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

Downscaling of non-standard parameters

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Authors: A. Casanueva, J. Bedia, S. Herrera, M. D. Frías, J. M. Gutierrez, C. Giannakopoulos, A. Karali and K. Zaninovic

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1. Introduction

Many stakeholders request local climate information to assess the relationships between climate forcings and impacts on ecosystems in different sectors (fire, agriculture, tourism, energy, etc). However, General Circulation Models (GCMs) are not able to produce future climate scenarios at the proper scale required for the different impact-orientated applications. An approach to bridge the gap between the coarse resolution of the global models and the high resolution required by end-user applications is the downscaling (dynamical or statistical downscaling). In particular, the statistical downscaling methodologies provide local scale information from the large scale integrations from the GCMs taking into account the empirical relationships between large (used as predictors) and local scale variables (Zorita and von Storch, 1999). In the framework of the CLIM-RUN project a statistical downscaling portal (https://www.meteo.unican.es/downscaling/climrun, see D3.2 and Gutierrez et al, 2013 for more details) has been delivered by the UC partner to connect data producers with end-users in order to satisfy the general public and stakeholders' requirements. Several statistical downscaling methodologies are implemented in this portal and this tool has been considered in the present study to analyze the performance of the statistical downscaling methods for non-standard parameters.

Statistical downscaling methods are commonly applied to derive local scale information of surface variables such as precipitation or temperature, which are the variables more often estimated. Many references can be found in the literature for these two variables over different regions around the world (Hewitson and Crane, 1996; Timbal and McAveaney, 2001; Frias et al, 2010). Although, these variables are the most demanded, to a lesser extent statistical downscaling is also applied to estimate non-standard parameters such as wind or snow (Curry et al, 2012; Pons et al, 2010). In fact, one advantage of the statistical downscaling versus the dynamical approach is that the former offers the possibility to produce local information of non-climatic variables such as wind power (García-Bustamante et al, 2013), river flows (Tisseul et al, 2010) or indices which are computed from several meteorological variables. In the last group we can consider two indices of interest for the CLIM-RUN project: the Fire Weather Index (FWI) and the Physiological Equivalent Temperature (PET). The FWI is one of the most popular fire danger indicators (Moriondo et al, 2006; Groissman et al, 2007) and the PET is a thermal comfort index used to characterize the thermal bioclimate at any given place (Höppe, 1999; Matzarakis et al, 1999). The FWI and the PET are commonly considered by stakeholders from the wild fires and tourism sectors respectively and in particular, they are of great interest for stakeholders working in representative target areas defined in CLIM-RUN: Spain and Greece for wild fires and Croatia for tourism. The suitability of performing statistical downscaling to these two non-standard parameters is the aim of the present deliverable.

The formulation of the FWI and the PET depends on meteorological parameters and the statistical downscaling can here be applied indirectly through the meteorological drivers (component downscaling hereafter) or directly on the index (direct downscaling hereafter). In the former case, the selected approach must guarantees physical and spatial consistency of the downscaled variable, therefore the analog based method is a proper option for this problem. In the latter case, the performance of applying the downscaling directly to the index is also assessed, and in this case different statistical downscaling methods can be considered (analogs, linear regression, etc). The

comparison of both methodologies, component and direct downscaling, exhibits value-added information for CLIM-RUN. The stakeholders involved in this project (from energy, wild fires and tourism sectors) consider different indexes defined from meteorological variables and it would be interesting to obtain local information directly for these indices by means of the statistical downscaling approach. This study assesses the suitability of performing downscaling directly to these non-standard parameters of interest for CLIM-RUN instead of applying the downscaling to each meteorological variable.

2. Statistical downscaling of non-standard parameters

Statistical downscaling methodologies are commonly applied to estimate local values of surface variables like precipitation or temperature with historical records available whereas other climate variables like wind, snow or humidity are less frequently downscaled. The application of these methods has been extended in the last years to other non-climatic variables (wind power, runoff studies, river flows, etc) with promising results. The aim of these studies is to satisfy the demand of local scale information by different impact models considered in an extensive variety of sectors. In particular tourism and wild fires are two sectors analyzed in the framework of the CLIM-RUN project and both require climatic and non-climatic information at local spatial scales to manage the impacts of climate change on the ecosystems. The performance of the statistical downscaling approaches is here applied to two indices commonly considered in the wild fire and tourism sectors: the FWI and the PET, respectively for particular regions of interest. As mentioned above, the downscaling approaches can be applied indirectly through the meteorological drivers prior to the index calculation or directly on the index. Both approaches are assessed in this deliverable.
The performance of the statistical downscaling approach is here first validated using data from the ERA-Interim reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF) (Dee et al, 2011) (perfect model conditions). Then, transient projections from the IPCC-AR4/CMIP3 ECHAM5 model are also considered for the future. Here, the downscaled future projections are compared to the control scenario (20C3M) .

2.1.Fire Weather Index application

The analysis of the fire risk is essential to identify fire-prone regions and to implement appropriate fire management over vulnerable areas. Wild fires highly depend on climatic drivers, so it is important to identify and understand the relationships between wild fires and weather in order to assess the potential impacts of climate change on future fire activity. In particular, one of the objectives in CLIM-RUN is the analysis of the fire risk in areas where forest fires represent a major hazard located in specific target regions over the Mediterranean. One of the areas of particular interest in terms of vulnerability to climate change is Spain which has already been identify as a hot spot (Giorgi, 2006) and is at particularly high risk of fires during summers. The fires occurred during 2005 over Spain are a good example of the worst year in the last decade concerning the number of burned surface and the number of fires. Southern continental Greece and especially the Peloponnese is also a fire prone region which was severely affected by the devastating fires of 2007. Then, fire management planing is of national significance in the last years.

2.1.1.Results over Spain

The Fire Weather Index (FWI) is one of the most popular fire danger indicators (Moriondo et al, 2006; Groissman et al, 2007) that takes into account the effects of fuel moisture and wind on fire behavior. 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. Local weather observations from Spain were obtained from 45 meteorological stations belonging to the Spanish Meteorological Agency (AEMET) recording the required data for FWI calculation. Locations for these stations are represented in Figure 1 by circles. The AEMET dataset provides instantaneous values at 13UTC of temperature, relative humidity and wind speed, and accumulated values of precipitation in the previous 24 hours, measured at 07UTC. For the computation of FWI, the accumulated precipitation before noon is considered. Thus, we adjusted the AEMET precipitation by shifting one day ahead the whole precipitation series to match the dates of the rest of variables. In summer local time, these measurements correspond to 15:00 (temperature, relative humidity and wind) and 09:00 (precipitation). Figure 1 presents the observed climatologies for the four variables considered in the calculation of the FWI for the period 1979-2003. Spatial mean values for the whole year and also for the season of critical fire danger composed of values from June to September (JJAS) are indicated for each map. The stations in northern Spain (north-western part and the Cantabrian coast) correspond to the Atlantic range of Spain and are characterized by milder temperatures and higher precipitation and relative humidity.

