns).

Original RCM data

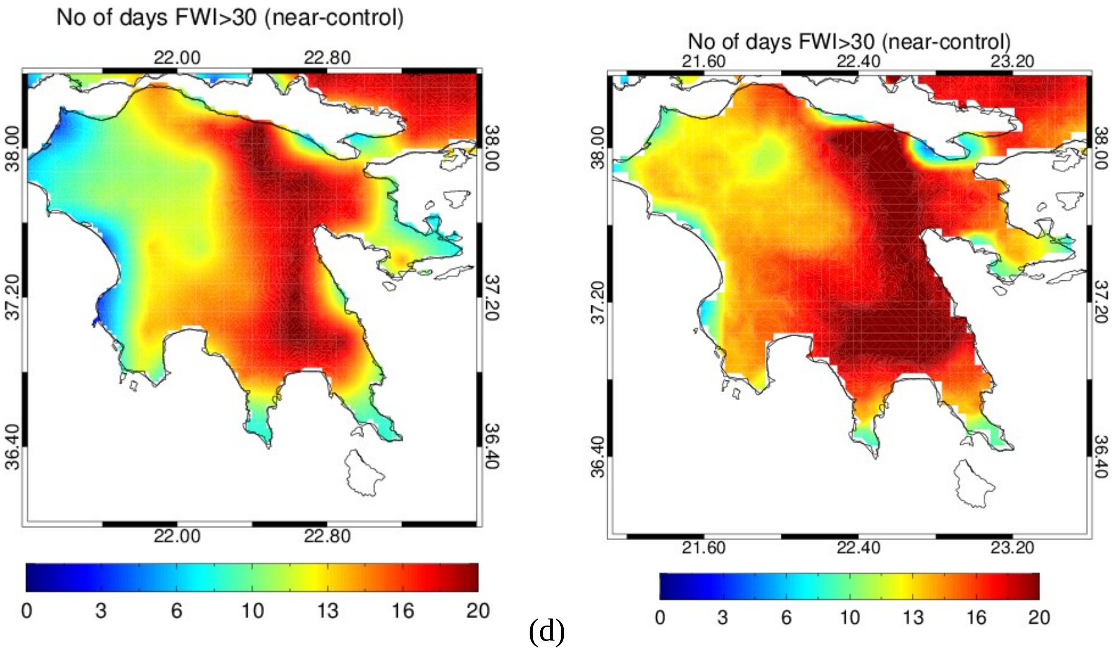
Downscaled RCM data



(a)



(b)



(c) (d)

Figure 5: Number of days with FWI>30 using downscaled (right) and original (left) rCM data for the control period (top) and the differences between the control period and future (A1B emission scenario) period 2021-2050 (bottom).

As we can see in Fig.5a,b when TPS method is applied greater spatial information occurs in our results. In particular, the differences between coastal and mountainous regions stand out, depicting the influence of altitude on the meteorological values and therefore on the FWI values. The same pattern seems to apply to the differences between the future and the reference period (Fig 5c, d), when the downscaled results are used.

The TPS method was also applied to the FWI values. The results indicate that the spatial distribution of the downscaled index (not shown) is similar to the original, but smoother. On the contrary, when downscaled meteorological data are used (Fig. 5), the FWI spatial distribution corresponds better to the topographical aspects of the examined region.

2.2. Tourism

The tourism case study is also analysed using the CLIM-RUN statistical downscaling portal. As for the analysis performed for the assessment of the fire risk indices, in this section we focus on the weather variables related to the Tourism Climatic Index (TCI) in order to obtain these data at local scale.

The TCI was developed by Mieczkowski (1985) to quantify the most favourable atmospheric conditions for tourism based on outside activities. The variables involved in this index are combined in five subindices: daytime comfort index (CID), daily comfort index (CIA), precipitation (R), sunshine (S) and wind (W). The weather variables and their influence on TCI are summarized in Table 8.

Subindex	Monthly Climate Variables	Influence on TCI
Daytime Comfort Index (CID)	Maximum daily temperature (ºC) (Tmax) and minimum daily relative humidity (%) (Hmin)	Represents thermal comfort when maximum tourist activity occurs
Daily Comfort Index (CIA)	Mean daily temperature (ºC) (T) and mean daily relative humidity (%) (H)	Represents thermal comfort over the full 24h period, including sleeping hours
Precipitation (P)	Total precipitation (mm)	Reflects the negative impact that this element has on outdoor activities and holiday enjoyment
Sunshine (S)	Total hours of sunshine (h)	Rated as positive for tourism but can be negative because of the risk of sunburn and added discomfort on hot days
Wind (W)	Average wind speed (m/s or km/h)	Variable effect depending on temperature (evaporative cooling effect in hot climates rated positively, while “wind chill” in cold climates rated negatively)

Table 8. TCI description.

