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ADRIADAPT D.3.2.2

Release of the final set of climate data and indicators made available through the project platform

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1 Abbreviations

AR5:	5th Assessment Report of the Intergovernmental Panel on Climate Change
CCA:	Canonical Correlation Analysis
CGCMs:	Fully coupled General Circulation Models
CMIP5:	5th phase of the Coupled Model Intercomparison Project
CMCC:	Fondazione Centro euro-Mediterraneo sui Cambiamenti Climatici
DJF:	December-January February
ENS:	Ensemble Average
GCMs:	General Circulation Models
IPCC:	Intergovernmental Panel on Climate Change
JJA:	June-July-August
MAM:	March-April-May
MSLP:	Mean Sea Level Pressure
NetCDF:	Network Common Data Form
RCMs:	Regional Climate Models
RCP4.5:	Representative Concentration Pathway to a radiative forcing of 4.5 W/m2 at the end of 2100 wrt preindustrial values
RCP8.5:	Representative Concentration Pathway to a radiative forcing of 8.5 W/m2 at the end of 2100 wrt preindustrial values
SON:	September-October-November
SD:	Statistical Downscaling
Z500:	Geopotential at 500hPa

2 Introduction

The document (D3.2.2) provides a description of the climate data that has been delivered by CMCC, Arpae and DHMZ to the ADRIADAPT project users, both in terms of dynamical and statistical downscaling outputs. These tools are shortly presented in Section 2, the climatic variables delivered within the project are presented in Section 3. The report also includes a deep analysis of the performance/skill of the statistical downscaling technique implemented by Arpae-Simc, This work completes the historical validation process that has been already provided for the dynamical downscaling in the previous deliverable (D3.2.1). The results of statistical validation over Italian and Croatian case studies are presented in Sections 4 and 5 for temperature and precipitation indices. The analysis of statistical validation of SD is concluded with a description of trends in simulated and observed time series of temperature and precipitation, presented in Section 6.
The validation of statistical downscaling (SD) has been done for the seasonal mean and extreme indices of temperature and precipitation described in D3.1.1: “Definition of a set of climate change indicators for stakeholders“.

As already anticipated in D3.2.1, within ADRIADAPT project, the simulated data cover the period 1961 to 2100, following historical forcing up to 2005 and two different possible radiative emission scenarios to the end of the century: a business as usual (RCP8.5) one and a more moderate one (RCP4.5).

The evaluation of future projection will be the subject of D3.3.1 “Detailed quantification of climate change signal in the region of interest with special emphasis on severe impacting events” due at month 24.

3 Description of Models and parameters

3.1 Regional Climate Models

One of the ways to investigate the climate system and its variability is through climate models. Considering the global scale, a climate model can be an atmosphere (or ocean)-only general circulation model (GCM) or a fully coupled general circulation model (CGCM). To improve the ability of a climate model in representing small-scale features, instead of a general circulation model, regional climate model (RCM) and statistical downscaling technique (SD) can be used: this approach makes it possible to increase the spatial resolution, reducing the extension of the domain considered. In fact, the performance and the spatial resolution of GCMs have continuously improved in the recent years, but the typical state of the art spatial scale is still too coarse to realistically reproduce present climate and eventually project climate change signals on local scales, especially in the presence of complex orography (Rummukainen, 2010; IPCC, 2001) such as over the European domain.
The EURO-CORDEX (COordinated Regional climate Downscaling EXperiment) (Nikulin et al., 2012) on the 12.5 km EUR-11 spatial domain is one source of data foreseen within ADRIADAPT and in the next chapters we will evaluate model ability in representing the climate over the ADRIADAPT domain (Figure 1), not only in terms of averages but also extremes, comparing them with observational data-sets.
EURO-CORDEX is the European branch of the international CORDEX (COordinated Regional climate Downscaling EXperiment) initiative, which is sponsored by the World Climate Research Program (WRCP) to organize an internationally coordinated framework to produce improved regional climate change projections, through regional climate models, for all land regions world-wide (http://www.euro-cordex.net/). The CORDEX-results serve as input for climate change impact and adaptation studies within the timeline of the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) and beyond. The experiments used to provide the RCM dataset described in this report are based on the standard setup of the model for the CORDEX ensemble simulations (Nikulin et al., 2012, Vautard et al. 2013) over the EUR-11 domain thus over the European domain with a horizontal resolution of 12.5 km. This means that the RCMs compute the "climate equations" over each grid cell (one cell represent an area of 12.5km x 12.5km), based on previous values (the model time step is of the order for few minutes) and adjacent cell values. The model is able to evolve in time, with the only constrain of radiative forcing (atmospheric concentration of greenhouse gasses, ozone and aerosols) and boundary conditions: ocean conditions are expected at the lower boundary of the RCM (such as sea surface temperature, current velocities, etc.) and atmospheric conditions (temperature, wind, water fluxes, etc.) of the surrounding area are expected at

the border of the cube on which the model is planned to simulate. As already stated in this way the model is able to evolve in time, providing also long term time series of climate data, based on different potential assumptions in terms of radiative forcing.
Four RCMs are considered in this contest (Scoccimarro et al. 2017). Table 1 lists the considered RCMs. In Table 1 the list of the driving GCMs, furnishing boundary conditions to the relative RCM is also provided. Model biases typically depend on the region analyzed and are partly related to parametric uncertainty and choices in model configuration and can be affected by internal variability as well as by uncertainties of the observational reference data themselves (Kotlarski et al. 2014).

Table 2 lists the raw and derived fields that we already compared to observations in D3.2.1. This is a subsample of the Table 2 and Table 3 parameters defined in D3.1.1. Anyway, at this stage, all of the raw data required for the computation of derived indices are already available on the CMCC ftp server (see below for ftp credentials).

Model name	**Driving GCM**	**Institute**
SMHI-RCA4	CNRM-CM5	Swedish Meteorological and Hydrological Institute, Rossby Centre
KNMI-RACMO22E	ICHEC-EC-EARTH	Royal Netherlands Meteorological Institute
INERIS-WRF331F	IPSL-CM5A-MR	IPSL (Institut Pierre Simon Laplace) and INERIS (Institut National de l Environnement industriel et des RISques)
CNRM-ALADIN53	CNRM-CM5	Centre National de Recherches Meteorologiques

Table 1: Regional Climate Models involved in ADRIADAPT data collection (same as Table 1 in D3.1.1).

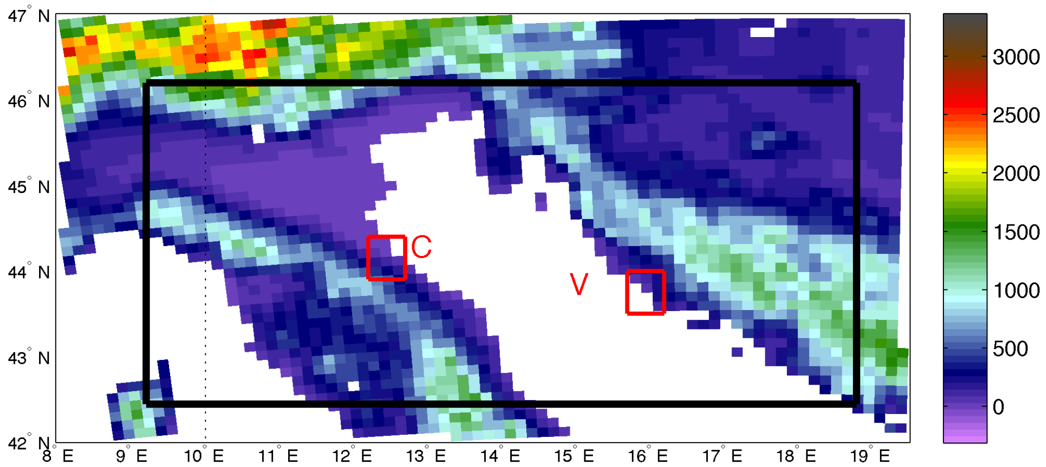

Figure 1: Domain selected (black contour) for the provision of climate (table 2) and extreme (table 4) parameters within ADRIADAPT. Red boxes indicate three sub-regions (C=Cervia, V=Vodice) considered in the next sections. Colours represent the local orography. Units are [m]. (same as Figure 3 in D3.1.1).

The data format used is NetCDF (http://www.unidata.ucar.edu/software/netcdf/). NetCDF is an abstraction that supports a view of data as a collection of self-describing, portable objects that can be accessed through a simple interface. Array values may be accessed directly, without knowing details of how the data are stored. Auxiliary information about the data, such as what units are used, is stored with the data. Generic utilities and application programs can access NetCDF datasets and transform, combine, analyse, or display specified fields of the data.
Data are now available through the CMCC ftp server (download.cmcc.bo.it – user and password sent privately to the ADRIADAPT partner reference person).

Field Description (the corresponding code in D3.1.1, table 4, is also indicated)	**Field Acronym**	**Vertical level**	**Field Unit**	**Relative validation figures**
2 meter Air Temperature	tas	2 meter	[°C]	2,3,4
99 percentile of temperature: rare events of high temperature (7)	tas_99 (about 100 events in 30y)	2 meter	[°C]	5
99.9 percentile of temperature: extremely rare events of high temperature (7bis)	tas_99.9(about 10 events in 30y)	2 meter	[°C]	6

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99 percentile of max daily temperature: rare events of high temperature (8)	tasmax_99 (about 100 events in 30y)	2 meter	[°C]	7
99.9 percentile of max daily temperature: extremely rare events of high temperature (8bis)	tasmax_99.9 (about 10 events in 30y)	2 meter	[°C]	8
99.9 percentile of Perceived Temperature: extremely rare events (20bis)	Humidex_99.9(about 10 events in 30y)	2 meter	[]	9
Precipitation	pr	Surface	[mm/d]	10,11,12
Extreme precipitation (1)	pr_99	Surface	[mm/d]	13
Intense Precipitation (2)	pr_95	Surface	[mm/d]	14

Table 2: List of meteorological fields investigated in this document over the historical period (in brackets the relative parameter number consistent with table 2 of D3.1.1)

The indices presented in Table 2 are selected within the list defined in D3.1.1 to describe the frequency and the intensity of extreme events. The extreme events are here defined based on threshold percentile (STARDEX (http://www.cru.uea.ac.uk/stardex).
In order to give an idea on the percentile approach, considering daily data, over the whole year, the 99 percentile of a 30-year time series of temperature data, corresponds to the temperature value reached in about 100 days only: about 4 days in a year. For the identification of even more rare and potentially impacting events, also the 99.9 percentile is taken into account for some of the investigated parameters, representing events happening 10 times only in a 30y time series of daily values: one event every three years. In other words, the 95th/99th/and 99.9th percentiles are used to represent moderately rare / rare / extremely rare events in the right tail of the event distribution. In this document we present some of the parameters defined within the D3.1.1 in terms of comparison with observational data sets. In particular temperature and precipitation data and derived parameters are compared with E-OBS observational data set (Cornes et al. 2018), a gridded version of the ECA dataset with daily temperature, precipitation and pressure fields. The ECA dataset contains series of daily observations at meteorological stations throughout Europe and the Mediterranean.
On the other hand, parameters derived also based on relative humidity, such as the humidex index used to represent the perceived temperature, are compared to JRA-55 reanalysis data set (Kobayashi et al 2015), since there are no gridded observations of

relative humidity. A reanalysis product is obtained running a General Circulation Model, adapting, time step after time step, the “computed climate” to the observed one, based on Data Assimilation processes building on available observations.
This is done to increase the spatial and temporal resolution of climate data, remaining as much as possible close to the observed (coarser) values. JRA-55 reanalysis cover the entire globe. The Japanese 55 year re-analysis data set has a spatial resolution of 0.5◦ longitude by 0.5◦ latitude and 60 vertical levels with a top layer at 0.1 hPa. The data assimilation system in JRA-55 has been improved since the time of the production of the prior JRA-25, including the introduction of a new radiation scheme, and a 4D-Var assimilation scheme, a state of the art algorithm which uses observations to update the past in addition to the current model state. The use of a reanalysis data set is necessary to obtain relative humidity gridded data at the daily time frequency. Noteworthy 2m temperatures from JRA-55 reanalysis compare favourably well with the observed values (Simmons et al 2017) over Europe (not shown).
For the sake of simplicity we will refer to JRA-55 climate fields as ‘observations’ in the rest of the paper.

This document is intended to complement the validation process through the statistical downscaling technique, dynamically downscaled was already presented in deliverable 3.2.1.

