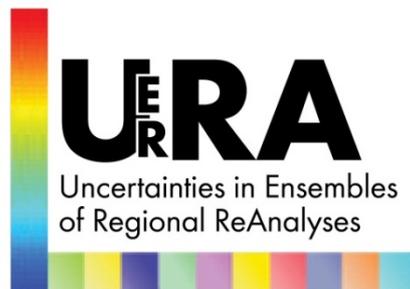




Seventh Framework Programme
Theme 6 [SPACE]



Project: 607193 UERRA

Full project title:
Uncertainties in Ensembles of Regional Re-Analyses

Deliverable D3.8:
**User friendly synthesis report on
evaluation and uncertainty of regional
reanalyses**

WP no:	3
WP leader:	DWD
Lead beneficiary for deliverable :	KNMI
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Nature:	Other
Dissemination level:	PU
Deliverable month:	49
Submission date:	January, 2018



Report for Deliverable 3.8 (D3.8): User friendly synthesis report on evaluation and uncertainty of regional reanalyses

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1. Scope of this document

Within work package 3 (WP3), the applicability, quality and uncertainty of UERRA data product were investigated. Within this work various experiences, concerning specific model issues and remaining problems are collected and presented. In combination with selected examples of model data application, this information gives support and advice to potential users of regional reanalysis data, produced in the UERRA project. This document includes information on the data access from the UERRA archive and first steps for the selection of desired time and location. It summarises the time and space coverage, as well as the temporal and spatial resolution of UERRA products.



2. Introduction

2.1. What reanalyses are produced in UERRA?

Within the EU-FP7 funded project UERRA, a number of regional reanalysis are produced (Table 2.1).

UERRA product	Data assimilation	Grid res (Nominal)	Ensemble members	Time coverage
COSMO REA12 ensemble	Nudging conventional observations	0.11deg	Ensemble member 0 is unperturbed 20 ensemble members with perturbed observations	2006-2010
HARMONIE V1	3D-Var	11Km		1961-2015
HARMONIE V2	3D-Var	11Km	2 ensemble members with perturbed physics	2006-2010
MESCAN Ensemble	HARMONIE V1 (dynamically downscaled) and/or 2D assimilation of stations	5.5Km	1 optimized 5 additional members with changing backgrounds/assimilations/station networks	1981-2016 2000-2010, 2006-2010
UKMO Unified Model deterministic	4D-Var	0.11deg	deterministic	1979-2016
UKMO Unified Model ensemble	3D-Var	0.33deg	20 ensemble members	1979-2016

Table 2.1: List with reanalysis produced in the UERRA project.



2.2. What is a reanalysis?

A meteorological reanalysis is a data analysis project which aims to provide an estimate of the atmosphere and climatic components like the soils, cryosphere and possibly the ocean which is as close as possible to the actual situation as it has occurred. The way to do this is to assimilate historical observational data into a meteorological model and to force the model, using a single consistent assimilation (or "analysis") scheme, to reproduce the observations as closely as possible. The advantage of reanalysis is that they provide a multivariate, spatially complete, and coherent record of the global atmospheric circulation – far more complete than any observational dataset is able to achieve.

The reanalysis approach has much in common with operational numerical weather prediction, in which forecast models are used to predict future states of the atmosphere, based on how the climate system evolves with time from an initial state. The initial state provided as input to the forecast must consist of data values for a range of "prognostic" meteorological fields – that is, those fields which determine the future evolution of the model. The technique of data assimilation is therefore used to produce an *analysis* of the initial state, which is a best fit of the numerical model to the available data, taking into account the errors in the model and the data. Unlike archived weather analyses from operational forecasting systems, a reanalysis is produced with a single version of a data assimilation system –including the forecast model used –and is therefore not affected by changes in method.

Within the UERRA project, *regional* reanalyses are produced. The domain in the UERRA model is Europe and in this approach observations from the European domain are used for assimilation in the (regional) models whereas global reanalysis, like the ECMWF ERA-Interim reanalysis, are used to provide the required information of the prognostic variables at the boundaries of the domain. The main advantage of a regional reanalysis is that the horizontal and vertical spacing of the numerical grids, and therefore the time step as well, can be much smaller than in a global reanalysis. This provides much more detail to the reanalyzed fields. Figure 2.1 illustrates the difference in detail between a global and a regional reanalysis for averaged temperatures for July 2008 and for wind for February 2007.

Of the regional reanalyses produced, the MESCAN reanalysis is somewhat different. It is based on a regional reanalysis as described above, but it has added an additional step to increase the spatial resolution even further. The resolution was reduced from the original 11 km to 5.5 km using statistical techniques.

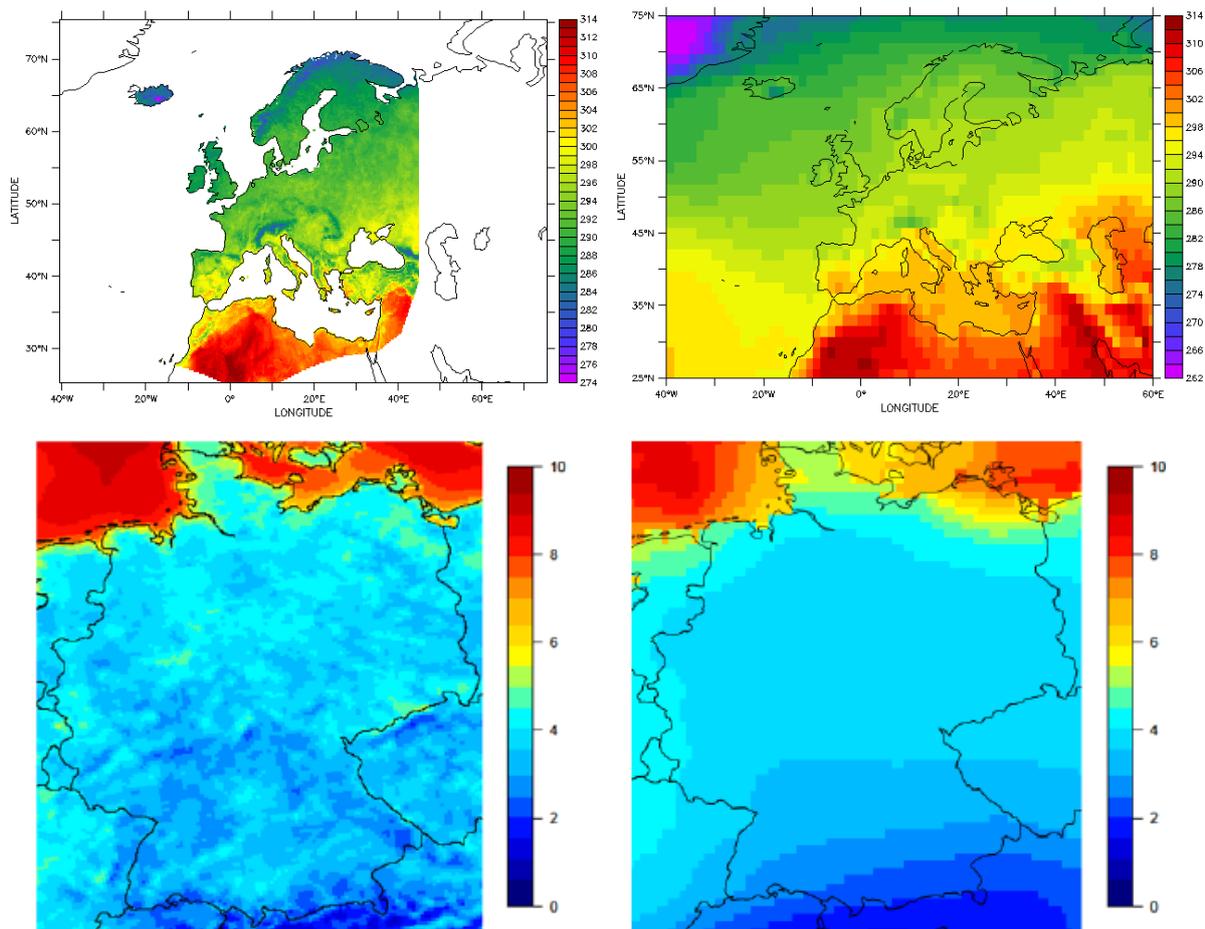


Figure 2.1: Two examples of the increase in detail obtained when using a regional reanalysis rather than a global reanalysis. Top row: 2m temperature averaged over July 2008 for the SMHI Harmonie regional reanalysis (left) and the ERA Interim global reanalysis (right). Note that the former has been combined with a land-sea mask to mask-out air temperatures over sea. Bottom row: 10m surface winds from COSMO-REA6 regional reanalysis (6km) compared to the global ERA20C reanalysis with a resolution 125 km for February 2007 (Kaiser-Weiss et al. 2015).