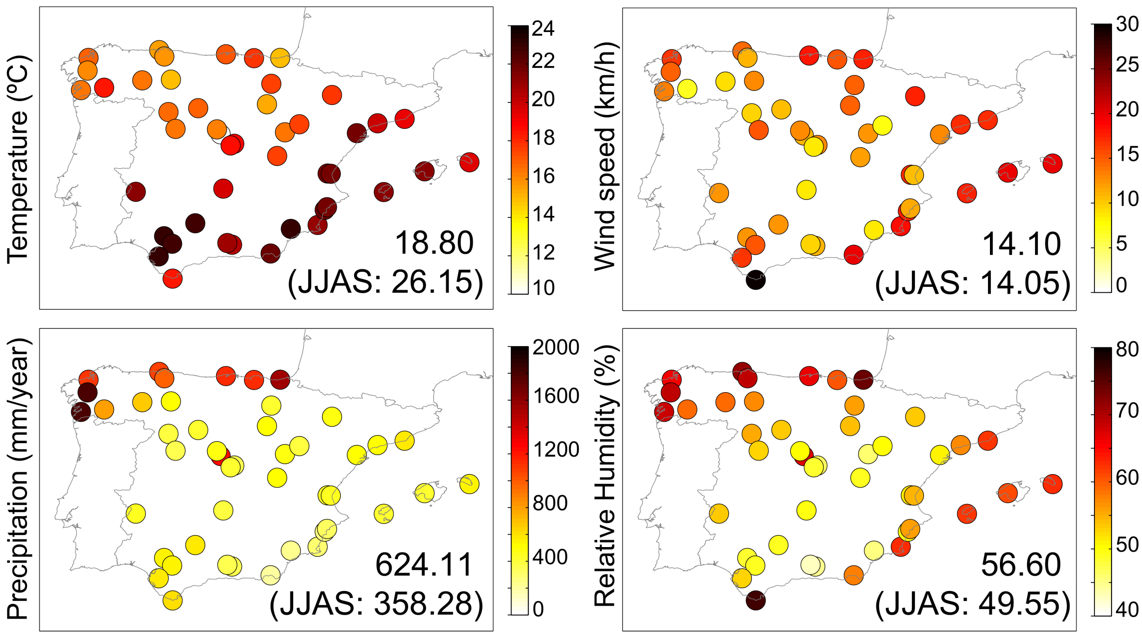

Figure 1: Observed annual climatology for the four variables used for the FWI calculation. Numbers in each panel indicate the spatial mean values for the whole year and for the fire season (JJAS).

The FWI 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 of the FWI 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 build-up index. See van Wagner and Pickett (1985) for more details about the equations to compute the FWI. Following this formulation, the AEMET station data were used to compute the FWI over Spain. Figure 2 presents the mean and standard deviation (Std) of the resulting FWI values for the whole year and for JJAS. In general, this index presents lower values over the north coast of Spain where higher precipitation and milder temperatures are registered and higher values over the south and the Mediterranean coast. As expected, the FWI increases in summer over the whole area.

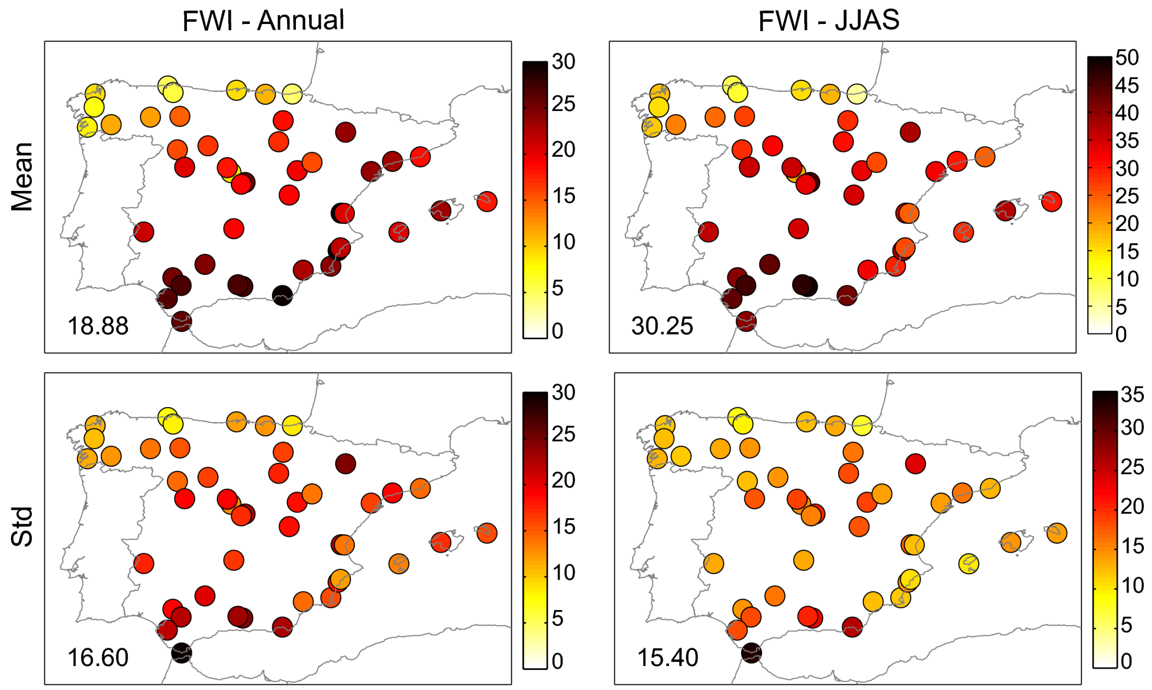

Figure 2: Observed FWI climatologies and standard deviation values for the whole year (left panels) and for the fire season (JJAS) (right panels). Values in each map correspond to the spatial mean.

2.1.1.1. Statistical downscaling

The increasing interest of assessing the future fire danger impacts at fire-prone areas has roused the consideration of statistical downscaling methods which offer the possibility to locally project the available global climate scenarios (Bedia et al, 2013). A statistical downscaling approach based on analogs is here applied over Spain. This technique is one of the most popular methods of statistical downscaling (Zorita and von Storch, 1999, Frias et al., 2010) and consists of finding the most similar situation in terms of the Euclidean distance to the present one in a pool of historical cases. That situation is chosen as the analog or nearest-neighbor and the subsequent evolution of this analog state is assumed to also occur for the base case. A clear advantage of this method is that it

provides physical and spatially coherent series for all the meteorological variables driving the FWI. For this reason, this approach has been applied in this study to each input meteorological variable prior to the FWI calculation. The same methodology is also applied directly to the FWI in order to assess the best practical application of the statistical downscaling approach.

The definition of the atmospheric pattern for the analog method is here based on the results obtained in the Spanish National Program on regional scenarios, Escenarios-PNACC 2012 (Gutierrez et al, 2012). One of the tasks in this project was the assessment of the performance of different downscaling methods taking into account several geographical domains over Spain and different sets of predictors. According to these results, the geographical domain considered here is a window centered on the Iberian Peninsula limited by the coordinates 45ºN, 35ºN, 10ºW and 5ºE. Different sets of predictors were tested in the present study for the statistical downscaling approach including the typical large scale variables used in other statistical downscaling studies developed over different regions in Europe (see e.g. Gutierrez et al, 2013 and references therein). Here only results from the pattern based on temperature at 2 meters (2T), temperature (T850), relative humidity (R850), U and V wind components (U850 and V850) for 850 mb are presented since no significant improvements were attained with the other configurations. The predictor combinations were chosen to meet the needs of fire danger climate change studies, and in particular of FWI, and include "signal-bearing" predictors (e.g. temperature) in order to capture a potential climate change signal.

First, predictors were taken from the ERA-Interim reanalysis (Dee et al, 2011) covering from 1979 to 2000. Then, a single GCM (the IPCC-AR4/CMIP3 ECHAM5 model, (run 3)) for the control 20C3M scenario (1979-2000) and for the transient A1B scenario (for the periods 2011-2040, 2041-2070 and 2071-2100) was also considered. Here, the downscaled future projections are compared to the control scenario (20C3M) for the period 1971-2000 using the delta method. Due to their different native horizontal resolutions, both reanalysis and GCM data were re-gridded using bilinear interpolation to a regular 2º grid. We considered 12 UTC in addition to 00 UTC and daily mean values, since FWI is calculated at noon, however similar results were obtained in both cases. Results for the 00 UTC are shown since this output is available in the GCM considered.

