Met Éireann's contribution to package D6.2 of the JPI Climate INDECIS climate indices project

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1 Summary

The very high resolution regional reanalysis for Ireland, called MÉRA - the Met Éireann Regional Reanalysis, has been evaluated by Gleeson et al., 2017 and Whelan et al., 2018, particularly regarding extremes of precipitation and wind speed. Here the evaluation is extended to climate indices using gridded observations of temperatures and precipitation as references. The years 1981 to 2017 inclusive were included in the analysis. This evaluation confirms the ability of MÉRA to capture basic features about Ireland's climate including its variability in time and space. We have also identified some deficiencies such as wet and dry biases for sub-regions, and warm and cold temperatures biases. Of course, the observations themselves are not perfect and also also subject to a range of errors from instrumental to human to the methods of gridding and interpolation due to the sparseness of the observation station network.

The Met Éireann contribution to the INDECIS ERA4CS project involves an evaluation of a range of maximum and minimum temperature and precipitation climate indices using MÉRA and gridded observation data. Summary statistics relating to daily mean precipitation and temperature maxima (TMAX) and minima (TMIN) are provided in Table 1. 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.

Table 1: Statistics Summary

Precipitation	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
Bias (mm)	0.04	-0.04	0.25	0.05	-0.09
RMSE (mm)	0.55	0.67	0.50	0.50	0.65
Correlation	0.88	0.91	0.85	0.72	0.90
TMAX	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
Bias (°C)	-1.42	-1.15	-1.48	-1.59	-1.44
RMSE (°C)	1.45	1.18	1.52	1.65	1.47
Correlation	0.95	0.96	0.95	0.94	0.95
TMIN	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
Bias (°C)	0.38	0.36	0.29	0.38	0.50
RMSE (°C)	0.52	0.52	0.48	0.49	0.63
Correlation	0.89	0.90	0.86	0.88	0.88

2 Data and Methods

Output from the Met Éireann very high resolution regional reanalysis, called MÉRA, was used for this analysis and compared to Met Éireann's gridded observation datasets. Gridded observation datasets are available for precipitation, maximum temperatures and minimum temperatures. For this reason, the analysis presented here is limited to those 3 meteorological parameters and their associated climate indices.

2.1 The MÉRA Reanalysis Dataset

The MÉRA reanalysis dataset is described in detail in Gleeson et al., 2017 and Whelan et al., 2018. Technical details about the files are provided in Whelan et al., 2017. Details about some of the many projects that involve the use of the MÉRA dataset are provided in the 2018 and 2019 workshop proceedings (Gleeson and Whelan, 2018, 2019).

The dataset spans the period 1981 to 2019 but for the purpose of this work the period up to 2017 was 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 (Figure 1c) can be appreciated when compared with the global ERA-Interim ($\tilde{7}$9 km, Figure 1a) and UERRA HARMONIE-ALADIN ($\tilde{1}$1 km, Figure 1b) grids.

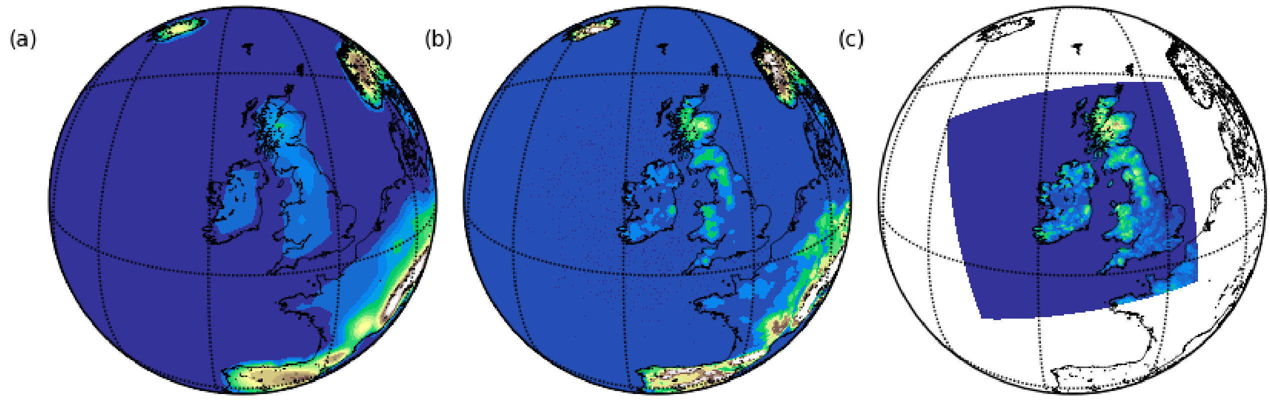


Figure 1: (a) ERA-Interim (79 km grid spacing), (b) UERRA HARMONIE-ALADIN (11 km grid spacing) and (c) MÉRA (2.5 km grid spacing) orographies.

2.2 Gridded Observations

Gridded datasets of daily maximium and daily minimum temperatures and 24-hour rainfall accumulations were prepared from station data archived in the national climate archive. Further information on the preparation of these datasets can be found in Walsh et al., 2012 and Gleeson et al., 2015. These data are usually generated on a 1 km regular lat-lon grid. However, for the purpose of this analysis, the point observations were prepared on the 2.5 km HARMONIE-AROME grid, the same grid that the MÉRA dataset is on, and converted from ascii to grib data format.

2.3 Climate Indices

The CDO, Climate Data Operator, software (Schulzweida, 2019) was used for much of the analysis presented in this report due to its built-in climate indices functions. The precipitation and maximum and mimimum temperature indices considered are summarised in Tables 2 and 3. In the tables Pr is precipitation, TX is maximum temperature and TN is minimum temperature.

Table 2: Precipitation Climate Indices

Index Code	Index Name and Description	Units	ECV
CDD	Consecutive dry days index per time period	Days	Pr
CWD	Consecutive wet days index per time period	Days	Pr
R10mm	Heavy precipitation days index per time period	Days/year	Pr
R20mm	Very heavy precipitation days index per time period	Days/year	Pr
RR1	Wet days index per time period	Days/year	Pr
RX1day	Highest one day precipitation amount per time period	mm	Pr
RX5day	Highest five day precipitation amount per time period	mm	Pr

Table 3: Temperature Climate Indices

Index Code	Index Name and Description	Units	ECV
CFD	Consecutive frost days index per time period	days	TN
CSU	Consecutive Summer days index per time period	days	TX
FD	Frost days index per time period	days/year	TN
ID	Ice days index per time period	days/year	TX
SU	Summer days index per time period	days/year	TX
TN	Tropical nights index per time period	days/year	TN

3 Results

The results are split into nine sections, three for each ECV - precipitation averages and trends, corresponding climate indices and Taylor diagrams, maximum temperature averages and trends, corresponding climate indices and Taylor diagrams and finally minimum temperature averages and trends, corresponding climate indices and Taylor diagrams.

All of the postage-stamp style plots shown in this section have the same general format of five rows by three columns. The rows represent: Annual, DJF, MAM, JJA and SON where DJF = December, January, February and so on for the remaining three seasons. Column 1 represents observation data, column 2 shows the MÉRA data and column 3 shows the difference between MÉRA and observations. This information is hereafter omitted from the figure captions to reduce some repetition. Note that in many of the plots, the annual and seasonal subplots are on different scales.

3.1 Precipitation Annual and Seasonal Averages and Overall Trends

In terms of biases, a similar trend in seen in the seasonal plots as in the annual average (Figure 2). There is a general positive bias of the order of 1 mm per day but there are negative biases in the southwest and west. Some of this is due to mismatches between the orography in MÉRA and the actual orography. Another reason may be that our domain is small and therefore the west coast is closer to the boundaries than it ideally should be (see presentation by Belušić et al., 2018). As most of our weather systems come from the Atlantic, this could be a possible source of error. Nevertheless, overall there is very good agreement between the reanalysis dataset and observations. This was also shown in Whelan et al., 2018 where the MÉRA dataset matches observations very well in terms of relative frequency and the Heidke skill score. Figure 3 (top) shows the monthly average domain-averaged time-series of precipitation for both the MÉRA and observation datasets, along with the corresponding 12-month running means. The lower panel shows the same datasets but with the 1981-2010 averages substracted from each dataset. It is clear that the trends in each are similar with the bias in MÉRA varying in sign but mostly positive compared to observations.

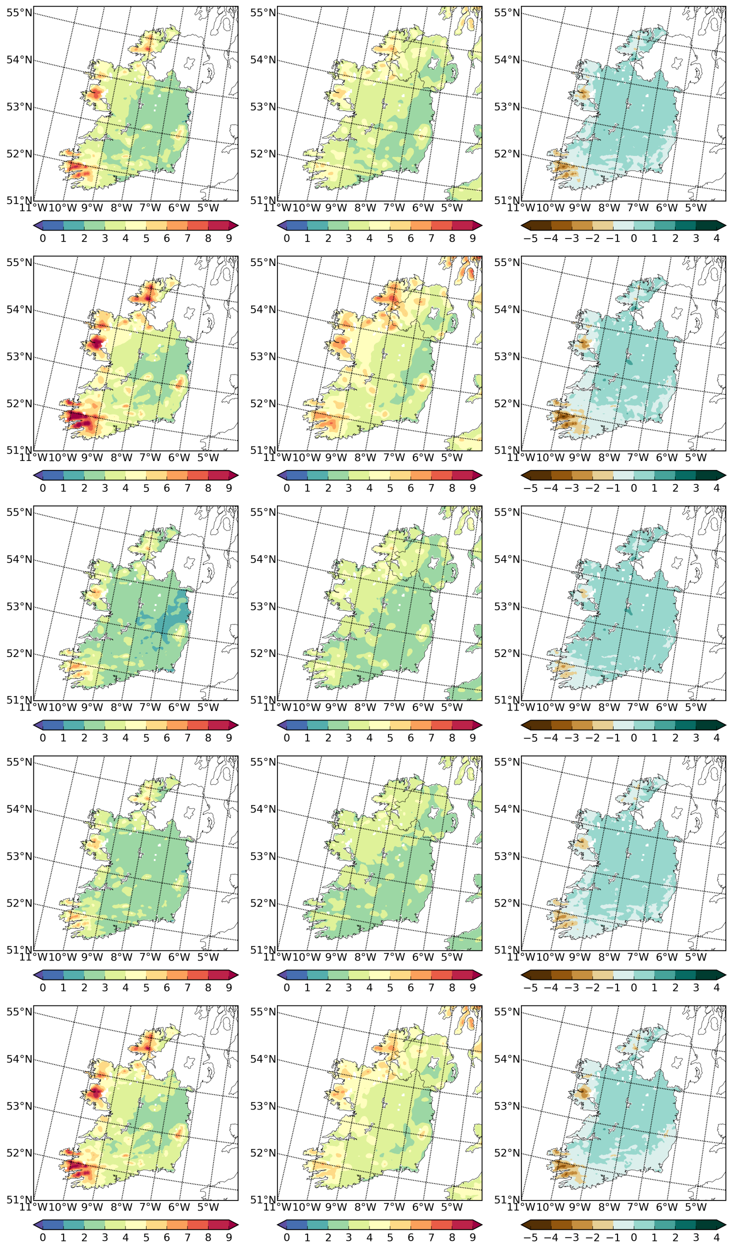
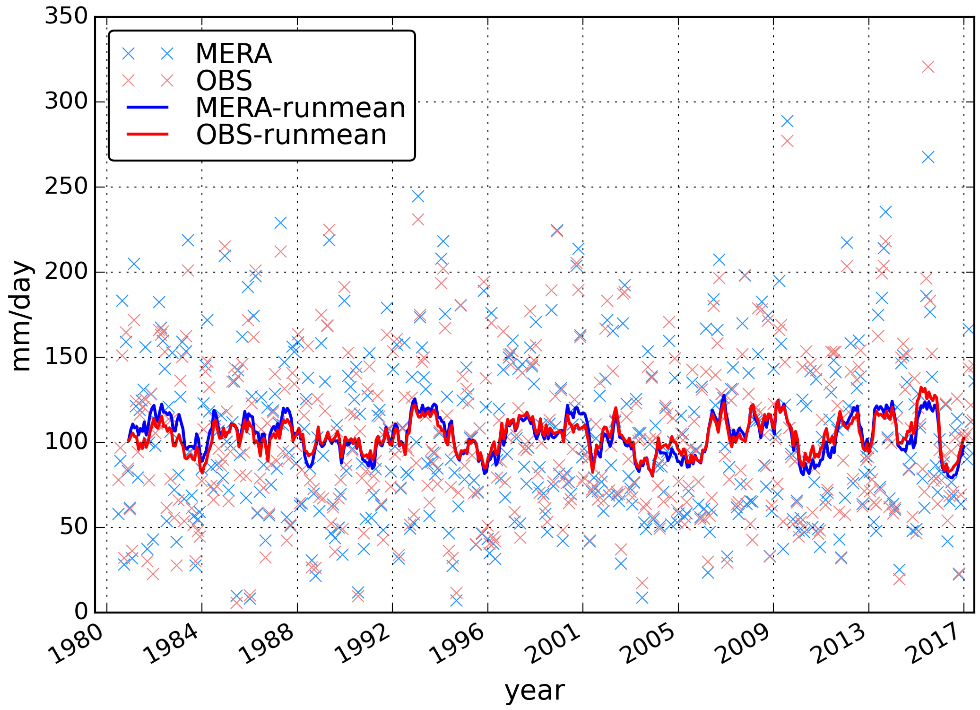


Figure 2: Mean daily precipitation for the period 1981-2017 inclusive. Unit [mm/day]



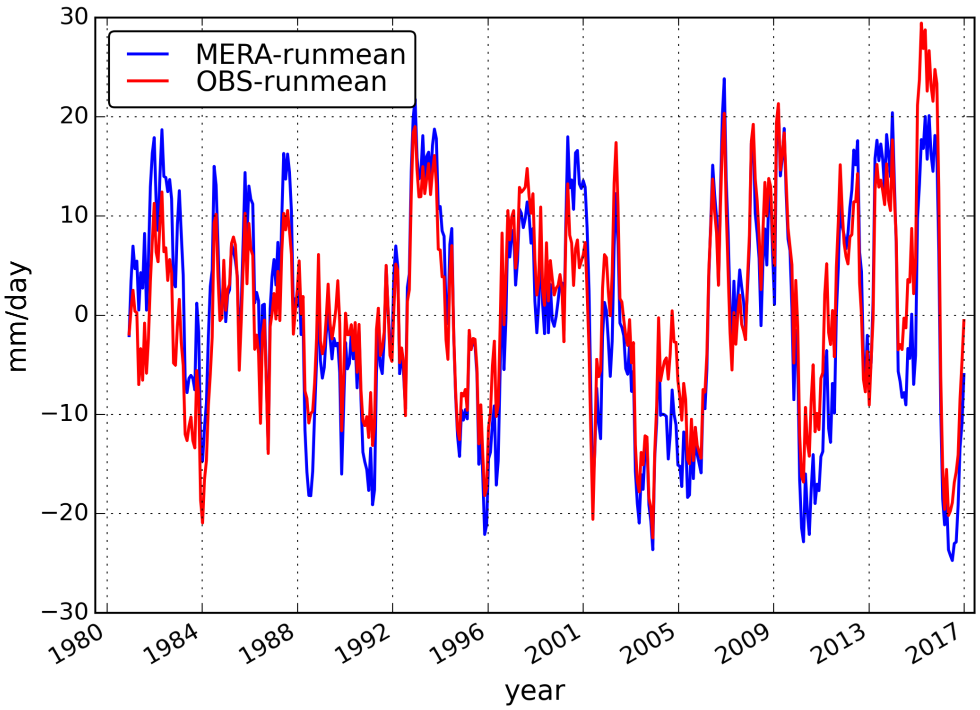


Figure 3: Monthly means of daily precipitation averaged over the domain for the period 1981-2017. Top: Time series of MÉRA (blue) and observation (red) datasets. 12-month running means are shown as continuous lines. Bottom: Similar but each dataset is de-trended by subtracting its 1981-2010 mean

3.2 Precipitation Climate Indices

3.2.1 Consecutive Dry Days (CDD)

This index refers to the largest number of consecutive days where the daily rainfall total is less than 1 mm. In general there is good agreement between MÉRA and the gridded observations (Figure 4). As expected, and consistent with the rainfall averages over the 37-year period which show a mostly positive bias, there is an overall negative bias in the largest number of consecutive dry days. The exception to this is Summer which has more areas of positive bias, particularly over the southern half of the country. However, overall the patterns in the MÉRA and observations plots are similar. For example, in the annual plots, the largest CDDs are in the east and southeast in both datasets. In Winter (DJF) the southwest is wettest (lowest CDD). In Spring MÉRA is wetter over much of the country.