2.3. What can we learn from a reanalysis and what not?

While (regional) reanalyses are a powerful tool to describe the state of the atmosphere in its full complexity, there are limitations to these reanalyses in their capacity to reproduce the actually observed situation. Figure 2.2 shows a schematic of the reanalysis, which starts in an analysis which is an (calculated) estimate of the atmospheric state vector using available observations. Starting from this point, a 6-hour forecast is made which results in the background. The background has useful information because it contains observational information from previous analyses.

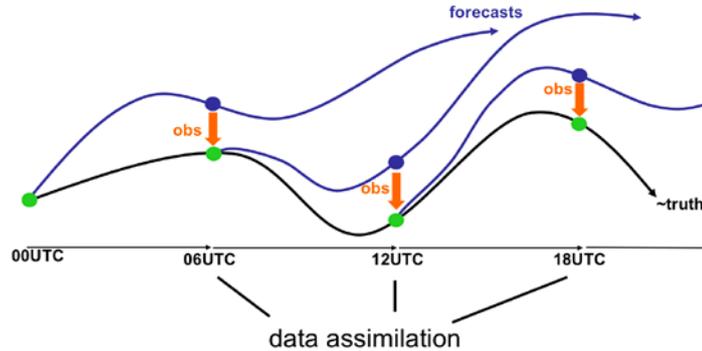


Figure 2.2: Schematic showing the simulation of the atmospheric state in the reanalysis (black lines), which starts from the analysis (green dots) and resulting in the background (blue dots). Note that the background usually does not coincide with the true observed state of the atmosphere.

The point of this section is to illustrate that a comparison between the background and the observations gives the user additional information – both on the quality of the reanalysis and on the quality of the observations.

The effects of the assimilation of observational data on the background are nicely illustrated by figure 2.3 which shows the rate at which the 12-hour 500 hPa height forecast error degrades in ECMWF's reanalysis system on removal of satellite data (after Fisher 2004). This diagram demonstrates that it takes about 7 days before the influence of the satellite data is lost in the reanalysis.

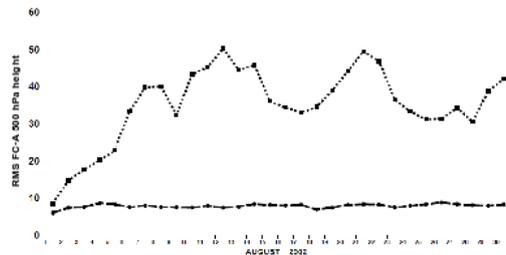


Figure 2.3: Diagram showing the rate at which 12-hour 500 hPa height forecast error degrades after removing satellite data as input to the reanalysis (Fisher 2004). The vertical axis gives the rms error of the forecast and horizontally is time, spanning the August 2002 period. The lower graph shows the rms error of the reanalysis including satellite information, the upper graph shows the evolution of the error when the satellite data is removed.

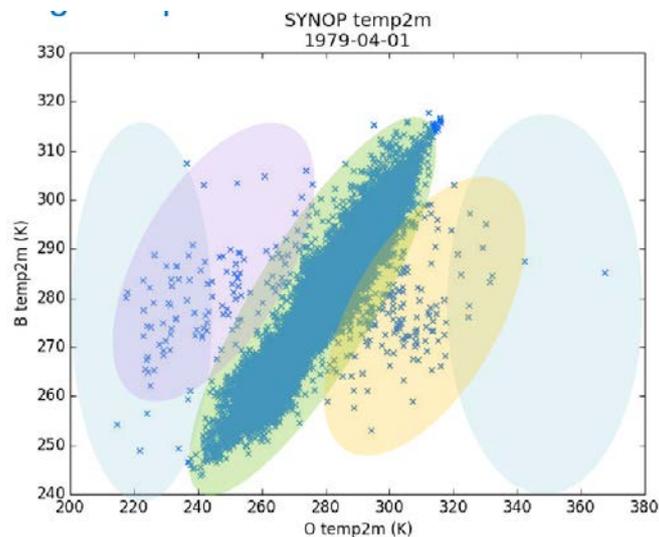
The process of creating the analysis in data assimilation involves minimization of a cost function. A typical cost function would be the sum of the squared deviations of the analysis values from the observations weighted by the accuracy of the observations, plus the sum of the squared deviations of the forecast fields and the analyzed fields weighted by the accuracy of the forecast:

$$J(x) = J_o(x) + J_b(x)$$



where $J_o(x)$ is the fit to the observations ($\sim ob$) and calculated as the sum over $[(x - ob)^2 / ob \text{ error variance}]$ and $J_b(x)$ is the fit to the background x_b and calculated as $[(x - x_b)^2 / background \text{ error variance}]$. This has the effect of making sure that the analysis does not drift too far away from observations and forecasts that are known to usually be reliable.

While a dense network of high-quality observations are required to produce a reanalysis, the reanalysis itself can inform us on the quality of the observations. A comparison between the background and the analysis, or the observational feedback, is able to specify which observations degrade the reanalysis, which points to e.g. measurement errors. Figure 2.4 shows a comparison between the background 2m temperature and the observations. The vast majority of points are near the $x=y$ line, indicating a tight similarity between the background and the observation. However, in the purple and yellow ovals, and even more so in the blueish ovals, background/observations pairs are present which do not agree.



Figur. 2.4: A scatter plot showing 2m temperature from the background (vertical axis) and observation (horizontal axis). The points in the green oval are close to the $x=y$ line, indicating a strong similarity between background and observation.

The difference between observation and background for the 2m temperature can be shown on a map as well. Figure 2.5 gives this map for the UKMO reanalysis for the period 1 May 1979 to 1 June 1979 (left) and for two stations, time series of the observation minus background value is shown (right).

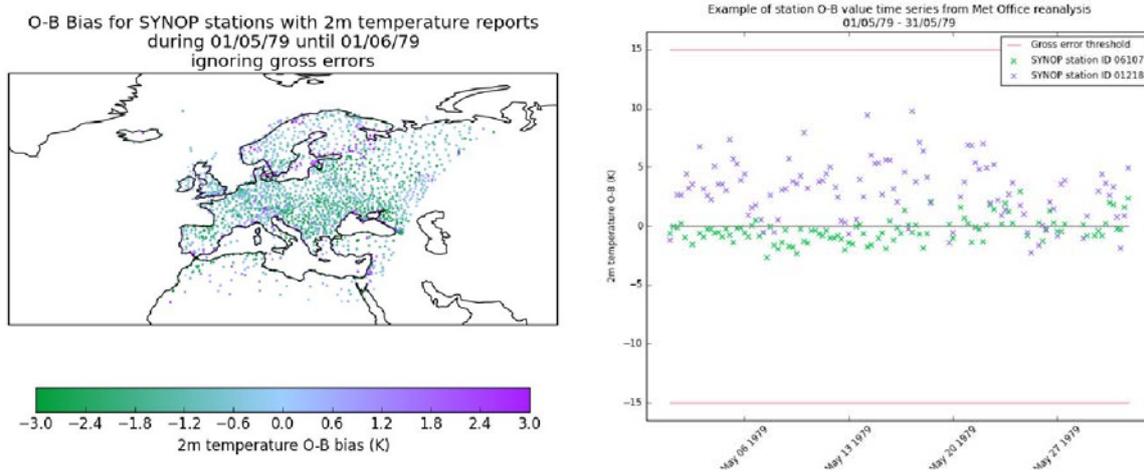


Figure 2.5: Map of the observation - background (O-B) bias for the UK Met Office reanalysis for May 1979 (left panel) and time series of this bias for two stations (right panel).

