Indecis
Sectorial Climate Services

Integrated approach for the **d**evelopment across **E**urope of user oriented **c**limate **i**ndicators for GFCS high-priority **s**ectors: Agriculture, disaster risk reduction, energy, health, water and tourism

Work Package 6

Deliverable 6.2

Report on the datasets inter-comparisons with regard to selected ECVs and INDECIS-ISD

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Overview

The main objective of the inter-comparison exercise is to document the limits and strengths in using reanalysis and modelled climate data as alternative data sources for climate indices computation in the absence of observations. To this end, as a first step, the comparison focuses on differences and similarities between selected datasets and the observations for the Essential Climate Variables (ECVs) selected in the project (t2m, rh, w10m, precipitation, radiation); this should help to interpret the differences between the climate indices derived from the selected alternative datasets and those based on observations. In the second step, the comparison focuses on the climate indices derived from the alternative datasets compared to the reference ones derived within WP4.

The overall work encompasses 5 global/European/regional reanalysis datasets described in the D6.1 report, 19 model outputs, 4 ECVs and 14 climate indices. Regarding climate indices 11 are included in the INDECIS list of indices developed in WP4. The choice of datasets, ECVs and climate indices to be analyzed (Table 1) was based on specific interests of the partners, in order to answer to distinct needs of the partner countries and/or institutions. However, the analysis followed a common methodology in response to the general objective of the project regarding institutional integration.

In the following, the methodology used in the analysis, as well as a summary of work developed, is presented. Some of the extended results of this work are available on the project website, as annexes to this document, with restricted access (only for project partners).

Methodology

For the ECVs the method for comparison of selected datasets and reference data involves comparing the values in the gridded dataset with the closest gridbox in the reference data. It should be noted that in the case of reference data from meteorological stations or wind masts this means comparing grid cell average values against point values, which may lead to differences due to for example (spatial) representativity. However, this method is largely used (e.g. UERRA-D2.8, 2018; Jones et al, 2016; Nkiaka et al, 2016; Tetzner et al, 2019) when employing in-situ/point observational data.

The accuracy indicators used for analyzing the ECV are the mean (e.g. monthly/seasonally/entire period of record) and Taylor diagram (including RMSE, STDEV, Pearson correlation coefficient). For the comparison of climate indices derived from selected datasets, the main accuracy indicators used are the bias (mean difference) for the entire period of record and the Taylor diagram.

The period for comparison is 1980-2010 or the longest common period available for the analyzed data.

Table 1. Overview of datasets, ECVs and indices used in the analysis performed by each partner.

Partner	***Dataset***	***Period of analysis***	***ECVs analyzed***	***Indices of interest/to be analyzed***
MeteoRo	UERRA MESCAN-SURFEX COSMO-REA6 ERA5 vs homogenized temperature series obtained in the Horizon 2020 EUSTACE Project	1995-2017	TMAX TMIN TAVE	STX32- Sums of maximum temperatures ≥32˚C D32 -Number of ~~(consecutive)~~ days with maximum temperature ≥32˚C from June to August Spring index (PTG) - Sums of positive average temperatures calculated for the 1st of February to the 10th April interval STN15- Sums of minimum air temperatures ≤-15˚C recorded in December-February interval
Met Éireann	MÉRA (regional reanalysis) versus station data, gridded observations, ERA-Interim and UERRA reanalysis	1981-2015	Precipitation TMAX TMIN 10m wind speed	CDD, CWD -consecutive wet and dry days R10mm, R20mm, RR1, Rx1day, Rx5day FD, CFD - frost days, consecutive frost days SU, CSU - summer days, consecutive summer days ID- ice days TN - tropical nights
BSC	MERRA2 (global/European scale reanalysis) ERA5 Vs in-situ data from instrumented tall towers	1980-2017	Wind	capacity factor wind power density (seasonal time scale)

UC/IHC	EURO-CORDEX reanalysis-driven simulations validated against E-OBS v17 and Iberia01; 8 models	1989-2008	TMAX TMIN Precipitation	TN- Tropical nights SU- Number of summer days RR1- Wet-day frequency SDII- Simple precipitation intensity index
CZECHGLOBE	EUROCORDEX simulations validated against station network data over Czech Republic ; 11 historical simulations in the context of RCP4.5 and RCP8.5 climate change scenarios	1981-2010 2021-2100	TAVE Precipitation 10m wind speed Relative Humidity	RR1- Wet days frequency R10mm-Annual count of days when daily precipitation amount > 10mm; HPD –Heavy precipitation days (no of days with precipitation amount >50mm) IDs –Ice days (Tmin < 0˚C) No of tropical days (Tmax > 30˚ C)

