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CLIMATE DATA, EXPECTED VARIATIONS IN CLIMATE PROXIES, IMPACT INDICATORS FOR APPLICATION IN TOOLBOX

WORK PACKAGE T2 - INTEGRATION: CC-ARP-CE TOOLBOX FOR CLIMATE CHANGE ADAPTATION AND RISK PREVENTION IN CE

ACTIVITY T2.1- INTEGRATED TOOLBOX FOR CLIMATE CHANGE ADAPTATION AND RISK PREVENTION -VERSIONS FOR TESTING

DELIVERABLE D.T2.1.1

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List of abbreviations

CC-ARP-CE	Integrated toolbox for Climate Change Adaptation and Risk Prevention in Central Europe
CC	Climate change
CE	Central Europe
CORDEX	Coordinated Regional Downscaling Experiment
GHG	greenhouse gases
IPCC	Intergovernmental Panel on Climate Change
RCP	Representative Concentration Pathway
SSP	Shared Socioeconomic Pathways
WRCP	World Climate Research Program

1. Introduction

The Deliverable D.T2.1.1 is aimed at supporting the development of the Toolbox CC-ARP-CE by assessing the variations, potentially due to climate change, between future time spans and the reference one in climate indicators assumed as proxies for several impacts that could affect the water management in Central Europe. Fifty-three indicators have been selected accounting for Project Partners and stakeholders' requirements collected by using a web-survey (see D.T1.1.3) or during the stakeholder workshops held in Autumn 2020. Furthermore, a sub-sample of indicators has been first computed within PROLINE-CE INTERREG Project.

The indicators have been assessed by exploiting the modeling chains included in EURO-CORDEX initiative (Jacob et al., 2014). It represents the European branch of "the international [Coordinated Regional Downscaling Experiment] CORDEX initiative, which is a program sponsored by the World Climate Research Program (WRCP) to organize an internationally coordinated framework to produce improved regional climate change projections for all land regions world-wide". Specifically, the outputs are provided by nineteen modeling chains where the dynamical downscaling of Global Climate Models has been carried out at a horizontal resolution of about 12 km (0.11°). Moreover, two scenarios for the future concentrations of climate-altering gases: the Representative Concentration Pathway (RCP) 4.5 considered as "mid-way scenario" and RCP8.5 assumed as the most pessimistic one. The variations under the two RCPs are computed for two future time spans: 2021-2050 and 2071-2100 while 1971-2000 is considered as the reference thirty years.

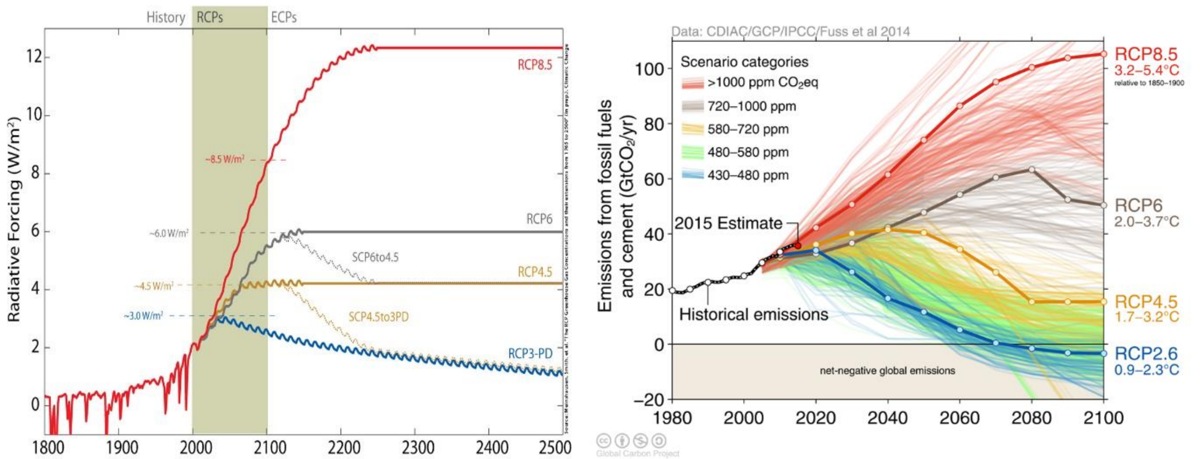
In this regard, such Deliverable should be viewed as a sort of an Engineering Guide supporting the informed adoption of the information provided by the indicators. To this aim, the section 1 provides details about the modeling chains adopted to derive the weather forcing required for the computation of the indicators. Section 2 reports the table where all the indicators are recalled and described. Finally, Section 3 reports brief insights for a proper interpretation of the results and their use from the practitioners.