The reanalysis observation feed back can be used to improve the reanalysis by simple 'blacklisting' observations that degrade the reanalysis. For January 1979, Figure 2.6 shows such a decision plot, indicating that the vast majority of stations are included in the final reanalysis while a small number of stations, mainly from Norway and the Alpine region, are excluded from the reanalysis.

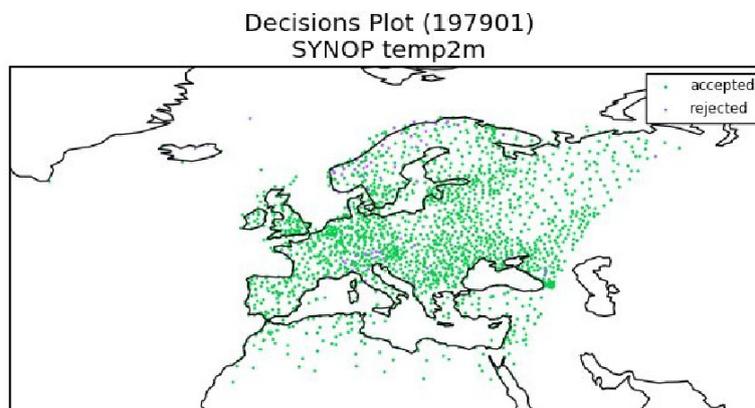


Figure 2.6: Decision map showing synoptical stations that are included (green) and excluded (purple) in the UK Met Office regional reanalysis based on the observational feed back.

3. Results and examples of applications

3.1. Comparisons against satellite radiation data.

The quality of the radiation data from the UERRA regional reanalyses is evaluated using two independent datasets. These are the satellite-based Surface Solar Radiation Dataset - Heliosat (SARAH)) dataset provided by CM-SAF and the MeteoSat second generation HelioMont Solar Radiation Climatology. Specifics of these datasets are given in Table 3.1.



	SARAH	HelioMont
<i>spatial resolution</i>	0.05°x0.05°	15'/25m/2km (depending on temporal resolution)
<i>temporal resolution</i>	instant, hourly means	
<i>spatial coverage</i>	METEOSAT-Prime full disk	Europe (and Africa)
<i>temporal coverage</i>	1983-2015	2004 - now
<i>aspects</i>	uses METEOSAT 2 to 10 (MVIRI/SEVIRI) satellites	multi-channel algorithm with cloud-snow separation, terrain shadow, snow radiative aspects, radiative transfer model.

Table 3.1: Observational datasets used to evaluate the reanalysis radiation fields.

The regional reanalysis of the German Weather Service DWD (COSMO-REA6 and COSMO-REA12), the Harmonie reanalysis of SMHI, the reanalysis/downscaling MESCAN of MeteoFrance and the reanalysis based on the Unified Model from the UKMO are compared by first regridding all reanalyses and observational datasets to a common grid of 0.1° spatial resolution, use a common domain (covering Europe and part of the Atlantic Ocean) and focus on 2008. The temporal resolution of the comparison is hourly. Figure 3.1 shows the bias, averaged over the year 2008 for these five reanalysis compared against the SARAH dataset.

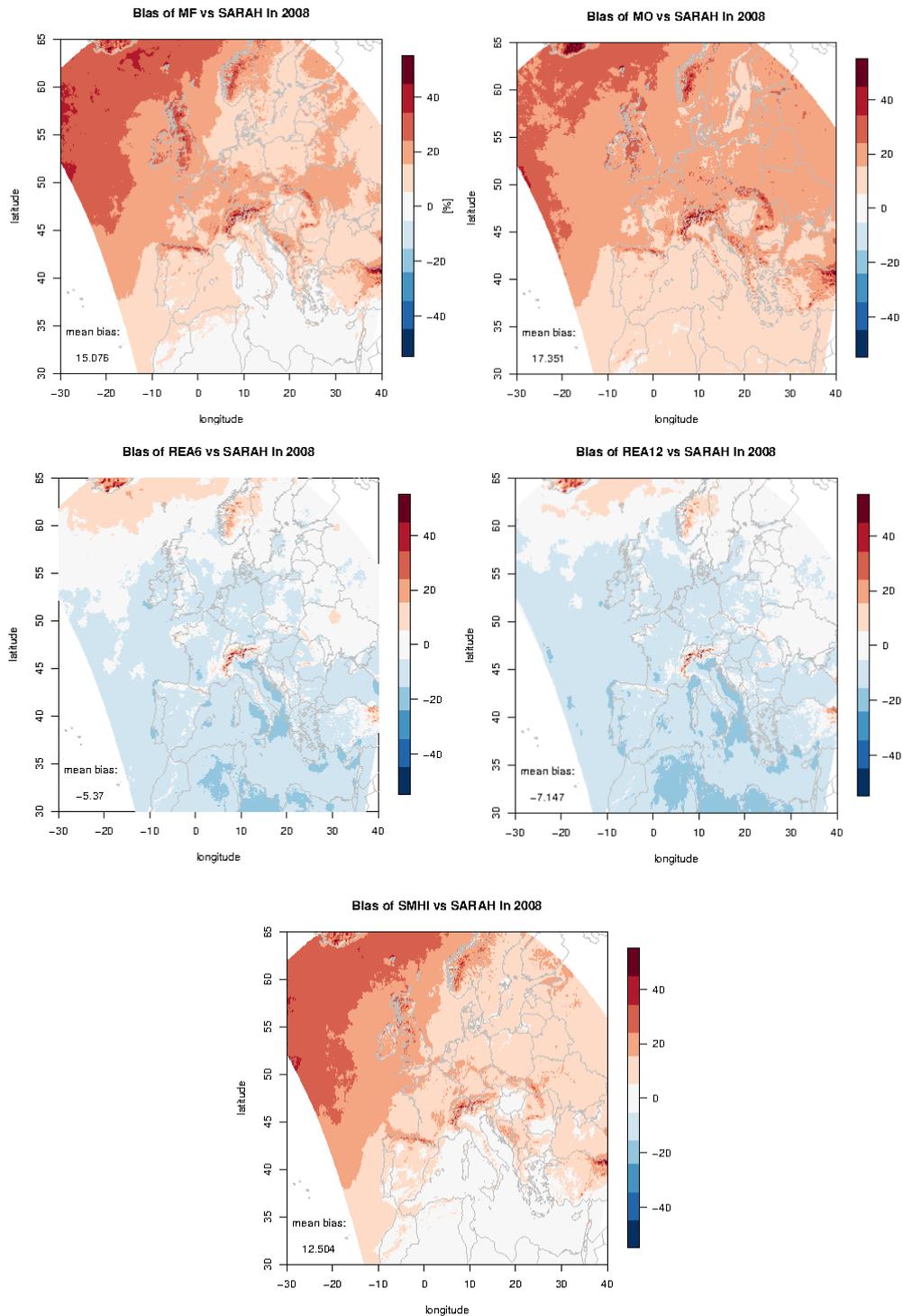


Figure 3.1: Mean annual bias in radiation for the year 2008.

These maps show that the reanalyses of MeteoFrance, the UKMO and SMHI overestimate radiation in the European domain for this particular year, while the two reanalyses from the DWD generally underestimate radiation. Over snow and mountainous regions, the HeliMont dataset performs much better than SARAH. While Figure 3.1 show high biases



between the reanalyses and SARAH over the Alpine area, the overestimations vanish for comparisons between the reanalyses and HelioMont.

3.2. Comparisons of precipitation over complex terrain

To look into the quality of the precipitation fields as generated by the regional reanalyses, which is a notoriously difficult parameter to model, two comparisons are made. One is over the Greater Alpine Region where the APGD is used as reference. The other is made over the Nordic countries, where the NGCD is used as reference. Figure 3.2 shows these comparisons for the Greater Alpine Region, figure 3.3 shows the annual precipitation for the Nordic countries.