3.2 Statistical Downscaling schemes (SDs)

The statistical downscaling (SD) is a tool used to perform simulations at local scale, stations or grid points. There are different statistical downscaling tools applied in the climatology, ranging from Perfect-Prog (PP) approaches to Model Output Statistics (MOS). Perfect Prog is based on the assumption that the local climate is correlated with the state of the large-scale fields and the local features such as topography or land-sea distribution (Von Storch 1995,Wilks 2006). Taking into account these assumptions, the local climate information is derived from the construction of a statistical relationship that links *observed* large –scale atmospheric fields (*predictors*) with *observed* local fields (*predictands*). As regards the Model Output Statistics technique (MOS) this is based on a statistical scheme that is calibrated using *simulated* predictors and *observed* predictands.
In the present project the Perfect Prog approaches is used by Arpae to simulate seasonal future climate changes over the case studies. The link between local climate and large scale is detected through the canonical correlation analysis –CCA-(Von Storch 1995).

The most important patterns provided by the CCA are used in a multivariate regression SD schemes -CCAReg (Tomozeiu et al., 2007; 2014).
The main advantages of SD are that they are computationally inexpensive and allow the direct downscaling of indices related to extreme weather events, even up to local scale (station or grid point). The SD disadvantages refer to the fact that they need long and homogeneous observational time series for calibration and validation of the statistical relationship.
In the present work, the SD is implemented at *seasonal time scale* for the following domain:

- Cervia (Figure 2, "**C**"-yellow area) and Savio Valley Municipalities Union (Figure 2, "**SVMU"**-green area), both of them belong to Emilia-Romagna region and are referred in the report as Italy case studies (Figure 2). The ***SVMU*** area includes: Cesena, Mercato Saraceno, Sarsina, Bagno di Romagna and Verghereto municipalities. The grid points that belong to ***C*** and ***SVMU*** are presented in ANNEXES in Table A, information extracted from Eraclito climatic data set available at https://arpaeprv.datamb.it/dataset/erg5-eraclito.
- Sibenik (***S***) and Knin (***K***) meteorological stations - referred in the report as Croatia case studies.

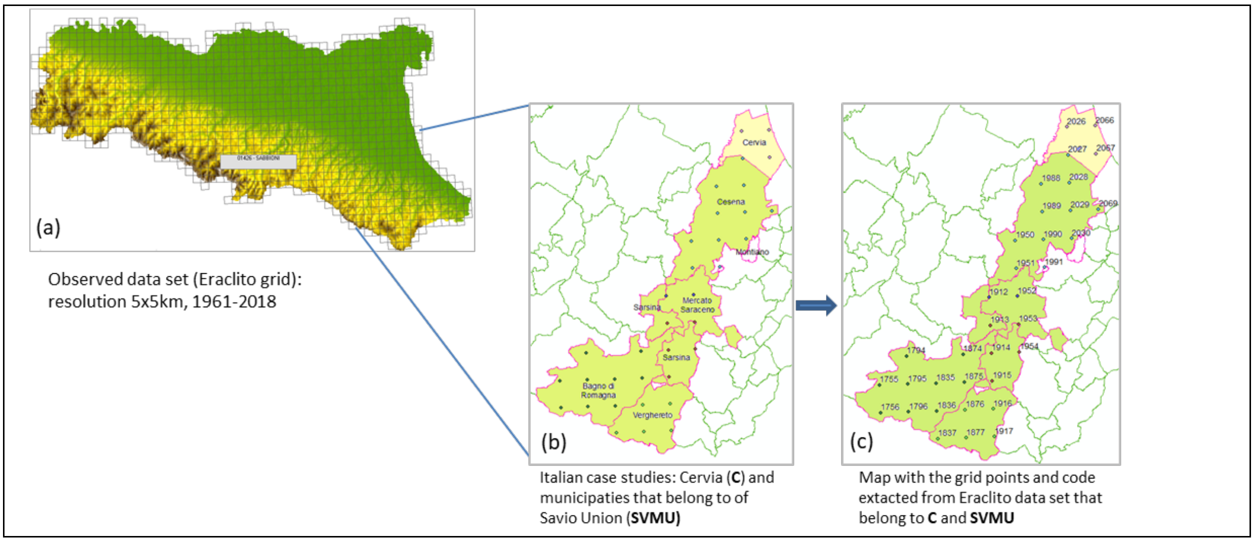

Figure 2: (a) Resolution of observed data set of temperature and precipitation –Eraclito data set; Italian case studies: Cervia-***C***- (yellow) and the Savio Valley Union Municipalities- ***SVMU*** (green); (b) Eraclito grid points and associated codes (c)

A description of SD implemented in ADRIADAPT project is summarised in two steps:

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- ***Step1: calibration and validation of SD (CCAReg scheme)***

In this step of SD implementation, the model/scheme is calibrated and validated using *observed* data, namely: large-scale *predictors* from ECMWF-ERA40 + ERA-interim *re-analysis* (https://www.ecmwf.int/en/forecasts/datasets/archive-datasetsand local *observational predictands* from Italy and Croatia. The calibration (construction) of SD is done over the period 1961-1985 and 2006-2010 while the **validation** is done over 1986-2005. Before the calibration, firstly the local and large scale fields are filtered through empirical orthogonal functions (EOFs) then is performed the CCA analysis. A subset of CCA pairs is then used in the multivariate linear statistical model (CCAReg) to estimate the *seasonal predictands* (Tomozeiu et al.,2007, 2014).

The **predictands** are represented by the **seasonal mean and extreme indices of temperature and precipitation** over the Italian and Croatian case studies. The seasonal climate indices are described in Table 3, and are computed from daily observed minimum, maximum temperature and precipitation.
As regards Cervia and Savio Valley Municipalities predictands, these are computed using daily data of temperature and precipitation from Eraclito climatic data set, available online at https://arpaeprv.datamb.it/dataset/erg5-eraclito. This data set has a spatial resolution of 5kmx5km, cover the period 1961-2015 (Figure 2a), data deeply described by Antolini et al (2015). The observed Croatia predictands, seasonal climate indices (Table 3), are derived from daily temperature and precipitation from Sibenik and Knin stations over 1961-2010 period, data provided by the Croatian project partner. The indices presented in Table 3 are selected within the list defined in D3.1.1 and describe the frequency and the intensity of extreme events. Some indices are based on threshold percentile (STARDEX, https://crudata.uea.ac.uk/projects/stardex/), and represent part of indices simulated also by dynamical downscaling.
As regards **predictors**, these are the large scale fields: namely geopotential at 500hPa (Z500), mean sea level pressure (MSLP), temperature at 850hPa derived from ERA40 and ERA interim ECMWF archives (https://www.ecmwf.int/en/forecasts/datasets/archive-datasetscover the window 90°W-90°E and 0°-90°N and the period 1961-2013 period.

Taking into account the different periods available for predictands and predictors, we choose a common period of analysis, namely 1961-2010.

Field	Field Acronym	Field Description	Unit
Precipitation	pr	Amount of seasonal precipitation	[mm]

Maximum temperature	tasmax	Seasonal average of maximum temperature	[C]
Minimum temperature	tasmin	Seasonal average of minimum temperature	[C]
Intense Precipitation	pr_90p	Seasonal 90th percentile of daily precipitation	[mm]
Consecutive dry days	cdd	Seasonal maximum number of consecutive days with precipitation lower than 1 mm	[d]
High maximum temperature	tasmax_95p	Seasonal 95th percentile of daily maximum temperature	[C]
Low minimum temperature	tasmin_5p	Seasonal 5th percentile of daily minimum temperature	[C]
Frost days	fd	Seasonal number of days with minimum temperature below 0°C	[days]
Tropical night index	tr	Seasonal number of days with minimum temperature greater than 20°C	[days]
Heat Wave Duration index	hwd	Seasonal maximum number of consecutive days with maximum temperature greater than 90th percentile	[days]

Table 3: List of local fields (climate indices) used in statistical downscaling (SD) over ADRIADAPT case studies

An important step in SD is the validation process. The SD models are built for each season and index, choosing each time a different subset of predictors, fields extracted from the ECMWF re-analysis. Finally, only the optimum SD scheme for each field and each season is retained and used then for future projections.
The validation of SDs over 1986-2005 period helps to select the best SD model. The performance (skill) of the downscaling model is quantified at grid point/station for each index/season in terms of: BIAS, correlation coefficient (CORR), root-mean square-error (RMSE). Tomozeiu et al (2007) underlined that the skill of the downscaling models is dependent on: predictands, predictors (large-scale field, single or combined), domain (area) of predictors, and filtered data process. The sensitivity of SDs to these factors is also tested in this work.
Another important aspect in SD is to test how work the SDs when is feed with predictors from GCMs (Table 4) simulated during control run/historical period. In this case, the results depend by the performance of GCMs to reproduce the predictors. This analysis is also done in the report.

- ***Step2: simulations of future changes of local climate (grid points/stations spatial resolution)***

In the second step, ones the schemes built and selected the best ones for each season and index, these SDs are then applied to the future anomalies of predictors simulated by GCM from CMIP5 experiments (https://pcmdi.llnl.gov/mips/cmip5/terms-of-use.html) in the framework of RCP4.5 and RCP8.5, in order to obtain seasonal future changes of local indices over ADRIADAPT case studies.

The ***future*** periods are: 2021-2040, 2041-2060, 2061-2080, 2081-2100 while the historical period is 1986-2005 period. The list of GCM CMIP5 experiments used to feed the SDs scheme for the ADRIADAPT case studies is presented in Table 4.

Global Climate Model (GCMs name)	**Modelling Centre**
CMCC-CM	Centro Euro-Mediterraneo per i Cambiamenti Climatici
MPI ESM-MR	Max Planck Institute for Meteorology
CNRM -CM5	Centre National de Recherches Meteorologiques
Can-ESM2	Canadian Centre for Climate Modelling and Analysis

Table 4: List of GCMs from CMIP5 experiment that feed the statistical downscaling scheme (CCAReg scheme) in ADRIADAPT project

The analysis of future projections obtained at this step will be the aim of the next deliverable, namely D3.3.1 “Detailed quantification of climate change signal in the region of interest with special emphasis on severe impacting events” due at month 24.

4 Description of the whole data set available (dynamical and statistical downscaled data) available

The aim of this section is to list the full dataset obtained following the two downscaling approaches. Table 5 shows the data availability for historical and future scenarios as from dynamical downscaling (results from the four model listed in table 1 are available for all of the mentioned parameters).

					Dynamical whole domain					
	Field		Field Description	unit	Raw series	seasonal values over 1986:2005	seasonal values over 2021:2040	seasonal values over 2041:2060	seasonal values over 2061:2080	seasonal values over 2081:21000
A	pr	Precipitation	Precipitation	[kgm-2s-1]	daily	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
B		Surface relative humidity	Surface relative humidity	[%]	daily	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
C	sfcWind	Wind Module	Wind Module	$[ms^{-1}]$	daily	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
D	sfcWindmax	Wind Module max	Wind Module max	$[ms^{-1}]$	daily	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
E	tas	2 meter air temperature	2 meter air temperature	[°C]	daily	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
F	tasmaax	2 meter air temperature max	2 meter air temperature max	[°C]	daily	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
G	tasmin	2 meter air temperature min	2 meter air temperature min	[°C]	daily	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
1	pr_99p	Extreme Precipitation	99 percentile of precipitation: rare events	[kgm-2s-1]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
2	pr_95p	Intense Precipitation	95 percentile of precipitation: moderately rare events(for SD with threshold of 90th percentile)	[kgm-2s-1]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
3	r95n	R95N	number of days with daily precip. exceeding the long term 95th percentile.	[d]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
4	r10mm	R10mm - Heavy precip. index	Number of days with precip. higher than 10mm	[d]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
6	cdd	CDD	Consecutive dry days, where dry is defined when precipitation is lower than 1 mm/d(for SD:maximum number of consecutive dry days)	[d]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
7	tas_99p	Extr. High Temperature	99 percentile of temperature: rare events of high temperature	[°C]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
8	tasmax_99p	Extr. High Max Temperature	99 percentile of max daily temperature: rare events of max high temperature	[°C]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
11	tas_95p	High Temperature	95 percentile of temperature: moderately rare events of high temperature	[°C]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
12	tasmax_95p	High Max Temperature	95 percentile of max daily temperature: moderately rare events of maximum daily temperature (representative of max diurnal values)	[°C]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
14	tasmin_5p	Low min Temperature	5 percentile of min daily temperature: moderately rare events of minimum daily temperature	[°C]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
15bis	fd	Fd	Frost days: number of days with Tmin <0°C	[d]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
16	tr	Tropical nights index	N.of days with temperature newer below 20oC(for SD no.of days with Tmin greater than 20°C)	[d]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
17	hwdi	HWDI	heat wave duration: number of days where, in intervals of at least 6 consecutive days, daily max temp is higer than averaged daily max temp + 5 °C	[d]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
18	hwfi	HWFI	warm spell days index: number of days where, in intervals of at least 6 consecutive days, daily temp is higher than 90th perc of temp in the period.	[d]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
7bis	tas_99.9p	Extr. Rare High Temperature	99.9 percentile of temperature: extr. rare events of high temperature	[°C]		djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
8bis	tasmax_99.9p	Extr. Rare High Max Temperature	99.9 percentile of max temperature: extr. rare events of high temperature	[°C]		djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
20bis	humidex_99.9p	Extr. Rare HUMIDEX	99.9 percentile of Perceived Temperature: rare events	[]		djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
21	sfcWind_99p	Extreme Wind	99 percentile of daily wind: rare events	[m/s]	annual	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja

Table 5: List of fields (climate indices), descriptions and periods of availability, delivered by dynamical downscaling for the whole ADRIADAPT domain. “djf” indicates December to February period. “jja” indicates June to August period.