Summary of work

1. Validation of reanalysis against point- based and gridded observational data

1.1 European Reanalysis ERA5, UERRA MESCAN-SURFEX, COSMO_REA6 compared to station-based data (extended results in Annex A)

(Contribution from MeteoRo)

The European reanalysis datasets **ERA5, UERRA MESCAN-SURFEX, COSMO_REA6** have been validated against the homogenized temperature series obtained in the Horizon 2020 EUSTACE Project, with respect to **daily minimum, maximum and average 2m air temperature**. The UERRA MESCAN-SURFEX dataset is available from Copernicus Climate Data Store (https://cds.climate.copernicus.eu/). Although the UERRA-HARMONIE/V1 dataset was selected for the intercomparison exercise and described in D6.1, in this study the MESCAN- SURFEX dataset was used as it presents the finest spatial resolution (5.5km) for near-surface air temperature among the UERRA reanalysis datasets.

The study employed data from 2163 European stations, covering the period 1995-2017, which represents the common period for the three datasets. The comparison made use of common accuracy indicators (ME, MAE, RMSE, Pearson correlation coefficient), seasonal scatterplots and Taylor diagrams (e.g. Fig. 1). The analysis was performed using the INDECIS software for intercomparison of reanalysis datasets (interdecis) (https://github.com/alexdum/interdecis) developed in WP6.

The results show a high correlation (above 0.85) between each reanalysis dataset and the reference data, for each variable and season, averaged over the entire European area. The ERA5 and COSMO-REA6 datasets have a very similar behavior with regard to the reference data, while UERRA MESCAN-SURFEX presents the best accuracy scores, for all variables and all seasons, possibly due to the improved representation of physical processes in the SURFEX land surface platform (Masson et al, 2013).

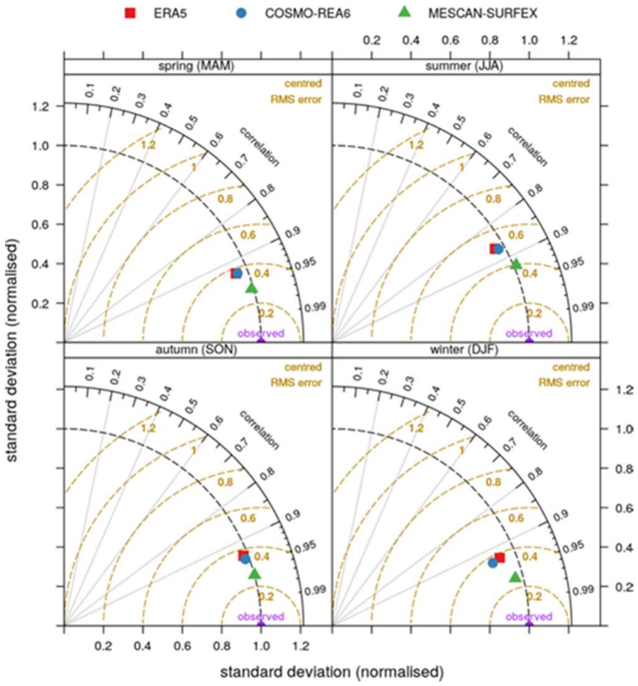

Fig. 1 Taylor diagram of the pairwise observed and reanalysis daily minimum air temperature.

For the investigation of the changes in the regime of four extreme temperature indices (STN32, PTG, STN15, STC32) over Europe, selected from the list of indices developed in D4.1, we used two of the above mentioned European reanalysis datasets (COSMO-REA6 and UERRA MESCAN-SURFEX) for the interval 1995 – 2017, the reference data being developed in the Horizon 2020 EUSTACE Project.

The results show that the correlation between the reanalysis datasets and observations is higher in the first part of the interval, while after 2005 this decreases significantly. The COSMO-REA6 reanalysis dataset correlates better with the observation data for the D32, STX32 and PTG indices. In the case of the STN15 climate index, the UERRA reanalysis is better correlated with the observational data, especially in the last years of the interval.

1.2 Met Éireann Regional Reanalysis (MÉRA) compared to station data and other reanalysis datasets (extended results in Annex B).