Overall, it can be concluded that the regional reanalyses have a tendency to overestimate precipitation amounts and frequency, especially in complex terrain. The regional reanalysis shows better small scale structures and performance than observational gridded datasets in region of low station density. The exception is in the wet-day frequency which is generally over estimated by the reanalyses. When the best-performing reanalyses need to be selected, the COSMO-REA6 and COSMO-ENS12 show the best performance.

For the downscaling efforts, it can be concluded that there is additional value in regions with a dense station network and it gives a clear improvement especially for the fraction of wet days.

Regarding the model error: it is mostly bigger than the uncertainty of the reference dataset, especially for days >10mm/d precipitation and for the global reanalyses.

An interesting result from the UERRA comparisons is from a scale dependent analysis. This clearly shows that more information about the performance of the datasets can be obtained when focussing on the application/scale of interest. Biggest differences from the reference and the lowest Brier skill scores are found in complex topography, small catchment sizes and for higher precipitation amounts.

Finally, the annual cycle is mostly well reproduced in all datasets.

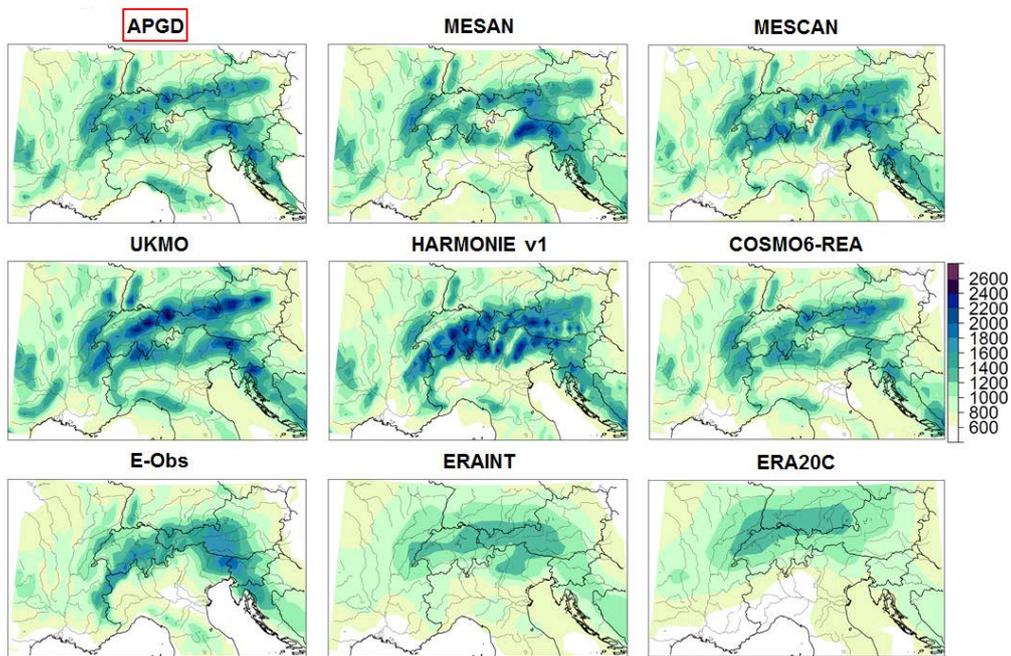


Figure 3.2: Mean annual precipitation (mm/year) over the 2006-2008 period over the Greater Alpine Region. Reference: APGD (top left panel).

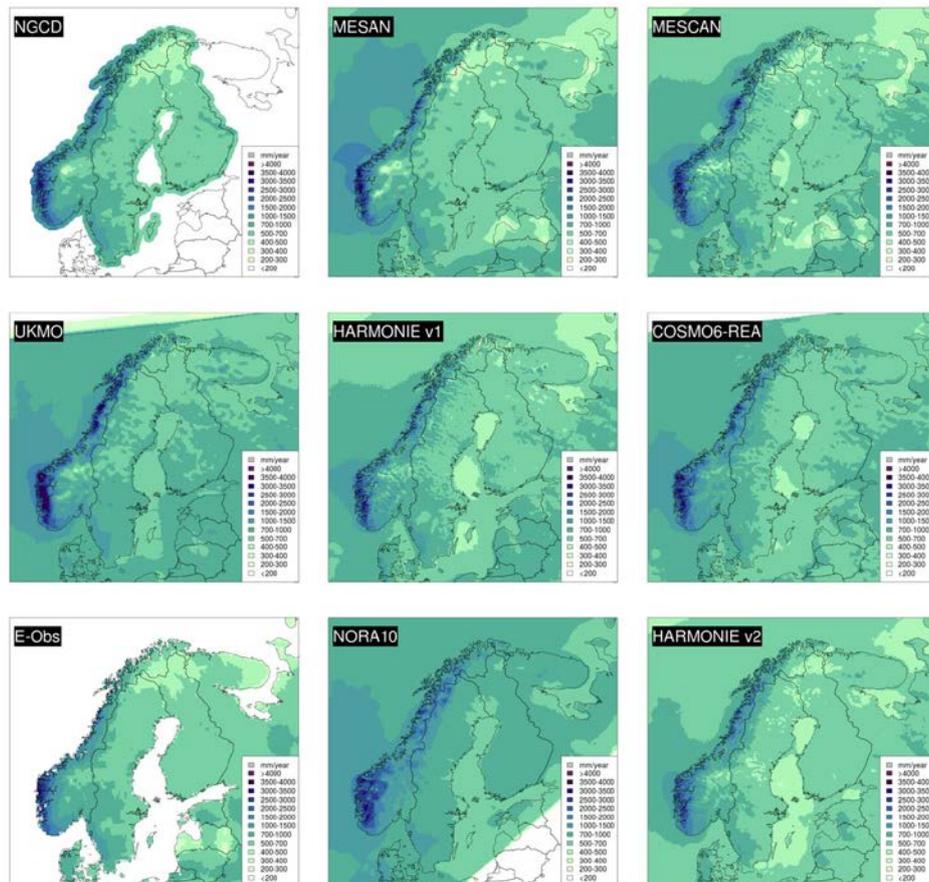


Fig. 3.3: Mean annual precipitation (mm per year, 2006-2010). Rescaled to 5km coordinate system. Reference: NGCD (top left panel).



3.3. Comparisons for drought-related parameters

Over the area of Romania, a detailed analysis has been made of the quality of the UK Met Office reanalysis in a comparison against the ROCADA observational dataset which is in operational use at the Romanian National Meteorological Institute. A comparison for two years for precipitation and potential evapotranspiration are shown in figure 3.4 and 3.5 respectively.

It is observed that both precipitation and evapotranspiration are overestimated in the Unified Model deterministic reanalysis, but spatial features are quite well captured by the reanalysis. Further analyses indicate that temporal evolutions of precipitation in observations and Unified Model deterministic reanalysis correlate quite well on monthly and daily time scales.

A large part of intermonth and interannual variability of the potential evapotranspiration in the warm season (May to August 1979-1990) over Romania is well captured by the Unified Model deterministic reanalysis. Furthermore, the reanalysis data shows realistic details of spatial configuration in the potential evapotranspiration field.

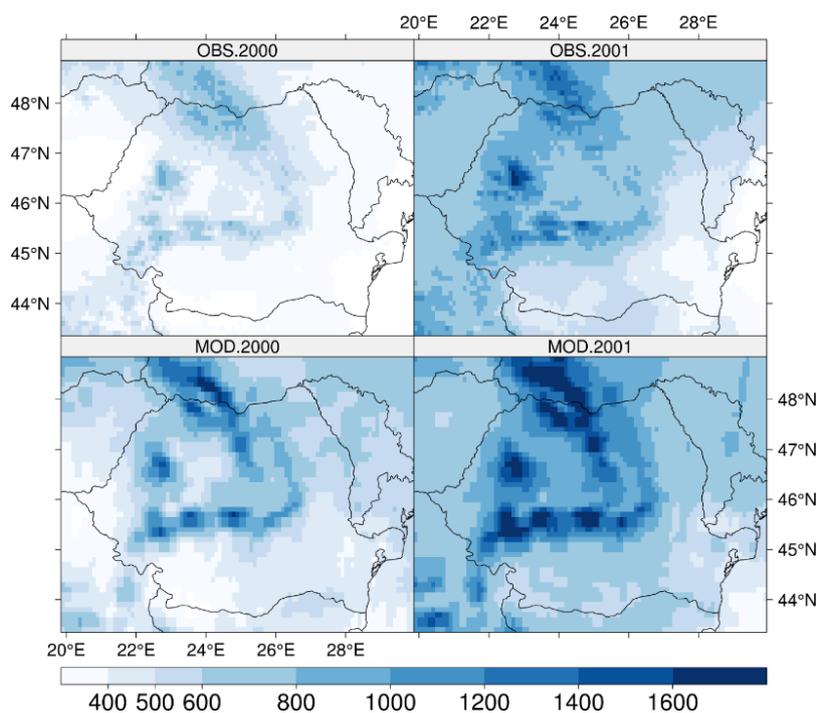


Figure 3.4: Annual observed precipitation (upper panels) from the ROCADA observational dataset and annual precipitation from the deterministic reanalysis developed at the UK Met Office (lower panels) for the years 2001 and 2002. Values are in mm/year.