2. Description of the modeling chains

The climate indicators are computed by exploiting a widely consolidated simulation chain according to which:

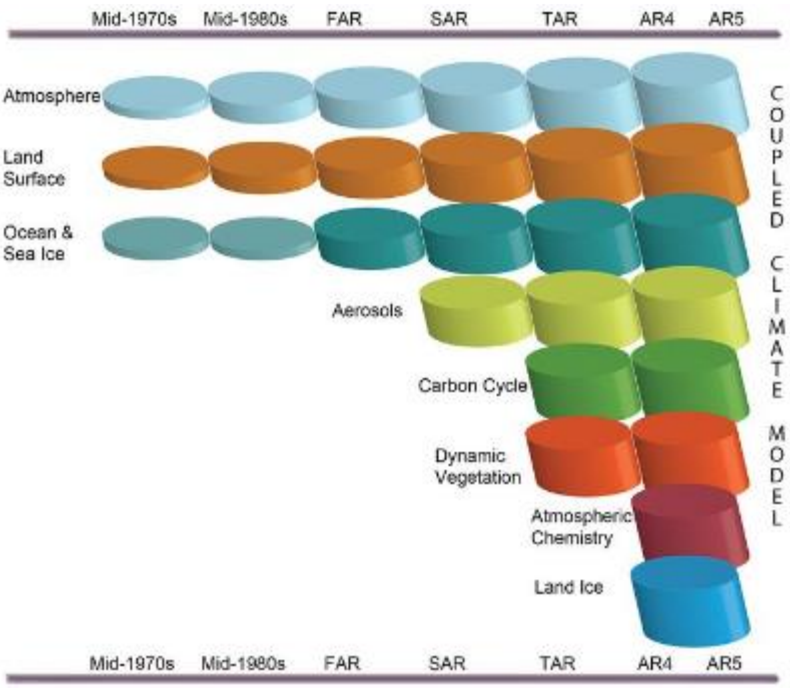
Based on assumptions about future evolutions of economic development/growth and demographic changes at global and regional scale, Integrated Assessment Models (IAM) provide evaluations for future concentrations of greenhouse gases (GHG), aerosols, chemically active gases (climate-altering gases) and changes in land use over the next centuries. In this regard, Intergovernmental Panel on Climate Change (IPCC) has selected four reference standard pathways (commonly known as RCP Representative Concentration Pathways) allowing subsequent analysis by means of Climate models (CMs) following reference assumptions about baselines and starting points and permitting the comparisons among climate projections. The four pathways respectively estimate an increase in radiative forcing levels of 8.5, 6, 4.5 and 2.6 W/m^2, by the end of the century compared to pre-industrial era (1750). Of course, the first one is recognized as more pessimistic under which no or very limited mitigation measures are implemented and the last one more optimistic and feasible only assuming high mitigation measurements (Figure 8). More specifically, RCP2.6 should be the only one permitting to achieve the Paris Agreement targets.