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Table 6 shows the data availability within the project, derived from statistical downscaling techniques (SD) over the grid points that belong to Cervia (***C***), Union Valley Municipalities (***SVMU***) (Table A from ANNEXES) and for Sibenik (***S***), Knin (***K***) stations. As could be noted, the outputs are seasonal. The seasons are defined standard, namely: winter includes December, January and February (djf); spring includes March, April, May (mam); summer includes June, July, August (jja) and autumn includes September, October and November (son).

Field		Field Description	unit	Statistical downscaling subdomain	Raw series 1985:2006 2021:2100	seasonal values over 1986:2005	seasonal values over 2021:2040	seasonal values over 2041:2060	seasonal values over 2061:2080	seasonal values over 2081:21000
A	Precipitation	Amount of seasonal precipitation	[mm]	C, Š, K, SVMU	seasonal	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son
F	Maximum temperature	Seasonal average of maximum temperature	[C]	C, Š, K, SVMU	seasonal	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son
G	Minimum temperature	Sesonal average of minimum temperature	[C]	C, Š, K, SVMU	seasonal	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son
2	Intense Precipitation	Sesonal 90th percentile of daily precipitation	[mm]	C, Š, K, SVMU	seasonal	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son	djf / mam / jja / son
6	Consecutive dry days	Seasonal maximum number of consecutive days with precipitation lower than 1 mm	[d]	C, Š, K, SVMU	seasonal	djf / jja	djf / jja	djf / jja	djf / jja	djf / jja
12	High maximum temperature	Seasonal 95th percentile of daily maximum temperature	[C]	C, Š, K, SVMU	seasonal	jja	jja	jja	jja	jja
14	Low minimum temperature	Seasonal 5th percentile of daily minimum temperature	[C]	C, Š, K, SVMU	seasonal	djf	djf	djf	djf	djf
15bis	Frost days	Seasonal number of days with miinimum temperature below 0°C		C, Š, K, SVMU	seasonal	djf / mam	djf / mam	djf / mam	djf / mam	djf / mam
16	Tropical night index	Seasonal number of days with minimum temperature greater than 20°C		C, Š, K, SVMU	seasonal	jja	jja	jja	jja	jja
17bis	Heat Wave duration index	Seasonal maximum number of consecutive days with maximum temperature greater than 90th percentile		C, Š, K, SVMU	seasonal	jja	jja	jja	jja	jja

Table 6: List of fields (climate indices), descriptions, domain, periods and type of data availability delivered by statistical downscaling (SD)

Green colour in tables 5 and 6 indicates that the data are already available (June, 30 2020) on the CMCC ftp site. Yellow colour indicates that data are under preparation and will be ready on July 2020. White color indicates that these data are not provided: the 99.9 percentile of a time series is not provided when there are less than 1000 numbers in the series (as in the case of a single year).

5 Temperature climate indices statistically downscaled: evaluation over the present period (1985-2006)

In this Section we present the validation of SD (CCAReg) model constructed using *observed predictors* from ECMWF-ERA40 + ERA-interim *re-analysis* and, local *observational* temperature indices-*predictands* from Italy and Croatia. To this aim the downscaled indices over 1986-2005 are compared with observed climate indices. Skill coefficients (correlation coefficients, BIAS and RMSE) are computed between observed and downscaled time series over the validation period (1986-2005).

The work done in the setup of CCAreg schemes for temperature indices underlies that T850 and Z500 are good predictors for these indices. Similar results had been obtained in previous work done over Emilia-Romagna and over Northern Italy (Tomozeiu et al.,2007,2014), using different periods for calibration and validation. This underlies the robustness of selected predictors.

5.1.1 Temperature climate indices over Italy: validation of SD simulations (predictors from ERA40)

The SD schemes implemented over Italian case studies shows in generally good skill for seasonal temperature-mean and extremes indices.
Figure 3 (a,b,c) displays for each season the skill coefficients (BIAS, RMSE and CORR) for Cervia –***C***- and Savio Valley Municipalities Union –***SVMU***- (mean over grid points). As could be noted, BIAS of seasonal minimum temperature shows values comprised between 0.3 °C (winter) and -0.2°C (autumn) while BIAS of seasonal maximum temperature is comprised between -0.4°C (spring) and -0.8°C (summer). The model underestimates the maximum temperature during all seasons, more in summer. The RMSE is between 0.6 and 1 for seasonal minimum temperature and between 0.8 and 1.2 for seasonal maximum temperature (Figure 3b). As regards correlation coefficient, this is statistically significant (significance level 0.05) during all seasons, except for autumn maximum temperature where the significance level is 0.10 (Figure 3c).

a)
b)
c)

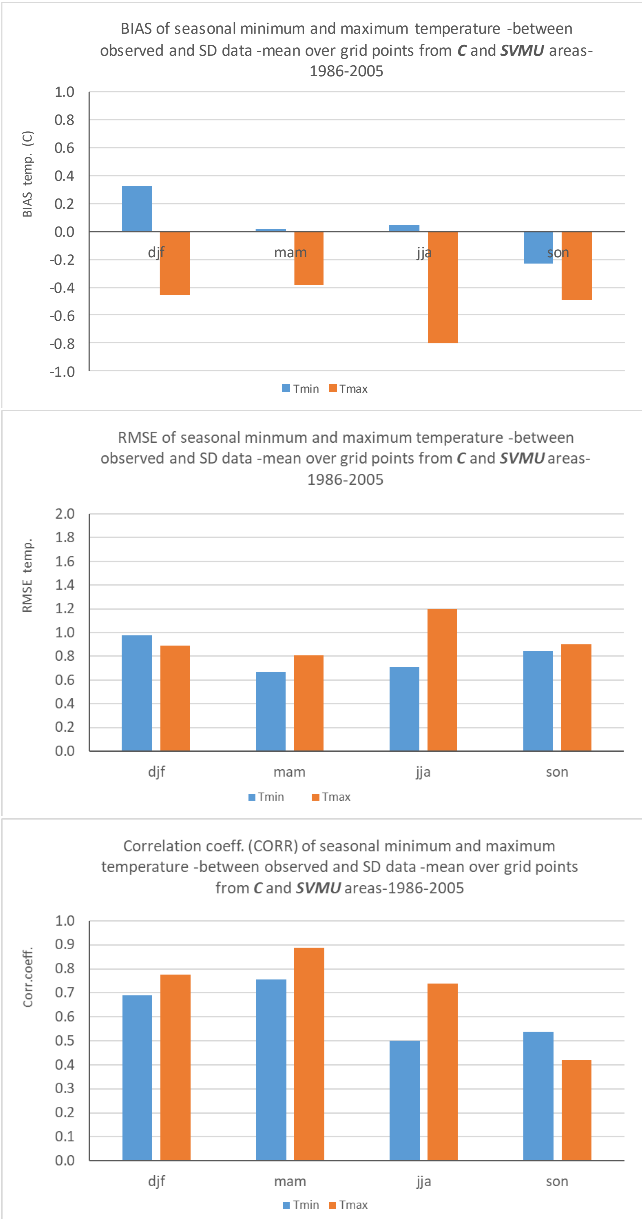
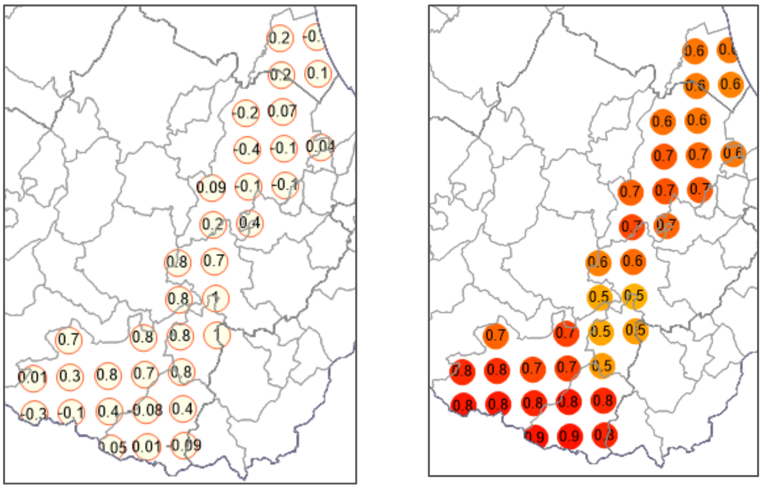


Figure 3: Skill of SD computed between downscaled time series of temperature- (°C) (ERA40 predictors) and observed data –mean over Cervia (***C***) and Savio Valley Municipalities Union (***SVMU***) -1986-2005 period

An example of the spatial distribution of BIAS and CORR coefficients over Cervia and Savio Valley Municipalities Union (***C*** and ***SVMU***) are presented in Figure 4 for winter minimum temperature, similar distributions are obtained for other seasons (maps not shown).



a) b)

Figure 4: Spatial distribution of BIAS-(°C)-(a) and CORR (b) for winter minimum temperature computed between SD and observed data (1986-2005) over ***C*** and ***SVMU*** areas

Figure 5 presents an overview of the distribution of the correlation coefficients for: the 5th daily percentile of winter minimum temperature (tasmin_5p djf), 95th daily percentile of summer maximum temperature (tasmax_95p jja), winter frost days (fd djf), summer heat wave duration (hwd jja), summer tropical nights (tr jja). The results are represented as box plots including all grid points from ***C*** and ***SVMU*** areas**.**
The median values from the box plots reveal correlation above 0.5 (significance level 0.05) for all indices, for some grid points the correlation reach 0.9 but there are also some grid points where the correlation is lower (0.3).
Figure 6 displays BIAS of summer heat wave duration, summer tropical nights and winter frost days. The model underestimate tropical nights and heat wave duration with one day (-1 day) and with four days in the case of frost days (-4 days).

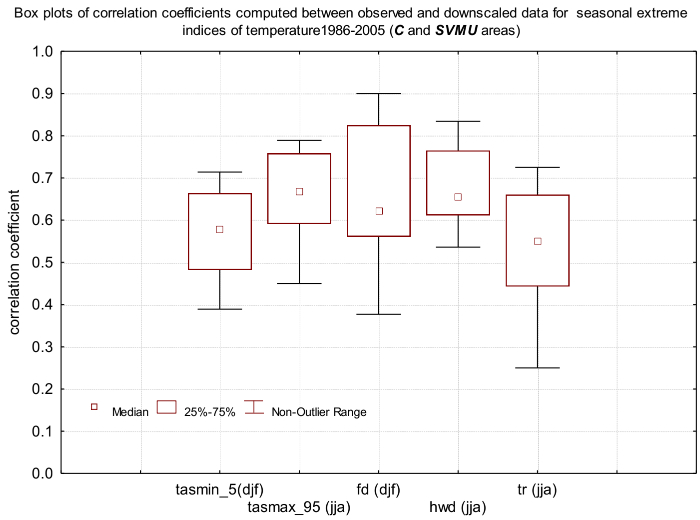


Figure 5: Box plots of correlation coefficients for extreme temperature (***C*** and ***SVMU*** areas-all points)

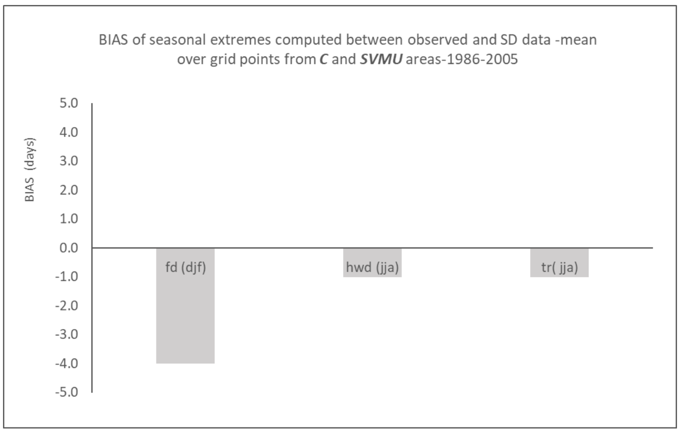


Figure 6: BIAS of seasonal extreme temperature (***C*** and ***SVMU*** areas-all points)