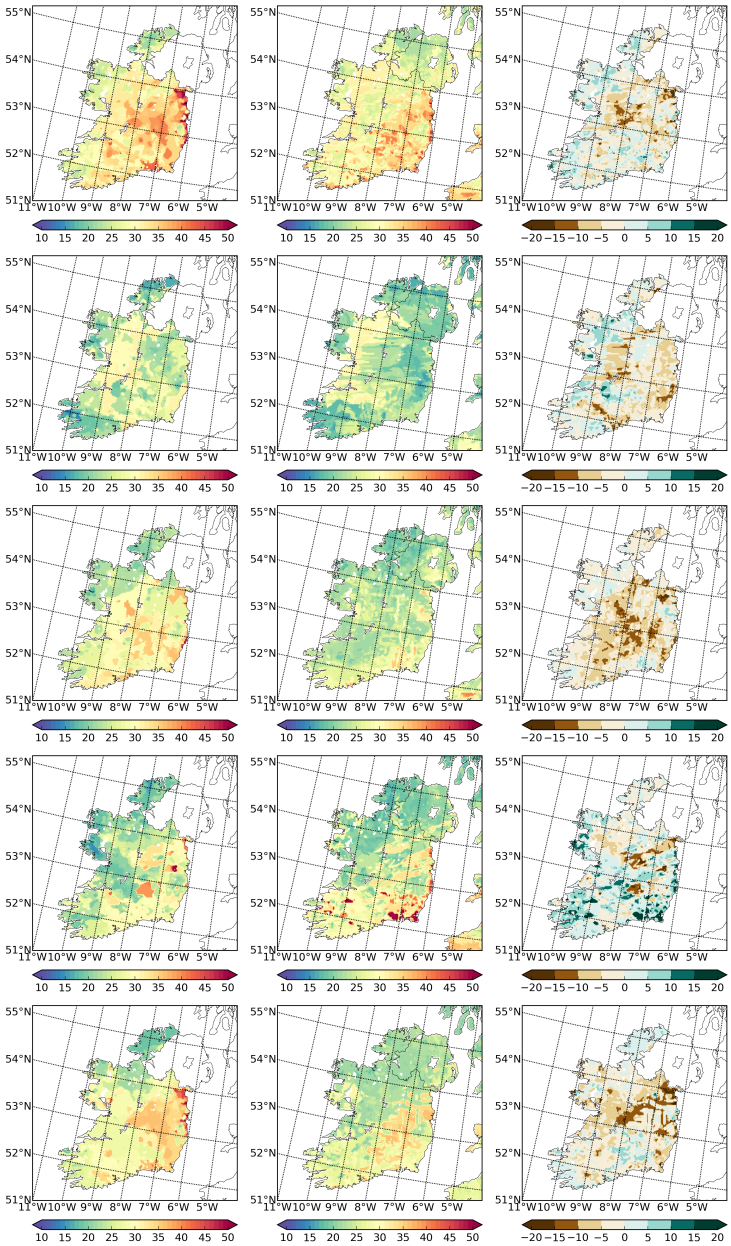


Figure 4: The largest number of consecutive days in the period 1981-2017 inclusive where the daily rainfall total is less than 1 mm.

3.2.2 Consecutive Wet Days (CWD)

This index refers to the largest number of consecutive days where the daily rainfall total is at least 1 mm. The largest biases occur in Winter and are mainly negative and along Atlantic coastal counties. The largest biases are in the southwest where Ireland's orography is most complex and the mountains highest (Figure 5. Biases are much smaller for the other seasons and mostly positive except in the southwest, west and northwest. This index is also shown for a threshold of 5 mm (Figure 6). Similar trends are seen in the biases, largest in Winter, but overall there is good agreement between MÉRA and observations.

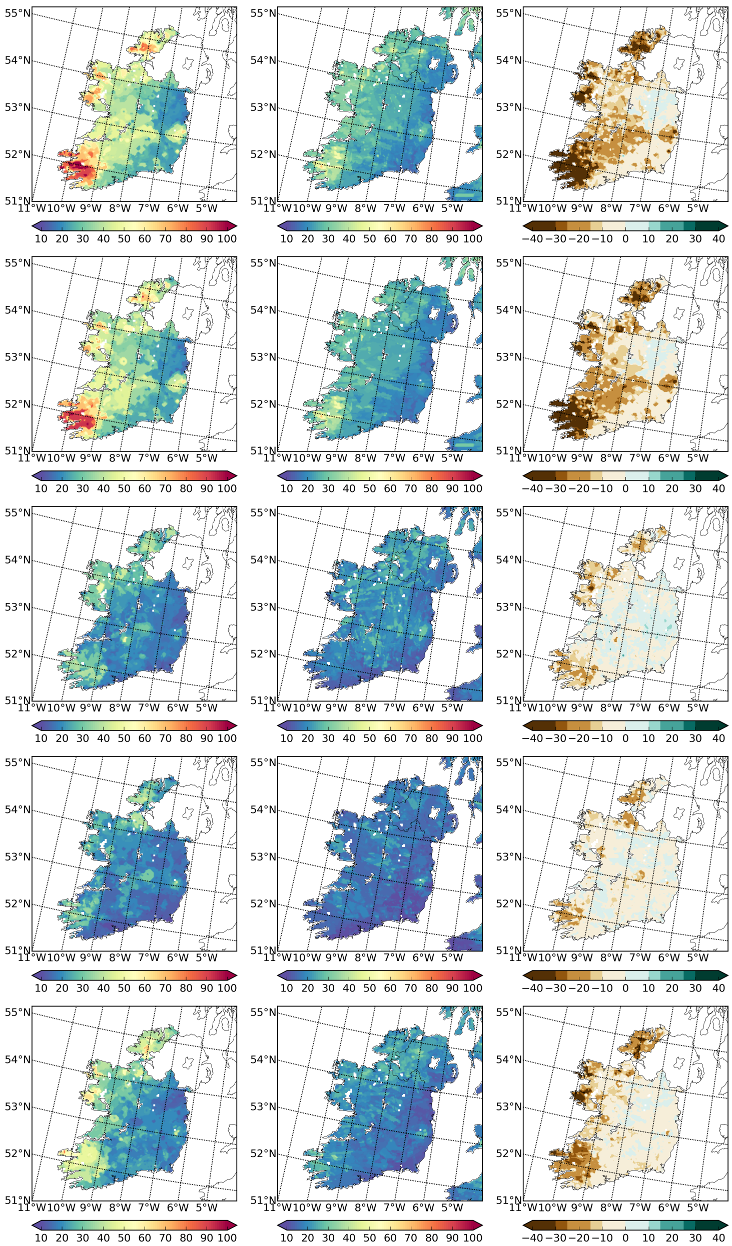


Figure 5: The largest number of consecutive days in the period 1981-2017 inclusive where the daily rainfall total is at least 1 mm.

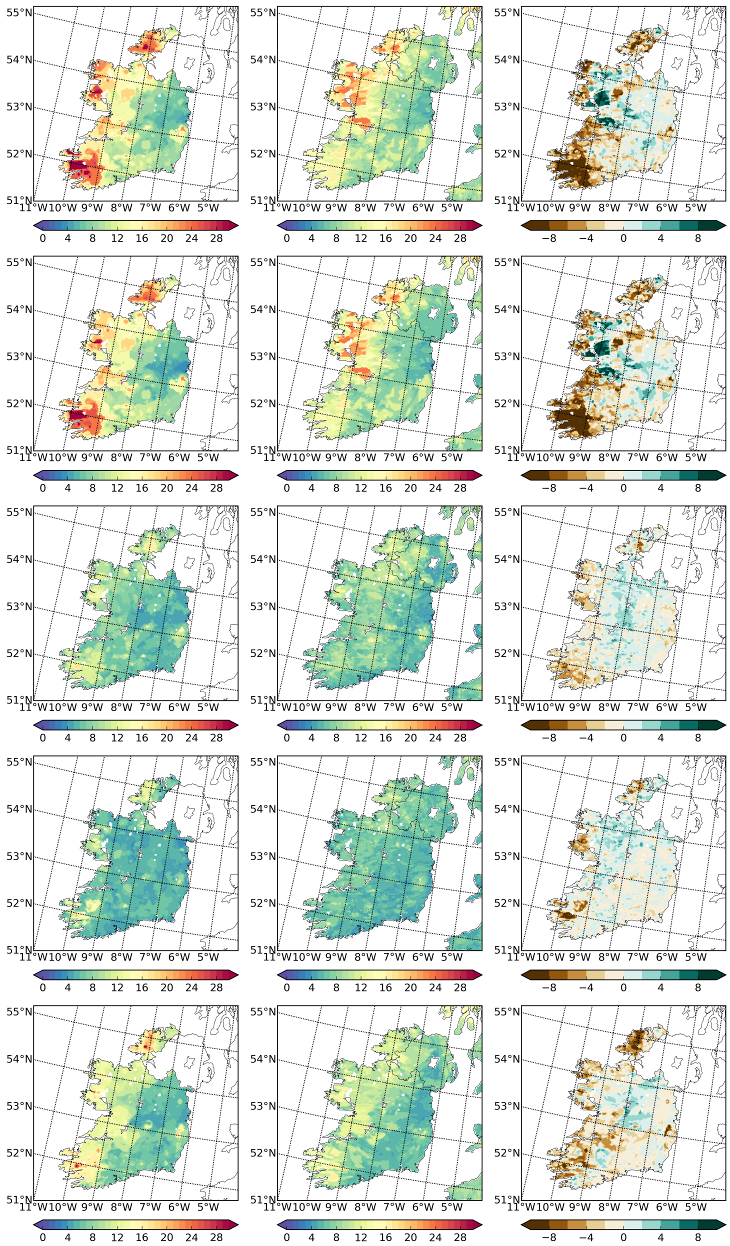


Figure 6: The largest number of consecutive days in the period 1981-2017 inclusive where the daily rainfall total is at least 5 mm.

The fact that the CDD and CWD indices involve counting the maximum number of consecutive days means that models have an unfair disadvantage as they are subject to both spatial and timing errors. Also small differences of the order of 1 mm can make a large difference regarding these indices. The remainder of the precipitation indices presented involve the number of days where precipitation exceeds 1 mm, 10 mm and 20 mm thresholds and the maximum 1-day and 5-day rainfall totals.

3.2.3 Wet Days (RR1)

This index refers to the number of wet days in the time period i.e. the number of days with daily precipitation totals exceeding 1 mm. In this case we have plotted the number of wet days per year by dividing the number in the time period by 37, the number of years in the dataset (Figure 7). Comparing the left and centre columns it is clear that MÉRA captures the gradient of the trend in wet days (highest in the west and northwest to lowest in the southeast) very well. However, as before there is a clear negative bias along the Atlantic coast, most pronounced in Autumn and Winter (> 10 days per year), the wettest seasons in Ireland. There are areas of positive bias in the midlands and east but these are much smaller (mostly < 5 days per year).

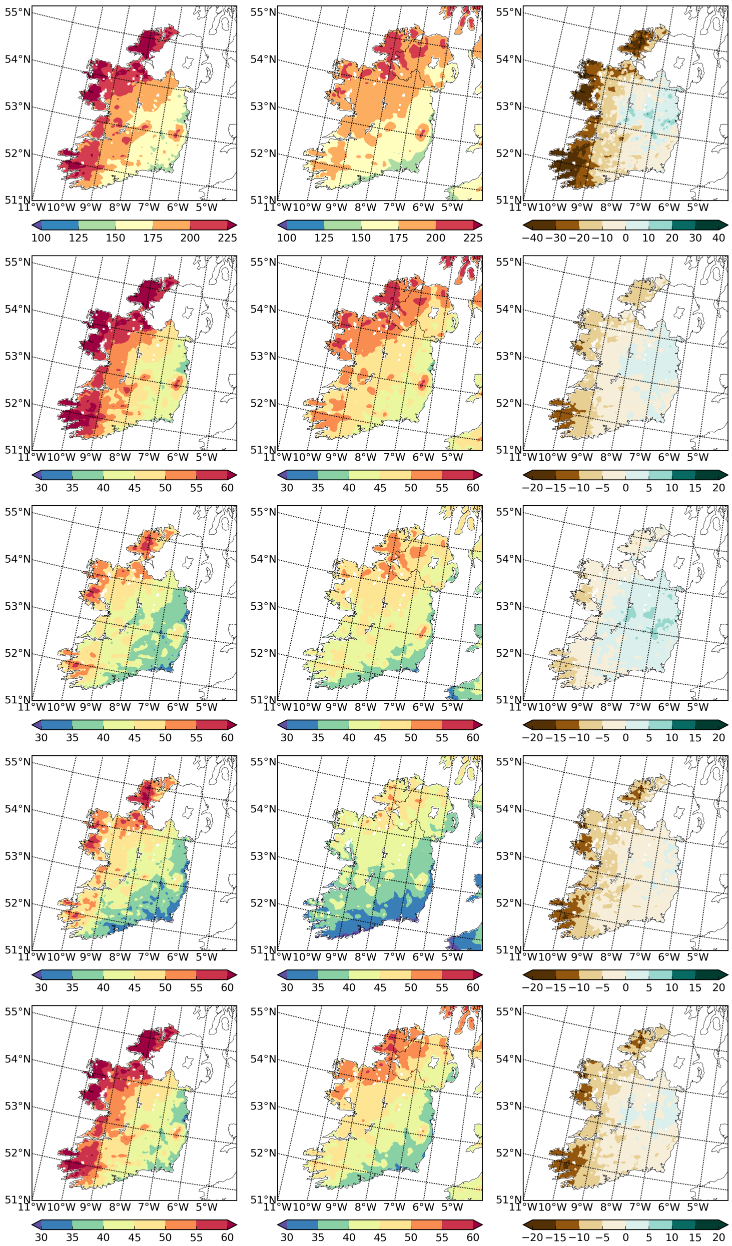


Figure 7: Wet days index (R>1mm) for the period 1981-2017 inclusive scaled by the number of years in the time period.

3.2.4 Heavy Precipitation Days (R10mm)

This index is similar to RR1 but refers to the number of heavy precipitation days in the time period i.e. the number of days with daily precipitation totals exceeding 10 mm. As for the case of RR1, I have scaled the result by the number of years in the time period, 37 (Figure 8). The bias in heavy precipitation days is negative over higher ground in the west and southwest in all seasons but slightly greater in Autumn and Winter. This is in contrast to RR1 where there was a strong negative bias all along Atlantic coastal counties and not just in mountainous regions as is the case here. There are also small negative biases along the south and southeast coasts but elsewhere, which in fact covers most of the country, there are positive biases of up to 4 days per year.