Figure 1: left) expected trends in radiative forcing following the different RCPs [Meinshausen et al.,2011]; right) assessed increases in global temperature and emissions under the different concentration scenarios



Such assessments are used as forcing for Global Climate Models (GCMs). They are numerical and physically-based representation of the atmospheric processes aimed to assess the impacts on the climate system of variations of greenhouse gases. Nevertheless, due to their coarse horizontal resolution (at the moment, hardly exceeding 70-80km) they are able to simulate only large-scale atmospheric state (IPCC, 2014). Numerous studies (IPCC, 2014) show that they are able to reproduce the climate and the global response to the changes of climate-altering gases with higher reliability for some variables (temperature) and lower for others (precipitation). However, despite significant developments in recent years (Figure 2) permitting to account for also biogeochemical processes in the last generation of Earth System Models, because of the horizontal resolutions today permitted, these models are inadequate for estimates of trends and impacts at the local/regional level for which the features of the area (distance from the sea, topography) are crucial (even with respect of large-scale atmospheric circulation). GCMs used for the assessments of the indicators have been produced in the framework of the Coupled Model Intercomparison Project Phase 5 (CMIP5) initiative exploiting as forcing RCPs. Within the sixth phase (CMIP6), CMIP6 will consist of the “runs” from around 100 distinct GCMs from 49 different modelling groups are expected to be run to produce updated climate projections exploiting also information from Shared Socioeconomic Pathways (SSPs)

Figure 2: The evolution of Global models in terms of considered physical dynamics (from Wilby, 2017)



To improve the assessments at regional scale, several techniques were developed in last years; they largely differ for computational costs, prerequisites, and limitations; they are classifiable as "statistical" and "dynamical" downscaling approaches. The first ones adopt frameworks based on empirical statistical relationships between "predictors" large-scale and “predictand” local climate variables, calibrated and validated on observed data and then applied to GCMs variables. They require limited computational burden and also allow analysis at station scale but need long series of observed data for the definition of the statistical relationships. The latter ones involve the use of climate models at limited area and highest resolution (RCM Regional Climate Model) nested for the area of interest on the global model from which they draw the boundary conditions. Currently adopted resolutions, in the order of 10 km, on the one hand, allow a better resolution of the orography and, on the other one, solve a substantial fraction of the local atmospheric phenomena. Moreover, different experiments have proven their good capability in reproducing regional climate variability and changes.

Even if this refinement makes it possible to accurately evaluate a remarkable fraction of weather patterns, dynamical approaches may misrepresent orography, land surface feedbacks and sub-grid processes, thus inducing biases preventing their direct use for impact analysis (Maraun, 2016). To overcome this issue, different approaches, known as Bias Correction (BC) methods, have been proposed in recent years (Maraun & Widmann, 2017). They can be defined as statistical regression models calibrated for current periods in order to detect and correct biases, which are assumed to systematically affect the climate simulations. Although the advantages, limitations and warnings regarding their adoption are widely debated in recent literature (Maraun & Widmann, 2017), they are currently recognized as a necessary stage in producing weather variables to use as inputs for impact-predictive tools. Otherwise, under the assumption that climate modeling chains could be affected by similar errors in current and future time spans, considering the anomalies between time spans is expected limiting the influence of errors potentially affecting the modeling chains.

Moreover, as well-known different sources of uncertainties deeply affect the robustness and reliability of climate projections (e.g. due to natural variability, model limitations, future development of non-climatic forcing; Hawkins & Sutton, 2009); in last years, several consortiums have promoted “ensemble” initiatives to evaluate uncertainties associated to different realizations of climate experiments and favor the comparison among the simulations. Among these ones, in more recent years, the WCRP Coordinated Regional Downscaling Experiment (CORDEX) project (Giorgi et al. 2009) has been established; it provides a global coordination for Regional Climate Downscaling experiments over fixed domains and agreed horizontal resolution. The included climate projections form a multi-model ensemble where different GCMs and RCMs (or statistical approaches) concur to provide assessments for the area of interest.