2.1.1.2. Results in perfect model conditions

The analog downscaling method is first applied in perfect model conditions to the four input meteorological variables in order to analyse the performance of the method. Then the downscaled meteorological variables are used to compute the FWI. Some form of cross validation is necessary since the same dataset is used for calibrating and testing the model. In particular, we considered a k-fold cross-validation approach for the 25-year calibration period (1979-2003), using k = 5 different combinations of calibration and test periods, each containing 20 years for calibration and 5 years for testing. We considered a stratified regular sampling, where the first test sample was formed by the years: 1979, 1984, 1989, 1994, 1999, the second by the years 1980, 1985, etc. (see e.g. Gutierrez et al, 2013, for more details). The resulting five test periods cover the whole validation period (1979-2003), so they were concatenated into a single final test series which was used to compute the different validation scores.

The Spearman rank correlation coefficient was calculated for the observed and predicted variables to assess the predictive performance of the downscaling approach. This score is robust to outliers values and can deal with possible non-linear relationships between both series of data. Figure 3 presents the values of the Spearman correlation and the resulting bias for the FWI obtained from the

component and the direct downscaling approaches. Slightly higher correlation values are obtained for the component downscaling, especially over the western part of Spain whereas the direct downscaling yields lower bias almost in every station.

The performance of the analog downscaling method is analysed in more detail in Table 1. This table presents the correlation values for the daily and the JJAS-averaged series for the downscaled input FWI variables, for the resulting FWI (FWI) and the direct downscaled FWI (FWId). In general, the method performs adequately considering the annual daily time series, which is the native time resolution of FWI. However, not all input FWI variables are downscaled with the same skill, and the relatively high performance of the method for temperature and relative humidity contrasts with the poor correlations attained in the case of wind, and to a lesser extent, precipitation. It is also observed that the performance of the analog downscaling decreases notably when considering the cross-correlations of averaged JJAS data. This is explained by the lower variability of the fire danger indices during the summer, that maintain high values due to the scarce precipitation and the high temperatures. In contrast, when computing the correlations with the annual daily series, the method is able to properly capture the seasonal cycle yielding better results. In consequence, performing the downscaling on the whole annual series is the recommended approach.

Considering the suitability of applying the statistical downscaling directly to the FWI, it would be reasonable to apply other statistical downscaling methods to this index, since in this case the preservation of the physical coherence it is not required unlike the component statistical downscaling. A statistical downscaling method based on the linear regression model is here applied to the FWI. In particular this method is applied to the JJAS values since they are normally distributed. In this case a Principal Component Analysis is used to the spatial patterns given by the first 10 principal components (PCs) that yield a fraction of explained variance around 90%. The correlation and bias values obtained from this approach are shown in Figure 4. The skill of this downscaling method is higher than the analog approach in terms of correlation and bias for this season (JJAS) Spatial mean correlation value of 0.49 results for the regression based model versus 0.34 for the analog one (see Table 1) whereas the spatial mean bias is -0.16 for the regression downscaling approach versus the -0.43 for the analog based downscaling model. Note that, as expected, the performance of the regression model for JJAS is lower than the results obtained for the analog approach for the whole year (see Figure 3, right panels).

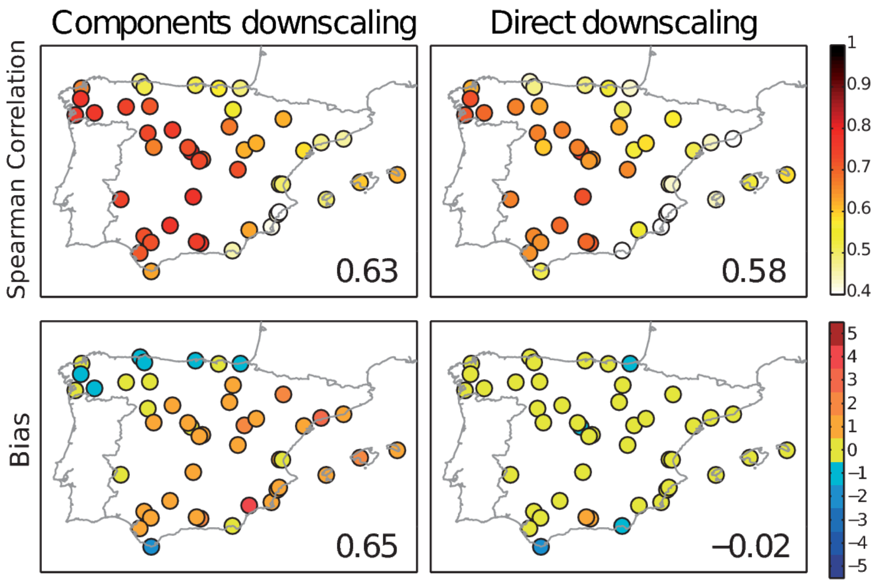

Figure 3: Correlation and bias of the downscaled FWI from the component (left panels) and the direct downscaling approaches (right panels).

		Spearman Correlation	Bias
W	daily	0.27	-0.12
	JJAS	0.12	0.09
H	daily	0.51	-0.40
	JJAS	0.30	0.09
P	daily	0.35	-1.64
	JJAS	0.21	-1.15
T	daily	0.89	0.15
	JJAS	0.79	0.06
FWI	daily	0.63	0.65
	JJAS	0.31	0.53
FWId	daily	0.58	-0.02
	JJAS	0.34	-0.43

Table 1: Spatial mean values of the Spearman correlation and the bias for the daily and JJAS-averaged series resulting from the statistical downscaling.Values correspond to the downscaled primitive FWI variables (W, H, P and T), the resulting FWI and also the direct downscaled FWI (FWId).

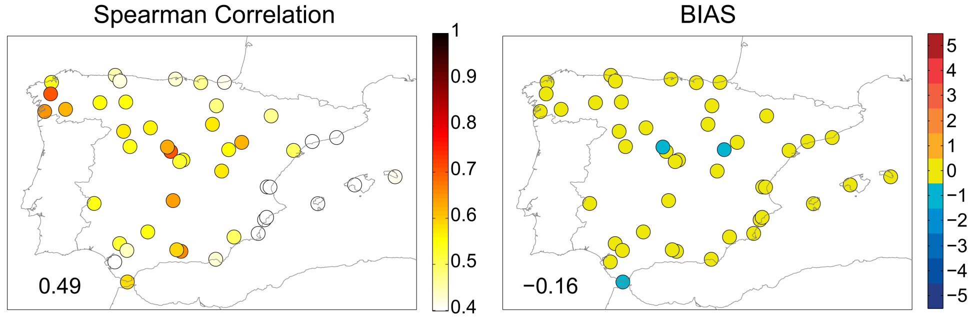

Figure 4: Correlation and bias of the JJAS FWI from the direct linear regression downscaling approach.

2.1.1.3. Results from climate projections

GCM large scale variables from the IPCC-AR4/CMIP3 ECHAM5 model (run 3) are also considered for the 20C3M scenario to verify the suitability of the GCM outputs for the statistical downscaling method. The period overlapping with the ERA-Interim reanalysis is here used to compare the results. In contrast to the perfect model approach, note that in this case there is no day-to-day correspondence between the model outputs and the observations, even though the projections are done in an historical period. A comparison of the climatological downscaled and observed values for the annual and the JJAS series is presented in Table 2 for the ECHAM5 20C3M control scenario by the computation of the relative errors of the mean (μ) and the standard deviation (σ). The results considering the ERA-Interim reanalysis are also shown for comparison. Moderate biases in both the mean and standard deviation in the 20C3M scenario, with similar magnitudes to that corresponding to the reanalysis ones, and even smaller in some cases, are found.

		Annual		**JJAS**	
		REA	*CTL*	*REA*	*CTL*
W	μ	0.1	2.1	-1.1	0.6
	σ	-1.8	-0.3	-2.3	-0.6
H	μ	-0.4	-1.0	0.5	-0.9
	σ	-2.0	-0.1	-1.5	0.6
P	μ	-8.8	-0.6	0.0	1.1
	σ	-8.6	-2.8	-9.3	-10.4
T	μ	0.1	1.1	-0.5	-0.1
	σ	-1.9	-0.9	0.8	8.1
FWI	μ	2.6	3.4	0.6	2.7
	σ	-4.1	-1.5	-5.3	-4.2
FWId	μ	-1.3	-0.3	-2.4	-1.9
	σ	-3.7	-5.2	-2.9	-6.8

Table 2: Relative errors of the mean and standard deviation climatological values of the downscaled w.r.t. the observed values (pred/obs-1 in %) for the ERA-Interim reanalysis (REA) and the ECHAM5 20C3M control scenario (CTL). Results correspond to the primitive FWI variables (W, H, P and T), the resulting FWI and also the direct downscaled FWI (FWId).