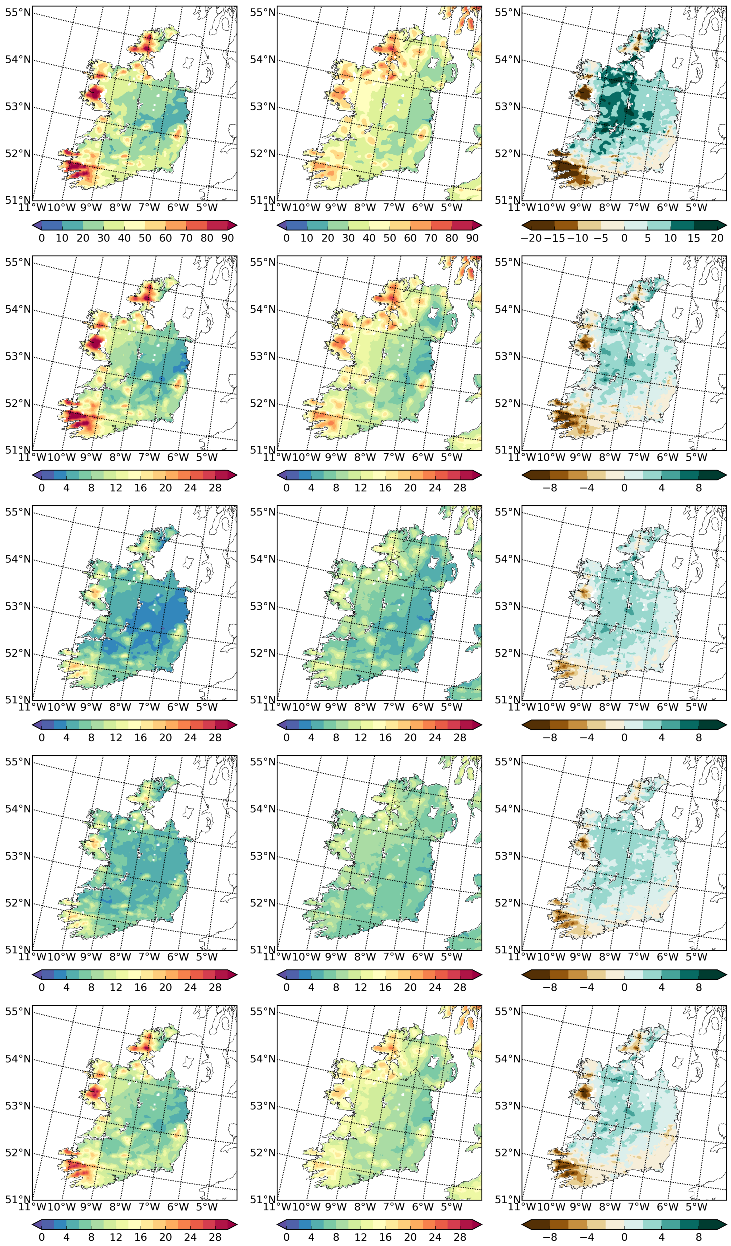


Figure 8: Heavy precipitation days index (R>10mm) for the period 1981-2017 inclusive scaled by the number of years in the time period.

3.2.5 Very Heavy Precipitation Days (R20mm)

This index is similar to RR1 and R10mm but refers to the number of heavy precipitation days in the time period i.e. the number of days with daily precipitation totals exceeding 20 mm (Figure 9). As before, we have scaled by the number of years in the time period. In general, the trend in term of biases is similar to R10mm with negative anomalies over the mountains of the west and southwest but positive anomalies over most of the country, though in absolute terms, as expected, there are fewer days per year, where rainfall exceeds the 20 mm threshold assigned to the "very heavy precipitation" category.

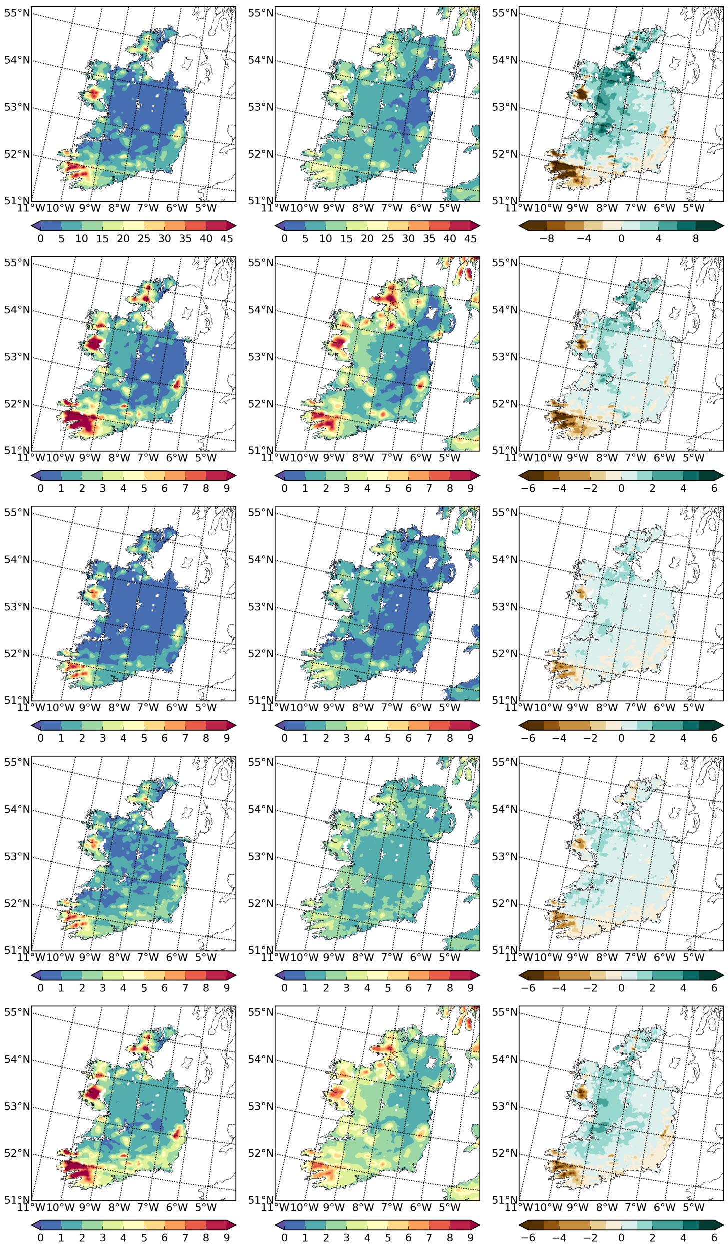


Figure 9: Very heavy precipitation days index (R>20mm) for the period 1981-2017 inclusive scaled by the number of years in the time period.

3.2.6 Highest One-day and Five-day Precipitation Amounts in the time period (RX1day, RX5day)

The highest one-day and five-day precipitation amounts in the time-series are shown in Figure 10 because the outcome is the same for each. Overall the patterns in the observations and MÉRA dataset match well. In general the negative biases occur over the mountains, particularly in the southwest. However, there are positive biases over most of the country which are generally less than 20 mm.

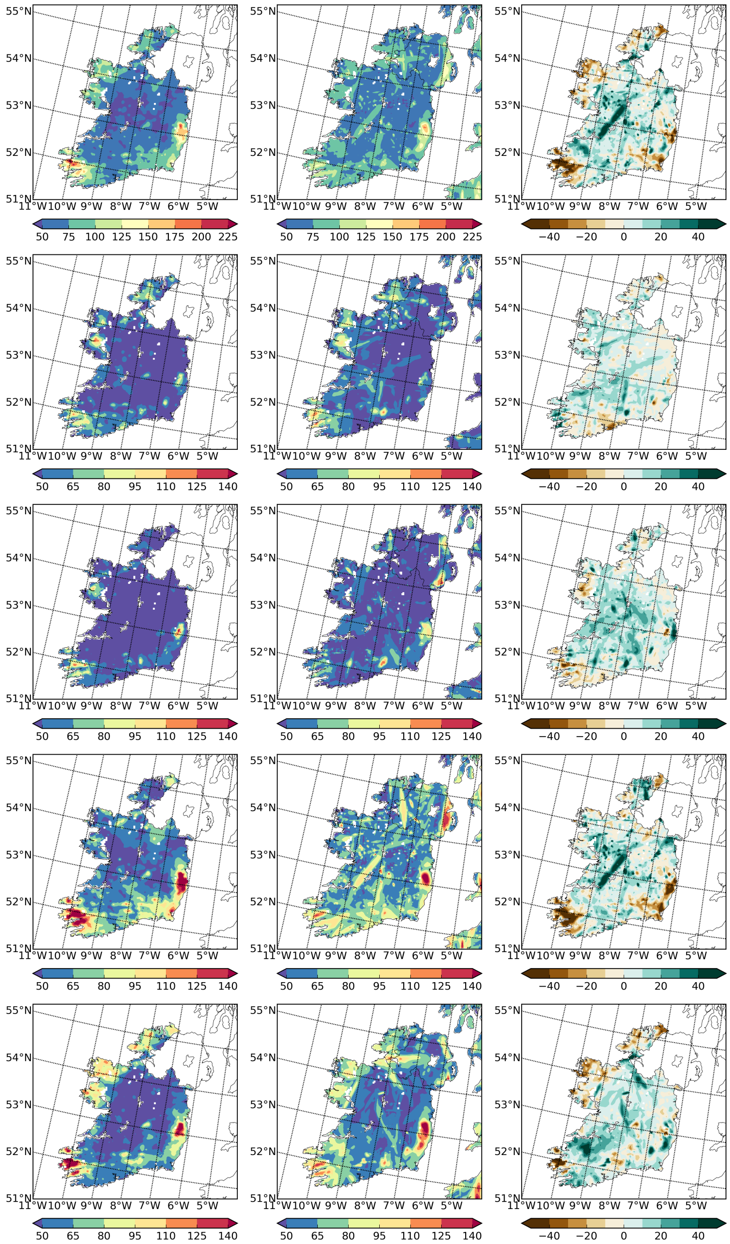


Figure 10: Maximum one-day or five-day precipitation in the period 1981-2017 inclusive.

3.3 Precipitation Taylor Diagrams

This section includes all of the precipitation-related Taylor diagrams. The Taylor diagram for annual mean precipitation is shown in Figure 11. The standard deviation of the observations exceeds 1 mm in Autumn and Winter but is otherwise less than 1 mm. The standard deviation of the MÉRA dataset is less than that of the observations. Correlations exceed 0.85 in all seasons except Summer.

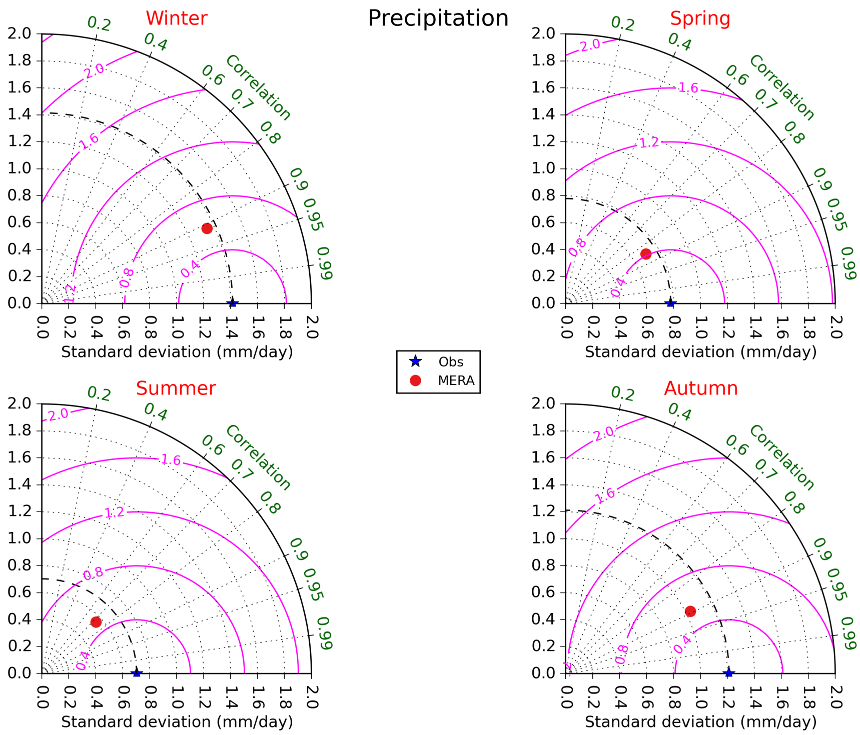


Figure 11: Taylor diagram for daily mean precipitation for the period 1981-2017.

For the CDD and CWD indices correlations are much lower as expected - as low as 0.4. Standard deviations and RMSEs are of the order of 5 days mostly (Figures 12- 14).

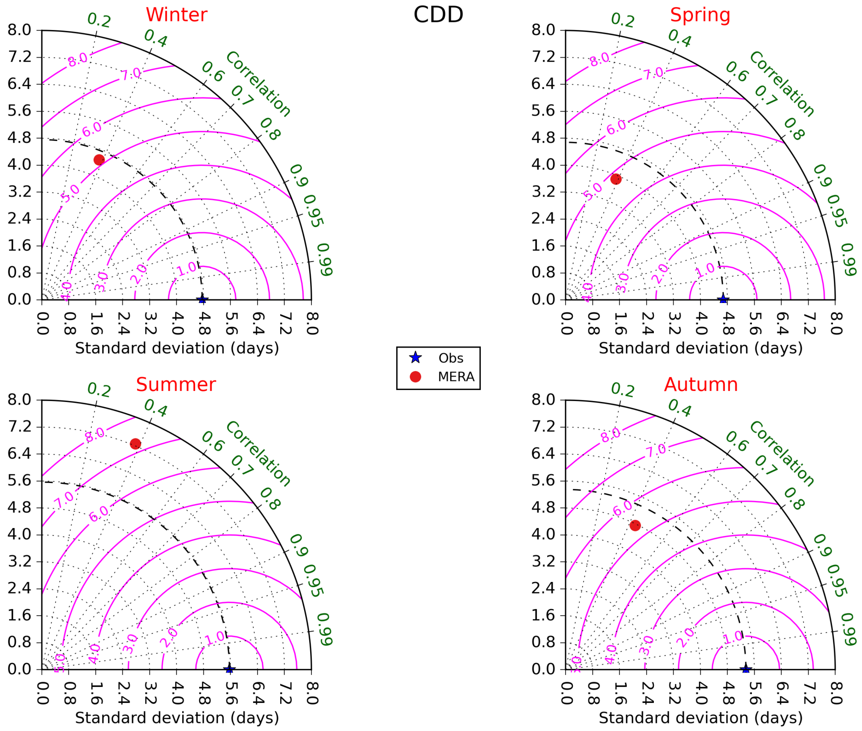


Figure 12: Taylor diagram for the consecutive dry days index for the period 1981-2017.