As reported above, the indicators are computed exploiting 19 climate simulation chains included in EURO-CORDEX multi-model ensemble where dynamical downscaling by using RCMs is carried out at a horizontal resolution of about 12 km (0.11°). The list of considered modeling chains is reported in Table 1.

Table 1:Adopted EURO-CORDEX simulations at a 0.11º resolution (~12km) over Europe (EURO-CORDEX ensemble); they are identified reporting providing institution, driving model and adopted RCMs

Code	Institution	Driving model	RCM
1	CLMcom	CNRM-CM5_r1i1p1	CCLM4-8-17_v1
2	CNRM	CNRM-CM5_r1i1p1	Aladin53
3	RMIB-Ugent	CNRM-CM5_r1i1p1	Alaro
4	SMHI	CNRM-CM5_r1i1p1	RCA4_v1
5	KNMI	EC-EARTH	RACMO22E_v1
6	DMI	EC-EARTH	HIRHAM5_v1
7	CLMcom	EC-EARTH	CCLM4-8-17_v1
8	KNMI	EC-EARTH	RACMO22E_v1
9	SMHI	EC-EARTH	RCA4_v1
10	IPSL-INERIS	IPSL-CM5A-MR_r1i1p1	WRF331F_v1
11	SMHI	IPSL-CM5A-MR_r1i1p1	RCA4_v1
12	CLMcom	HadGEM2-ES	CCLM4-8-17_v1
13	KNMI	HadGEM2-ES	RACMO22E_v1
14	SMHI	HadGEM2-ES	RCA4_v1
15	CLMcom	MPI-ESM-LR_r1i1p1	CCLM4-8-17_v1
16	MPI-CSC	MPI-ESM-LR_r1i1p1	REMO2009
17	SMHI	MPI-ESM-LR_r1i1p1	RCA4_v1
18	MPI-CSC	MPI-ESM-LR_r1i1p1	REMO2009
19	DMI	NorESM1-M	HIRHAM5

The modeling chains are forced by two RCPs: RCP4.5 and RCP8.5. Furthermore, the climate indicators are given as anomalies between the future 30 years periods (2021-2050 and 2071-2100) and the reference time span 1971-2000.

3. Definition of the indicators

Table 2: Lists of the computed indicators

	Acronym	Description	Required variables	Anomaly expressed as
1	RR_DJF	Cumulative precipitation during the Winter season (December-January-February)averaged over 30 years	P	Relative anomaly (%): $\frac{X_{fut} - X_{pres}}{X_{pres}}\%$
2	RR_MAM	Cumulative precipitation during the Spring season (March-April-May)averaged over 30 years	P	Relative anomaly (%): $\frac{X_{fut} - X_{pres}}{X_{pres}}\%$
3	RR_JJA	Cumulative precipitation during the Summer season (June-July-August)averaged over 30 years	P	Relative anomaly (%): $\frac{X_{fut} - X_{pres}}{X_{pres}}\%$
4	RR_SON	Cumulative precipitation during the Autumn season (September-October-November) averaged over 30 years	P	Relative anomaly (%): $\frac{X_{fut} - X_{pres}}{X_{pres}}\%$
5	PRCPTOT	Annual total precipitation in wet days	P	Absolute anomaly (mm): $X_{fut} - X_{pres}$
6	Rx_1D	Yearly maximum 1-day precipitation averaged over 30 years	P	Relative anomaly (%): $\frac{X_{fut} - X_{pres}}{X_{pres}}$
7	R20mm	Annual count of days when daily precipitation ≥ 20mm averaged over 30 years	P	Absolute anomaly (days): $X_{fut} - X_{pres}$
8	R30mm	Annual count of days when daily precipitation ≥ 20mm averaged over 30 years	P	Absolute anomaly (days): $X_{fut} - X_{pres}$
9	Rx5day	Yearly maximum value of cumulative precipitation over 5 days averaged over 30 years	P	Absolute anomaly (mm): $X_{fut} - X_{pres}$
10	R95pTOT	Precipitation fraction in very wet days (%).Precipitation fraction due to precipitation greater than 95th percentile over the annual cumulative value averaged over the thirty years.	P	Absolute anomaly (%): $X_{fut} - X_{pres}$