Once verified that the GCM outputs are suitable for the statistical downscaling method, we proceeded with the calculation of the FWI increments/deltas for three different future periods: 2011-2040, 2041-2070 and 2071-2100. The deltas have been obtained as the period-averaged differences from the A1B and the 20C3M downscaled values. The resulting deltas for the 90th percentile (FWI90) are shown in Figure 5 for the critical fire danger season (JJAS) and for the component statistical downscaling. The FWI90 is frequently used as an indicator of extreme fire danger situations (Andrews et al, 2003; Dowdy et al, 2010) and it is here analyzed in more detail. The deltas obtained with the analog based method exhibit a similar pattern for the first two periods considered, whereas in the last decades of the 21st century (2071-2100) the warming signal is more evident. In the last period the spatial pattern of these deltas shows an unrealistic spatial variability, with large and small increments depending on the location. This may be the result of the complex interaction of the deltas for the four variables forming the FWI and is also an indication of the lack of robustness of the analog based method in this period as has been reported by Gutierrez et al (2013).

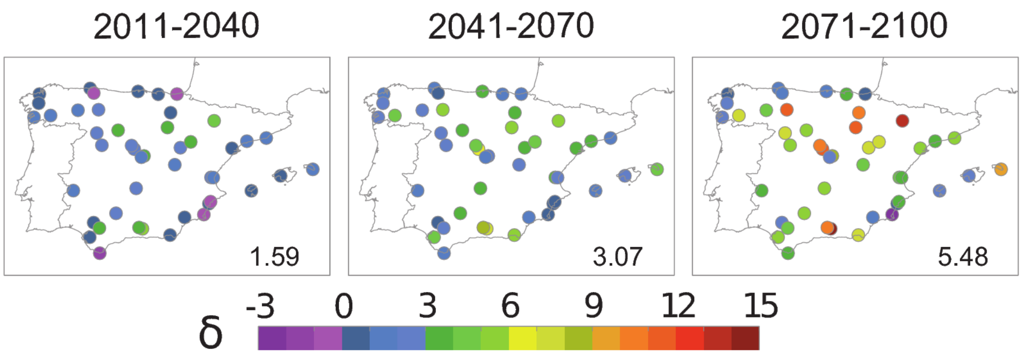

Figure 5: Projected future FWI90 regimes (A1B scenario) in terms of anomaly (delta) w.r.t. the control 20C3M scenario (1971-2000) for the three future periods considered. Spatial mean values are indicated at the bottom of each panel.

The point-based FWI90 deltas from the component statistical downscaling method versus the direct values are illustrated in Figure 6 for JJAS and for the three future periods considered. In general, these results show that the values from the component analog method are comparable to those from the direct downscaling method. Both approaches register higher values in the last decades of the 21st century and a spatial pattern less robust.

A comparison of the FWI90 deltas from the direct analog downscaling method and the linear regression based downscaling is shown in Figure 7 for the three future periods considered. Results from both methods are comparable for the first two periods, whereas higher differences are observed for the last period (2071-2100) depending on the station considered. Both statistical downscaling approaches also present higher spatial variability for this period.

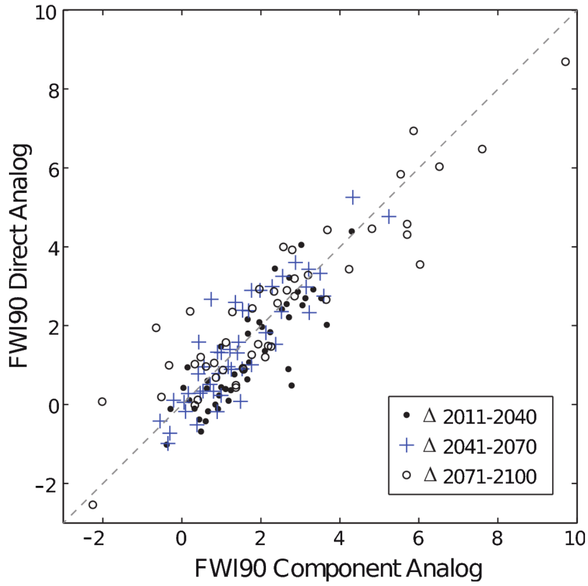

Figure 6: Point-based delta values for the FWI90 from the component statistical downscaling versus the direct statistical downscaling.

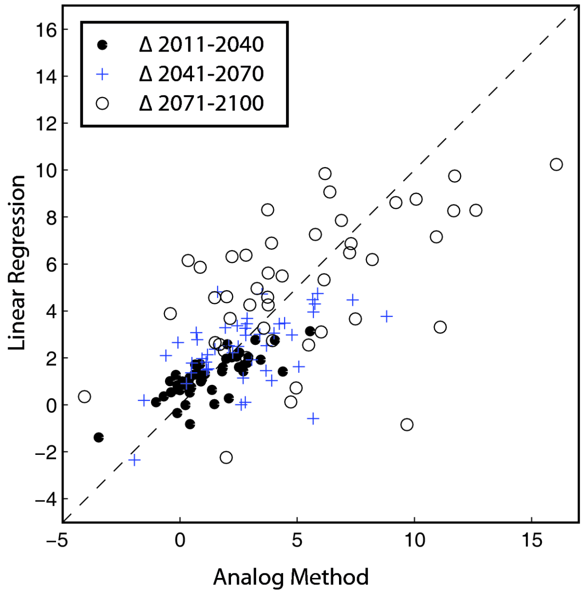

Figure 7: Point-based delta values for the FWI90 from the direct statistical downscaling using analogs versus linear regression.

2.1.2.Results over Greece

The suitability of performing statistical downscaling directly to the FWI is also analysed over the souther part of Greece which is at particularly high risk of fires (Figure 8). In this case, the predictors for the statistical downscaling experiment were taken from the ERA-Interim reanalysis data, covering the period from 1/1/1979 to 31/12/2010. The large scale variables used as predictors were chosen in accordance to the results of the D3.3. These variables are the relative humidity at 850hPa, U and V wind horizontal components at 850hPa and air temperature at 850hPa. The statistical downscaling portal was used considering the ERA-Interim reanalysis as predictands (pseudo-observations) due to the lack of observations at noon over this region. According to previous studies the ERA-Interim data set has been proven to be the most suitable reanalysis product for FWI estimation (Bedia et al., 2012), offering, among other advantages, an improved resolution with regard to its predecessor ERA-40.

Figure 8: The domain of study according to the ERA-Interim resolution. The red dots represent the places where the downscaling was performed.

Additionally, the analogs method was used in order to downscale the AR4-ECHAM5 GCM data for the control period (1961-2000, 20C3M scenario) and the future period (2021-2050, A1B scenario). This method offers clear advantages since it provides physically coherent series for all the meteorological variables driving the FWI (Herrera at al., 2012). Furthermore, the analog method is used for the projection of future scenarios. Only results for the first half of the 21st century are computed since the lack of robustness already observed at the second half of the century.