5.1.2 Temperature climate indices over Croatia: validation of SD simulations (predictors from ERA40)

The SD scheme has been implemented separately for stations from Croatia. Daily station data from Croatia have been provided to Arpae, 1961-2010 period. The data have been

analysed before index computation and, only time series with more that 80% of data have been retained and use in the SD implementation. The ADRIADAPT case studies are referred to Sibenik (***S***) and Knin (***K***) stations**.** The fields downscaled are the same as in Italian case (see Table 3). The same calibration and validation period have been used in the setup of SD (CCAreg scheme). The work done in the setup underlines that T850 and Z500 are good predictors for temperature, mean and extremes.
An overview of the validation of SD, for Sibenik (***S***) and Knin (***K***) in terms of correlation coefficients, BIAS and RMSE computed between observed and downscaled data over 1986-2005 is presented in Table 7 and Table 8.

tasmin	BIAS (°C)	RMSE	CORR
Winter (djf)	0.24	0.71	0.76
Spring (mam)	-0.05	0.64	0.89
Summer (jja)	-0.23	0.44	0.95
Autumn (son)	-0.12	0.71	0.76

tasmax	BIAS (°C)	RMSE	CORR
Winter (djf)	-0.19	0.55	0.83
Spring (mam)	-0.36	0.50	0.90
Summer (jja)	-0.81	0.50	0.93
Autumn (son)	-0.23	0.71	0.69

Table 7: Sibenik –SD skills of seasonal minimum and maximum temperature, period 1986-2005

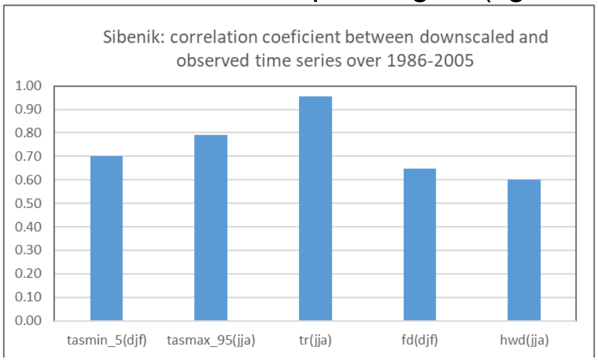
tasmin	BIAS (°C)	RMSE	CORR
Winter (djf)	0.58	0.94	0.65
Spring (mam)	0.18	0.53	0.83
Summer (jja)	-0.06	0.39	0.91
Autumn (son)	-0.11	0.67	0.71

tasmax	BIAS (°C)	RMSE	CORR
Winter (djf)	-0.21	0.63	0.88
Spring (mam)	0.11	0.46	0.94
Summer (jja)	-0.57	0.79	0.93
Autumn (son)	0.13	0.68	0.80

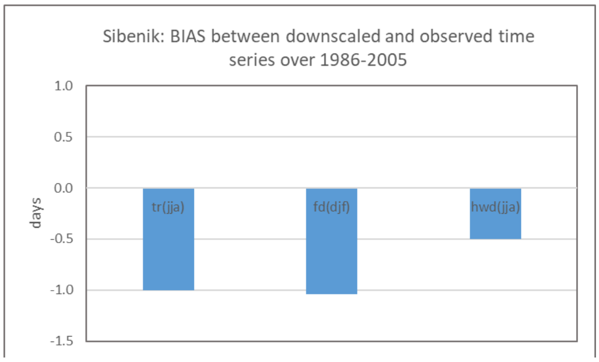
Table 8: Knin – SD skill of seasonal minimum and maximum temperature, period 1986-2005

As seen from the tables above, the correlation coefficient is statistically significant for all seasons and indices (significance level 0.05), the BIAS is in generally bellow +- 0.5°C except for summer maximum temperature (see table 7). The RMSE is between 0.4 and 1.
The SD scheme provides good skills also for seasonal extreme temperature indices. Figure 7 displays for Sibenik station the correlation coefficients (a) and BIAS (b) for some

extremes, similar results are obtained for Knin (not shown). The CORR (Figure 7a) is statistically significant with values that range from 0.6 to 0.9, BIAS is around 1-2 days for index as HWD / Fd/Tropical nights (figure7b).



a)



b)

Figure 7: Sibenik- skills of validation of SDs computed over 1986-2005 period

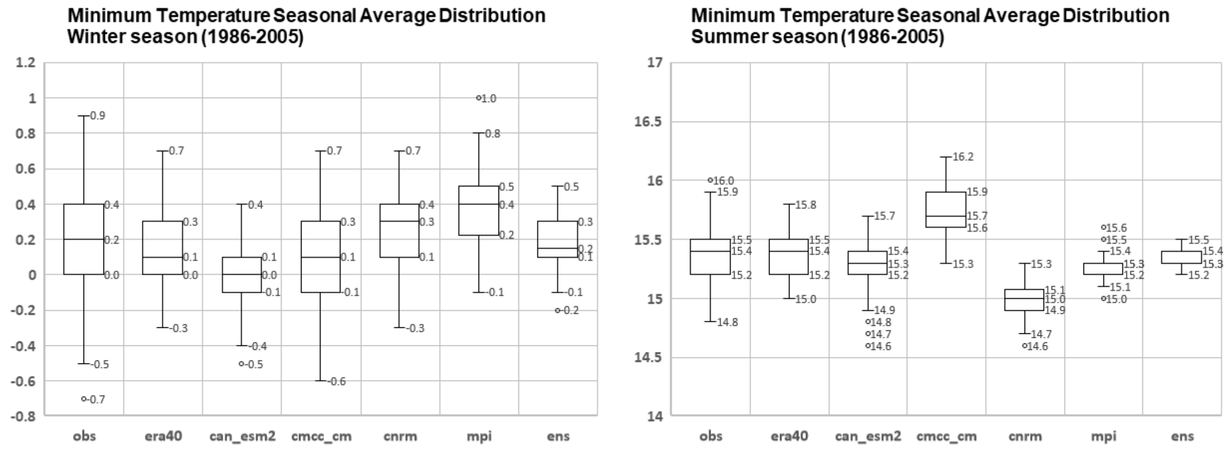
Summarising the results over Italy and Croatia we can say that the SD works well for seasonal mean and extreme temperature.

How works these SD schemes when are fed with predictors simulated by four GCMs during present, namely 1986-2005 (historical periods)?

5.1.3 Temperature climate indices: validation of SDs over Italy and Croatia (predictors from four GCMs)

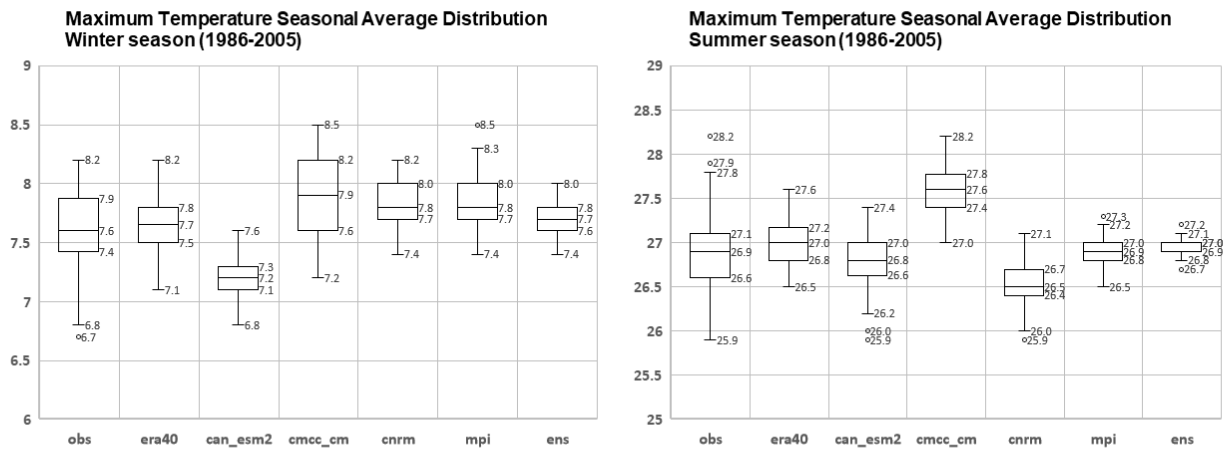
A comparison of the local climate indices simulated by the SD fed with predictors from 4 GCMs (Table 4) during 1986-2005 is presented below. The figure are box plots and are referred to observed data, simulated data with predictors from ERA40 (era40) and with predictors from 4GCMs: Can_ESM2 (can_esm2), CMCC-CM (cmcc), CNRM-CM5(cnrm) and MPI-ESM-MR (mpi). In addition the Ensemble Mean computed from 4SD applied to 4GCMs is computed and represented (***ens***). The box plots are referred to the distribution of the mean value of each index (mean or extremes) computed over 1985-2006, obtained throughout the ***bootstrap method*** (due to short period-20years).

Figures from 8 to 11 show the results for mean and extreme indices during winter and summer seasons-Italy case study.



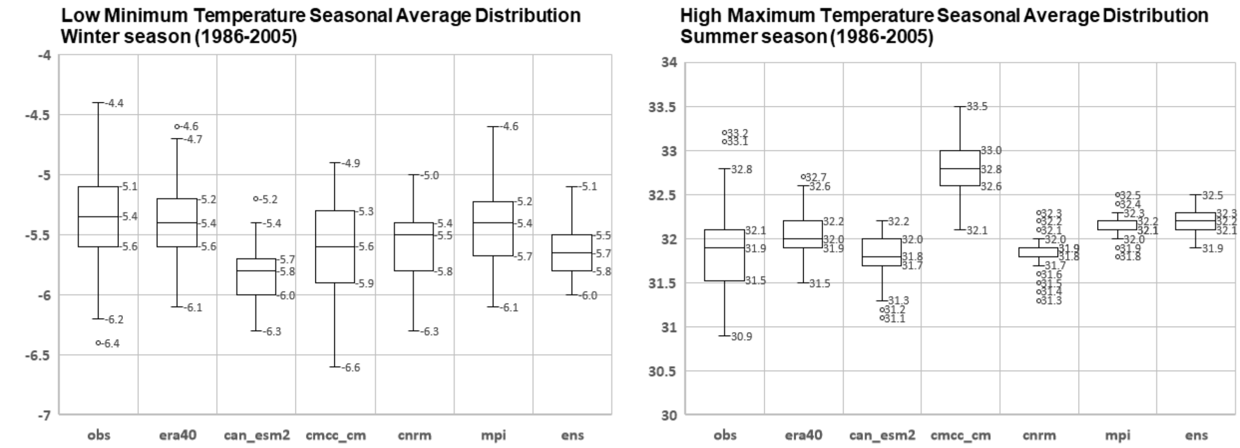
a) b)

Figure 8: Box plots of observed and simulated winter Tmin (a) and summer Tmin (b) over Italian case studies (mean over ***C*** and ***SVMU*** areas all points)(°C)



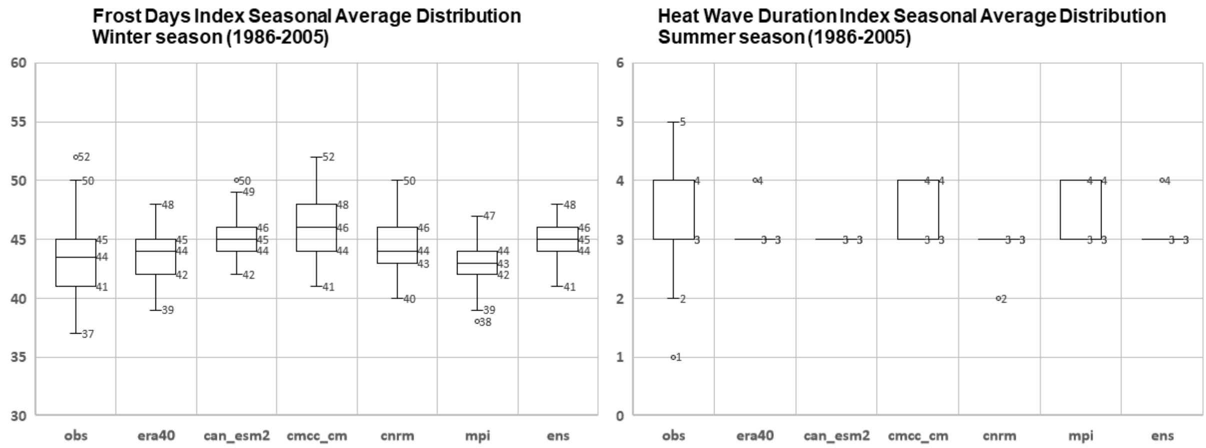
a) b)

Figure 9: Box plots of observed and simulated winter (a) and summer (b) maximum temperature (°C) over Italian case studies (***C*** and ***SVMU*** areas-all points)



a) b)