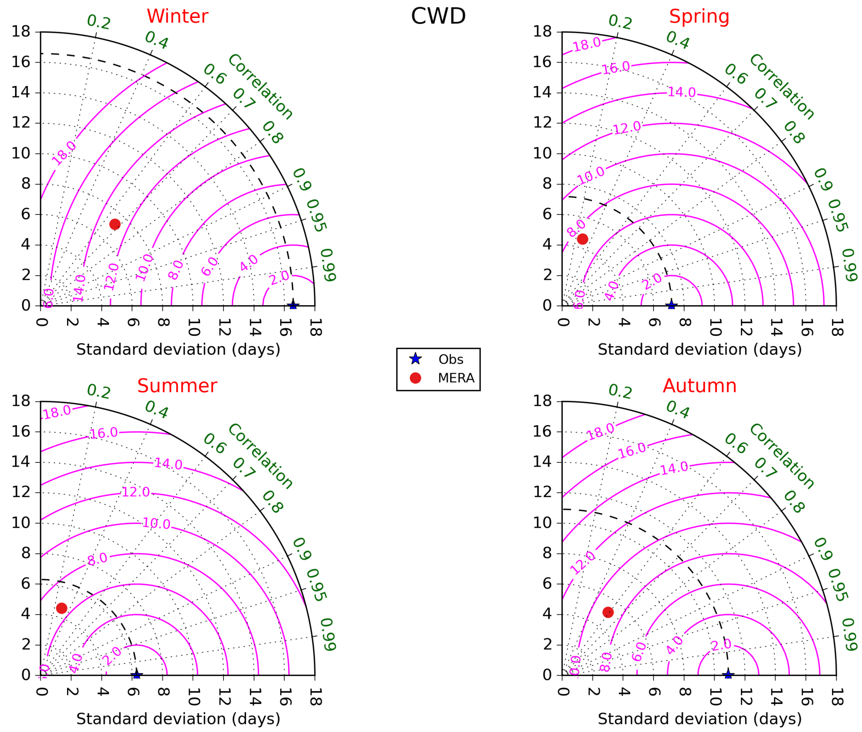


Figure 13: Taylor diagram for the consecutive wet days index for the period 1981-2017.

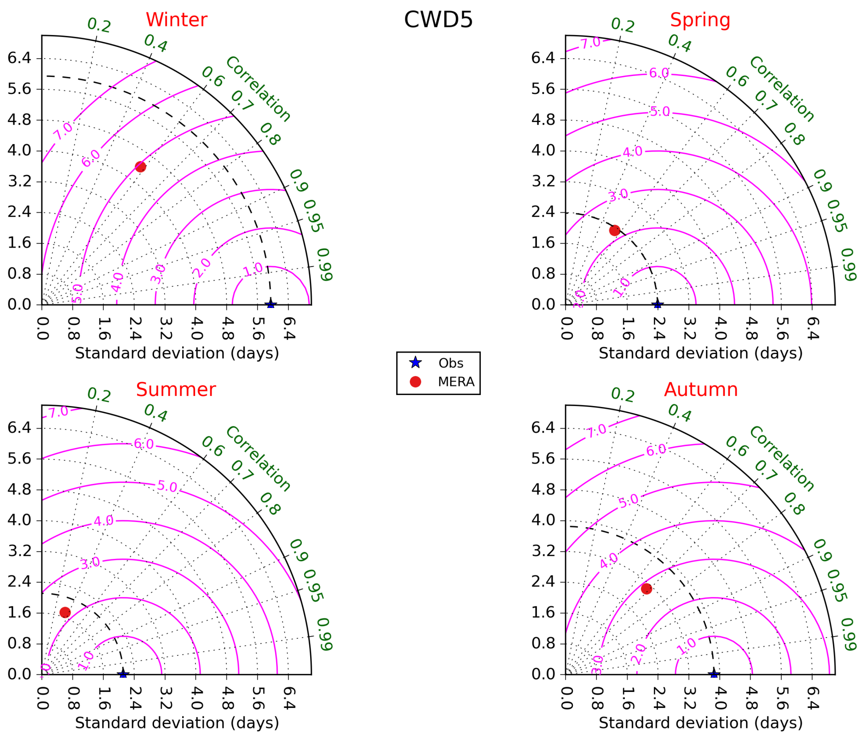


Figure 14: Taylor diagram for the consecutive wet days index (RR > 5 mm) for the period 1981-2017.

For wet days (RR1 - Figure 15) the correlations are between 0.8 and 0.9 with standard deviations of 5-8 mm in the observation dataset and a few mm less in MÉRA. RMSEs are less than 4 mm. For heavy precipitation (R10mm - Figure 16) correlations are between 0.7 and 0.9, lowest in Summer, most likely due to the convective nature of the rainfall where errors due to show displacements are much more common. Standard deviations are mostly less than 5 mm and RMSEs of the order of 2-3 mm. In the case of very heavy precipitation (R20mm - Figure 17) the correlations are 0.7 or higher with standard deviations of the order of 1-3 mm and RMSEs less than 2 mm.

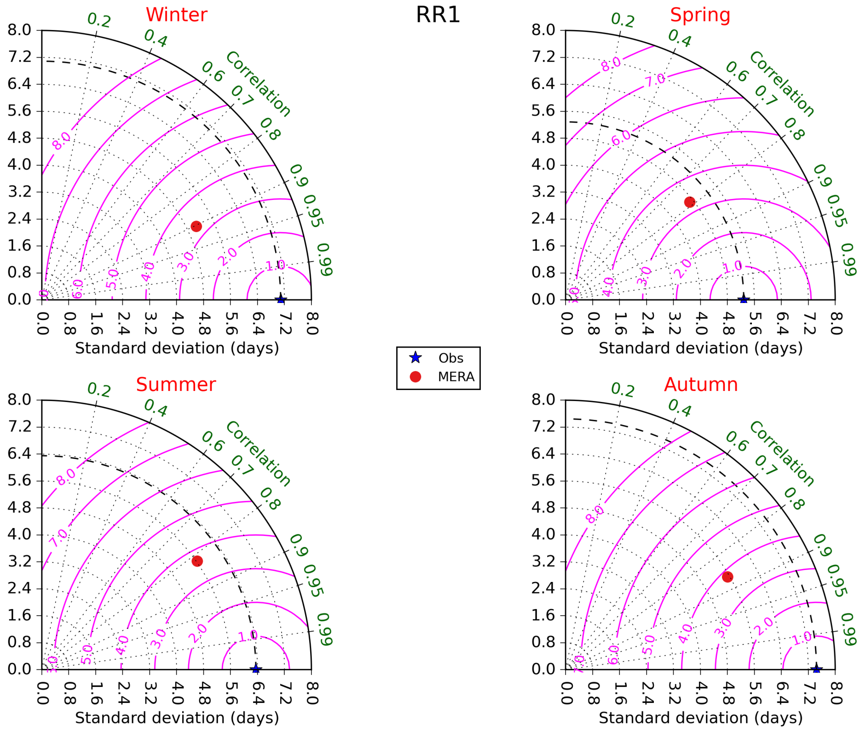


Figure 15: Taylor diagram for annual average wet days index for the period 1981-2017.

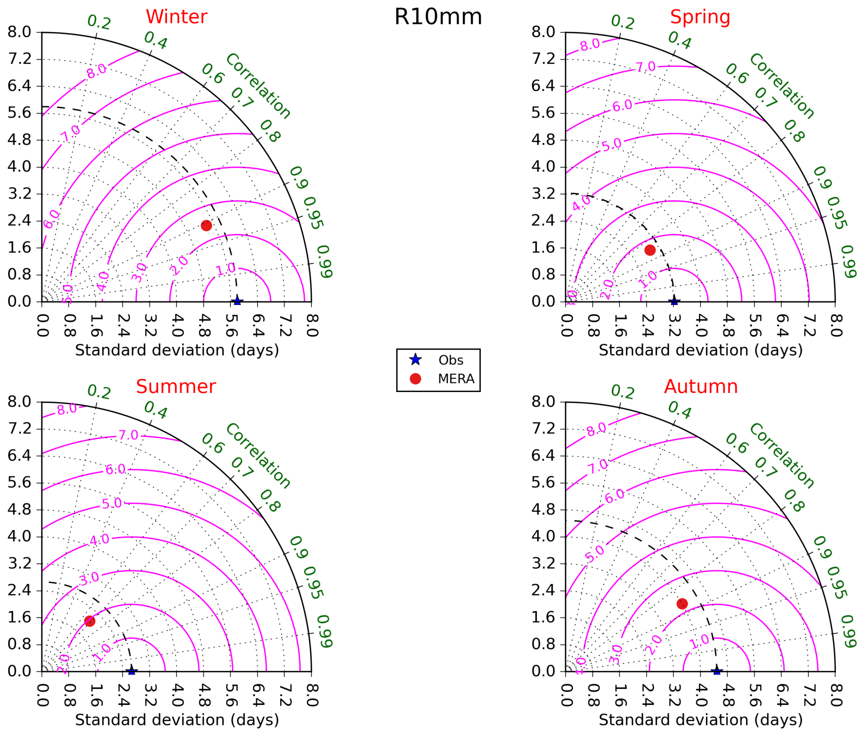


Figure 16: Taylor diagram for annual average heavy precipitation days index for the period 1981-2017.

As for the consecutive wet and dry day indices the correlations for highest 1-day precipitation (RX1day - Figure 18) are lower- 0.6 to 0.7 mostly and the standard deviations and RMSEs larger (over 20 mm in Summer and Autumn - again likely to be related to convection precipitation displacements).

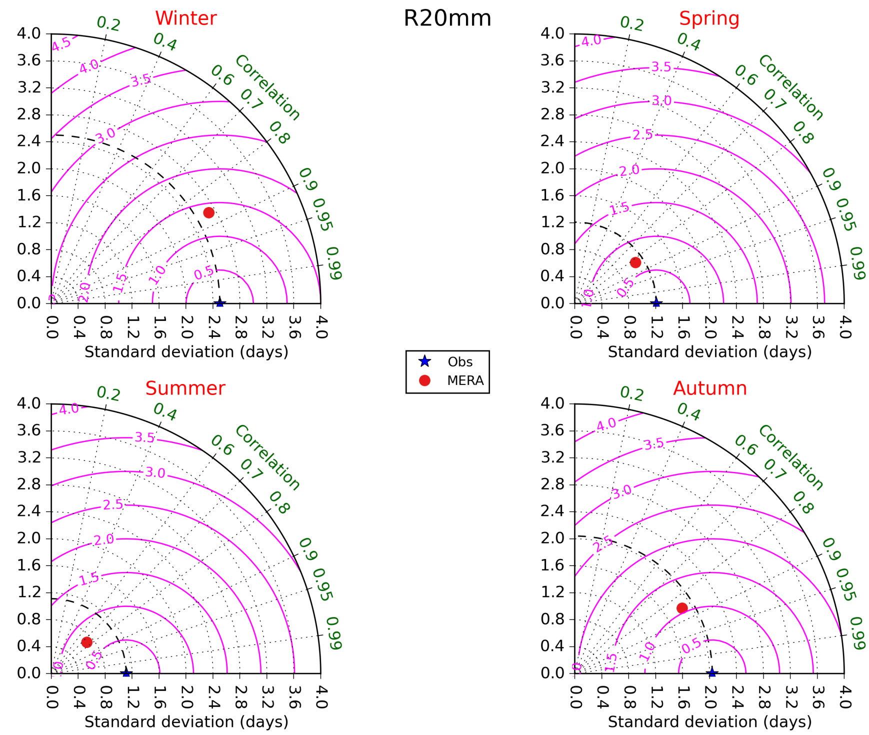


Figure 17: Taylor diagram for annual average very heavy precipitation days index for the period 1981-2017.

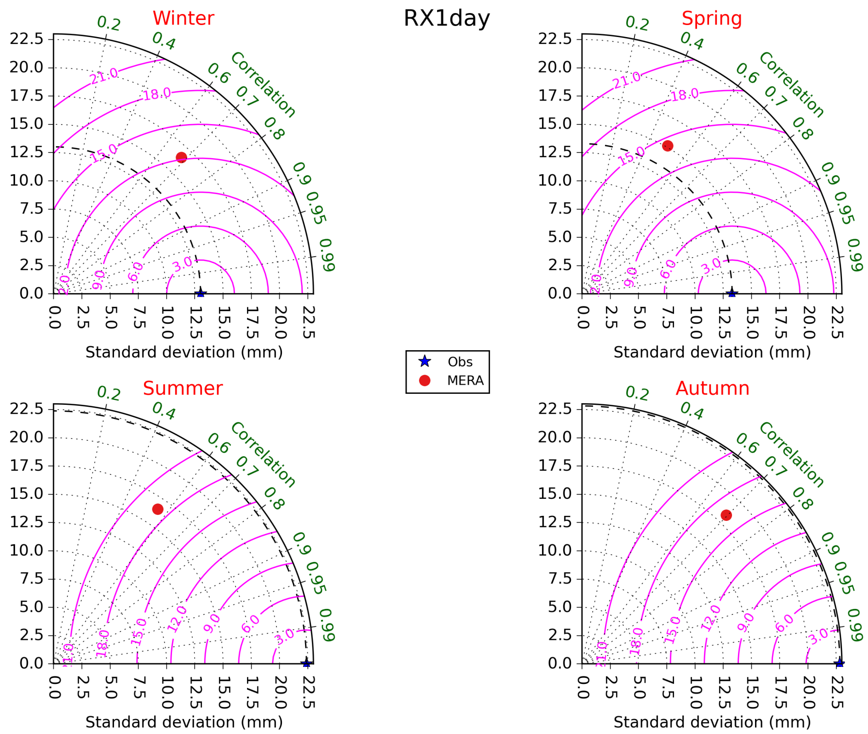


Figure 18: Taylor diagram for annual average highest one day precipitation amount for the period 1981-2017.

3.4 Annual and Seasonal Averages of Daily Minimum Temperatures and Overall Trends

Overall MÉRA captures the minimum temperatures very well with most of the biases lying within half a degree compared to the gridded observation dataset (Figure 19). The bias is mostly positive and higher over mountains. There are areas over the south of the country where the biases are slightly negative but the overriding trend is that of a positive bias.

One reason for the positive bias is an over-prediction of cloud - either in terms of cover or an over-estimation of the cloud condensate. This has been seen previously in studies by Gleeson et al., and Nielsen et al., 2018 where solar radiation measurements were used as a proxy for cloud condensate. Both studies highlighted the overestimation of cloud liquid in the thickness clouds in HARMONIE-AROME. Another reason for the positive bias could be a displacement of clouds in the model compared to the observation sites.

A small part of the bias is due to mismatches between the orography in the HARMONIE-AROME model used for MÉRA and the actual orography. This was corrected using a high resolution digital elevation model (DEM) dataset (30 m topographic dataset). The DEM dataset was firstly projected onto the MÉRA grid using the nearest neighbour method in CDO. The height different between the MÉRA orography and that of the DEM was used along with the international standard atmosphere lapse rate of 6.49 K/km, as defined by the International Civil Aviation Organization (ICAO), to apply a temperature correction based on the height difference between the model and DEM orographies. The result of this correction is shown in Figure 20. Over many areas the bias degrades further - this is particularly obvious in the Summer and Autumn plots.

Figure 21 shows a time series of monthly means of the daily mean minimum temperature, averaged over the domain, for the period 1981 to 2017 for both the MÉRA (blue) and observation (red) datasets. 12-month running means are also shown and highlight the clear consistent positive bias in TMIN. The lower panel shows de-trended TMIN, where the 1981-2010 30-year average is subtracted from the dataset. This plot clearly shows the excellent correspondance in terms of trend between the MÉRA and observation datasets.