11	PR95prctile	95th percentile of daily precipitation (mm) computed over thirty years	P	Absolute anomaly (mm) : $X_{fut} - X_{pres}$
12	PrRP_5	Daily precipitation expected for a return period of 5 years computed by using Generalized Extreme Value approach	P	Absolute anomaly (mm) : $X_{fut} - X_{pres}$
13	PrRP_10	Daily precipitation expected for a return period of 10 years computed by using Generalized Extreme Value approach	P	Absolute anomaly (mm) : $X_{fut} - X_{pres}$
14	PrRP_50	Daily precipitation expected for a return period of 50 years computed by using Generalized Extreme Value approach	P	Absolute anomaly (mm) : $X_{fut} - X_{pres}$
15	PrRP_100	Daily precipitation expected for a return period of 100 years computed by using Generalized Extreme Value approach	P	Absolute anomaly (mm) : $X_{fut} - X_{pres}$
16	CWD	Consecutive Wet Days- Maximum yearly length of wet spell (maximum number of consecutive days with RR ≥ 1mm) averaged over 30 years	P	Absolute anomaly (days): $X_{fut} - X_{pres}$
17	CDD	Consecutive Dry Days- Maximum yearly length of dry spell (maximum number of consecutive days with RR < 1mm) averaged over 30 years	P	Absolute anomaly (days): $X_{fut} - X_{pres}$
18	SPI3_SD	Standardized Precipitation Index- (cumulative value of precipitation over three months). Over the reference period, for each month, the 30 cumulated values are fitted to a gamma probability distribution which is then transformed into a normal distribution. SPI3value represents units of standard deviation from the long-term reference mean. The indicator represents the percentage of months in "severe dry" conditions (-1.5>x>-2) over the total number of months over the 30 years	P	Absolute anomaly (%): $X_{fut} - X_{pres}$
19	SPI3_ED	Standardized Precipitation Index- (cumulative value of precipitation over three months). Over the	P	Absolute anomaly (%):

		reference period, for each month, the 30 cumulated values are fitted to a gamma probability distribution which is then transformed into a normal distribution. SPI3value represents units of standard deviation from the long-term reference mean. The indicator represents the percentage of months in "extremely dry" conditions (x<-2) over the total number of months over the 30 years		$X_{fut} - X_{pres}$
20	TG_DJF	Mean temperature during the Winter season (December-January-February)averaged over 30 years	T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
21	TG_MAM	Average temperature during the Spring season (March-April-May)averaged over 30 years	T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
22	TG_JJA	Average temperature during the Summer season (June-July-August)averaged over 30 years	T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
23	TG_SON	Average temperature during the Autumn season (September-October-November)averaged over 30 years	T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
24	FD	Annual count of days when daily minimum temperature <0°Caveraged over 30 years	T_{min}	Absolute anomaly (days): $X_{fut} - X_{pres}$
25	SD	Annual count of days when daily maximum temperature > 25°C averaged over 30 years	T_{max}	Absolute anomaly (days): $X_{fut} - X_{pres}$
26	TR	Tropical Nights- Annual count of days when daily minimum temperature > 20°C averaged over 30 years	T_{min}	Absolute anomaly (days): $X_{fut} - X_{pres}$
27	HD	Hot days- Annual count of days when daily maximum temperature >30°C averaged over 30 years	T_{max}	Absolute anomaly (days): $X_{fut} - X_{pres}$
28	CFD	Consecutive Frost Days-Maximum yearly length of days when daily minimum temperature < 0°C averaged over 30 years	T_{min}	Absolute anomaly (days): $X_{fut} - X_{pres}$
29	CHD	Annual count of days with at least 3 consecutive days withmaximum	T_{max}	Absolute anomaly (days):