Figure 10: Box plots of observed and simulated winter 5th percentile of minimum temperature (a) and summer 95th percentile of maximum temperature (b) Italian case studies (***C*** and *SVMU* areas-all points) (°C), over 1986-2005

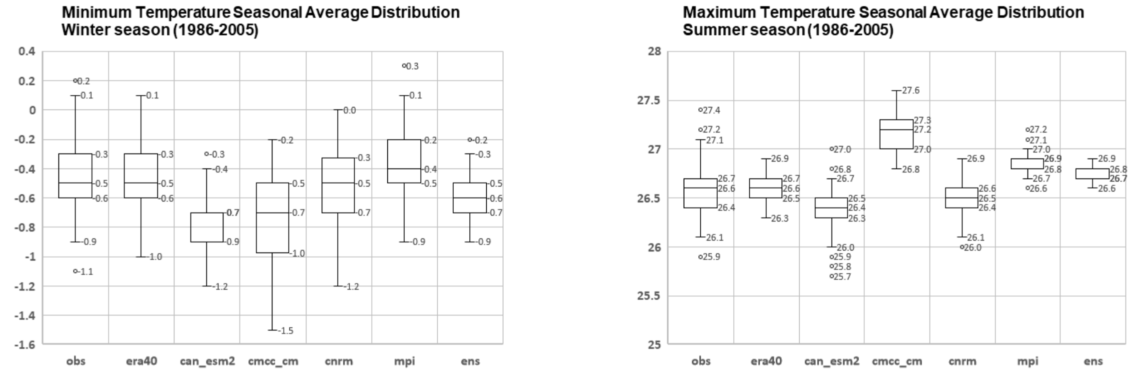


a) b)

Figure 11 Box plots of observed and simulated winter frost days (a) and summer heat wave duration (b) Italian case studies (***C*** and ***SVMU*** areas-all points) (°C),over1986-2005

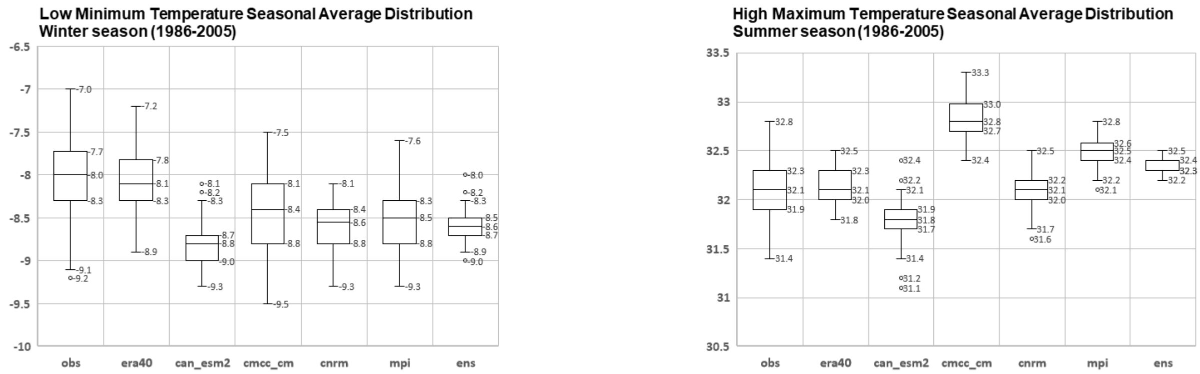
As could be noted the skill of simulations vary from season to season, from index to index and from model to model (GCMs). The median of box plots simulated by the 4 SD-GCMs is in generally similar with observed, except some situations when some of the GCM under/over estimates (figure 9b). The box plots includes also the 25th, 75th percentile as well as the minimum and maximum values. For some indices, the SD applied to GCMs is not able to catch the extreme values of indices (heat wave from figure 11b).

Similar results are obtained also over Croatia. One example is presented in Figure 12(a and b) and Figure 13(a and b).



a) b)

Figure 12 Box plots of observed and simulated (average over stations) winter minimum temperature (a) and summer maximum temperature (b) over Croatia case studies (°C), over 1986-2005



a) b)

Figure 13 Box plots of observed and simulated (average over stations) winter frost days (a) and summer heat wave duration (b) Croatia case study (days)-over 1986-2005

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As in the case of Italy, there is a variability between models, seasons and indices. The use of ensemble mean could be one solution to reduce the uncertainties, both for Italy and Croatia cases.

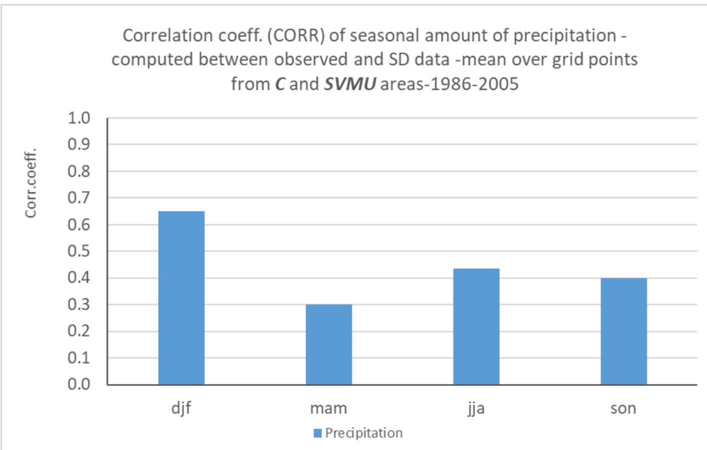
6 Precipitation climate indices statistically downscaled: evaluation over the present period (1985-2006)

In this Section we present the validation of SD (CCAReg) schemes calibrated, over 1961-1985 and 2006-2010, using *observed predictors* from ECMWF-ERA40 + ERA-interim *re-analysis* and local *observational* precipitation indices-*predictands* from Italy and Croatia. Some steps as for temperature are done also for SDs of precipitation. The downscaled indices over 1986-2005 are then compared with observed climate indices. Skill coefficients (correlation coefficients, BIAS and RMSE) are computed between seasonal observed and downscaled time series over the validation period.

6.1.1 Precipitation climate indices over Italy: validation of SDs simulations (predictors from ERA40)

Generally, the skill of SDs for precipitation indices from this work is lower than that of temperature. The skill is different from season to season. Figure 14 shows the correlation coefficients (CORR) (a), BIAS (b) and RMSE(c), mean over all grid points from ***C*** and ***SVMU*** of seasonal amount of precipitation. Even if the length of time series in validation is not enough for statistical significance-20 years- the results of correlation are also associated by significance level. Work done for precipitation using longer period for calibration and validation emphasis an improvement of the values of skill indices, even if the seasonal behaviour is the same, for example less skill in spring.

As could be observed from Figure 14, the season with high correlation coefficient for precipitation is winter (significance level 0.05) while, the season with lower correlation coefficient for amount of precipitation is spring. The BIAS shows an overestimation during winter (15mm) while an underestimation is during spring, summer and autumn.



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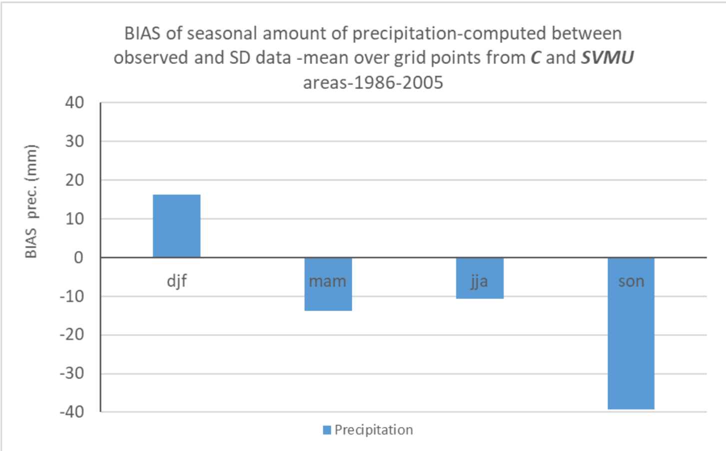
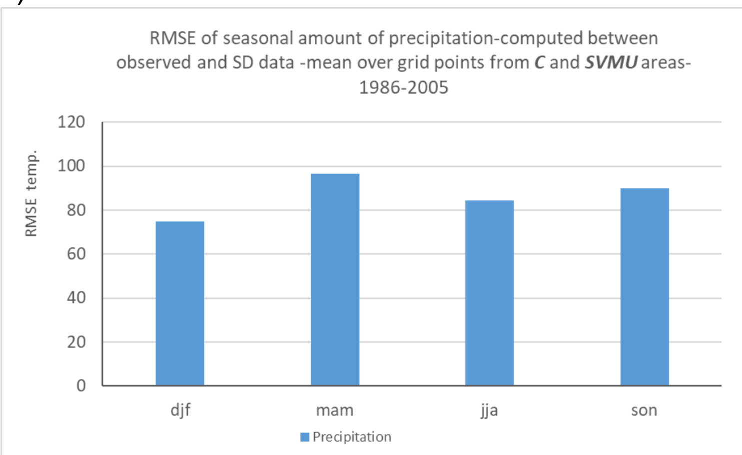
a)



b)



c)

Figure 14: Correlation coefficient (a), BIAS(b) and RMSE (c) of SDs computed between downscaled time series of precipitation (ERA40 predictors) and observed data –mean over Cervia (***C***) and Savio Valley Municipalities Union (***SVMU***) -1986-2005 period (units for BIAS mm/season)

The analysis of SDs skills implemented for extreme of precipitation, namely 90th percentile and maximum number of consecutive dry days, show similar results like in total amount of precipitation, a variability among the season.
An example of the spatial distribution of correlation coefficient is presented in figure 15, for winter precipitation and winter maximum number of consecutive dry days.

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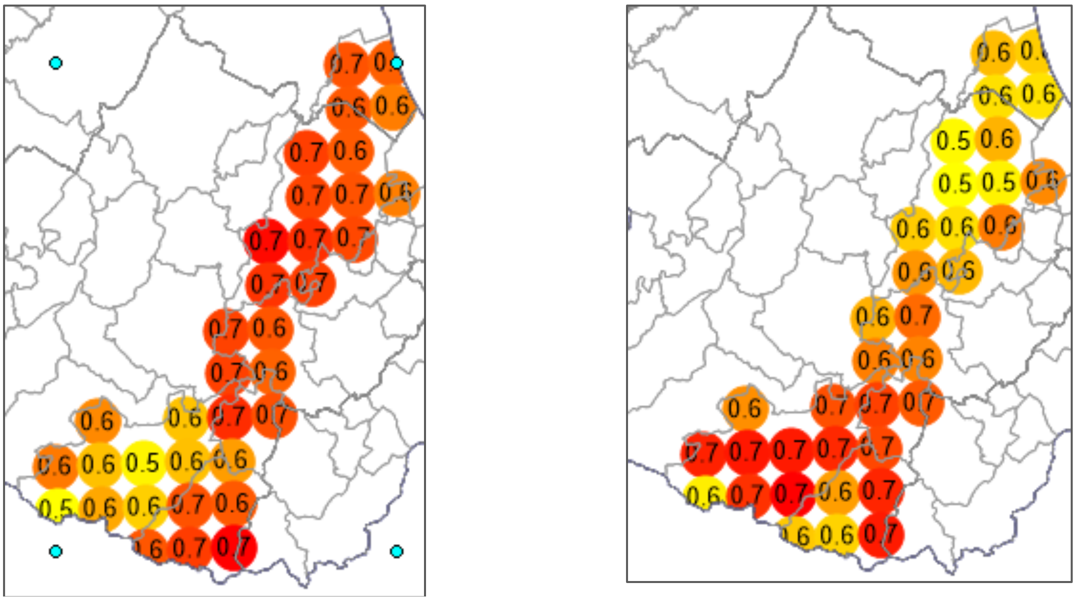

a) b)

Figure 15: Spatial distribution of correlation coefficient for winter precipitation (a) and winter maximum number of consecutive dry days (b), over Cervia (***C***) and Savio Valley Municipalities Union (***SVMU***) -1986-2005 period

6.1.2 Precipitation climate indices over Croatia: validation of SDs simulations (predictors from ERA40)

The SD schemes have been implemented separately for stations from Croatia. Daily stations data of precipitation from Croatia have been provided to Arpae, 1961-2010 period. Only time series with more that 80% of data have been retained and use in the SD implementation. The results are referred to Sibenik (***S***) and Knin (***K***) stations. The fields downscaled are the same as in Italian case (see Table 3). The same calibration and validation period have been used in the setup of CCAreg.