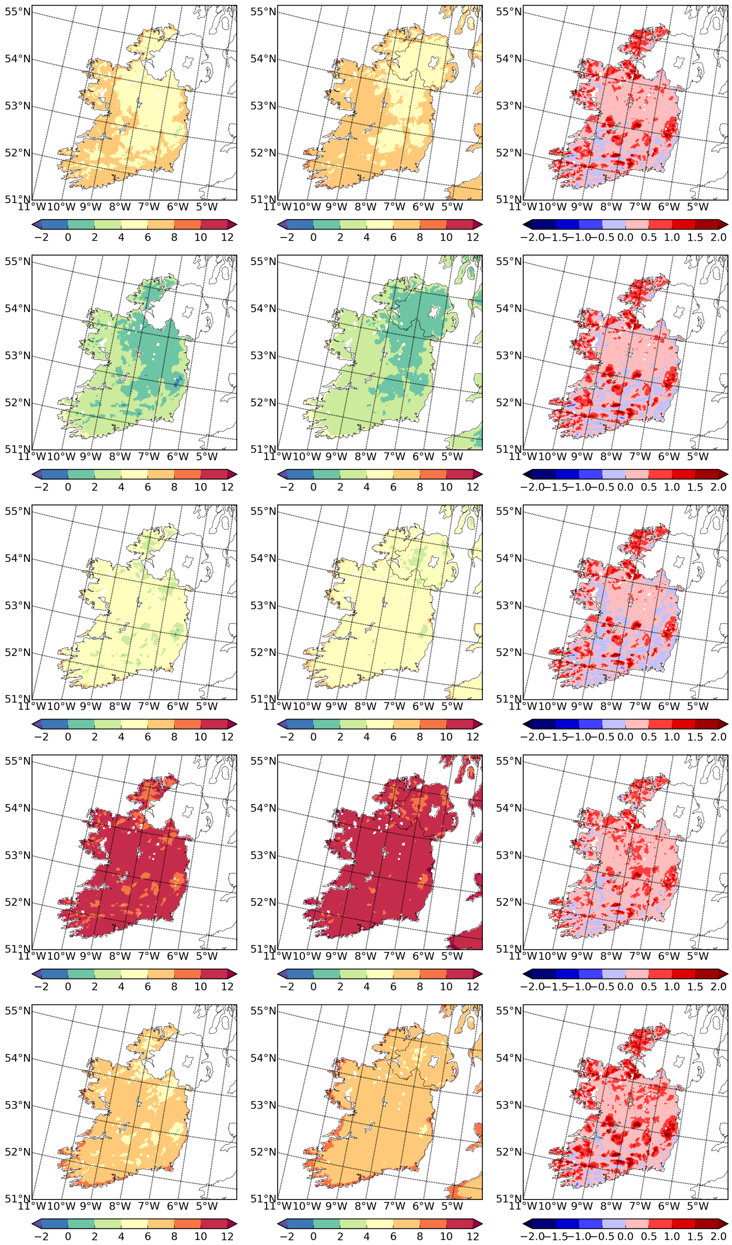


Figure 19: Mean daily temperature minima for the period 1981-2017 inclusive. Unit [°C]

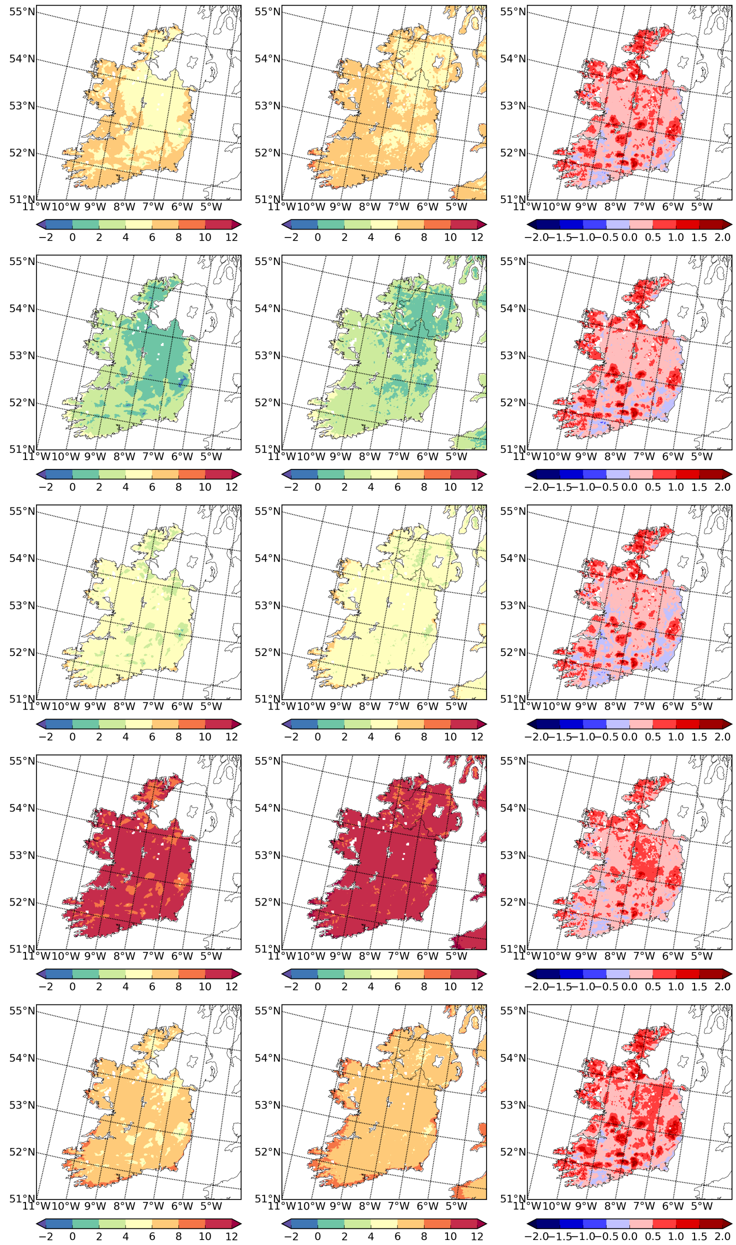
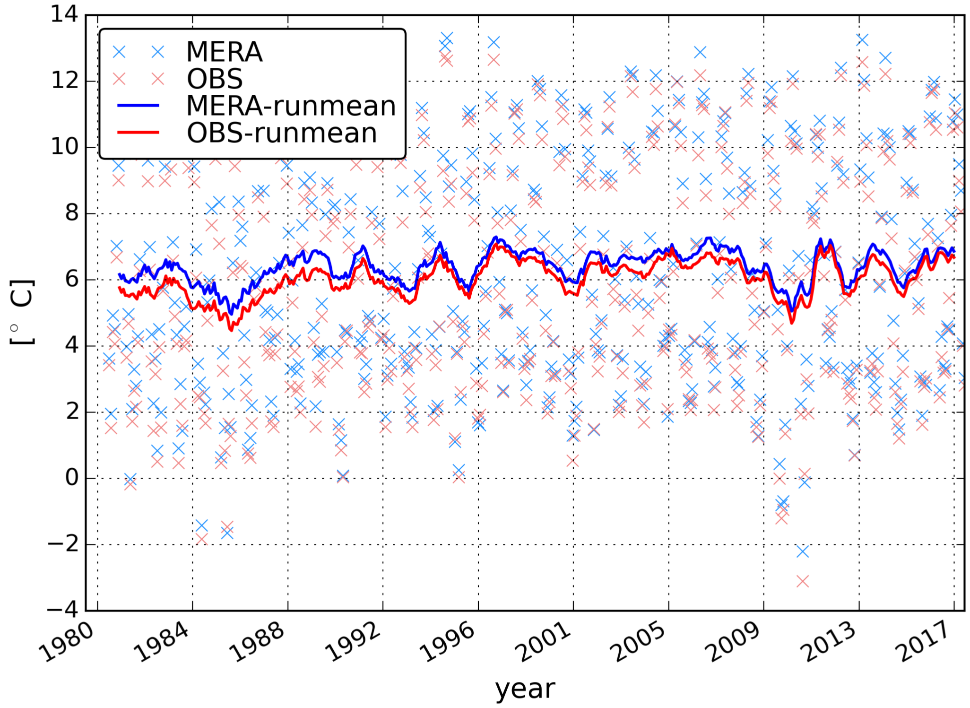


Figure 20: Mean daily temperature minima for the period 1981-2017 inclusive. The data have been corrected for orography mismatches. Unit [°C]



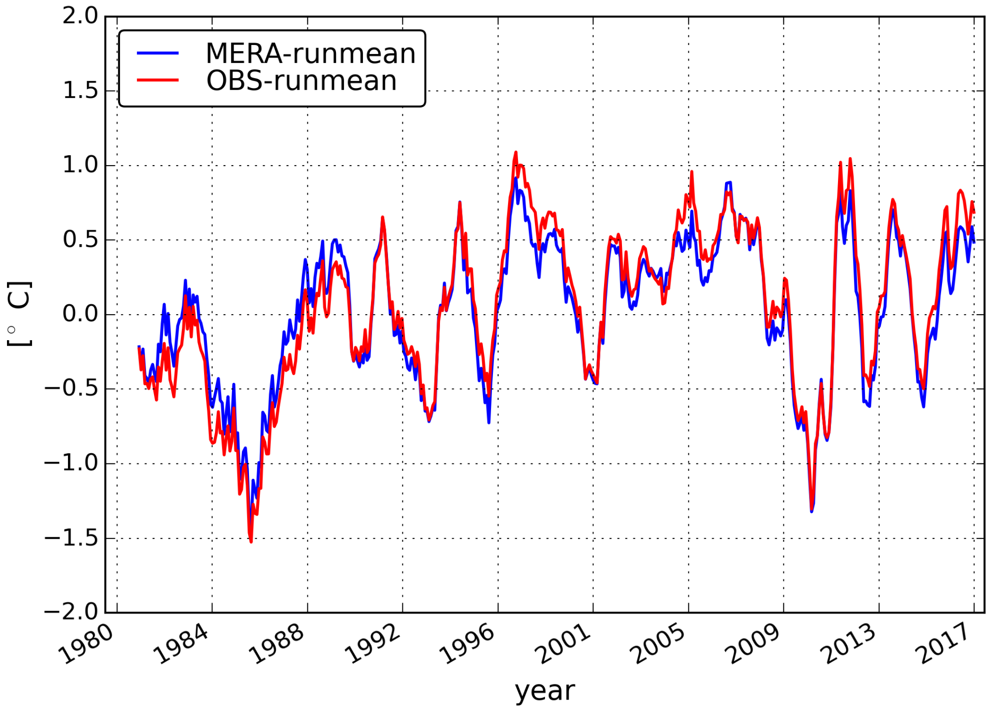


Figure 21: Monthly means of daily minimum temperature averaged over the domain for the period 1981-2017. Top: Time series of MÉRA (blue) and observation (red) datasets with 12-month running means shown as continuous lines. Bottom: Similar but each dataset is de-trended by subtracting its 1981-2010 mean.

3.5 Daily Minimum Temperatures Climate Indices

The orography-corrected minimum temperatures were used to calculate the indices presented in this section. In particular, the frost days index, consecutive frost days index and tropical index are shown in the following sub-sections.

3.5.1 Frost Days Index (FD)

The frost days index (FD) represents the number of days in the time period where the daily minimum temperature is < 0 °C. Here we have scaled the index by the number of years in the time period. As expected the bias is largest in the colder seasons and smallest in Summer when the number of frost nights is less than 5 (Figure 22). The trend in the bias is mixed - mostly negative over higher ground, consistent with the positive bias in daily temperature minima, and mostly positive elsewhere with the magnitude varying by season. The biases are mostly within 4 days per year as seen in Figure 22.

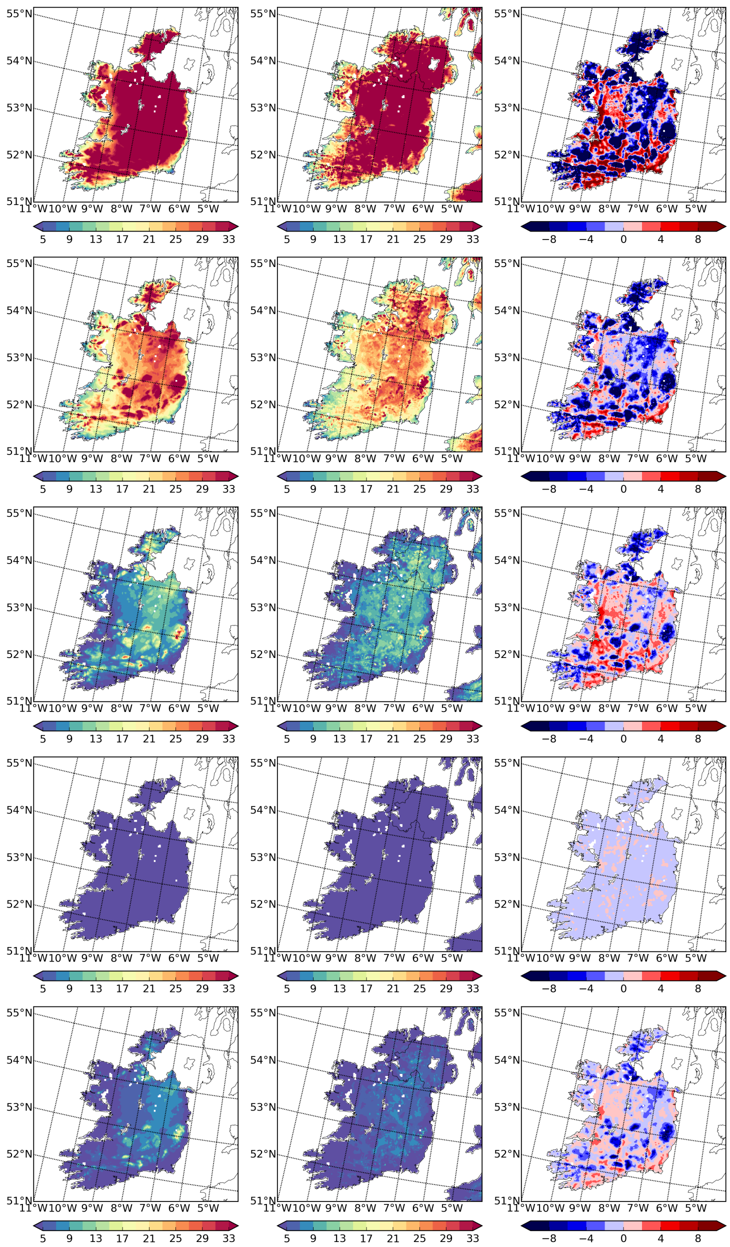


Figure 22: The number of frost days per year in the period 1981-2017 inclusive.

3.5.2 Consecutive Frost Days Index (CFD)

The consecutive frost days index (CFD) represents the highest number of consecutive days in the time period where the daily minimum temperature is < 0 °C. As for the case of the frost days index, the bias in CFD is similarly of mixed sign. It is smallest in Summer and slightly negative in the midlands (Figure 23). The biases in CFD are mostly negative but there are large areas of positive bias, particularly in the midlands. The errors are naturally larger than for FD because this index accounts for consecutive frost days.

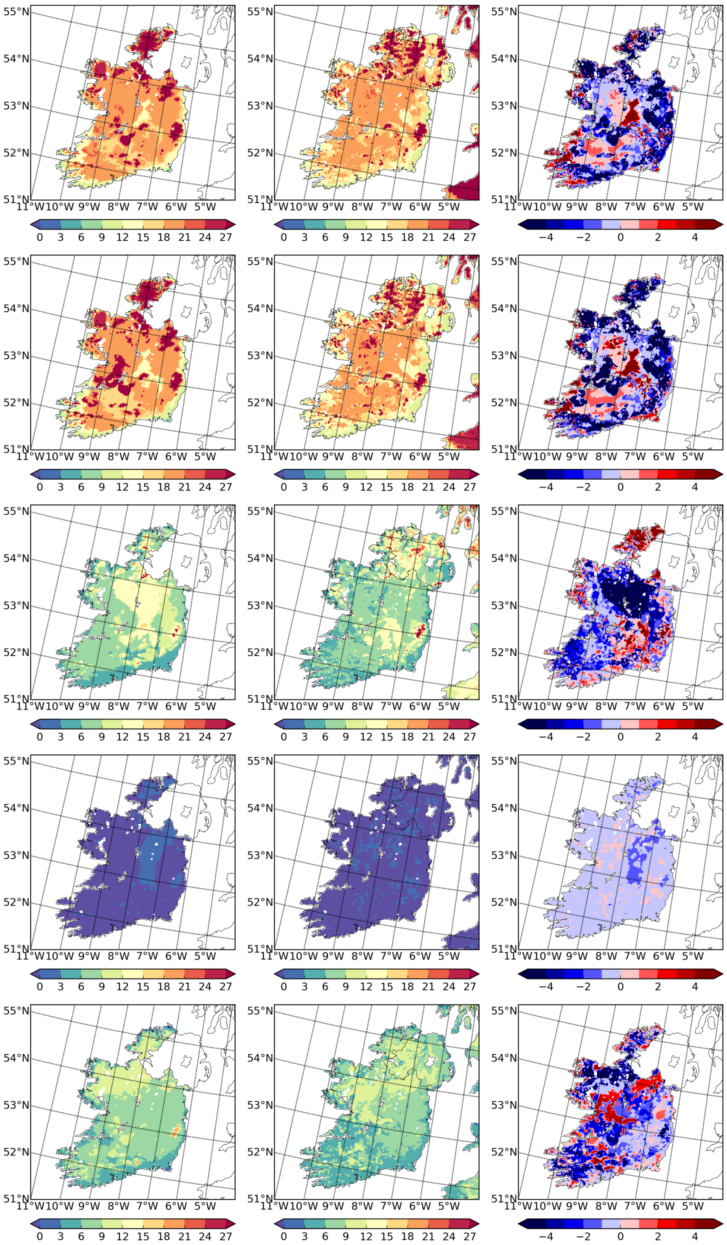


Figure 23: The largest number of consecutive frost days in the period 1981-2017 inclusive.