(Contribution from MetEireann)

The MÉRA reanalysis dataset is described in detail in Gleeson et al., 2017 and Whelan et al., 2018. The MÉRA dataset spans the period 1981 to 2019 but for the purpose of this work the period up to 2015 is used. The domain covers Ireland, the United Kingdom and an area of northern France. The extra orographic information gained by using the 2.5 km grid (Fig. 2c) can be appreciated when compared with the (global) ERA-Interim (~79 km, Fig. 2a) and UERRA HARMONIE-ALADIN (~11 km, Fig. 2b) grids.

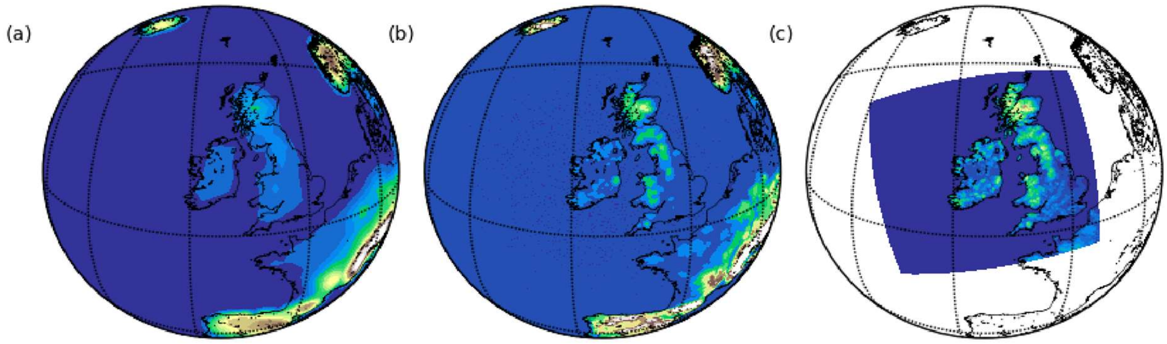

Fig 2. (a) ERA-Interim (79 km grid spacing), (b) UERRA HARMONIE-ALADIN (11 km grid spacing) and (c) MÉRA (2.5 km grid spacing) orographies.

For the purpose of INDECIS 2m temperature and precipitation ECVs are examined in detail using the CDO (Climate Data operator) software (Schulzweida, 2019) to calculate a range of climate indices available within the software which includes several indices (i.e. consecutive wet and dry days, R10mm, R20mm, RR1, Rx1day, Rx5day, frost days and consecutive frost days, summer days and consecutive summer days, ice days, tropical nights).

We have carried out other analysis using MÉRA, ERA-Interim and UERRA HARMONIE-ALADIN where the high resolution of MÉRA means that it trumps the other reanalysis datasets in terms of extremes of wind and precipitation (Whelan et al., 2018). The results of the precipitation analysis are included below.

Precipitation forecasts produced by MÉRA, ERA-Interim and UERRA were compared with observations of 24-hour accumulations of precipitation recorded by Met Éireann's network of (approximately 400) voluntary rainfall stations (0900 UTC to 0900 UTC). Fig. 3 shows areal comparisons of monthly precipitation (for winter, DJF) averaged over the period 1981-2015. The MÉRA, UERRA and ERA-Interim datasets were compared to gridded observations; the point observations were projected onto each reanalysis domain, by conservatively averaging the accumulations in each model grid box, in order to make appropriate comparisons between each reanalysis and the observations. The plots in the first column of Fig. 3 show the monthly observed DJF precipitation averaged over the period 1981-2015 on the ERA-Interim, UERRA and MÉRA grids; the second column shows the corresponding precipitation from each reanalysis while the third column shows the difference between each model and the observations. The coarse ERA-Interim grid mainly underpredicts monthly precipitation, particularly over mountainous areas where the biases are of the order of 50 mm. Both UERRA and MÉRA also underpredict the precipitation over mountains, due to mismatches in orography; the 2.5 km and 11 km grid spacings cannot account for mountain peaks contained within a grid box. UERRA underpredicts precipitation over most of the country whereas MÉRA overpredicts by ~10-20 mm the exception being over high ground. As anticipated, the higher resolution MÉRA shows a noticeable improvement over the coarser resolution ERA Interim and UERRA reanalys es, which underestimate precipitation over the MÉRA domain by up to ~50 mm per month. This can be attributed to model resolution and the mesoscale physics parametrizations which resolve convection in MÉRA. The bias patterns for MÉRA are similar for each season (not shown) i.e. negative biases over high ground and positive biases elsewhere. UERRA and ERA-Interim, on the other hand, are mainly negatively biased for winter (DJF) and autumn (SON) but positively biased for the other seasons.