An overview of the validation of SD, for Sibenik (***S***) and Knin (***K***) in terms of correlation coefficients, BIAS and RMSE computed between observed and downscaled data over 1986-2005 is presented in Table 9 for Sibenik (a) and Knin (***b***).

a)

precipitation	**BIAS (mm)**	**RMSE**	CORR
Winter (djf)	-5	63	0.8
Spring (mam)	7	49	0.35
Summer (jja)	30	82	0.5
Autumn (son)	35	64	0.6

b)

precipitation	**BIAS (mm)**	**RMSE**	CORR
Winter (djf)	12	62	0.8
Spring (mam)	-22	70	0.4
Summer (jja)	35	81	0.5
Autumn (son)	26	94	0.6

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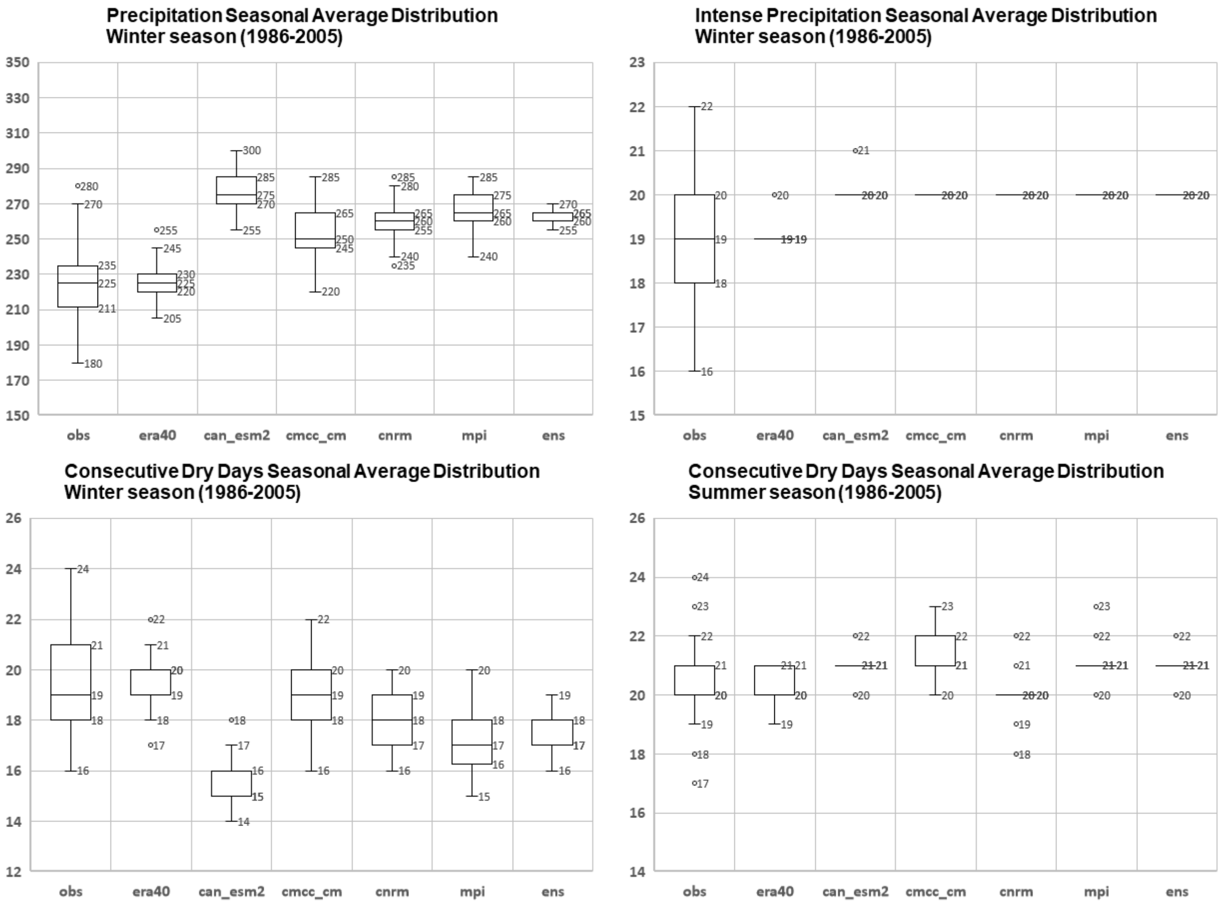
Table 9: Skill between observed and downscaled **seasonal precipitation (**ERA40 predictors, period 1986-2005) at Sibenik (a) and Knin (b)

As could be noted, the results are similar as in Italian cases. The skill of the amount of precipitation is higher during winter, where less skill is during spring. Similar results are obtained for the extreme precipitation. The SDs constructed for Sibenik and Knin, underestimates the maximum consecutive dray days during winter, spring and summer (-1 to-3days) and overestimates during autumn (6 days). As regards 90^{th} percentile of daily precipitation, the SDs underestimates the values for Sibenik and Knin during winter and spring and overestimate during summer and autumn (up to 3mm).

How works these SD schemes when are fed with predictors simulated by four GCMs during present, namely 1986-2005?

6.1.3 Precipitation climate indices: validation of SDs over Italy and Croatia (predictors from four GCMs)

A comparison of the local climate indices simulated when SD is feed with predictors from 4 GCMs during present with observations is present bellow. The figure includes box plots of: observed data, simulated data with predictors from ERA40 (era40), with predictors from 4GCMs: Can_ESM2 (can_esm2), CMCC-CM (cmcc), CNRM-CM5(cnrm), MPI-ESM-MR (mpi). The Ensemble Mean computed from 4SD applied to 4GCMs (ens) is also represented.
The box plots are referred to the distribution of the mean value of each index (mean or extremes) computed over 1985-2006, obtained throughout the ***bootstrap method*** (due to short period-20years). As regards amount of precipitation, the SDs applied to 4 GCMs show generally an overestimation during winter, spring and summer. The same signal, an overestimation have been obtained also for 90^{th} percentile of daily precipitation and consecutive dray days. An example of these simulations is presented in figure 16 for Italian case studies and figure 17 for Croatia.



Figures 16: Box plots of observed and simulated precipitation indices over Italian case studies (C and SVMU areas), period 1986-2005 (units for precipitation: mm/season)

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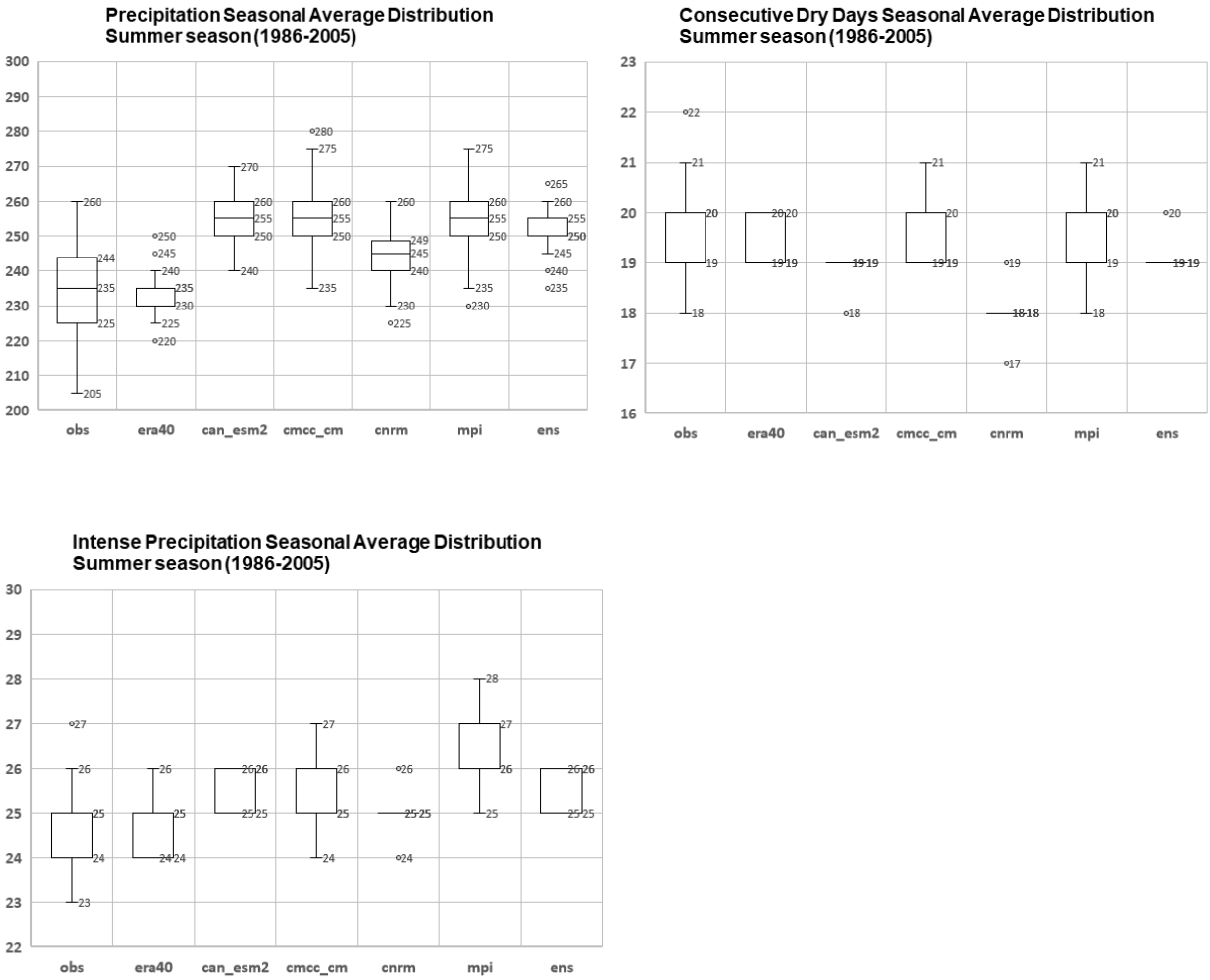

Figures 17: Box plots of observed and simulated precipitation indices over Croatia case study (average over stations) 1986-2005 (unit for precipitation is mm/season, days)

All the data, namely observed and simulated climate indices produced by statistical downscaling over the grid points from Cervia, Savio Valley Union Municipalities and Sibenik and Knin, are available on the CMCC ftp server (ftp credentials provided to project partners).

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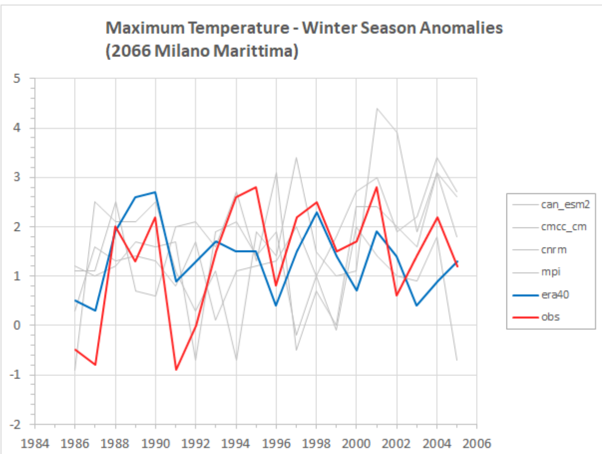
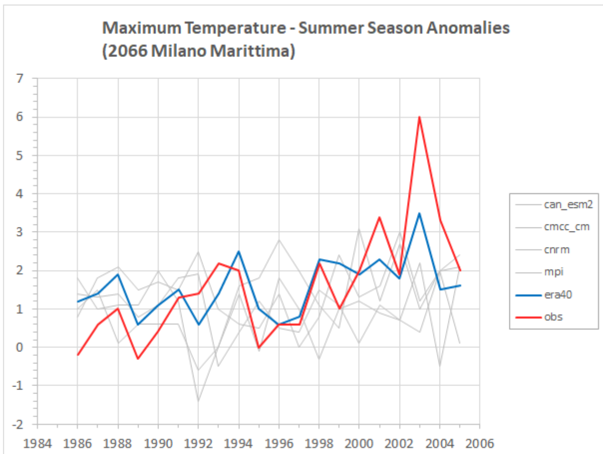
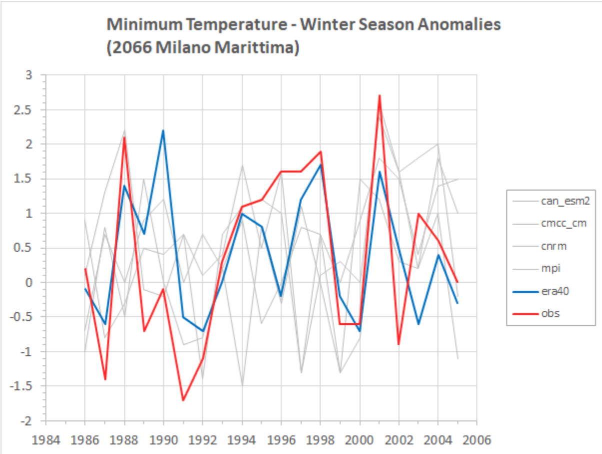
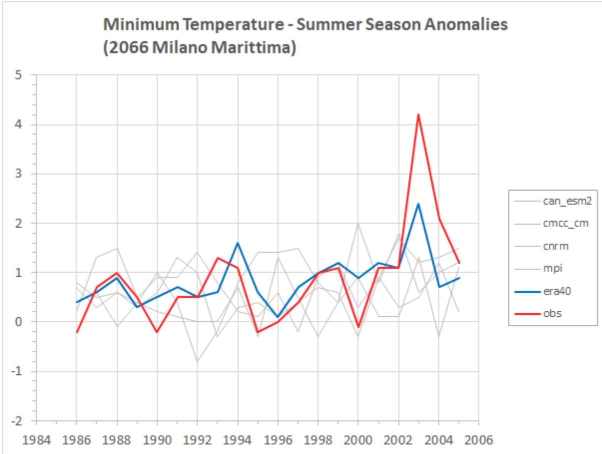
7 Trends of statistically downscaled climate indices time series