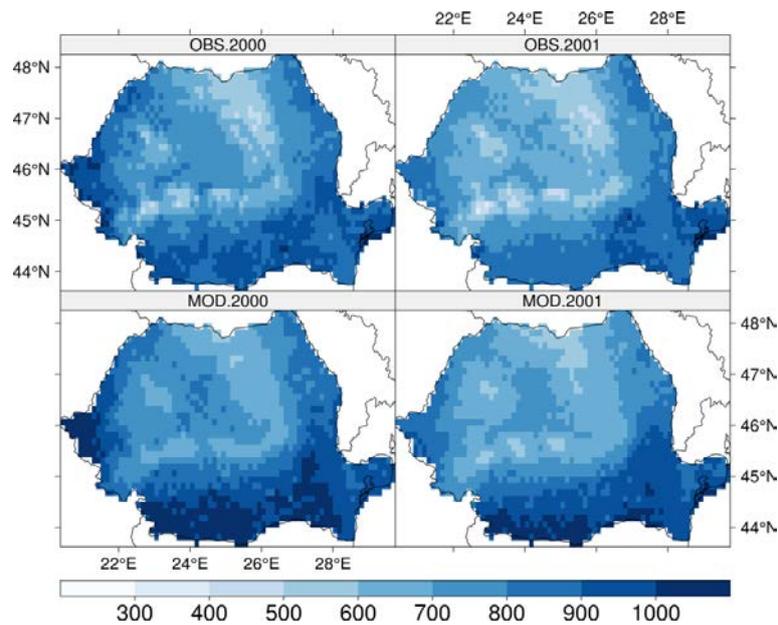


Figure 3.5: Annual potential evapotranspiration (upper panels) from the ROCADA observational dataset and annual potential evapotranspiration from the deterministic reanalysis developed at the UK Met Office (lower panels) for the years 2001 and 2002. Values are in mm/year.

3.4. Comparisons in terms of Climate Indices

Two of the UERRA reanalyses are compared against the E-OBS observational data. The procedure is to regrid the reanalysis to the E-OBS regular grid of 0.25° . For these comparisons, daily values of maximum and minimum temperature are used. Generally, the resemblance of the reanalyses against E-OBS is remarkably good! A clear demonstration of the capability of the reanalysis is shown in figure 3.6 where the seasonal cycle in daily maximum temperature over four selected regions is shown.

Differences between the observational dataset and the reanalyses start to appear when zooming-in on the extremes. Figure 3.7 shows probability plots of daily maximum temperature, averaged over the same four selected regions, and compares this with the observations. Especially in the tails of the distribution, the differences are large. Generally, SMHI reanalysis' cold extremes in winter are too cold, while in summer, the warm extremes are too hot. The UKMO reanalysis is often too warm in (both) extremes.

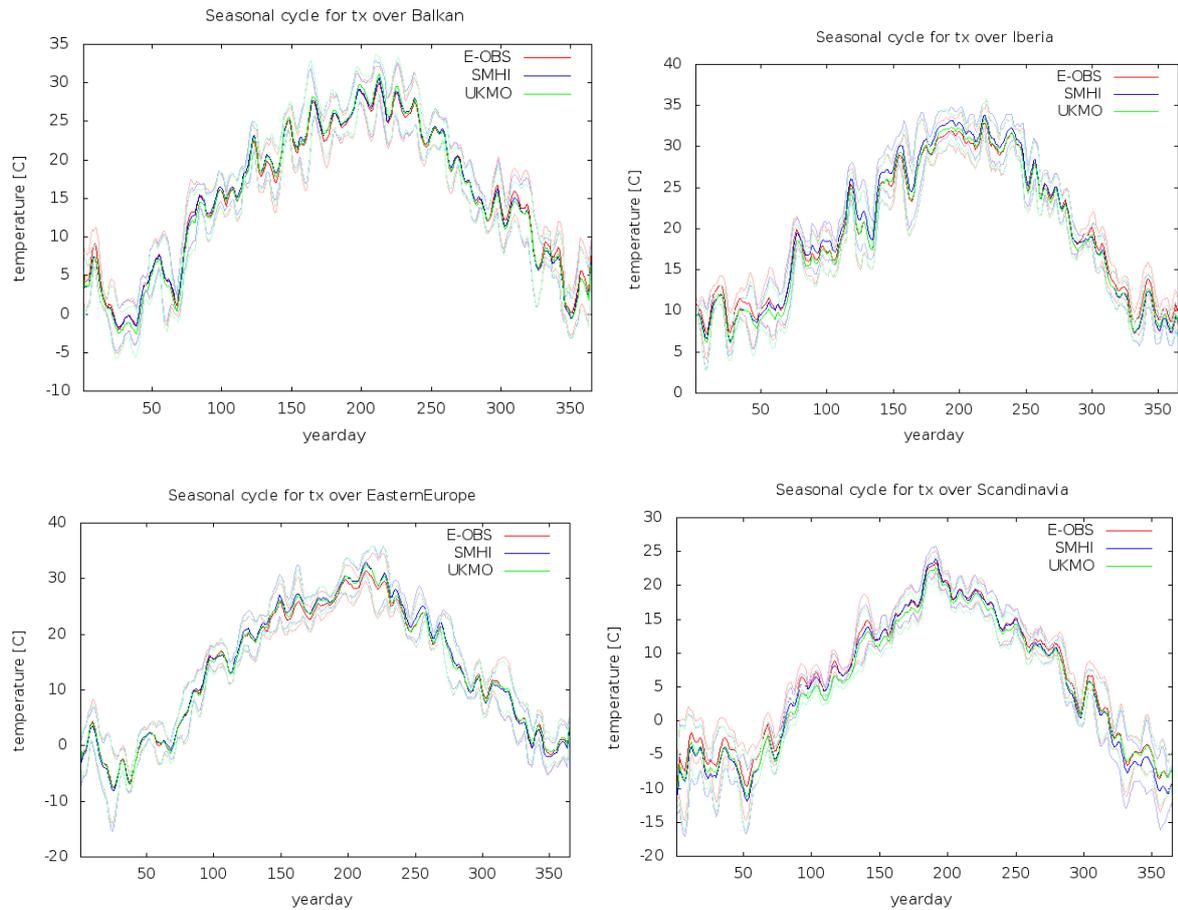


Figure 3.6: Seasonal cycle in daily maximum temperature over four regions in Europe, based on the observational data of E-OBS and the reanalyses of UKMO and SMHI.

Given the problems in the extremes, it is no surprise to see that for the Climate Indices focusing on (soft) extreme conditions like frost or ice days and summer days, the difference between reanalysis and observations can increase to up to 40 days/year (Figure 3.8).