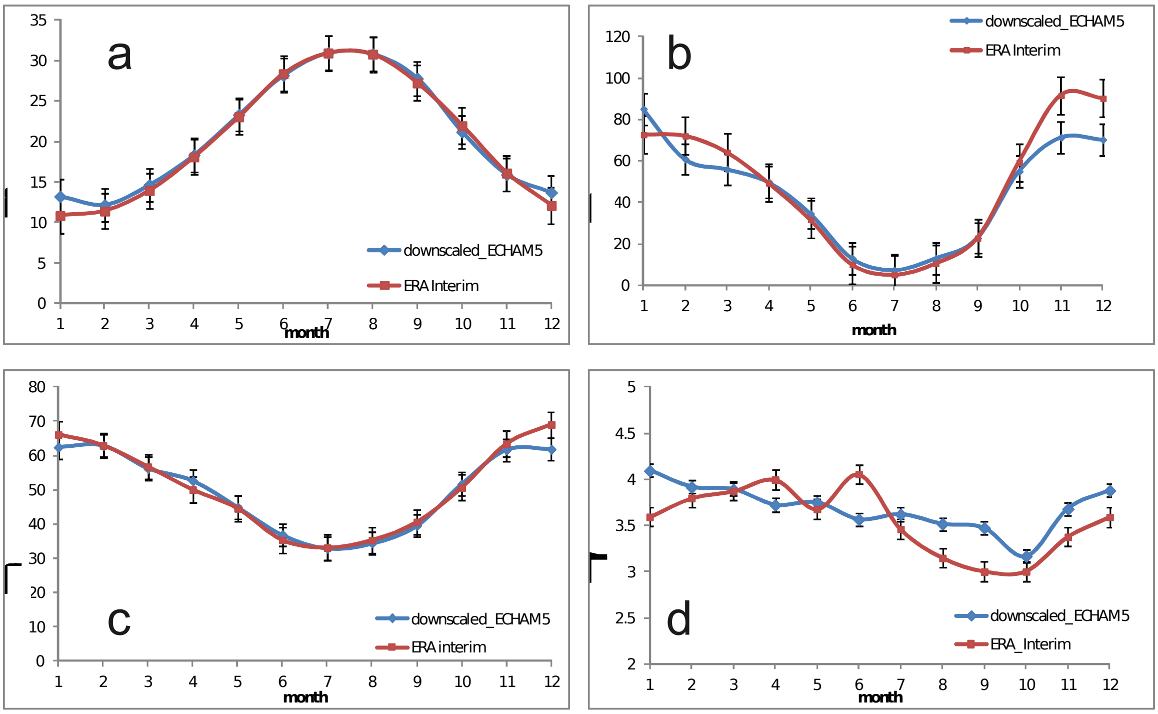

Figure 9: Mean monthly values for the period 1979-2000 of a) air temperature, b) total precipitation, c) relative humidity and d) wind speed of the downscaled ECHAM5 data (blue line) obtained by the downscaling portal and of the ERA-Interim data set (red line).

Firstly, the analogue downscaling technique was directly performed to the FWI index values and secondly the same downscaling technique was performed indirectly through the meteorological inputs used to derive the index. Figure 9 presents the results for the grid point with coordinates 21.75 longitude and 37.5 latitude, in central Peloponnese. This Figure depicts mean monthly values of the meteorological parameters that constitute FWI obtained by the downscaling portal and the ERA-Interim original data. As shown in the figure, the noon air temperature as well as the relative humidity are very well represented compared to the gridded observational data. As far as monthly total precipitation is concerned the downscaled values and the original ERA-interim data are in good agreement especially from April to October. Mean monthly downscaled wind speed has the worst performance when compared to the observational data.

In Figure 10 the evolution of FWI index throughout the year is depicted. The index was directly downscaled using the analog method (FWI_D) and was also calculated by using downscaled meteorological data (FWI_M). These results were compared to the FWI index values calculated from the ERA-Interim data set (FWI-Interim). As shown in this figure, both FWI_D and FWI_M are consistent to the ERA-Interim data. Moreover, FWI_D depicts slightly greater monthly values during the winter and spring while FWI_M depicts greater values during the summer with a slight shift towards the middle of July when compared to the FWI-Interim values.

Finally, Figure 11 shows mean summer values of FWI directly downscaled in the portal for the years 1961 up to 2050. A positive trend is observed with values ranging between 30 and 50 by the end of the first half of the 21st century.

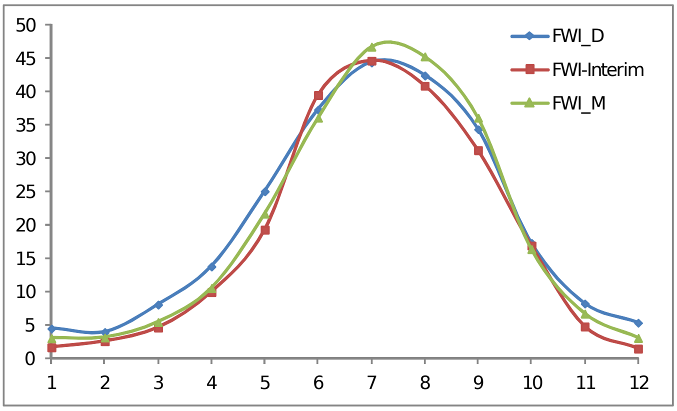

Figure 10: Mean monthly FWI downscaled directly in the portal (FWI_D), mean monthly FWI calculated using meteorological data from the ERA-Interim data set (FWI-Interim) and mean monthly FWI calculated using downscaled meteorological data obtained by the portal (FWI_M), for the period 1979-2000.

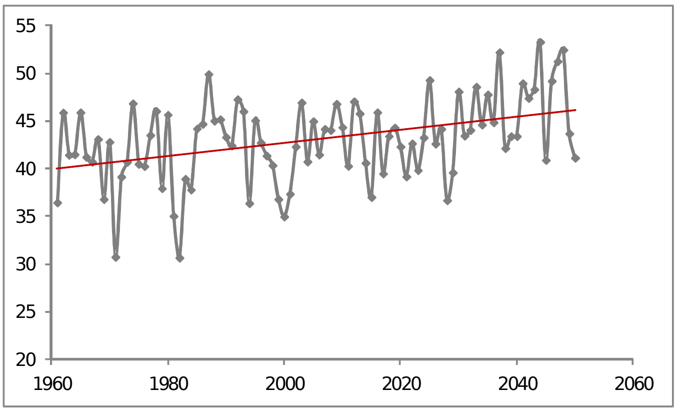

Figure 11: Mean summer directly downscaled FWI values for the period 1961-2050.

2.2. Physiologically Equivalent Temperature application

Tourism is one of the world's biggest industries and for many regions it is the most important source of income (De Freitas, 2003). Climate and weather play an important role in several economic activities and in particular in tourism. Although weather and climate are not necessarily determinants of tourism, they are pervasive factors for attracting visitors, together with other natural elements such as geographical location or landscape.
Climate is one of the key factors influencing development in the tourism sector (Boniface and Cooper, 1994). Optimal climate conditions have a major effect on tourism demand of particular destinations becoming an important economic asset. However financial losses can also result from unexpected weather conditions or weather variability. The potential usefulness of climatological information has increased the need to analyze climate information for tourism management and adaptation in the context of climate variability and change. Considerable effort has been done to develop climate related indices that integrate the effects of the atmospheric variables and provide useful information for both tourists and the tourism industry in a form relevant to them (De Freitas et al 2008). This information could be used to plan the best activity, period of time or destination for holidays, to estimate the potential number of visitors in a particular place, to promote a tourism destination with publicity campaigns, etc.
Different tourism climate indices have been developed over the last decades (Mieczkowski, 1985; Morgan et al, 2000; Freitas et al, 2008) which take into account several features of climate such as temperature, wind speed or sunshine hours. In this study we focus on a thermal comfort index derived from the human energy balance: the physiological equivalent temperature (PET). This index is well suited to the evaluation of the thermal component of different climates (Matzarakis et al 1999). It is equivalent to the air temperature at which, in a typical indoor setting, the heat balance of the human body is maintained with core and skin temperatures equal to those under the conditions being assessed (Höppe, 1999). Temperature, humidity (relative humidity or water vapor pressure), wind speed and radiation or cloudiness are the variables required for the calculation of this index.
The performance of the statistical downscaling approach is in this section applied to the PET for one of the target regions for the CLIM-RUN project in the context of the tourism sector: Croatia. Tourism has increased in last years in this country and nowadays it is one of the main branches of the economy with more than 11 million tourists in 2011 (Central Bureau of Statistics 2012). The role of climate is important in this region and the inclusion of selected climatological or bioclimatological data in any tourist promotion over the region can help the tourist industry in their decision-making. More information about the usefulness of this index to assist the tourism industry is presented in Zaninović and Matzarakis (2009) for Croatia.
Observed values for the input PET variables (temperature (T), relative humidity (H), wind speed (W) and cloudiness (C)) at 2pm are analysed for 21 stations over Croatia. Figure 12 shows the locations for these stations (red points) sparse over the whole country. These data were provided by the Meteorological and Hydrological Service of Croatia. The observed climatologies for these variables are presented in Figure 13 for a 30-year period, 1981-2010. Spatial mean values for the whole year and also for summer (JJA) are indicated in each panel. Stations in the coast are characterized by warmer temperatures, higher wind speed and lower cloudiness.