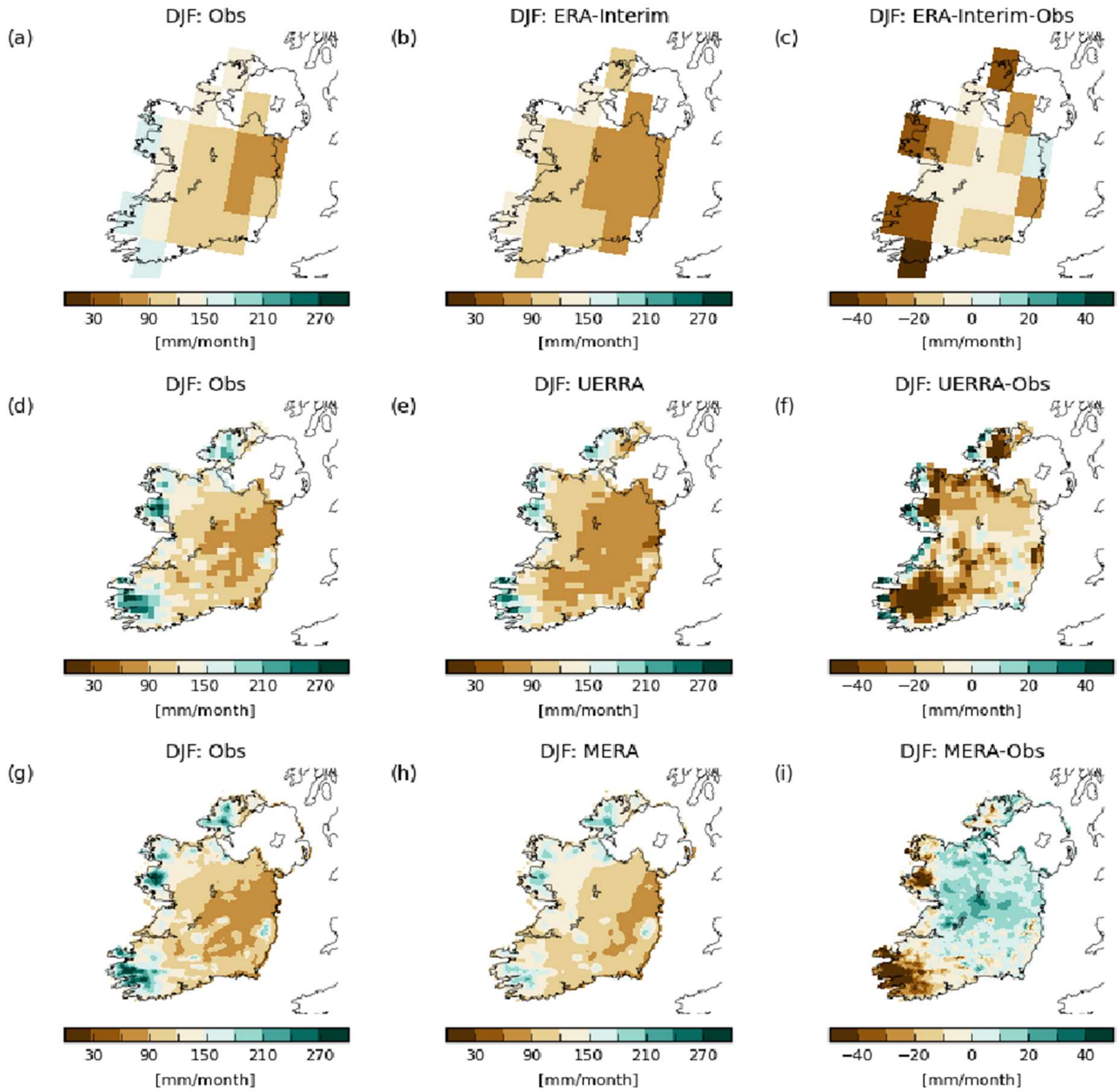

Fig 3. *Monthly mean DJF precipitation for the period 1981-2015 (a) Observations projected on to the ERA Interim grid (b) ERA-Interim (c) ERA-Interim minus observed. (d-f) are similar but represent UERRA. (g-i) are for MÉRA.*

Fig. 4a and Fig. 4b show the relative frequency distribution of monthly mean DJF 0900-0900 UTC precipitation accumulations for the models and observations. Figure 4a clearly highlights the fact that ERA-Interim overpredicts light precipitation and underpredicts extremes. MÉRA and UERRA also overpredict the frequency of light rainfall but MÉRA matches the observations more closely than UERRA for the distribution of precipitation extremes.