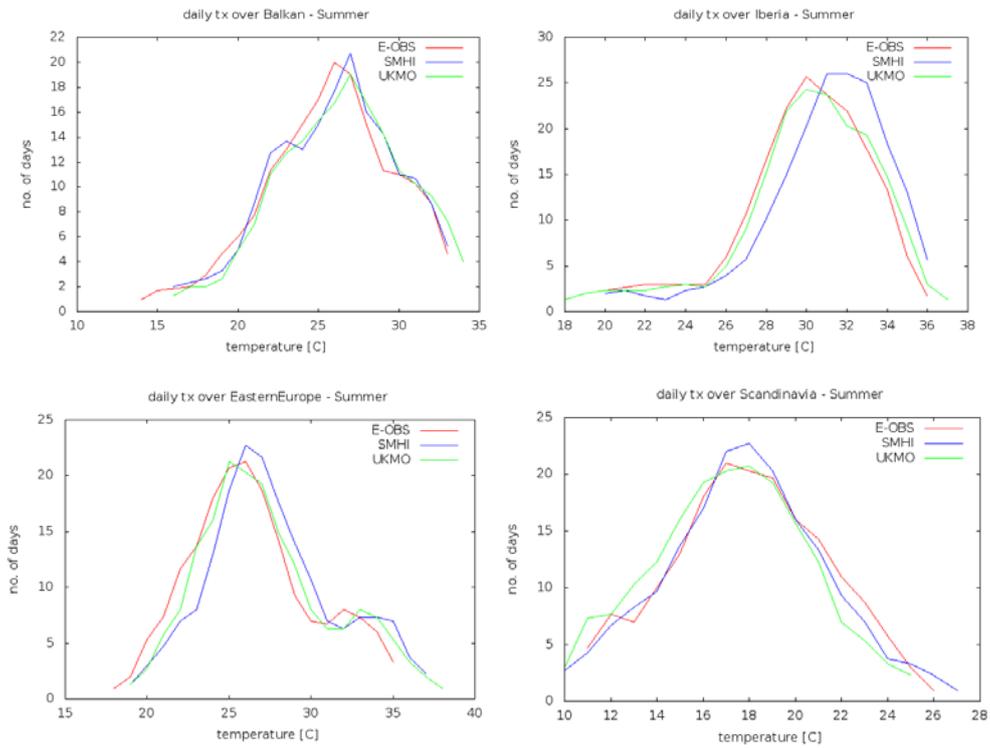


Figure 3.7: Probability plots of daily maximum temperature, averaged over four regions in Europe, as produced by the observational data of E-OBS and the reanalyses of UKMO and SMHI.

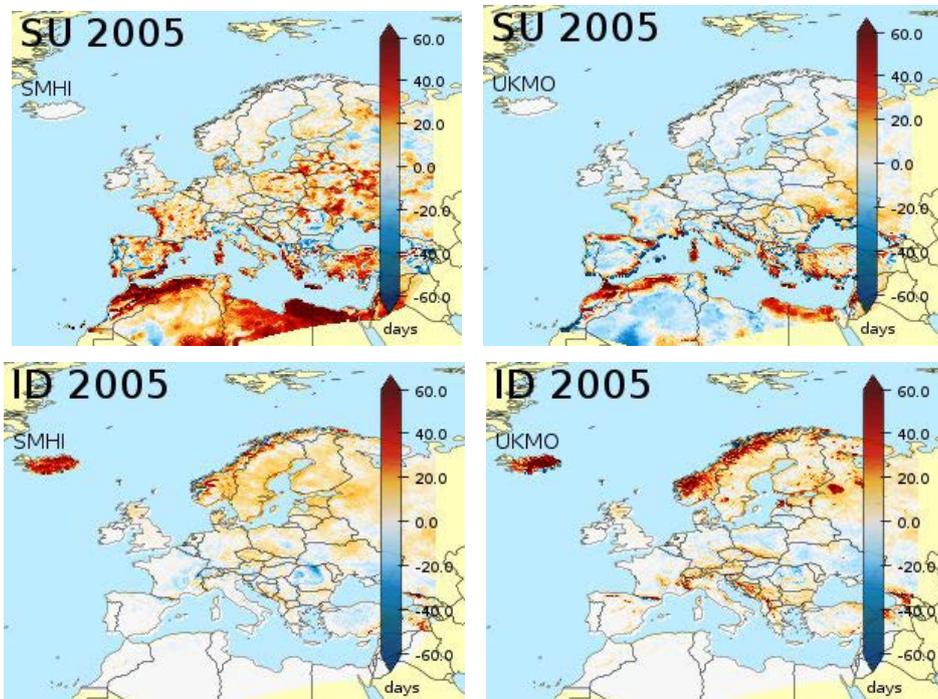


Figure 3.8: (top panels) Plots of the number of the difference in Summer Days ($T_x > 25^\circ\text{C}$) for the SMHI reanalysis (left panel) and the UKMO reanalysis (right panel) with respect to the E-OBS observational data. Bottom row: similar for the number of Ice Days ($T_x < 0^\circ\text{C}$).



3.5. Comparisons of wind against observations

Due to the problems of constructing an observational dataset for wind speed, a strong argument exists to use regional reanalyses for analyses of wind. The capability of reanalysis to model extreme winds is demonstrated in figure 3.9, which shows a snapshot of the storm Kyrill as reproduced by four UERRA reanalyses. The similarity in the wind fields is striking.

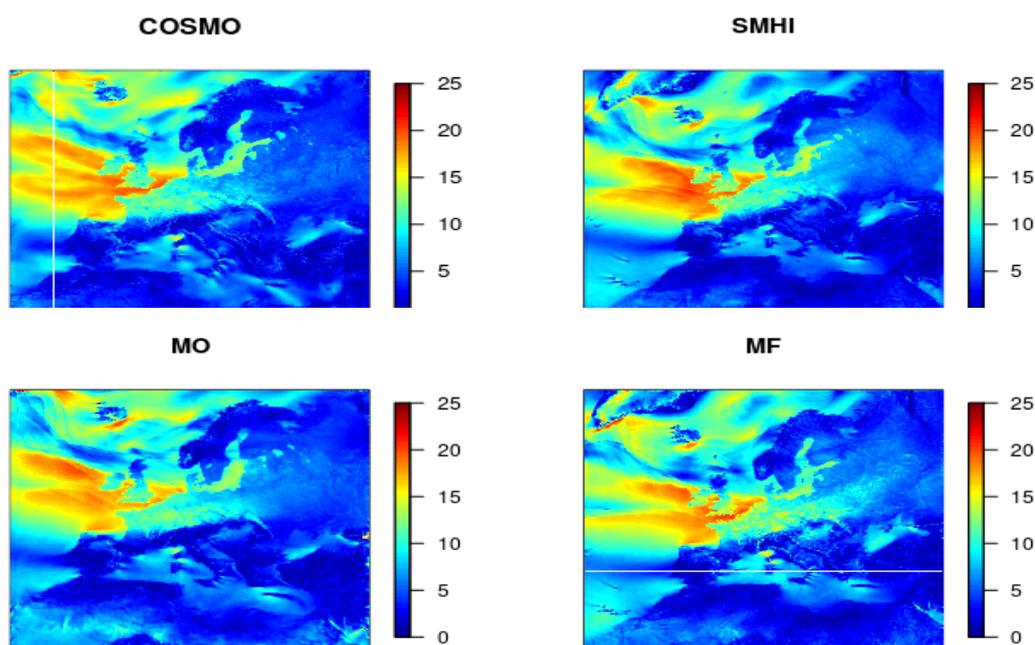


Figure 3.9: Wind speed in m/s during the Kyrill storm captured by the 4 UERRA reanalyses.

Another argument to use regional reanalysis over global reanalysis is the staggering amount of detail required to give a realistic of wind fields and of which only regional reanalysis are capable. An example of this feature has been given in the Introduction of this report (fig. 2.1). Apart from the detail the regional reanalyses offer, figure 3.10 demonstrates that regional reanalysis do a better job in comparing against ground-based wind measurements as well. It shows that correlation values are consistently higher for the regional reanalyses.

In a more detailed analysis, skill scores were calculated for five regional reanalyses and ERA-Interim. The results are shown in Figure 3.11 for station Hannover. 6-hourly data were used for a fairer comparison. The scores based on the contingency table measure different value ranges and properties. Thus examination of several scores is recommended, as is generally the recommended code of practise in verification studies. “Good” scores do not necessarily allow the conclusion that the model captures all statistics properly, especially when the sample size is varying and influencing the score behaviour, which makes the interpretation more challenging. Especially the behaviour for rare events differs for various scores. As the scores depend on the magnitude of the variable, and higher magnitudes are more rare events, an interpretation of the skills for these is not straightforward.