Figure 12: Geographical domain for the Croatia case study. Red points represent the 21 stations analyzed.

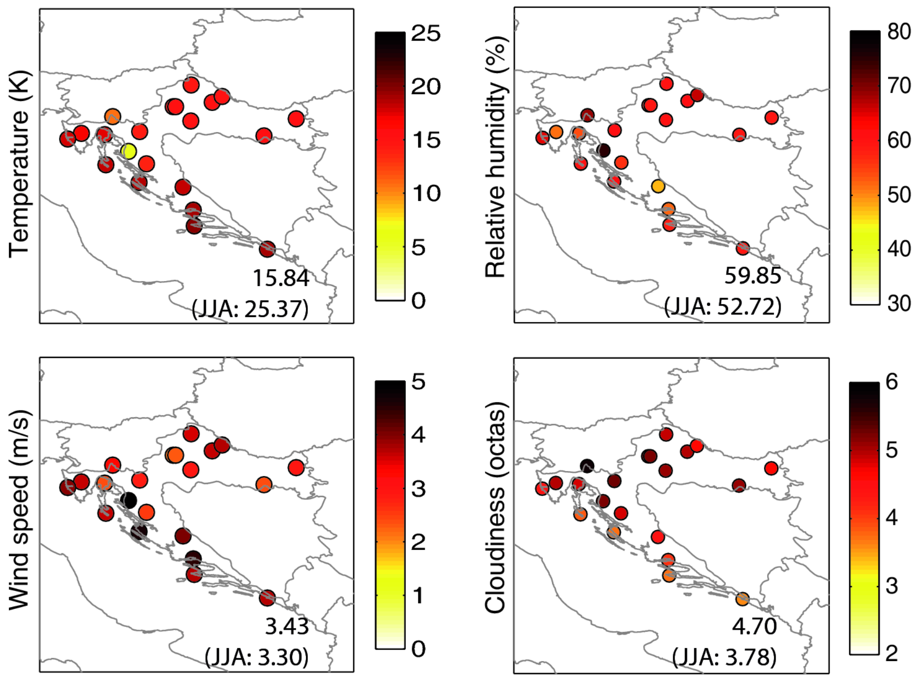

Figure 13: Observed annual climatology for the PET input variables for the period 1981-2010. Numbers in each panel indicate the spatial mean values for the whole year and for the summer (JJA).

These observed values are used to calculate the PET. This index is here calculated by means of the freely available RayMan software (http://www.urbanclimate.net/rayman) developed by Matzarakis et al (2007 and 2010). This model provides good simulation results for radiation flux densities and thermo-physiologically significant assessment indices (Matzarakis et al,2010). Figure 14 shows the

mean and standard deviation (Std) of the calculated PET for the whole year (left panels) and for summer (right panels). Higher values are mainly registered for stations in the south where warmer temperatures are observed. As expected, the PET increases in summer over the whole region and the standard deviation decreases.

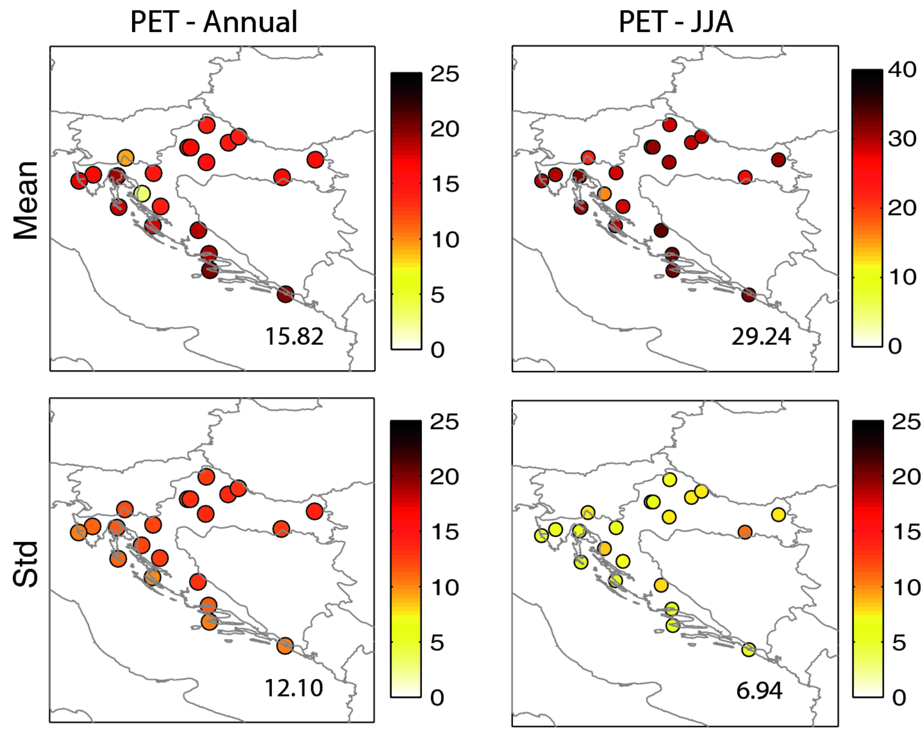

Figure 14: Observed PET climatologies and standard deviation values for the whole year (left panels) and for summer (right panels). Values in each map correspond to the spatial mean. Period analysed: 1981-2010.

2.2.1.Statistical downscaling in perfect model conditions

The statistical downscaling approach is here applied to obtain PET local values over the stations in Croatia. As for the FWI, the analog method is the first approach considered in this study in order to guarantee the physical and spatial consistency of the downscaled meteorological variables. Two set of predictors were tested over this region: a first pattern (P1) based on temperature at 2 meters (2T) and temperature (T850), relative humidity (R850), U and V wind components (U850 and V850) for 850 mb and a second pattern (P2) based on temperature at 2 meters (2T), temperature (T850) and specific humidity (Q850) for 850 mb, geopotential height for 500 mb (Z500) and sea level pressure (SLP). No significant differences were obtained from these two configurations, therefore only results from P1 are presented. No assessment of the downscaling performance depending on the geographical domain was developed for this region. Based on the results from Gutierrez et al 2013, a geographical domain centered on Croatia was considered (39.5ºN-49.5ºN, 9ºE-24ºE). Also predictors from the ERA-Interim reanalysis are here used for the period from 1981 to 2010.
The four meteorological variables considered in the PET formulation are first downscaled by using the analog model to assess the performance of the statistical downscaling method (Components

downscaling). Then, the downscaled local values are included in the RayMan software to calculate the PET. The same downscaling approach is also applied directly to the PET (direct downscaling).
A similar k-fold cross validation approach to that described in Section 2.1.1.2. is applied here to the calibrating period. In this part, due to the longer period analyzed, k=10 different combinations of calibration and test periods are considered to cover the whole validation period (1981-2010). Then, a stratified regular sampling was applied with 27 years for calibration and 3 years for testing (e.g. the first sample was formed by years 1981, 1991 and 2001). The resulting tests periods were concatenated into a single final downscaled series and validated considering different scores.
The performance of the downscaling approach is assessed in terms of the Spearman rank correlation coefficient and the bias. Figure 15 shows the resulting values for these two scores calculated for the observed and predicted PET. Panels on the left correspond to the outputs from the components downscaling and those on the right from the direct downscaling. Similar correlation values are obtained from both approaches, however slightly lower bias values result for the direct downscaling in almost every station. Table 3 analyzes the performance of the statistical downscaling method in detail. This table shows the correlation and bias values for the daily and the summer averaged series for the downscaled primitive PET variables (T, H, W, C), the resulting PET (PET) and the direct downscaled PET (PETd). As expected, higher correlation values are obtained for temperature for the annual daily series in contrast with the low correlation found for humidity, wind and cloudiness. Other studies have also shown poor results for wind (Bedia et al 2013) using the same statistical downscaling approach. Nevertheless, good skill is found for the calculated PET which show similar correlation and bias scores to those found for the direct downscaled PET. As found for the FWI