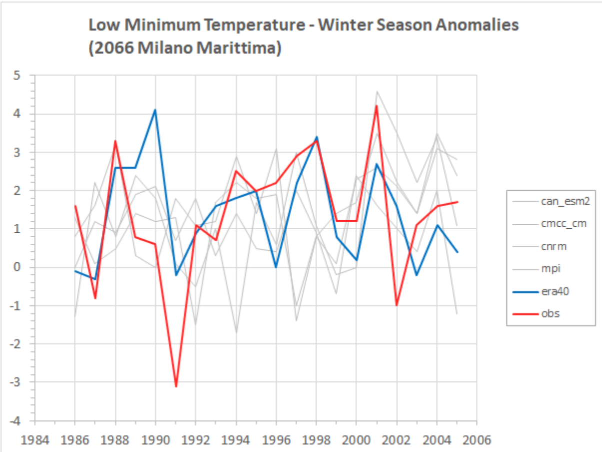
Another method to evaluate the performance of the SD implemented in this work is the analysis of trends over the validation period. The temporal variability is compared with observed one. Despite we can't expect year by year correspondence between observed and modelled values because the only model time constrain is relative to the radiative forcing (greenhouse gas and aerosols concentrations), it is important to verify if SDs is able to capture the observed tendencies, for the case of SDs fed by ERA40 and by 4GCMs predictors.
Taking into account that one advantage of SD is that down to the local scale, we select one grid point from "***C"*** area , namely Milano Marittima, and one grid point for ***SVMU*** namely Mercato Saraceno (see Annexes for code and coordination).
Trends of observed and simulated mean fields (tasmin, tasmax) and extremes such as low minimum temperature (5th percentile of Tmin) and high maximum temperature (95th percentile of Tmax), are presented in Figure 18 for Milano Marittima, Mercato Saraceno, and Sibenik.
In the figure 18, red line is the observed anomalies computed from Eraclito data set (obs), blue line represents the anomalies downscaled with predictors from ERA40 reanalysis (era) while the grey lines represent the downscaled values with 4GCMs members.

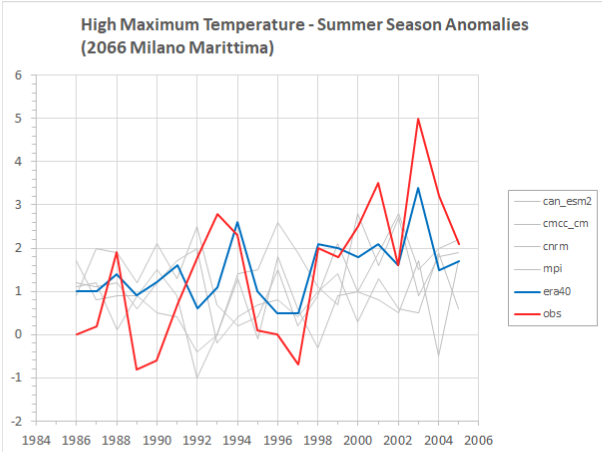


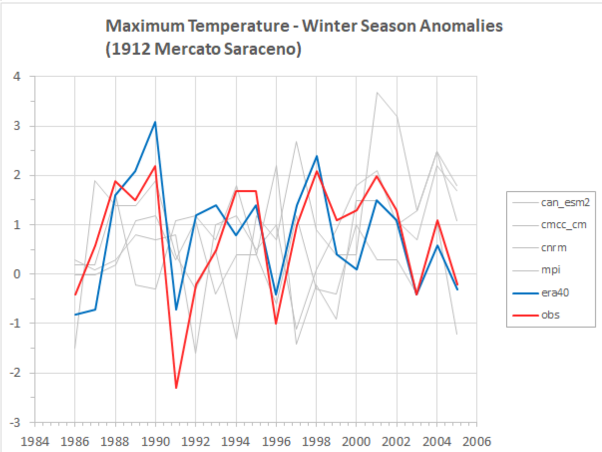


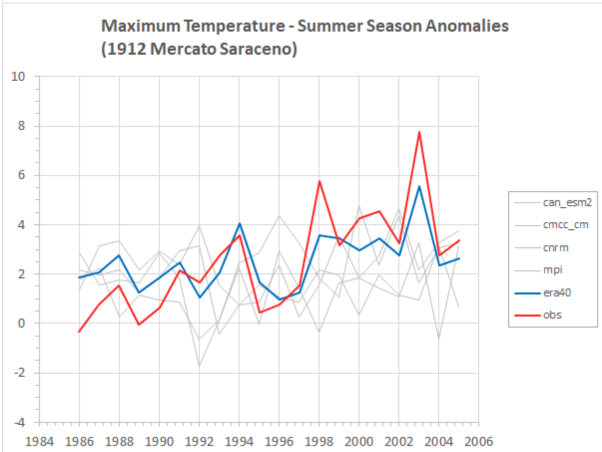












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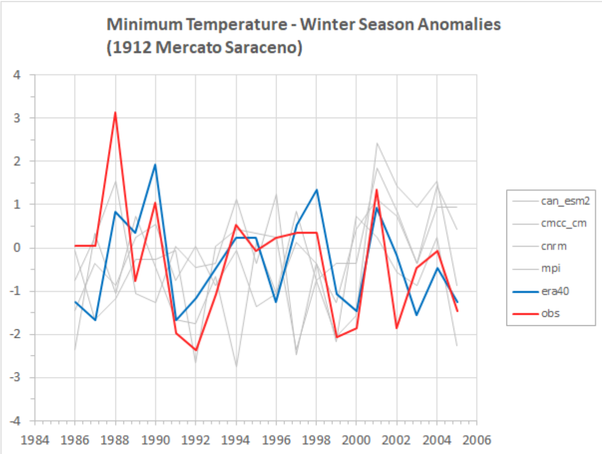
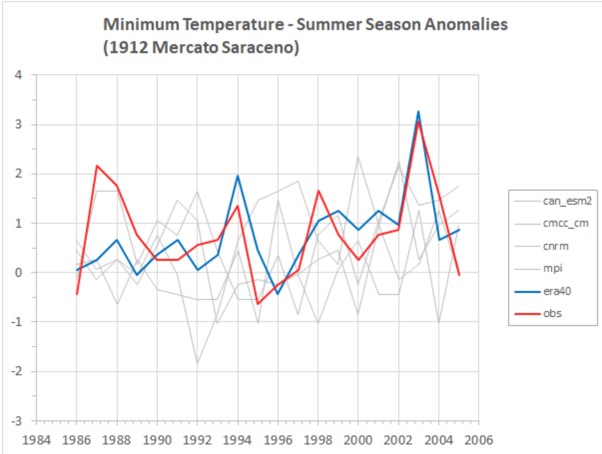
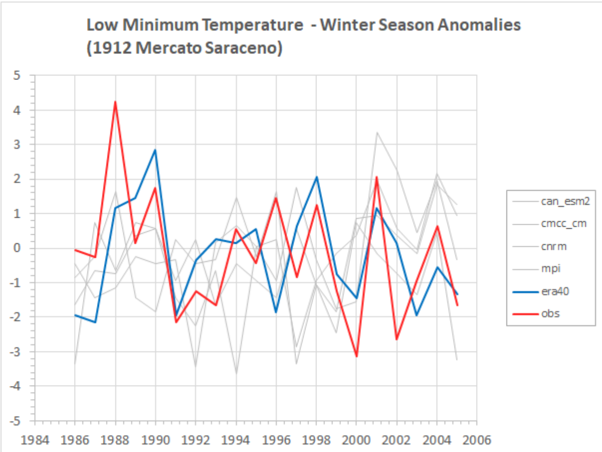
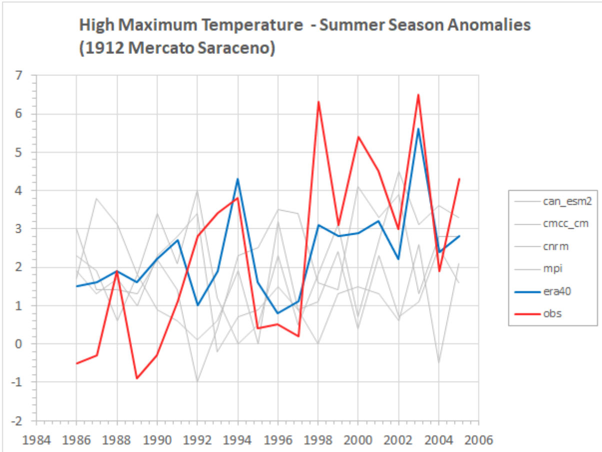
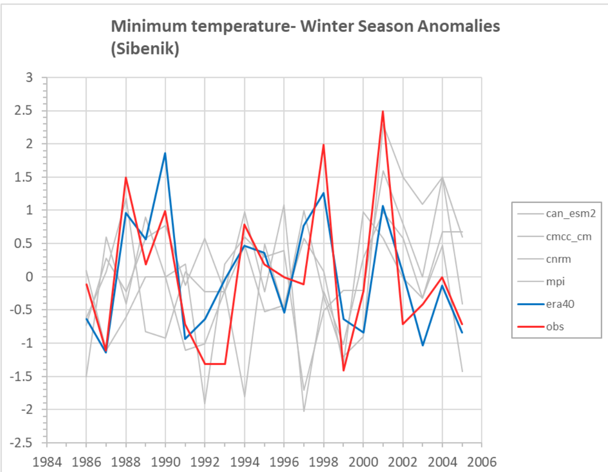

Minimum Temperature - Winter Season Anomalies
(1912 Mercato Saraceno)
4
3
2
1
0
-1
-2
-3
-4
1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006
can_esm2
cmcc_cm
cnrm
mpi
era40
obs


Minimum Temperature - Summer Season Anomalies
(1912 Mercato Saraceno)
4
3
2
1
0
-1
-2
-3
1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006
can_esm2
cmcc_cm
cnrm
mpi
era40
obs


Low Minimum Temperature - Winter Season Anomalies
(1912 Mercato Saraceno)
5
4
3
2
1
0
-1
-2
-3
-4
-5
1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006
can_esm2
cmcc_cm
cnrm
mpi
era40
obs


High Maximum Temperature - Summer Season Anomalies
(1912 Mercato Saraceno)
7
6
5
4
3
2
1
0
-1
-2
1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006
can_esm2
cmcc_cm
cnrm
mpi
era40
obs


Minimum temperature- Winter Season Anomalies
(Sibenik)
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006
can_esm2
cmcc_cm
cnrm
mpi
era40
obs