For the interpretation of model fitness for extreme events the verification score should be independent of the base rate or the event frequency. A light drop of skill for higher wind speed is noticeable, which indicates good model fitness for extreme events as well.



One has to keep in mind that these good scores are only valid for a relative measure (wind percentiles). When the absolute value is considered, all model systems lose skill, due to a strong local biases. For all investigated scores the different model systems are similar to each other, though ERA-Interim and HARMONIE have slightly lower and COSMO and the Unified Model have somewhat higher scores. However, one has to keep in mind that these statements are only valid for station Hannover. All verification results, shown in chapter 3, hint to strong local dependent model quality. There is no reanalysis outperforming the others at every location. Rather the decision which product is recommended for a specific application depends on the selected region.

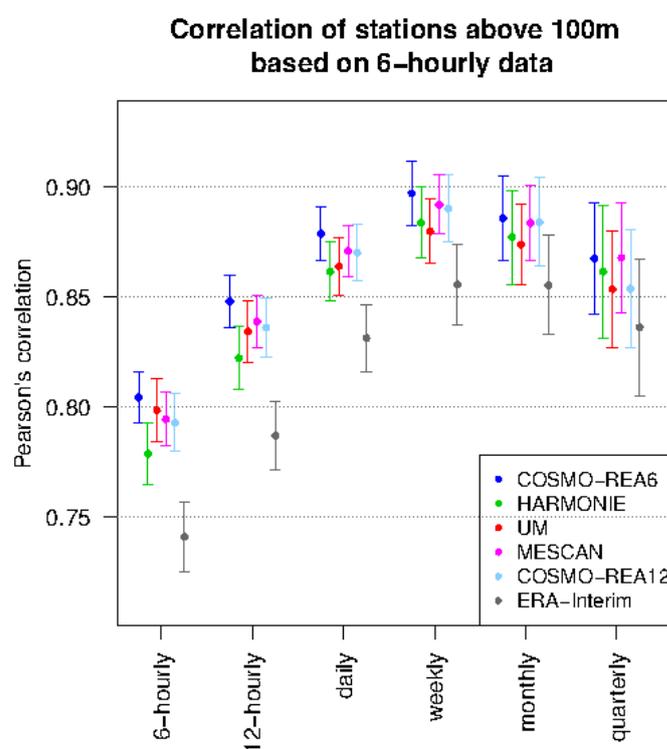


Figure 3.10: Correlation of 10m wind speed (from German stations) between UERRA regional reanalysis and the global ERA-Interim reanalysis. Correlation values are higher for the regional reanalyses.



Hit rate vs False alarm ratio of hourly data
at Hannover based on 6-hourly resolution

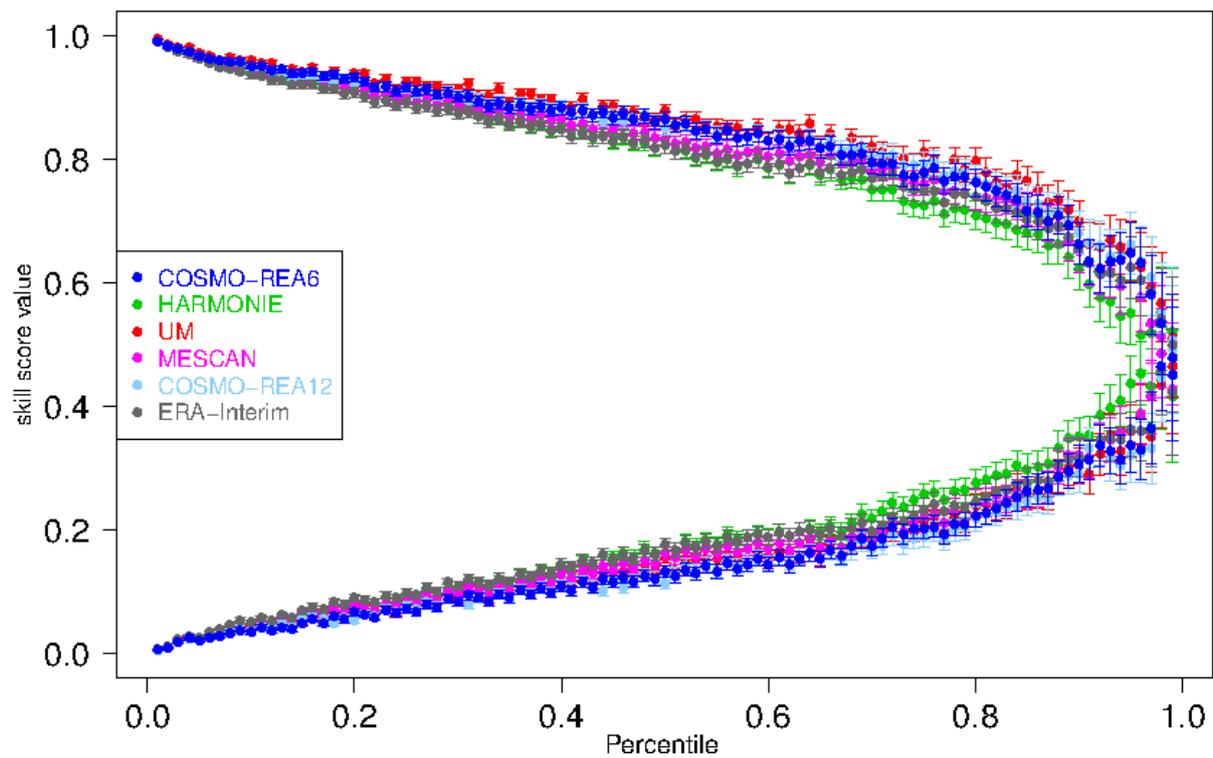


Figure 3.11: Hit rate and False alarm rate scores of 6-hourly data at station Hannover compared to the various reanalyses, computed for wind percentiles. All observations from 2006 to 2010 are taken into account.

4. Known issues

In the SMHI HARMONIE re-analysis there are a few things discovered that users need to be aware of. Some of these, possibly all, will be fixed and the archive updated. The problem is that this will take much time. Exactly when this re-archiving will start is unclear since we would like to collect everything that will be archived and correct several parameters at the same time.

Relative humidity: Due to a bug in one of the archiving scripts all relative humidity equal or larger than 100% was set to zero. This will be re-archived.

Accumulated surface fluxes of sensible and latent heat show a strange behaviour in the 1-6 hour forecasts over land. The instantaneous fields look fine but they are not archived. It means however, that the accumulated fields can be re-calculated correctly and re-archived.

There are too high wind speeds in some situations for the 1-3 hour forecasts. This is most likely a spin-up problem and is most pronounced in the wind gust but there is also a tendency for the same problem for the mean wind at 10 meter altitude. Test are currently ongoing to investigate how wide spread this problem is. A possible solution is also under testing and if this turns out well the shortest forecasts for the wind will be re-archived.



Then in general there is a spin-up problem for precipitation. It is therefore recommended not to use the first 6 hours in the forecasts. For example, if a user wants to use the 24 hour accumulated precipitation it is thus recommended to use the 30-6 hour forecasts.

For the reanalysis made with the Unified Model by the UKMO, an issue is the precipitation in the ensemble contribution (see table 2.1). The spread in the ensemble for precipitation is way off and users are advised not to use these data.

5. Summary

In general it can be concluded that the reanalyses are remarkably good! For some variables, like radiation and especially wind, the reanalyses may outperform datasets based on observations only. The relative variability in the reanalyses is also comparable to that of observational datasets. In many respects, the regional reanalyses not only show more detail than global reanalyses but also resemble the observations better than global reanalysis, like ERA-I and ERA-5.

However, there are a few issues users should be aware of. Mountain regions are difficult to get right in reanalysis. A high-density station-based precipitation dataset is likely to be more reliable than a reanalysis, although there are reanalyses that outperform others. Similar observations exist for the comparison of radiation. In general, the radiation fields in reanalysis fields are biased and should be used with care.