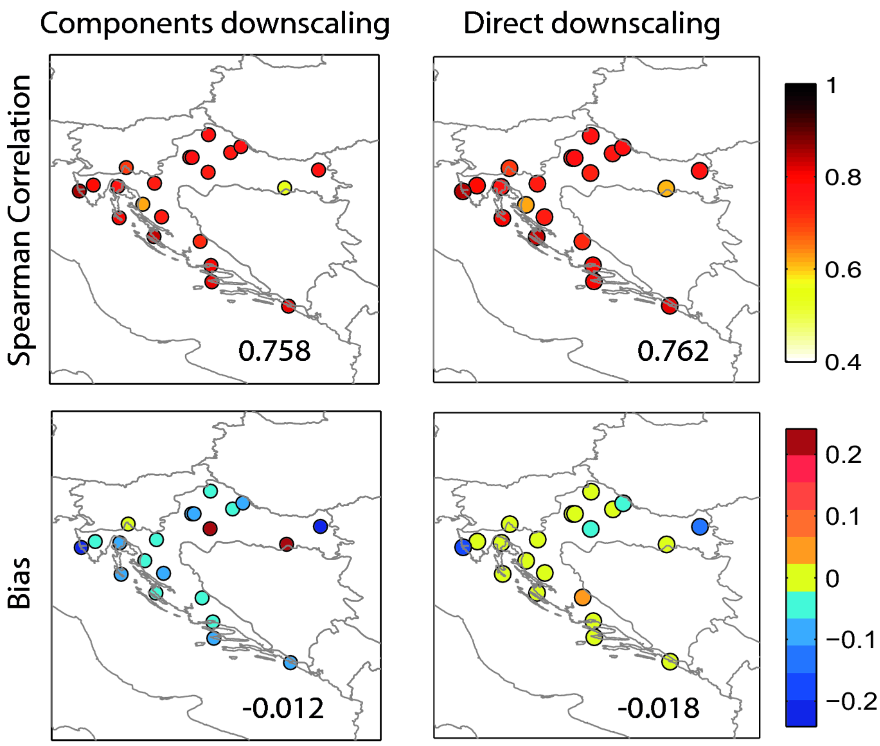

Figure 15: Correlation and bias of the downscaled PET from the component (left panels) and the direct downscaling approaches (right panels). Results using the analog downscaling method.

over Spain, the performance of the analog based method decreases when considering the averaged data for summer.

		Spearman Correlation	Bias
T	daily	0.77	-0.01
	JJA	-0.02	0.00
H	daily	0.16	0.01
	JJA	0.13	0.03
W	daily	0.06	0.00
	JJA	0.25	0.00
C	daily	0.07	0.00
	JJA	0.00	0.01
PET	daily	0.76	-0.01
	JJA	0.07	0.14
PETd	daily	0.76	-0.02
	JJA	0.10	-0.01

Table 3: Spatial mean values of the Spearman correlation and bias for the daily and summer averaged series resulting from the statistical downscaling. Values correspond to the downscaled primitive PET variables (T, H, W, C), the resulting PET (PET) and also the direct downscaled PET (PETd).

According to these results, a second statistical downscaling method is applied to the PET data. In this case, a downscaling method based on the linear regression model is considered taking into account that this variable is normally distributed. As applied for the FWI over Spain, a Principal Component Analysis is applied to the atmospheric pattern (P1). We consider as predictors the spatial patterns given by the first 10 principal components (PCs) which yield a fraction of explained variance of 88%. Figure 16 shows the resulting correlation and bias values of the PET from the direct linear regression downscaling approach. The performance of this downscaling method is higher than the analog approach (Figure 15, right panel) with correlation values around 0.9 for almost every station. The bias results are similar for both methods. A different version of the multiple regression model was also considered including the standardize values from the nearest grid-box as predictor (not shown). This option tries to solve the underestimation of the predicted variability taking into account local effects by means of the nearest grid point data selected. Similar results were found with both regression models.

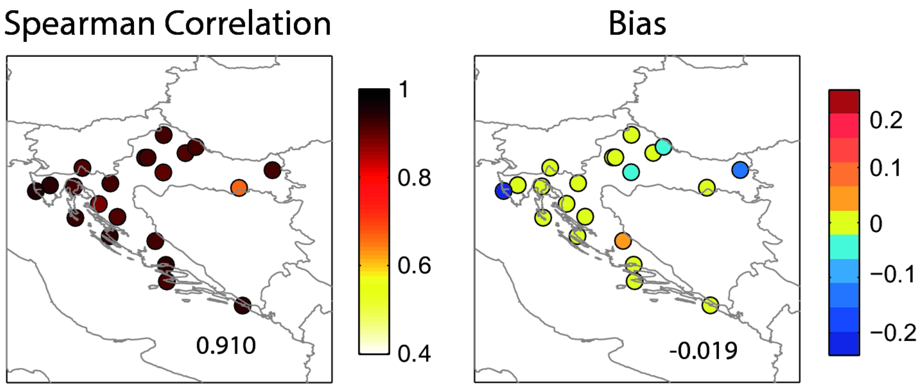

Figure 16: Correlation and bias of the PET from the direct regression downscaling approach.

2.2.2.Results from climate projections

After applying the statistical downscaling approach in perfect model conditions, we consider large scale variables from the IPCC-AR4/CMIP3 ECHAM5 model (run 3) for the 20C3M scenario to assess the performance of the GCM outputs for the statistical downscaling method. Table 4 compares the downscaled and observed values for the input PET variables, the computed PET and the direct dowscaled PET using the analog downscaling. Relative errors of the mean (μ) and the standard deviation (σ) are presented for the ECHAM5 20C3M control scenario (CTL) and for the ERA-Interim reanalysis for comparison. Results for annual and the summer series are shown. Moderate biases are found for the mean and the standard deviation in the 20C3M outputs.

The same 30-year future periods used for the FWI over Spain (2011-2040, 2041-2070, 2071-2100) are here considered to calculate the deltas for the PET. These delta values have been calculated as the period-averaged differences from the A1B and the 20C3M downscaled values. Figure 17 shows the resulting deltas obtained for the analog component downscaling. These maps show higher increments in the first and the last period of the 21st century over stations in the north of the country. As for the FWI over Spain, the spatial pattern of the deltas in the last decades (2071-2100) shows higher variability, with large and small increments depending on the location. This period also presents a more evident warming signal, with higher delta values than the other periods for all the stations.