According to the CLIM-RUN objectives, the TCI seems to be a good indicator of tourists' comfort since it is based on the variables that mainly influence tourism and has been widely used in previous studies (Scott and McBoyle, 2001; EU funded PESETA project (Amelung, 2011)).

2.2.1. Downscaling TCI using the statistical downscaling portal.

The CLIM-RUN statistical downscaling portal is here used to downscale the meteorological variables involved in the TCI in order to look for the best set of predictors to subsequently calculate the TCI. To do this, the ERA_Interim reanalysis has been also used as predictor and pseudo-observations although, ideally, the analysis should be extended to observations in the region of interest. The same statistical downscaling methods described in section 2.1.1 and the predictor combinations shown in Table 3 have been applied.

First, we present in Tables 9 and 10 the validation results for the variables involved in the TCI for the whole period and summer, respectively and over the Greek domain (Figure 1). Note that in these experiments results for temperature, relative humidity and precipitation are the same as those obtained for the simplest fire risk indices shown above. For this reason the tables are simplified and results for all variables are not shown here.

YEAR	OBS	P1	P2	P3	P4	P5
Tmax (ºC)						
μ	18.68	18.97|18.68|18.68	19.03|18.68|18.68	18.96|18.68|18.68	19.06|18.68|18.68	19.05|18.68|18.68
σ	8.37	8.31|8.15|8.16	8.28|8.16|8.17	8.30|8.16|8.17	8.28|8.16|8.17	8.29|8.10|8.12
r		0.94|0.97|0.98	0.94|0.97|0.98	0.94|0.97|0.98	0.94|0.97|0.98	0.93|0.97|0.97
b		0.29|-0.00|0.00	0.35|0.00|0.00	0.27|-0.00|-0.00	0.38|0.00|0.00	0.37|-0.00|0.00
Hmin (%)						
μ	54.74	54.48|54.74|54.74	54.50|54.74|54.74	54.58|54.75|54.74	54.49|54.74|54.74	54.51|54.74|54.74
σ	16.35	16.29|12.78|13.07	16.21|13.04|13.11	16.31|12.80|13.13	16.22|13.01|13.09	16.31|12.54|12.77
r		0.69|0.77|0.79	0.71|0.79|0.79	0.69|0.78|0.80	0.71|0.79|0.79	0.68|0.76|0.77
b		-0.26|0.00|-0.00	-0.24|0.00|0.00	-0.16|0.00|0.00	-0.25|0.00|0.00	-0.23|0.00|0.00

W (m/s)						
μ	2.86	2.77|2.86|2.86	2.77|2.86|2.86	2.77|2.86|2.86	2.77|2.86|2.86	2.77|2.86|2.86
σ	1.12	1.06|0.59|0.65	1.06|0.61|0.64	1.06|0.61|0.67	1.06|0.60|0.64	1.07|0.63|0.66
r		0.56|0.46|0.51	0.60|0.47|0.49	0.57|0.47|0.52	0.60|0.46|0.50	0.57|0.48|0.51
b		-0.09|-0.00|-0.00	-0.08|-0.00|-0.00	-0.09|-0.00|-0.00	-0.08|-0.00|-0.00	-0.08|-0.00|-0.00
S (s)						
μ ($*10^4$)	3.42	3.45|3.41|3.42	3.46|3.42|3.42	3.45|3.42|3.42	3.46|3.42|3.42	3.45|3.42|3.42
σ ($*10^4$)	1.06	1.06|0.82|0.84	1.05|0.86|0.86	1.05|0.83|0.84	1.05|0.86|0.86	1.06|0.80|0.82
r		0.73|0.81|0.83	0.74|0.85|0.85	0.74|0.82|0.84	0.75|0.86|0.85	0.72|0.80|0.81
b ($*10^4$)		0.03|-0.00|-0.00	0.04|-0.00|-0.00	0.03|-0.00|-0.00	0.05|-0.00|-0.00	0.04|-0.00|-0.00

Table 9: As in Table 4, but for the variables involved in TCI.