For temperature, the quality of the reanalysis is high and comparable to the E-OBS observational dataset. However, one issue with temperature relates to the representation of temperature extremes. While the general seasonal cycle in temperature is well captured by the reanalysis, the more extreme temperature events are rather poorly represented. Some of this behaviour can be remedied by a bias correction, but note that such bias removal cannot be generalized because it depends on the application (and its spatial and temporal resolution) what is considered as bias. These issues make that calculation of Climate Indices which are based on absolute thresholds, like Summer Days of Frost Nights, are likely to be less realistic in reanalysis.

6. Practical tips and tricks

Tip 1: How to access these data?

The easiest way to access the reanalyses data is through the ECMWF MARS archive. A link to available reanalyses is available at: <https://software.ecmwf.int/wiki/display/UER>. A web-based user interface gives access to smaller amounts of data. To access larger volumes of data, a scripted MARS request is advised. An example of a MARS request is shown in figure 6.1.



```

retrieve,
class=ur,
date=2007-01-01/to/2007-01-31,
expver=prod,
levtype=sfc,
number=0,
origin=edzw,
param=207,
step=1/2/3/4/5/6,
stream=enda,
time=00:00:00/01:00:00/02:00:00/03:00:00/04:00:00/
05:00:00/06:00:00/07:00:00/08:00:00/09:00:00/10:00:00/
11:00:00/12:00:00/13:00:00/14:00:00/15:00:00/16:00:00/
17:00:00/18:00:00/19:00:00/20:00:00/21:00:00/22:00:00/
23:00:00
type=an,
target=„Crea12_10mWS_ana0_2007-01.grb“

```

Figure 6.1. Example of a MARS request to extract large volumes of data.

Tip 2: How to handle the data format?

The reanalysis data generated in the UERRA project are in the GRIB2 format. The observational dataset produced in UERRA is in the NetCDF format. There are several standard (and free) tools available that help in processing and converting data. One example are the GRIB API/eccodes tools which are available at the ECMWF at: <https://software.ecmwf.int/wiki/display/ECC/ecCodes+Home>.

Very powerful and extensive are the CDO routines which have been developed at the Max Planck Institut für Meteorologie in Hamburg, Germany. The routines, available at <https://code.mpimet.mpg.de/projects/cdo/> allow conversions from one format to the other and a wide range of aggregation and statistical tools. Note that the header of rotated netcdf files is not retained after using a CDO routine so the files no longer comply with CF conventions. A simple – but helpful – tool from CDO is griddes, which gives a description of the grid. Figure 6.2 gives an example of the output of griddes and summarizes the grid which is used in the datafile.

```

gridtype      = lonlat
gridsize      = 161568
xname         = rlon
xlongname     = longitude in rotated pole grid
xunits        = degrees
yname         = rlat
ylongname     = latitude in rotated pole grid
yunits        = degrees
xsize         = 408
ysize         = 396
xnpole        = -162
ynpole        = 39.25
xfirst        = -27.495
xinc          = 0.11
yfirst        = -22.495
yinc          = 0.11

```

Figure 6.2: Example of output of the CDO routine griddes.



Tip 3: How to make a simple visualization?

A easy yet powerful way to visualize NetCDF datafiles is the open-source program `ncview` (figure 6.3). `Ncview` is a visual browser for NetCDF format files. Typically you would use `ncview` to get a quick and easy, push-button look at your netCDF files. You can view simple movies of the data, view along various dimensions, take a look at the actual data values, change color maps, invert the data, etc. Note that `ncview` is not suitable as a programming or analysis tool. Source code for `ncview` can be downloaded at: http://meteora.ucsd.edu/~pierce/ncview_home_page.html. More complex arithmetic and manipulation with NetCDF data are better performed by the NOAA developed Ferret program (<http://ferret.pmel.noaa.gov/Ferret/>) which also visualizes the data. Ferret is an interactive computer visualization and analysis environment designed to meet the needs of researchers in the geophysical sciences, analyzing large and complex gridded data sets. PyFerret, introduced in 2012, is a Python module wrapping Ferret. The `pyferret` module provides Python functions so Python users can easily take advantage of Ferret's abilities to retrieve, manipulate, visualize, and save data.

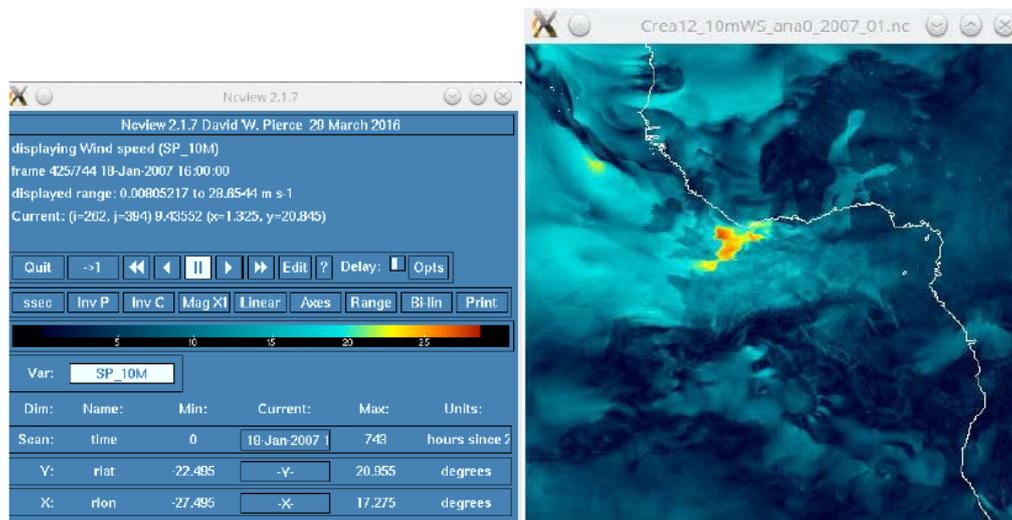


Figure 6.3: Example of `ncview` GUI (left) and (right) the corresponding plot of the NetCDF data file.

Tip 4: How to zoom-in to your area of interest?

From the MARS webinterface it is possible to download the complete domain UERRA uses for its reanalyses (which coincides with the EuroCORDEX domain). By using one of the tools of CDO (`sellonlatbox` or `selindexbox`), it is possible to extract a specified rectangular domain. Figure 6.4 gives an example of a zoom-in area of a wind storm over the North Sea region.

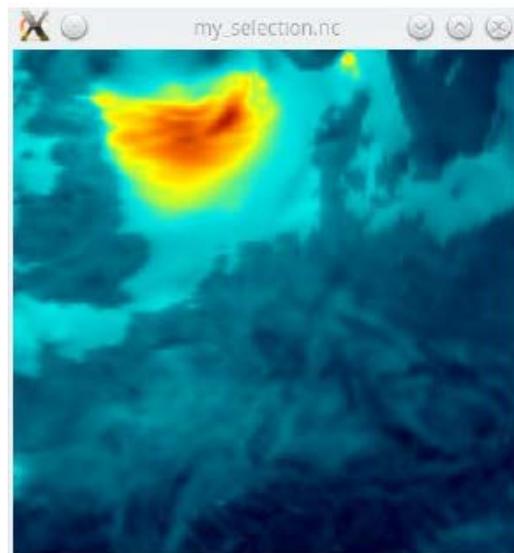


Figure 6.4: Example of a zoomed-in area using the CDO tool `sellonlatbox` or `selindexbox`

Tip 5: How to convert the various coordinate systems to something more ordinary?

The reanalysis datasets use various coordinate systems. A rotated latitude-longitude grid is used by the Unified Model and COSMO-REA12 models. A Lambert conformal conic projection is used by HARMONIE and MESCAN. Furthermore, observational E-OBS data is available on a regular longitude-latitude grid only. There are two suggestions to convert these grids into a common form. One is to use a python script of ECMWF (<https://software.ecmwf.int/wiki/display/GRIB/iterator.py>) which converts to a regular longitude-latitude grid (output in ASCII only). The second possibility is to use the 'recon' routines from CDO. There are various ways to remap available within CDO, like `remapcon` which uses a conservative remapping. These routines take as input the grid to which the input NetCDF needs to be regridded to.