3.5.3 Tropical Nights index per time period (TR)

The tropical nights index (TR) represents the number of nights in the time period where the daily minimum temperature is > 15 °C. By default it is 20 °C but there were no occurrences of such high night-time temperatures in Ireland. The index has been scaled by the number of years in the time period. The positive bias in daily temperature minima is also seen in the TR index (Figure 24). There are no tropical nights in Winter in both the observation and MÉRA datasets. The bias is small in Spring and Autumn but positive and up to 4 days per year in Summer.

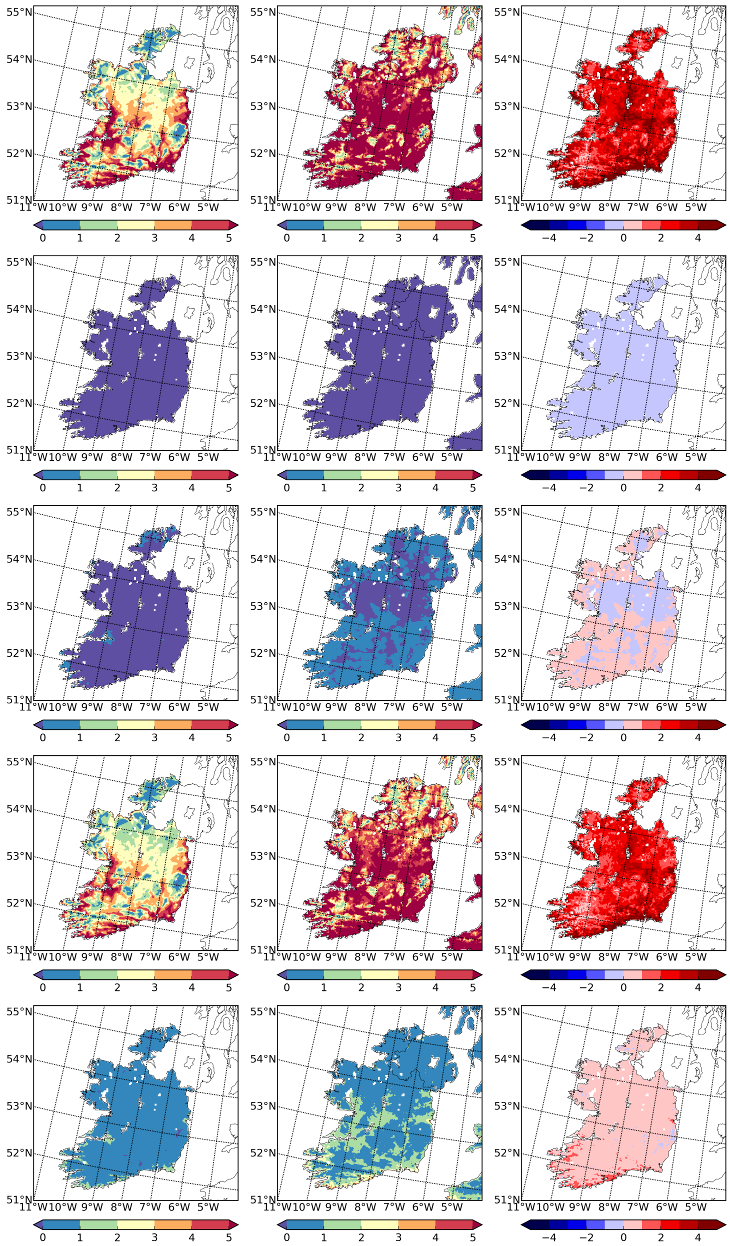


Figure 24: The average number of tropical nights per year in the period 1981-2017 inclusive.

3.6 Daily Minimum Temperatures Taylor Diagrams

The correlations between minimum temperatures are higher than those for rainfall. For example for mean daily minimum temperatures correlations are mostly greater than 0.9 (Figure 25). Standard deviations are mostly around 1 °C and RMSEs around 0.5 °C. Like rainfall equivalents, the correlations between CFDs are lower (~0.6 or less) and RMSEs much higher (up to 8 days in Winter) - see Figure 26. The correlations for frost days (FD) are better (> 0.6 and up to 0.8 in Winter, the season in which most frost days occur) but the RMSE is still up to 7 days (Figure 27). It only really makes sense to talk about TR in terms of Summer - here the correlation exceeds 0.8 with the RMSE around 2 days (Figure 28).

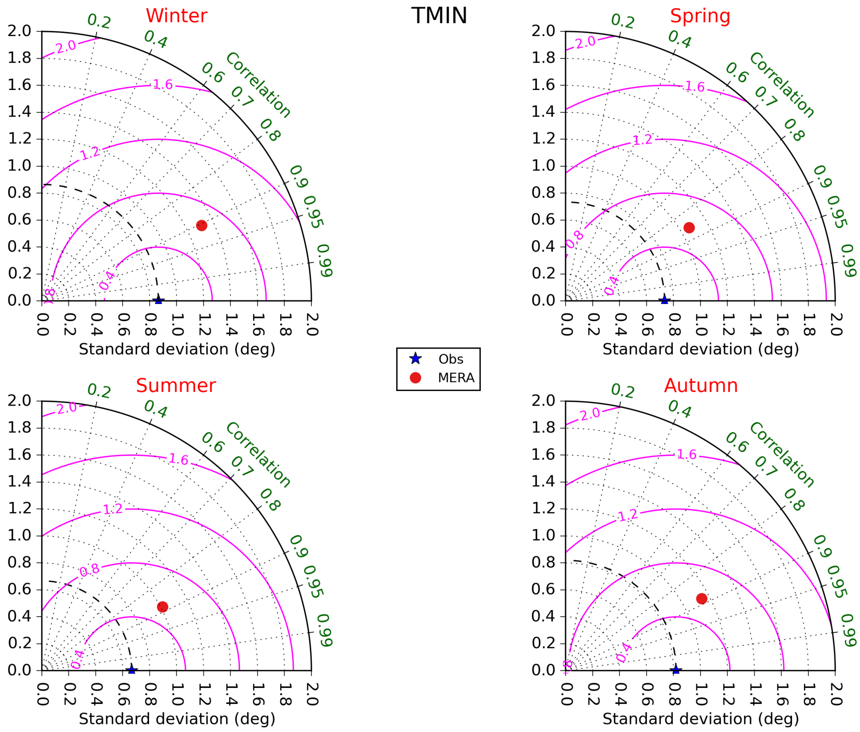


Figure 25: Taylor diagram for daily mean minimum temperatures for the period 1981-2017.

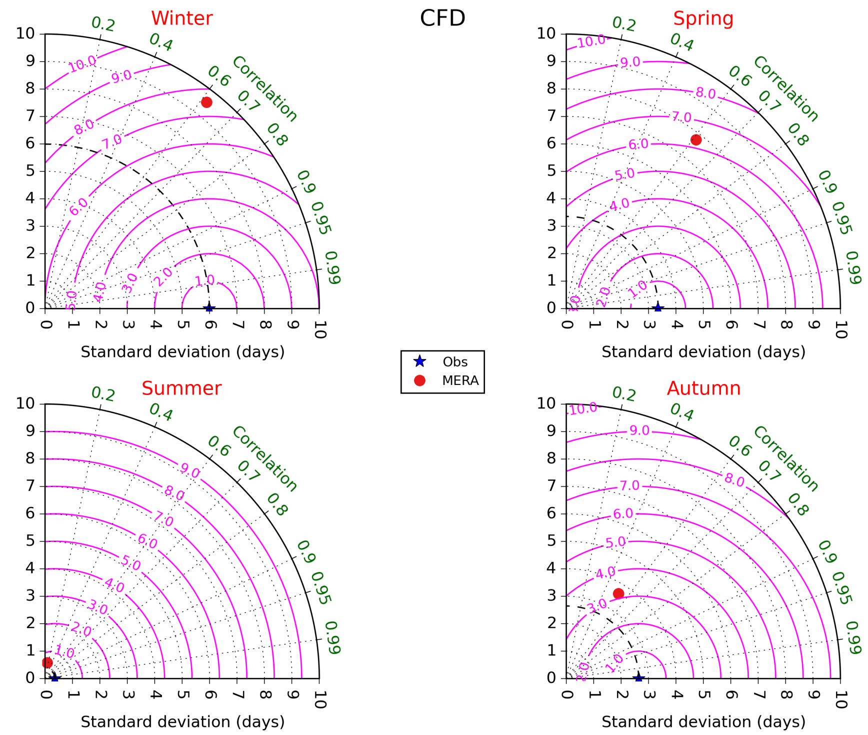


Figure 26: Taylor diagram for the consecutive frost days index for the period 1981-2017.

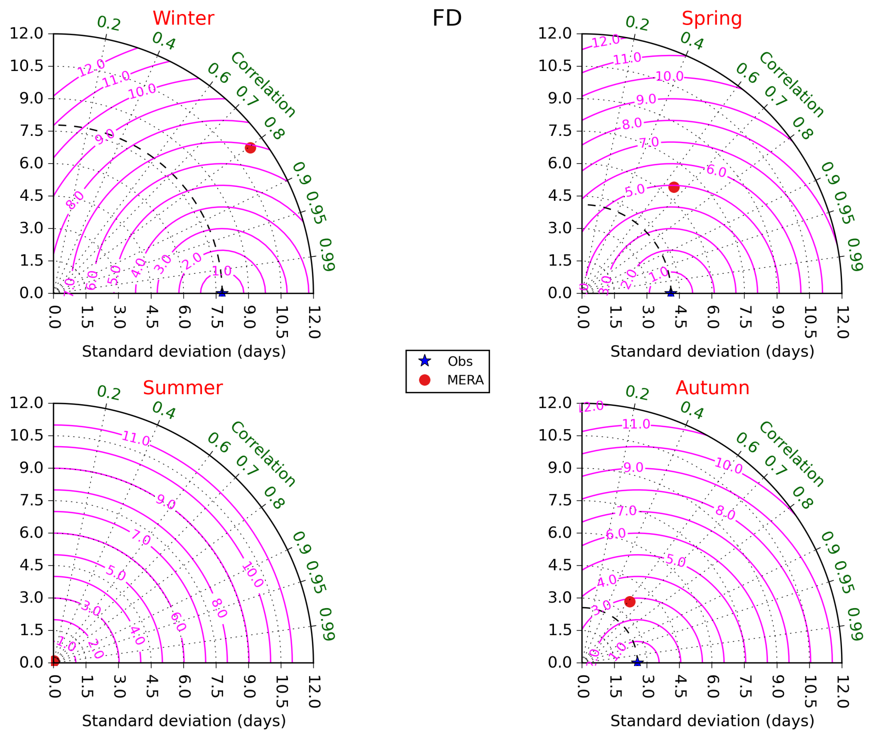


Figure 27: Taylor diagram for the annual mean frost days index for the period 1981-2017.

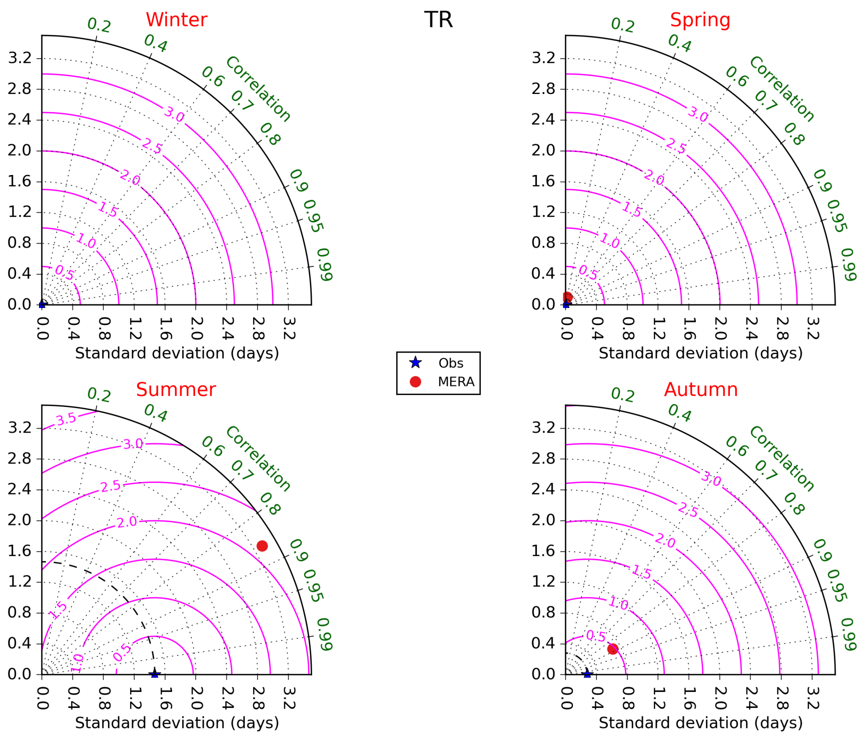


Figure 28: Taylor diagram for the annual mean tropical nights index for the period 1981-2017.

3.7 Annual and Seasonal Averages of Daily Maximum Temperatures and Overall Trends

As for the case of TMIN, we plot TMAX both uncorrected and corrected for orography mismatches as shown in Fgures 29 and 30 respectively. In this case the biases are negative across all seasons and mostly exceed a degree. The biases are more notable over higher ground, even after the corrections are applied. A negative bias in maximum temperatures is consistent with an over-prediction of cloud. As for the case of TMIN, mismatches in cloud positioning can also lead to a bias. The gridded observation dataset is generated using point observations and interpolated taking height and proximity to the sea into account. A mismatch in cloud cover at an observation station compared to the nearest grid points in MÉRA can lead to such a bias.

Trends in TMAX are shown in Figure 31 where arealy averaged monthly means of daily maximum temperatures are shown for the MÉRA (blue) and observation (red) datasets. 12-month running means are also shown and highlight the clear negative bias in TMAX. The lower panel shows the same data but de-trended by subtracting the respective 1981-2010 means. This plot clearly illustrates the excellent correpsondance between the trend in both datasets.