JJA	OBS	P1	P2	P3	P4	P5
Tmax (ºC)						
μ	28.46	28.44|28.40|28.41	28.48|28.45|28.46	28.47|28.39|28.40	28.53|28.44|28.42	28.43|28.18|28.16
σ	3.40	3.44|3.37|3.37	3.39|3.24|3.27	3.39|3.28|3.27	3.36|3.20|3.21	3.42|3.51|3.43
r		0.79|0.87|0.88	0.77|0.87|0.88	0.79|0.88|0.88	0.76|0.87|0.88	0.77|0.87|0.87
b		-0.01|-0.06|-0.04	0.02|-0.01|-0.00	0.01|-0.06|-0.06	0.07|-0.01|-0.04	-0.02|-0.28|-0.29
Hmin (%)						
μ	42.50	42.75|42.88|42.69	42.70|42.69|42.68	42.65|42.70|42.56	42.65|42.66|42.60	42.84|43.28|43.27
σ	10.92	10.94|6.85|7.10	10.90|6.83|6.97	10.84|6.90|7.05	10.90|6.82|6.99	10.89|7.14|6.96
r		0.54|0.63|0.66	0.56|0.65|0.67	0.53|0.62|0.66	0.56|0.65|0.66	0.53|0.61|0.62
b		0.24|0.38|0.19	0.20|0.19|0.18	0.16|0.20|0.06	0.15|0.16|0.10	0.34|0.78|0.77
W (m/s)						
μ	2.58	2.51|2.53|2.54	2.52|2.55|2.55	2.51|2.55|2.56	2.52|2.56|2.58	2.51|2.53|2.53
σ	0.88	0.84|0.46|0.51	0.84|0.46|0.49	0.84|0.43|0.49	0.84|0.45|0.48	0.84|0.44|0.48
r		0.57|0.40|0.46	0.59|0.45|0.47	0.56|0.42|0.47	0.58|0.44|0.47	0.56|0.44|0.47
b		-0.07|-0.05|-0.04	-0.06|0.03|-0.03	-0.07|-0.03|-0.02	-0.06|-0.02|-0.00	-0.06|-0.04|-0.05
S (s)						
μ ($*10^4$)	4.48	4.40|4.36|4.38	4.39|4.38|4.38	4.40|4.38|4.39	4.41|4.38|4.38	4.39|4.35|4.36
σ ($*10^4$)	0.27	0.37|0.35|0.35	0.38|0.35|0.34	0.34|0.34|0.34	0.35|0.34|0.34	0.36|0.36|0.34
r		0.24|0.13|0.16	0.20|0.21|0.22	0.19|0.08|0.11	0.20|0.19|0.20	0.15|0.04|0.05
b ($*10^4$)		-0.09|-0.00|-0.11	-0.09|-0.01|-0.01	-0.08|-0.01|-0.09	-0.07|-0.10|-0.10	-0.10|-0.13|-0.13

Table 10: As in Table 9, but for summer.

As expected a higher skill is found for the mean and maximum temperature which show higher correlation values and lower skill. The downscaled minimum relative humidity (Hmin) shows slightly lower skill than the mean variable for all the predictor combinations however, results are as good as for the mean humidity when the linear regression with 15 PCs + 1 neighbour is applied. Wind and precipitation present lower skill, with the analog method representing the best approach. The total hours of sunshine (seconds in the table) shows high skill, being even better when linear regression is applied. The different sets of predictors show quite similar results and in general the

P2 combination could be considered slightly better than the others. As observed in the fire risk indices the skill in general decreases in summer (Table 9), especially for precipitation and the total hours of sunshine.

Similar conclusions are found for Tunisia (one of the main regions of interest in the project for the tourism case study) and the Iberian Peninsula (Tables not shown). In particular over the Iberian Peninsula the set of predictors labelled as P5 seems to work slightly worse than the others for the mean relative humidity. On the other hand P2 and P4 present better skill over Tunisia for the mean wind and mean relative humidity.

3. Main conclusions and next steps

The present deliverable is intended for CLIM-RUN end-users with some basic knowledge on statistical downscaling and focused on the description of some particular examples applied to areas and local variables of interest for the project. The study presents different applications of specific statistical downscaling methods to the CLIM-RUN case studies (wild fires, tourism and energy) in several domains of interest over the Mediterranean basin: Greece, the Iberian Peninsula and Tunisia. In particular, it is focused on downscaling climate variables needed for the calculation of different fire risk indices (FWI, Angström index, Baumgartner index and Nesterov index) and the tourism climatic index which are of great interest for end-users. However, some of the downscaled climate variables (wind and hours of sunshine) are also useful for the energy case study.

The examples analysed through this deliverable try to explain the different steps that should be analysed in the downscaling process (domain size, predictors, statistical downscaling method, etc). Technical details about this issue are analysed for different predictands and areas of interest. The use of the CLIM-RUN statistical downscaling portal eases the downscaling process for the CLIM-RUN end-users who have to do similar applications for their particular regions and variables of interest.

The experiments presented in the deliverable should be considered as an overview of the possibilities that the statistical downscaling offers to end users who need local climate information. The technical details presented here show that the approach/methods are promising. And so next steps will be to provide some specific examples of future projections of FWI and TCI in formats and with brief documentation suitable for less technical end users. Ideally these will be based on more local (station) data provided for/by the case studies.

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