		Annual		JJAS	
		REA	*CTL*	*REA*	*CTL*
T	μ	-0.28	1.89	0.01	-0.94
	σ	0.23	0.14	0.43	12.97
H	μ	0.26	-1.66	0.67	-1.37
	σ	-0.07	1.14	-0.15	2.96
W	μ	-0.86	5.37	-1.01	3.73
	σ	-0.25	7.74	-0.18	9.64
C	μ	1.38	0.32	1.94	-0.39
	σ	-0.16	0.62	0.08	2.89
PET	μ	-1.06	0.88	-0.46	-1.87
	σ	-0.43	-0.29	-1.18	10.44
PETd	μ	-0.54	1.83	-0.36	-2.05
	σ	-0.18	1.13	0.68	13.98

Table 4: Relative errors of the mean and standard deviation climatological values of the downscaled w.r.t. the observed values (pred/obs-1 in %) for the ERA-Interim reanalysis (REA) and the ECHAM5 20C3M control scenario (CTL). Results correspond to the primitive PET variables (T, H, W, and C), the resulting PET and the direct downscaled PET (PETd).

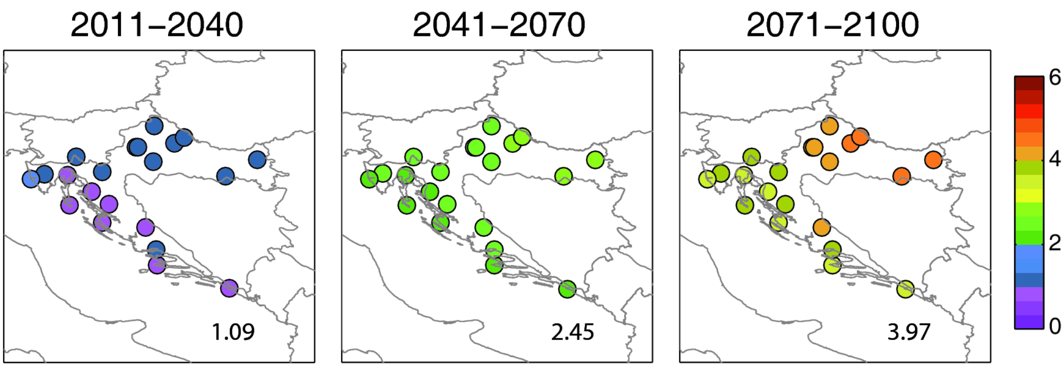

Figure 17: Projected future PET regimes (A1B scenario) in terms of anomaly (delta) w.r.t. the control 20C3M scenario (1971-2000) for the three future periods considered. Spatial mean values are indicated at the bottom of each panel.

The point-based PET deltas from the component statistical downscaling approach versus the direct downscaled values are shown in Figure 18 for the three future periods analyzed. Results show that downscaled values from the component analog method are similar to those from the direct downcaling approach. In this plot it is also clear the rise in PET registered for the second and the third future periods.

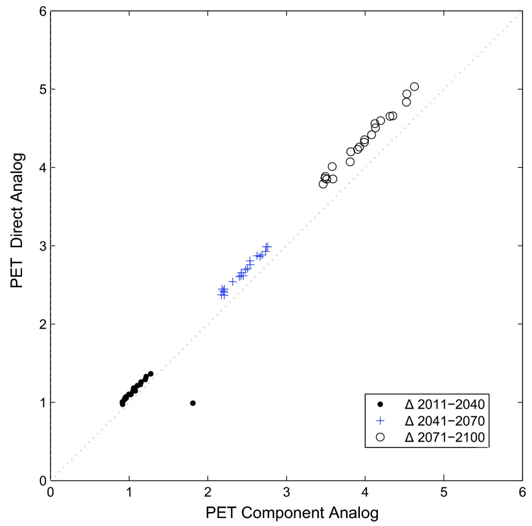

Figure 18: Point-based delta values for the PET from the component statistical downscaling versus the direct statistical downscaling.

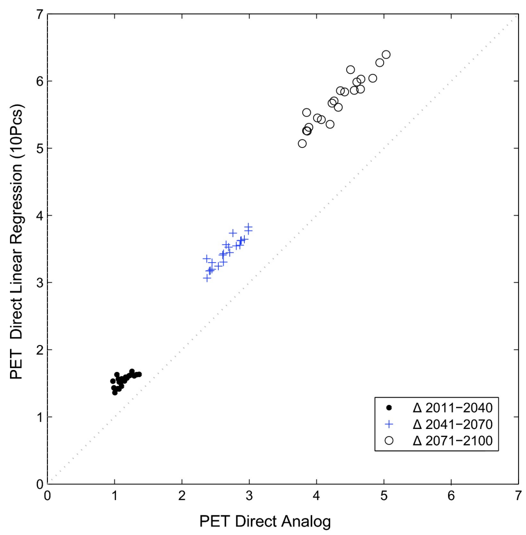

Figure 19: Point-based delta values for the PET from the direct statistical downscaling using analogs versus linear regression.

A point-based comparison of the PET deltas from the direct analog downscaling method and the direct linear regression downscaling approach are shown in Figure 19. Values from the direct analog method are comparable to those from the direct linear regression downscaling only in the first period (2011-2040). For the other two periods, the direct linear regression downscaling registered higher values than the analog based model. Gutierrez et al (2013) also found that the

analog based method underestimates the temperature anomalies of warmer periods within several methods analyzed. They suggest to consider the regression models as the most appropriate downscaling method for climate change studies.

3. Conclusions

Climate related indices are extensively considered in different sectors to analyze the impacts of climate forcings in different ecosystems. Local scale information is required for the calculation of these indices over particular regions of interest, however the GCMs are not able to produce simulations at the proper scale. Statistical downscaling methodologies provide local scale information required for the different impact-orientated applications from the large scale integrations derived from the GCMs. An added-value of this approach is that it is possible to apply the statistical downscaling method directly to these climate related indices in order to produce the local scale information required. This study analyze the suitability of performing statistical downscaling to two particular indices of interest for the CLIM-RUN project: the fire weather index and the physiological equivalent temperature. The former is relevant for stakeholders working on fires and the PET for those related to tourism. Both sectors are involved in the project and different target regions defined in CLIM-RUN were considered according to the observations available for this study: Spain for the FWI and Croatia for the PET. The comparison of both approaches was also performed over Greece taking into account ERA-Interim reanalysis as pseudo-observations since no observations were available over this region.

The statistical downscaling approach is applied indirectly through the meteorological drivers of both indices (component downscaling) and also directly on the indices (direct downscaling) for comparison. In the former case, physical and spatial consistency should be guarantee, so a statistical downscaling approach based on analogs was applied. Results in perfect model conditions are comparable for the component and the direct downscaling methods for both indices in terms of correlation and bias scores. According to this, a second statistical downscaling method based on linear regression was applied directly to the FWI and the PET. Higher correlation values than for the analog approach are obtained in this case for almost every station, especially for the PET. Component and direct downscaling approaches for the FWI were also comparable for Greece.

GCM large scale variables from the IPCC-AR4/CMIP3 ECHAM5 model (run 3) are also considered. This model is first validated for the FWI90 and the PET in present period using the 20C3M simulations. Then, delta values are calculated for three different future periods (2011-2040, 2041-2070 and 2071-2100). Similar results are obtained for the component and the direct downscaling for the first two periods and higher differences are observed for the last decades of the 21st century. In general, higher delta values are registered in the last decades of the 21st century which also presents higher spatial variability, with large and small increments depending on the location. This may indicate the lack of robustness of the analog based method in this period as has been reported in other studies (Gutierrez et al, 2013). Values obtained for the FWI and the PET from the direct analog method are comparable to those from the direct linear regression downscaling only for the first period (2011-2040). The last two future periods considered present higher delta values for the PET for the direct linear regression downscaling than for the analog based model.

The statistical downscaling portal delivered by the UC partner in the framework of the CLIM-RUN

project allow us to develop both direct and component downscaling approaches using a user friendly interface. According to the two experiments applied in this study for the FWI and the PET over different regions, results from both methodologies are quite similar. Therefore, for those impact studies where the intermediate climate information is not relevant, it is possible to apply the direct downscaling in order to provide local scale information for a particular climate related index.

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