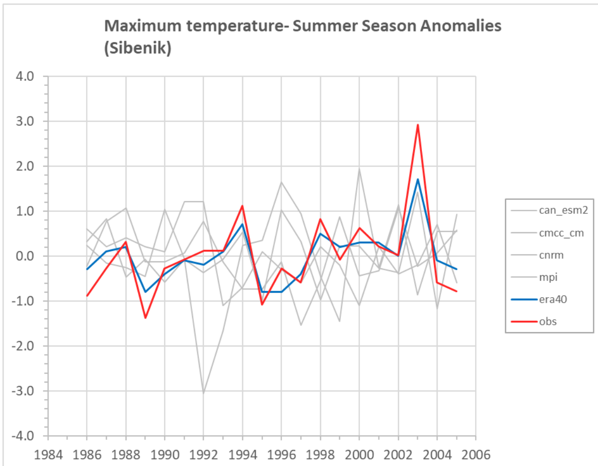
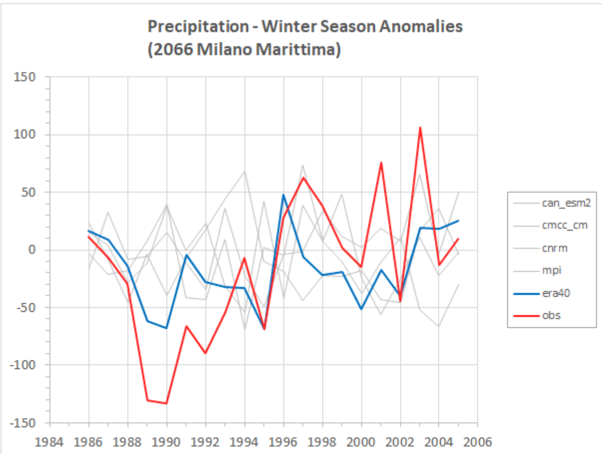
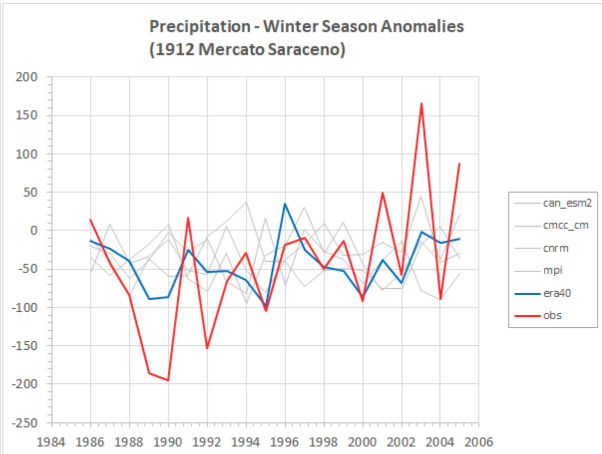

Maximum temperature- Summer Season Anomalies
(Sibenik)
4.0
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
-4.0
1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006
can_esm2
cmcc_cm
cnrm
mpi
era40
obs

Figure 18: Temporal variability of observed (obs) and simulated temperature indices (°C) (era40, mpi, cnrm, cmcc_cm, can_esm2) over validation period- Milano Marittima, Mercato Saraceno and Sibenik

As could be observed for temperature, trends are in generally well captured by the SD with ERA40 and SD applied to 4GCMs, even if for some models/seasons/indices the magnitude is not the same like that of observed time series. The SD is not able to capture “very extreme high anomalies” such as thus of 2003, but this is due to the fact that the data set used in the setup cover 1961-2010, and 2003 is “ a single “event during this period (poor statistics for the setup of SD).
As regards precipitation, trends are not statistically significant, the modelled precipitation interannual variability is reasonably in agreement with observations. Figure 19 presents temporal variability for some indices at Milano Marittima, Mercato Saraceno and Sibenik.





https://www.italy-croatia.eu/adriadapt

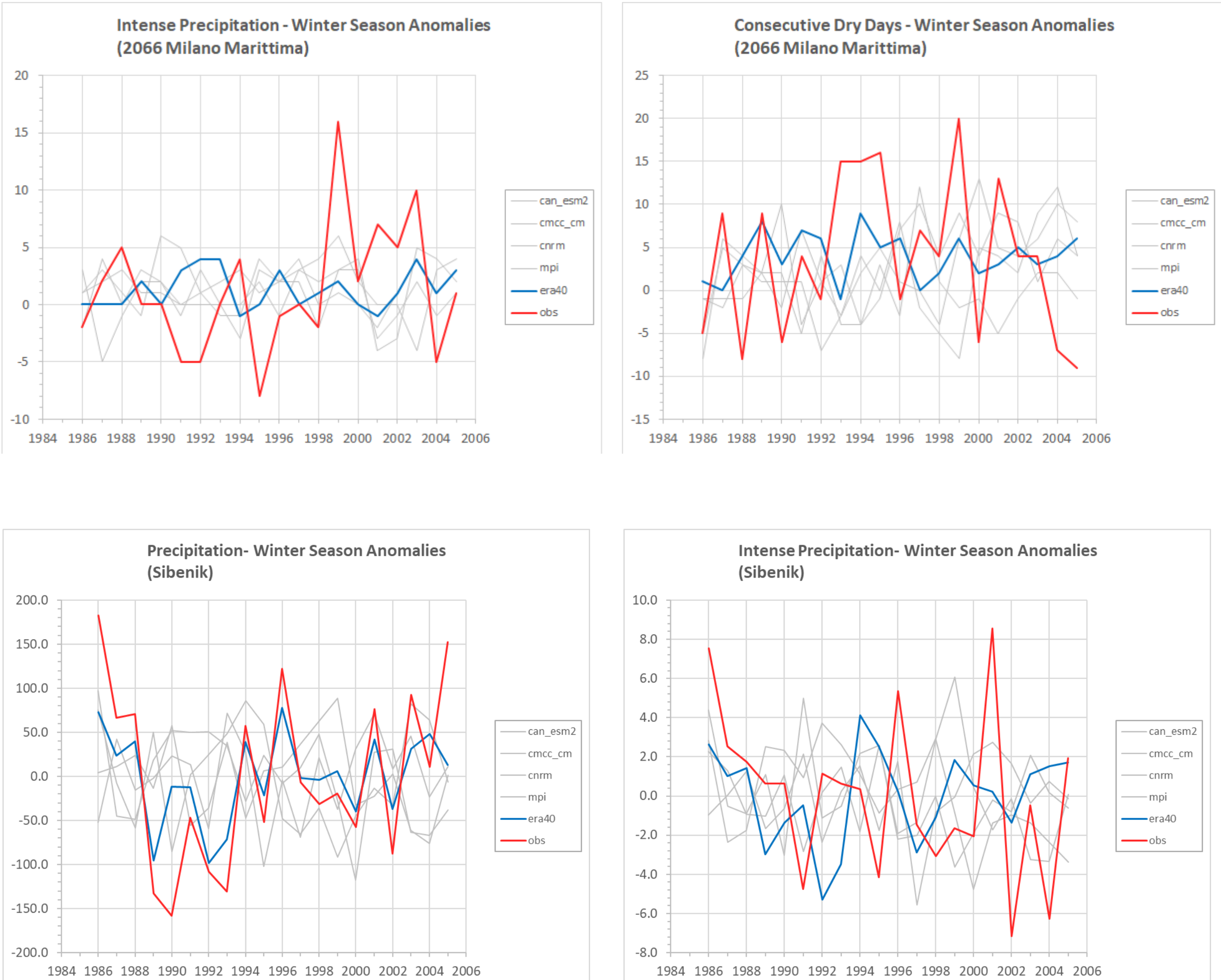


Figure 19: Temporal variability of observed (obs) and simulated precipitation indices (era40, mpi, cnrm, cmcc_cm, can_esm2) over validation period (mm/season)- Milano Marittima, Mercato Saraceno and Sibenik

The results presented in the sections above could be summarised as follows:

1) the SDs implemented works in generally well for temperature and precipitation indices; temperature indices present better skill than precipitation indices;

2) the SDs feed with predictors from 4 GCMs during historical period suggest to use the Ensemble Mean method, in order to reduce uncertainties due to 4 GCMs simulations, to evaluate signal of local future climate.

https://www.italy-croatia.eu/adriadapt

8 Conclusions

This document provides a description of the climate data that has been delivered by CMCC, Arpae and DHMZ to the ADRIADAPT project users, both in terms of dynamical and statistical downscaling outputs. These tools are shortly described and the climatic variables delivered within the project are presented. This report also includes a deep analysis of the performance/skill of the statistical downscaling technique implemented by Arpae-Simc, This work completes the historical validation process that has been already provided for the dynamical downscaling in the previous deliverable (D3.2.1). The results of statistical validation over Italian and Croatian case studies for temperature and precipitation indices and the analysis of statistical validation of SD is concluded with a description of trends in simulated and observed time series of temperature and precipitation.
The validation of statistical downscaling (SD) has been done for the seasonal mean and extreme indices of temperature and precipitation described in D3.1.1: “Definition of a set of climate change indicators for stakeholders“.

The simulated data cover the period 1961 to 2100, following historical forcing up to 2005 and two different possible radiative emission scenarios to the end of the century: a business as usual (RCP8.5) one and a more moderate one (RCP4.5).

9 Acknowledgements

We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups (listed in Tables 1 and 3 of this document) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

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11 ANNEXES

Table A: Coordination of grid points that belong to Cervia (***C***) and Savio Valley Union Municipalities (***SVMU)***

No.	Code	Nome	Comune	Prov	Lat.	Lon	Height(m)
1	1755	RIDRACOLI	BAGNO DI ROMAGNA	FORLI-CESENA	43.8675	11.8447	740.8
2	1756	LA LAMA	BAGNO DI ROMAGNA	FORLI-CESENA	43.8225	11.8447	1058.8
3	1794	POGGIO ALLA LASTRA	BAGNO DI ROMAGNA	FORLI-CESENA	43.9125	11.9077	524.9
4	1795	STRABATENZA	BAGNO DI ROMAGNA	FORLI-CESENA	43.8675	11.9077	716.7
5	1796	PIETRAPAZZA	BAGNO DI ROMAGNA	FORLI-CESENA	43.8225	11.9077	922.9
6	1835	S.PIERO IN BAGNO	BAGNO DI ROMAGNA	FORLI-CESENA	43.8675	11.9708	611.8
7	1836	BAGNO DI ROMAGNA	BAGNO DI ROMAGNA	FORLI-CESENA	43.8225	11.9708	719
8	1837	VERGHERETO	VERGHERETO	FORLI-CESENA	43.7775	11.9708	915.4
9	1874	MONTE MASCOLINO	BAGNO DI ROMAGNA	FORLI-CESENA	43.9125	12.0338	655.4
10	1875	PASSO DELL'INCISA	BAGNO DI ROMAGNA	FORLI-CESENA	43.8675	12.0338	662.6
11	1876	MONTE COMERO	VERGHERETO	FORLI-CESENA	43.8225	12.0338	1058.9
12	1877	MONTECORONARO	VERGHERETO	FORLI-CESENA	43.7775	12.0338	920.7
13	1912	MERCATO SARACENO	MERCATO SARACENO	FORLI-CESENA	44.0025	12.0969	299
14	1913	RULLATO	CIVITELLA DI ROMAGNA	FORLI-CESENA	43.9575	12.0969	457.4
15	1914	RUSCELLO	SARSINA	FORLI-CESENA	43.9125	12.0969	473.2
16	1915	LAGO DI QUARTO	SARSINA	FORLI-CESENA	43.8675	12.0969	542.1
17	1916	RIOFREDDO	VERGHERETO	FORLI-CESENA	43.8225	12.0969	862.3
18	1917	MONTE FUMAIOLO	VERGHERETO	FORLI-CESENA	43.7775	12.0969	1050.3

No.	Code	Nome	Comune	Prov	Lat.	Lon	Height(m)
19	1950	POLENTA	CESENA	FORLI-CESENA	44.0925	12.1599	193.5
20	1951	BORELLO	CESENA	FORLI-CESENA	44.0475	12.1599	179.8
21	1952	MONTE IOTTONE	MERCATO SARACENO	FORLI-CESENA	44.0025	12.1599	246
22	1953	MERCATO SARACENO OVEST	MERCATO SARACENO	FORLI-CESENA	43.9575	12.1599	388.2
23	1954	SARSINA	SARSINA	FORLI-CESENA	43.9125	12.1599	316.9
24	1988	MARTORANO	CESENA	FORLI-CESENA	44.1825	12.2230	23.3
25	1989	CESENA	CESENA	FORLI-CESENA	44.1375	12.2230	43.9
26	1990	MONTEREALE	CESENA	FORLI-CESENA	44.0925	12.2230	138.4
27	1991	SORRIVOLI	CESENA	FORLI-CESENA	44.0475	12.2230	240.6
28	2026	CASTIGLIONE DI CERVIA	CERVIA	RAVENNA	44.2725	12.2860	-0.1
29	2027	PISIGNANO	CESENA	FORLI-CESENA	44.2275	12.2860	4.4
30	2028	S.GIORGIO	CESENA	FORLI-CESENA	44.1825	12.2860	13.4
31	2029	CESENA EST	CESENA	FORLI-CESENA	44.1375	12.2860	31.3
32	2030	CALISESE	CESENA	FORLI-CESENA	44.0925	12.2860	101.9
33	2066	MILANO MARITTIMA	CERVIA	RAVENNA	44.2725	12.3491	0
34	2067	PINARELLA	CERVIA	RAVENNA	44.2275	12.3491	-1.2
35	2069	BULGARNO'	CESENA	FORLI-CESENA	44.1375	12.3491	15.7

Table B: Coordination of Sibenik and Knin stations (Croatia case studies)

No.	Nome	Lat.	Lon	Height(m)
1	SIBENIK	43°43'41''	15°54'23''	77

2	KNIN	44°2'27''	16°12'25''	255