		temperature>30°C averaged over 30 years		$X_{fut} - X_{pres}$
30	HDDs	Heating Degree Days (DD): yearly sum of difference between the reference temperature of 18°C and daily mean temperature when it falls below 15°C	T_{mean}	Absolute anomaly (degree days): $X_{fut} - X_{pres}$
31	GSL	Growing Season Length-1st Jan to 31st Dec in Northern Hemisphere. Annual count between first span of at least 6 days with daily mean temperature >5°C and first span after July 1st of 6 days with mean temperature <5°C	T_{mean}	Absolute anomaly (days): $X_{fut} - X_{pres}$
32	HCB	Hydroclimatic Budget- Annual difference between Cumulative Precipitation and Potential Evapotranspiration computed by using the formula suggested by Hargreaves et al. (1985)	P, T_{mean},T_{max},T_{min}	Absolute anomaly (mm): $X_{fut} - X_{pres}$
33	SFX1DAY	Maximum value of daily snowfall flux averaged over 30 years	Sf	Relative anomaly: $\frac{X_{fut} - X_{pres}}{X_{pres}}\%$
34	EWS	98th percentile of daily maximum wind speed (m/s) computed over thirty years	ws_max	Relative anomaly: $\frac{X_{fut} - X_{pres}}{X_{pres}}\%$
35	SCD	Snow Cover Duration (days): number of days with surface snow amount >= 30 cm (yearly computed over the period from 1st November to 31th March of the following year)	sc	Absolute anomaly (days) : $X_{fut} - X_{pres}$
36	BIO1	Annual mean temperature	T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
37	BIO2	Mean diurnal range. It is calculated by averaging, within the thirty years, the daily differences between the maximumand minimum temperature	T_{max},T_{min}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
38	BIO3	Isothermality- It is the ratio, expressed in %, of BIO2/BIO7 (see belowfor BIO7).	T_{max},T_{min}	Absolute anomaly (%): $X_{fut} - X_{pres}$
39	BIO4	Temperature seasonality- the average of daily mean temperature is calculated for each calendar	T_{mean}	Absolute anomaly $\%X_{fut} - X_{pres}$

		month in the selected period, and then the Standard Deviation is computed among the 12 monthly values obtained and expressed in percentage.		
40	BIO5	Maximum temperature of warmest month computed for each year and averaged over the thirty years	T_{max}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
41	BIO6	Minimum temperature of coldest monthcomputed for each year and averaged over the thirty years	T_{min}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
42	BIO7	Temperature annual range. It is the difference between Bio5 and Bio6	T_{min}, T_{max}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
43	BIO8	Mean temperature of the wettest quarter. After computing the wettest quarter of each year in the 30 years, the mean temperature among all wettest quarters is calculated	P, T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
44	BIO9	Mean temperature of the driest quarter. After computing the driest quarter of each year in the 30 years, the mean temperature among all the driest quarters is calculated	P, T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
45	BIO10	Mean temperature of warmest quarter. After computing the warmest quarter of each year in the 30 years, the mean temperature among all the warmest quarters is calculated	T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
46	BIO11	Mean temperature of coldest quarter. After computing the coldest quarter of each year in the 30 years, the mean temperature among all the coldest quarters is calculated	T_{mean}	Absolute anomaly (°C): $X_{fut} - X_{pres}$
47	BIO12	Annual precipitation	P	Absolute anomaly (mm): $X_{fut} - X_{pres}$
48	BIO13	Precipitation of wettest month. After computing the wettestmonth of each year in the 30 years, the average cumulative precipitation	P	Absolute anomaly (mm/month): $X_{fut} - X_{pres}$