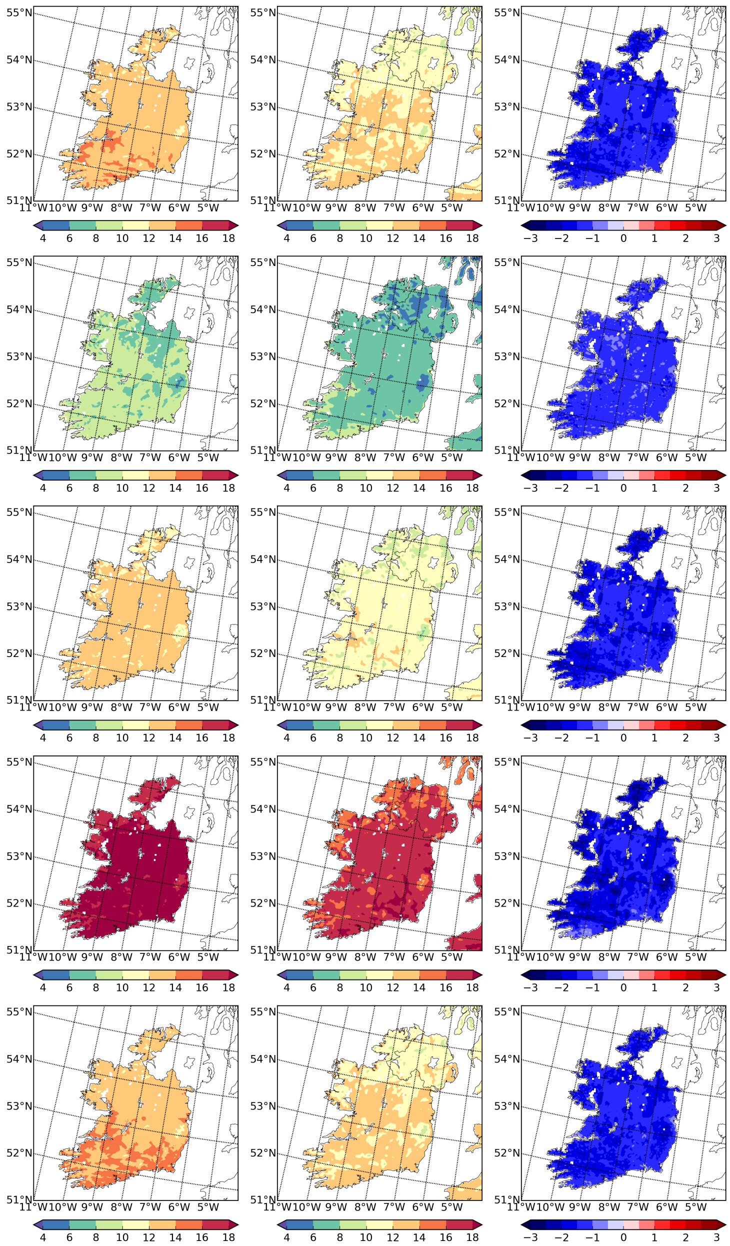


Figure 29: Mean daily temperature maxima for the period 1981-2017 inclusive. Unit [°C]

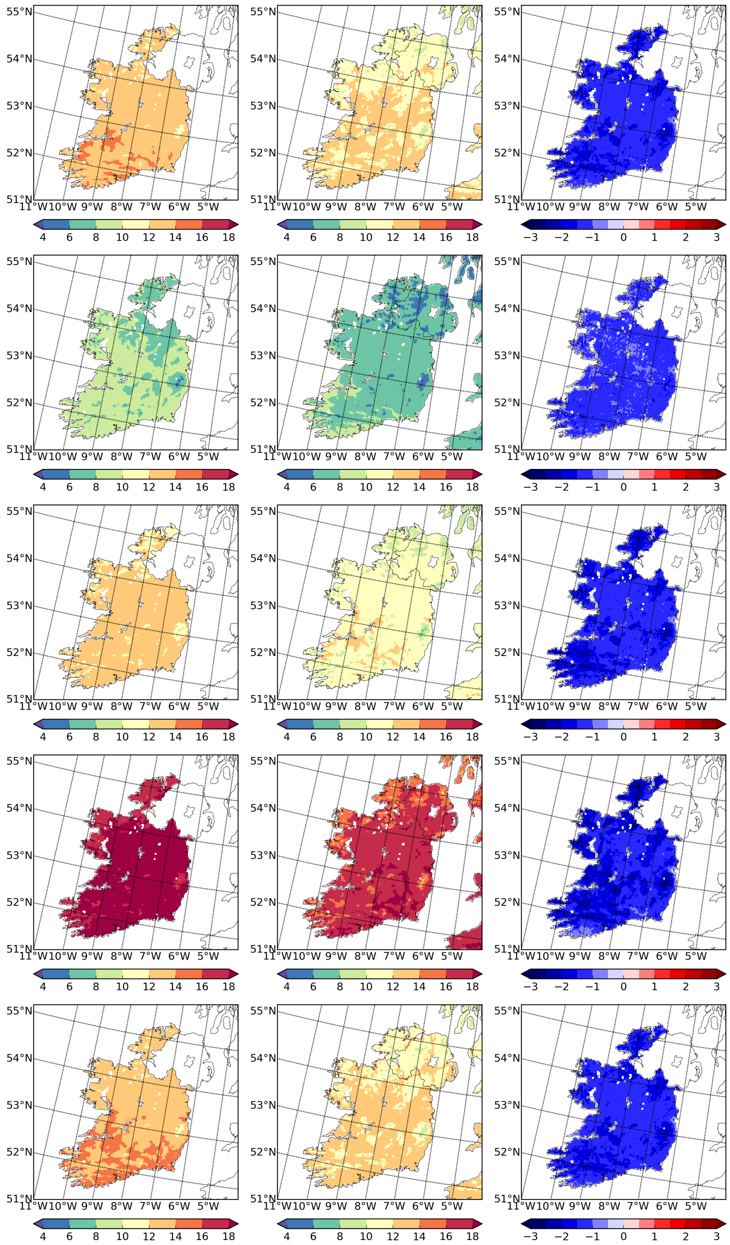


Figure 30: Mean daily temperature maxima for the period 1981-2017 inclusive. The data have been corrected for orography mismatches. Unit [°C]

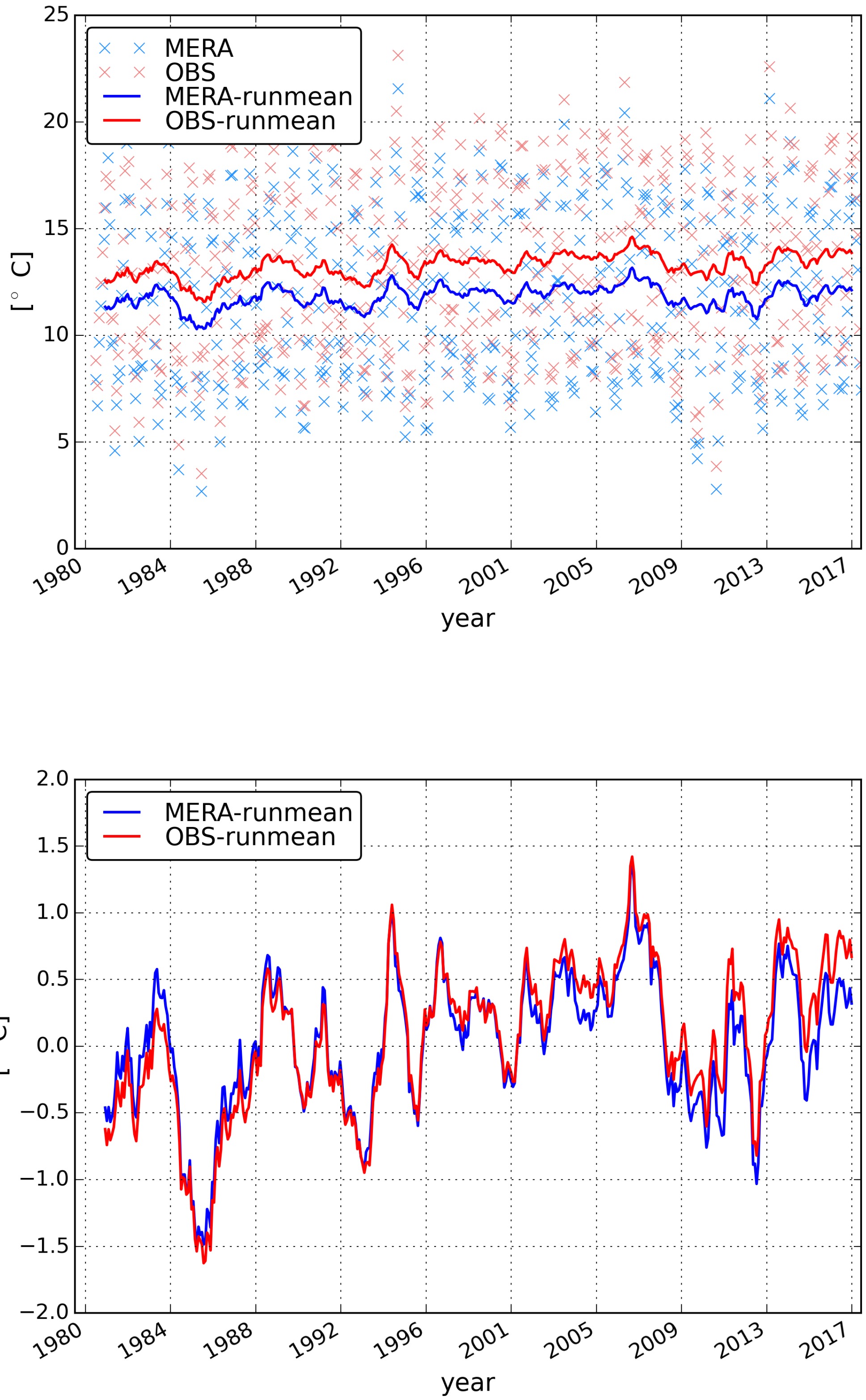


Figure 31: Monthly means of daily maximum temperature averaged over the domain for the period 1981-2017. Top: Time series of MÉRA(blue) and observation (red) datasets with 12-month running means shown as continuous lines. Bottom: Similar but each dataset is de-trended by subtracting its 1981-2010 mean.

3.8 Daily Maximum Temperatures Climate Indices

In this section 3 climate indices computed using daily temperature maxima are included: Summer days index. consecutive Summer days index and ice days index.

3.8.1 Summer Days (SU)

The Summer days index (SU) refers to the number of days in the time period where the maximum daily temperatures exceeds 25 °C. This index has been scaled by the number of years in the time period. The bias is small (Figure 32) but this is because Ireland has a maritime climate and there are not many days per year where maximum temperatures exceed 25 °C with most of these occurring in Summer.

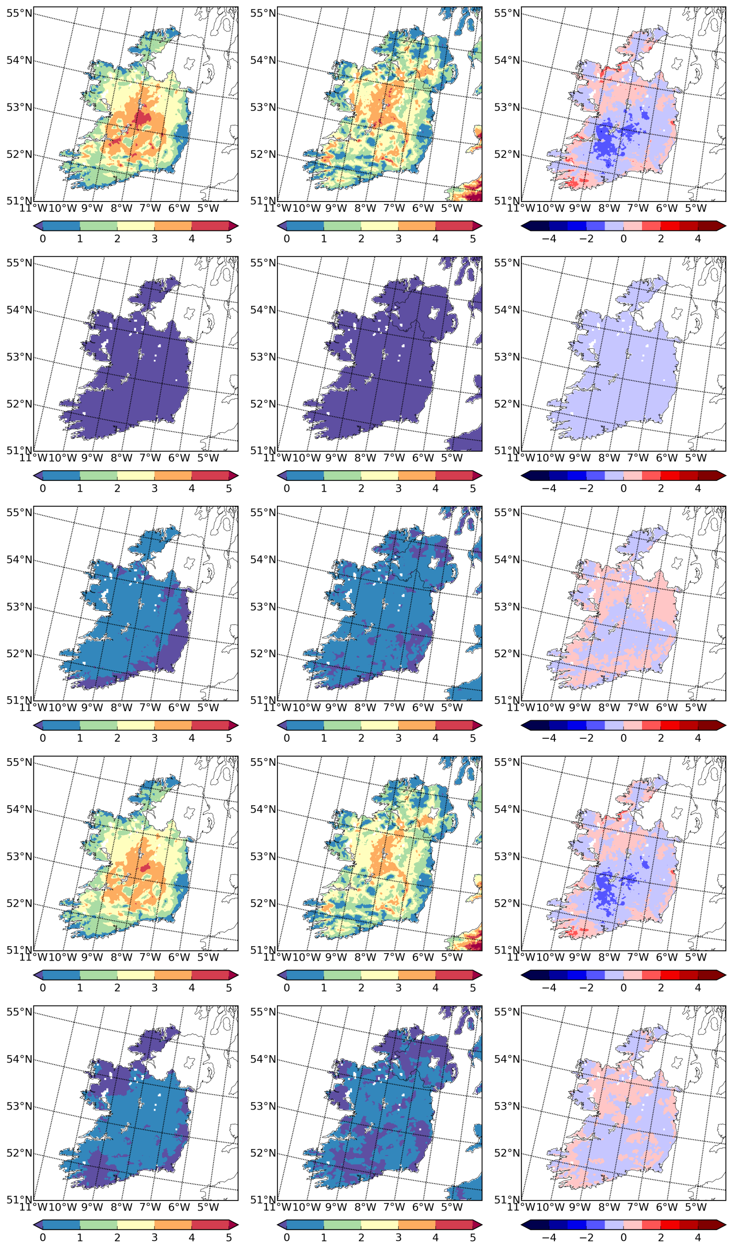


Figure 32: Summer days index for the period 1981-2017 inclusive scaled by the number of years.

3.8.2 Consecutive Summer Days (CSU)

The consecutive Summer days index (CSU) refers to the highest number of consecutive days in the time period where the maximum daily temperatures exceeds 25 °C. The largest biases occur in Summer are of the order of 2 to 4 days and mostly negative (Figure 33).

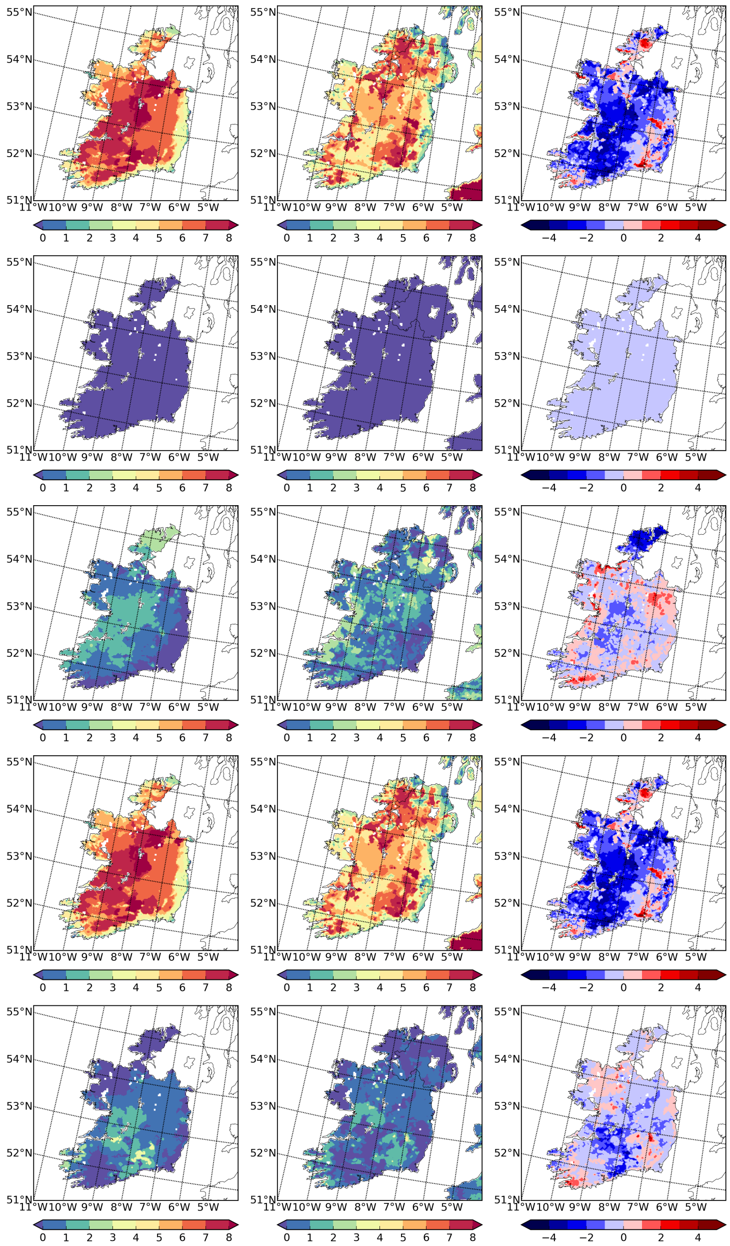


Figure 33: Consecutive Summer days index for the period 1981-2017 inclusive.