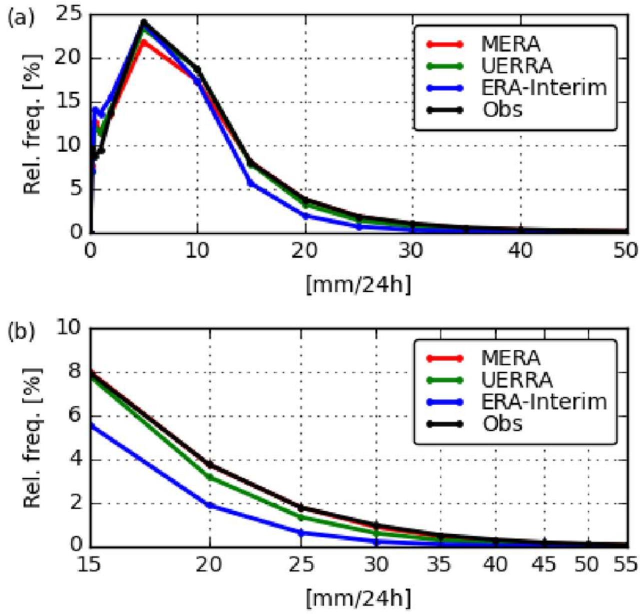

Fig 4. Frequency distribution of observed (black), ERA-Interim (blue), UERRA (yellow) and MÉRA (red) 0900 UTC to 0900 UTC 24-hour precipitation accumulations (a) shows the full range of 24-hour precipitation accumulations while (b) is focused on the extreme events.

This chapter summarizes MÉRA and its benefits over coarser resolution reanalysis datasets, particularly in terms of extremes of precipitation and 10m wind speeds. The work done on climate indices, specifically for INDECIS WP6.2, is included in Appendix B, where a large selection of indices related to precipitation and temperature maxima (TMAX) and minima (TMIN) are compared to gridded observations. This evaluation confirms the ability of MÉRA to capture basic features about Ireland's climate including its variability in time and space. We identified some deficiencies such as wet and dry biases for subregions, and warm and cold temperatures biases. Correlations between the model and observations are generally very good to excellent, exceeding 0.9 for TMAX. The correlations are a bit lower for precipitation but nevertheless very good, with the lowest occurring in Summer. This is probably due to the convective nature of Summer rain where shower displacements in the model can result in larger errors. In general, the precipitation errors are low with root mean square errors of around 0.5-0.7 mm/day. There are negative biases in temperature maxima of around 1 to 1.5 C, likely due to an over-prediction of cloud. The errors in minimum temperatures are lower and opposite in sign (around 0.5 C) but also suggest an over-prediction of cloud. The trends in precipitation, TMAX and TMIN follow those of the observations very closely.

1.3 ERA5 and MERRA2 compared to in-situ wind data (extended results in Annex C)

(Contribution from BSC)

An intercomparison of two global widely-used reanalysis datasets –**ERA5 and MERRA2**- with reference data has been performed in terms of **surface and near-surface wind speeds**, Capacity Factor (CF) and Wind Power Density (WPD). Both CF and WPD are energy indices extensively used within the wind energy field to anticipate the power production or evaluate the performance of a running wind farm, among others. The three parameters are computed using the ERA5 and MERRA2 reanalysis at 77 locations distributed worldwide where high-quality, in situ data are available from instrumented tall towers (Ramon et al. 2019, in review). A comparison against these data reveals that the reanalyses generally underestimate seasonal mean wind speeds, and so do the CF and WPD indices. Overall, the ERA5 shows better results than MERRA2 for all three studied parameters (ex. Fig 5).