		among all the wettest months is calculated		
49	BIO14	Precipitation of driest month. After computing the driest month of each year in the 30 years, the average cumulative precipitation among all the driest months is calculated	P	Absolute anomaly (mm/month): $X_{fut} - X_{pres}$
50	BIO15	Precipitationseasonality-It is the ratio between the standard deviation and the mean of 12 values representing the monthly average precipitation over the considered period. To avoiddivision by 0, the denominator is increased by 1	P	Absolute anomaly (%): $X_{fut} - X_{pres}$
51	BIO16	Precipitation of wettest quarter. After computing the wettest quarter of each year in the 30 years, the mean cumulative precipitation value among all wettest quarters is calculated	P	Absolute anomaly (mm/3months): $X_{fut} - X_{pres}$
52	BIO17	Precipitation of driest quarter. After computing the driest quarter of each year in the 30 years, the mean cumulative precipitation value among all driest quarters is calculated	P	Absolute anomaly (mm/3months): $X_{fut} - X_{pres}$
53	BIO18	Precipitation of warmest quarter. After computing the warmest quarter of each year in the 30 years, the mean cumulative precipitation value among all warmest quarters is calculated	P	Absolute anomaly (mm/3months): $X_{fut} - X_{pres}$
54	BIO19	Precipitation of coldest quarter. After computing the coldest quarter of each year in the 30 years, the mean cumulative precipitation value among all coldest quarters is calculated	P	Absolute anomaly (mm/3months): $X_{fut} - X_{pres}$

4. Brief insights

For each climate indicator, RCP and period (2021-2050 vs 1971-2000 or 2071-2100 vs 1971-2000), the values can be visualized in terms of median value of the anomalies aggregated at NUTS level (level 3 for all the Countries except Germany for which level 2 is used). For more Expert Users, beyond median values, data corresponding to the first and third quartiles are also provided at NUTS level and grid point level (exploiting the gridpoints as provided by EURO-CORDEX simulations).

When these data are used, it worths to consider several aspects:

- CMIP5 and, in cascade, Euro-CORDEX represent multi-model "ensemble of opportunity" (Tebaldi and Knutti, 2007) where the participant research centers are on a voluntary basis. So, the ensemble cannot have the ambition to explore, in a systematic way, all the sources of uncertainties associated to the modelling systems. In this regard, it is well known how participant global modelling often share assumptions, parametrizations making not suitable the assumption of independence among the models. For these reasons, the spread among the findings could be viewed as a "lower bound" for the characterization of uncertainties associated to the assessments. On the other side, several investigations carried out for Global Climate Models proved how the assumption of exchangeable or statistically indistinguishable ensemble (Annan & Hargreavas, 2010) according to which the "true" climate status is drawn from the same distribution as the ensemble members could work for characterizing the distribution of climate models better than the hypothesis of distribution centered around the truth ('truth plus error'; Tebaldi et al., 2005). The assumption of indistinguishable ensemble could result particularly adequate for the analysis of future projections (Sanderson & Knutti, 2012) or patterns at more detailed spatial and temporal scale. In this respect, the adoption of central value or relevant percentiles should be carefully used and accounting for the potential limitations.
- Climate indicators are expected acting as proxies for associated impacts. They can have only a limited information content compared to more complex (time and resource consuming) approaches as, for example, physically based modelling but they represent a consolidated and expeditious way to return information about the frequency and severity of weather-induced hazards. Indicators for extreme events are usually able to return information for «moderately rare» events while for rarer events, more complex statistical approaches are required (e.g. Extreme Value Analysis).The selection for the indicator has to represent a «trade-off» for maximizing the information content; e.g. the reference time span for cumulated precipitation in flooding events (concentration time) is dependent on the geomorphological features of the basin (size, sealed surfaces, orography); then, the related indicator can be proper for detecting some events but it fails for others.
- The values for the indicators are provided in terms of anomalies between future and current time spans in an attempt to minimize the influence of the potential biases affecting climate modelling and under the assumption that the performances of the models can be comparable over the entire period of analysis.

5. Aknowledgments

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