3.8.3 Ice Days Index (ID)

Contrary to SU and CSU, the ice days (ID) index refers to the number of days in the time period where daily maximum temperatures do not exceed zero °C. This index has been scaled by the number of years in the period (Figure 34). Ice days are most frequent in Autumn and Winter and over higher ground. The overall negative bias in TMAX also means a positive bias in ID where it is up to 4 days higher on average per year over high ground and of the order of a day per year higher elsewhere.

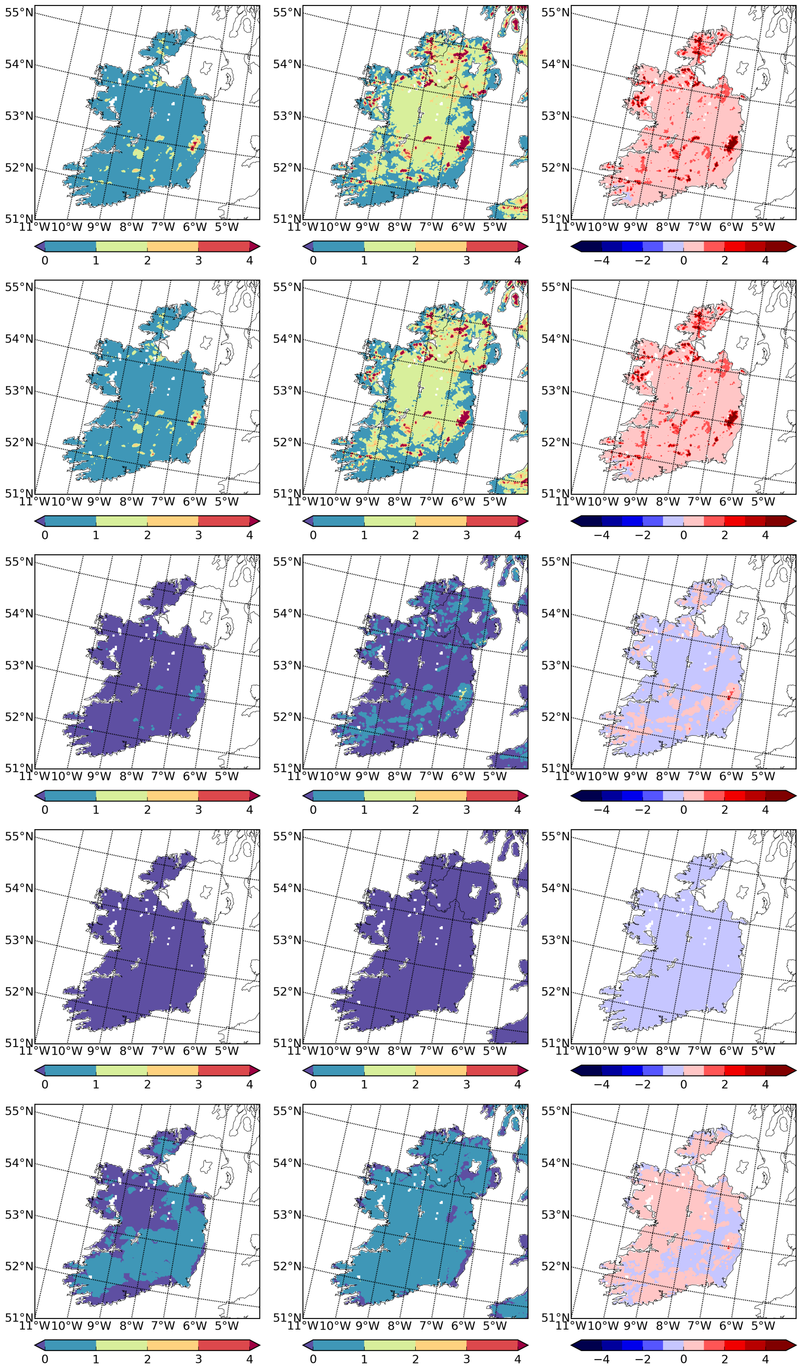


Figure 34: Number of ice days per year in the period 1981-2017 inclusive.

3.9 Daily Maximum Temperatures Taylor Diagrams

The final set of Taylor diagrams, those specific to maximum daily temperatures, are included in this section. Correlations for daily mean maximum temperature (Figure 35) are extremely good - 0.95 with RMSEs of around 0.8 °C. As for all of the indices involving consecutive days, the correlation for CSU is much smaller - 0.4 to 0.7 with RMSEs of the order of 1-2 days (Figure 36). Overall the correlations are a bit higher in the case of SU and RMSEs lower (1 day in Summer, Figure 37). Finally ice days are most common in Winter (correlation 0.9) but there is a large difference between the standard deviation of the observations (0.5 days/year) compared to MÉRA (4 days/year) - Figure 38.

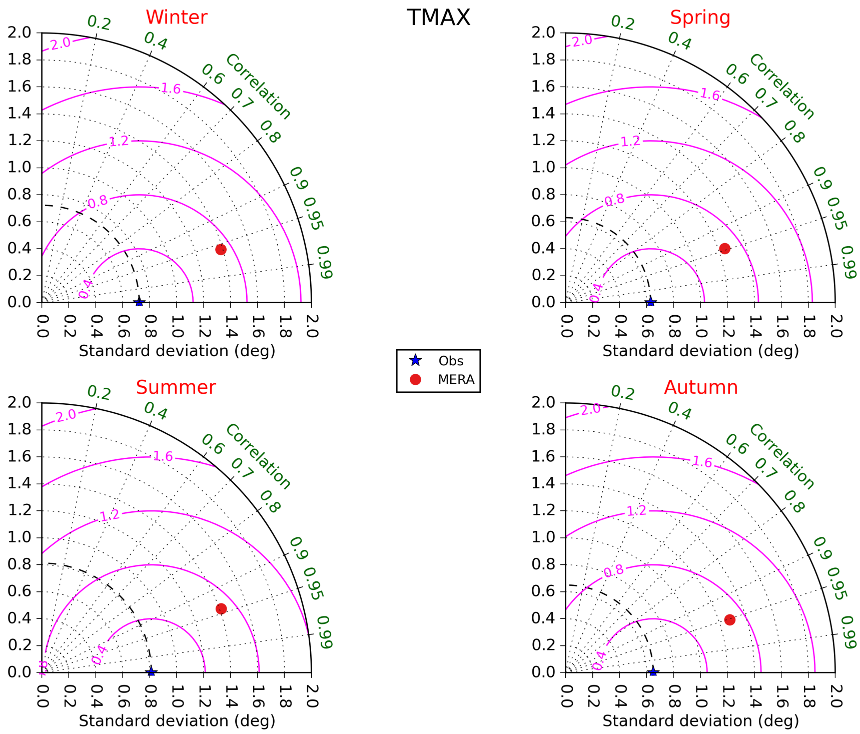


Figure 35: Taylor diagram for daily mean maximum temperatures for the period 1981-2017.

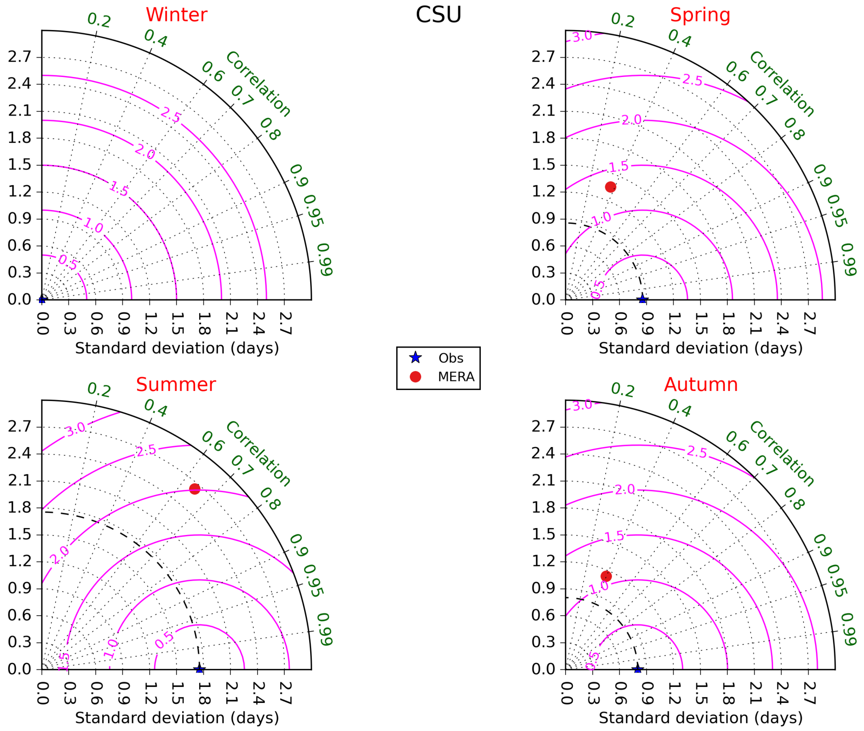


Figure 36: Taylor diagram for the consecutive Summer days index for the period 1981-2017.

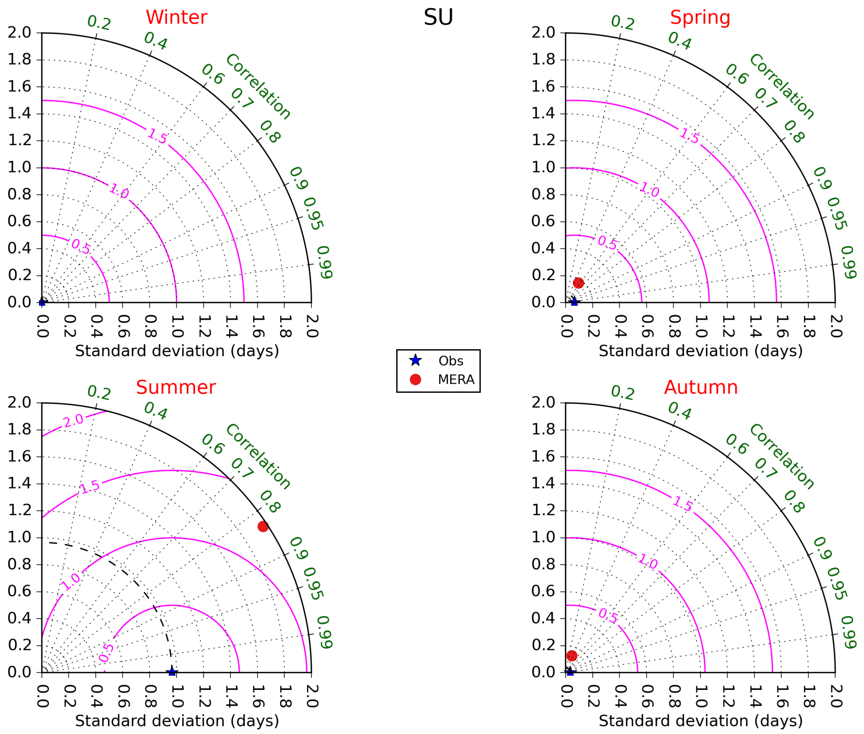


Figure 37: Taylor diagram for annual mean Summer days index for the period 1981-2017.

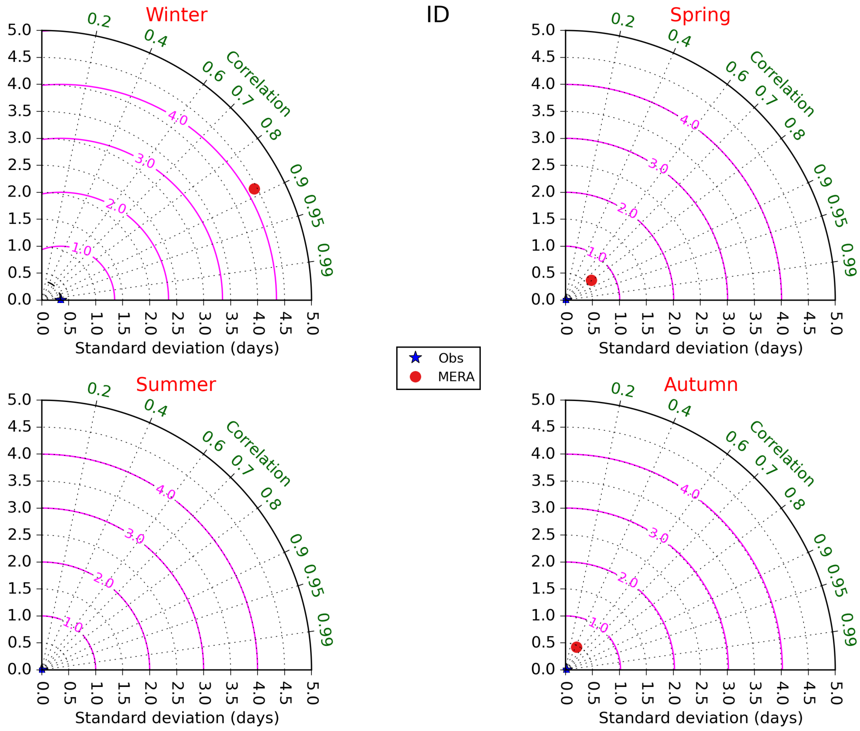


Figure 38: Taylor diagram for annual mean ice days index for the period 1981-2017.

4 Conclusions

The MÉRA dataset performs very well in terms of annual mean daily precipitation amounts, daily mean maximum temperatures and daily mean temperature biases with correlations in excess of 0.8. Time series of these parameters show excellent correspondence between the trends exhibited in the MÉRA and observation datasets. An attempt has been made to correct temperatures based on orography differences. A similar approach has not been applied to the rainfall datatset yet. Even with this correction there are persistent negative biases in TMAX and positive biases in TMIN. A further bias correction could be applied before using these data in climate applications.

In terms of climate indices MÉRA generally performs very well in terms of the threshold indices (correlations mostly exceed 0.8) but less so for counts of the number of consecutive days exceeding certain thresholds.

Local gridded datasets were used for this comparison rather than the E-OBS dataset due to their improved representation of local features not captured by E-OBS which only includes data from about 25 stations in Ireland.

In general MÉRA represents the observed spatial and temporal patterns of precipitation and maximum and minimum temperatures very well including most of the climate indices included in this report. One advantage of MÉRA over gridded observations for Ireland is the range of gridded availables available in MÉRA. For example, we only measure wind, humidity, radiation, soil and other variables at select locations in Ireland. Therefore, generating observation gridded datasets of such variables is not yet feasible. On the other hand, the MÉRA dataste has over 100 meteorological variables available on a 2.5 km grid covering Ireland. Such data have uses in wide range of applications that require meteorological data.

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