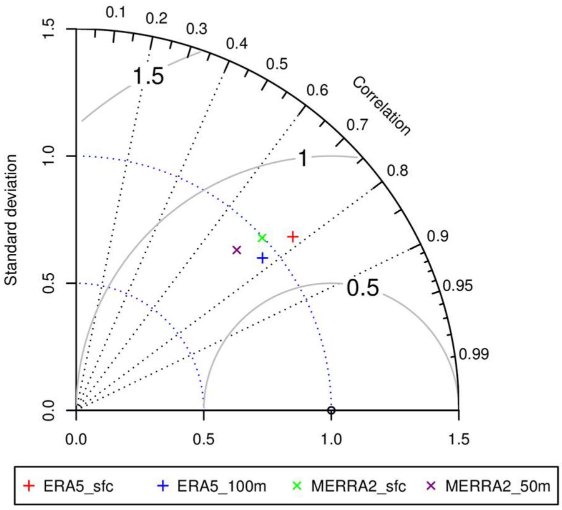

Fig. 5 Taylor diagram of the pairwise observed and reanalysis monthly-averaged winds.

2. Evaluation of ERA-INTERIM-driven regional climate model simulations (extended results in Annex D)

(Contribution from UC)

UC contribution evaluates daily precipitation and minimum and maximum temperature of eight **ERA-Interim-driven (control) simulations of EURO-CORDEX Regional Climate Models (RCMs) over the Iberian Peninsula** (IP), with a special focus on observational uncertainty. This study takes advantage of the recently developed high-resolution gridded dataset Iberia01 (Herrera et al. 2019), that can be used as an alternative evaluation reference in addition to E-OBSv19 (Haylock et al. 2008), thus providing an opportunity for a new EURO-CORDEX evaluation effort. We expect this contribution to clarify an often overlooked, yet critical aspect of climate indices evaluation in terms of observational uncertainty.

The results show clear differences between E-OBS and Iberia01 (e.g. Fig. 6), which have implications in RCM evaluation and bias correction. E-OBS shows lower values and smoother spatial patterns for the three ECVs analyzed (Table 1), mainly due to the less dense station network used to develop the dataset. The spatial pattern depicted by Iberia01 (not shown) highlights the complex orography of the Iberian Peninsula, which is better represented by the RCM data. The observed reference remains as a major factor of uncertainty for climate indices validation. The results suggest that the use of observational regional datasets is recommended whenever possible due to their much better representation of local-scale features.

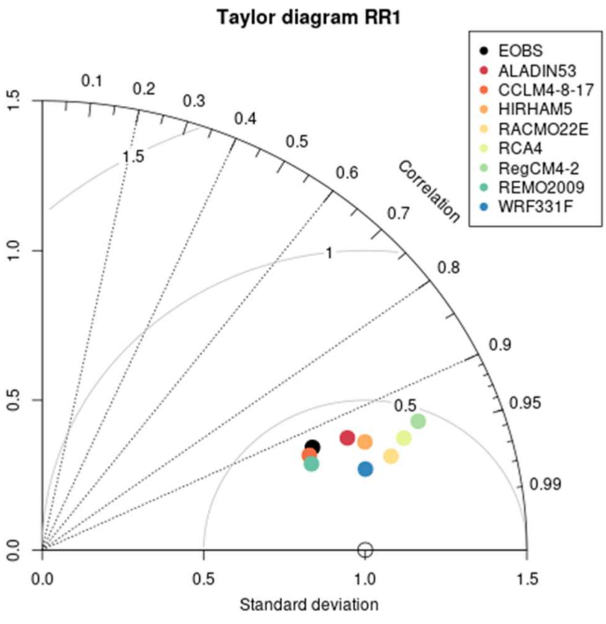

Fig. 6 Taylor diagram of the spatial pattern of RR1 (Iberia01 is used as reference)

3. Evaluation of GCM-driven model simulations (extended results in Annex E)

(Contribution from GCRI)

The contribution concentrates on the validation of RCM's in the area of the Czech Republic. We analyzed 11 experiments coming from pair combination of **5 GCM and 5 RCM available within the EURO-CORDEX initiative in the context of RCP2.6 (1 simulation), RCP4.5 and RCP8.5**. The analysis focuses on the period 1971-2010.

The reference data come from station network data, available from the Czech hydrometeorological institute within Global Change Research Institute (GCRI), Czech Academy of Sciences, from which only a certain portion is used for ECA&D creation and from which then E-OBS dataset is calculated. Data quality control, homogenization and filling missing values procedures (Štěpánek et al., 2009; Štěpánek et al., 2011; Štěpánek et al., 2013) were applied to the raw station data, leading to the creation of the so-called "technical" series for mean, maximum and minimum temperatures, precipitation totals, sums of sunshine duration, relative humidity and 10m wind speed. They were calculated for 268 climatological and 787 rain-gauge stations of the GCRI network in the 1961–2018 period and actual values are continually added.

One worth noting result of the analysis is that some of the RCM simulations showed critical biases for historical climate runs, some examples being presented in the following. For this analysis, 19 simulations (combination of GCMs and RCMs as available in 2019), were used (plotted in the Taylor diagram).

- CNRMCM5_ALADIN53: minimum temperature shows very low spatial correlations both in winter and summer (Fig. 7), and relative humidity is not well represented (in winter) either.

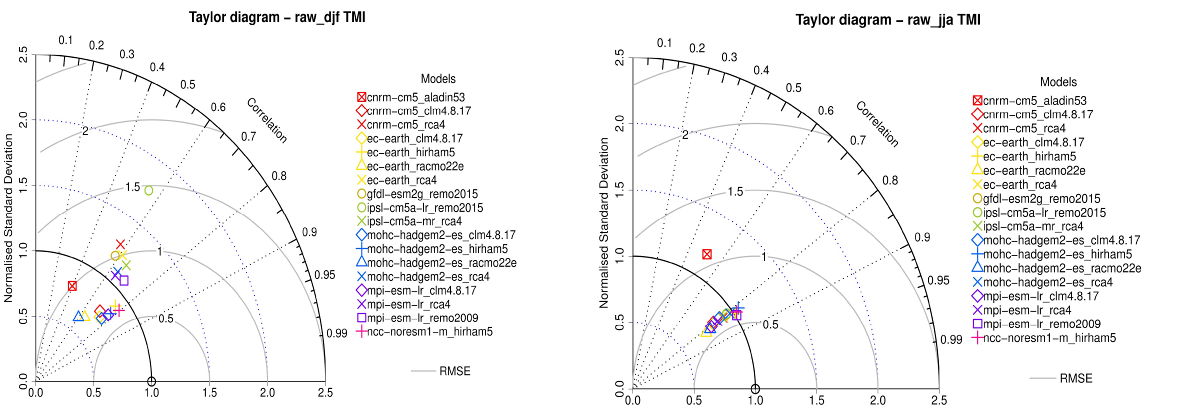

Fig. 7. Taylor diagrams for minimum temperature (denoted in the graphic as 'TMI') (DJF – winter – left diagram, JJA – summer right diagram) for original (non bias– corrected) model outputs.

- CNRMCM5_CLM4.8.17: poor representation of annual cycle for precipitation and low spatial correlations for precipitation and solar radiation in summer (Fig. 8).

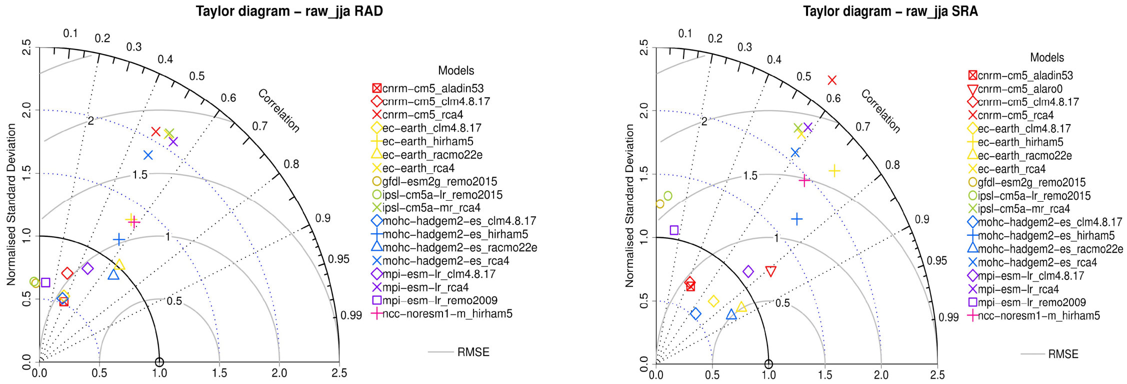

Fig. 8. Taylor diagrams for solar radiation (denoted as 'RAD') in JJA – summer (left diagram) and precipitation (denoted as 'SRA') in JJA – summer (right diagram) for original (non bias– corrected) model outputs.

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