Update: Downscaling of the SEAS5 to the Greater Region of Luxembourg

Verification

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Summary of work up to meeting in Trier

Creating a literature pool to acquire knowledge about task

Literature on:

- seasonal forecasting and products therefor
  - decided on the Seasonal Forecast System 5 (SEAS5) provided by the ECMWF
- dynamical downscaling and products therefor
  - decided on the COSMO-CLM provided by a range of meteorological services and maintained by the CLM community
- ensemble forecasting
- verification methods and measures
  - how to create a reference dataset
  - decided on E-OBS provided by European Climate Assessment and Dataset

.

First requirements concerning the necessary datasets

SEAS5:

- getting familiar with dataset in general
  - spatial resolution and driving atmospheric/ocean models
  - range of variables and temporal resolution of them
  - which data is available (sligthly pre-processed (monthly means/ensemble mean/etc.), completely raw (continuous, probabilistic values) and much more
- getting familiar with technicalities surrounding the dataset
  - "streams" through which different, above mentioned data is provided
  - getting familiar with Meteorological Archival and Retrieval System (MARS)
  - getting familiar with the specific dataset descriptions via "confluence", the wiki and collaboration platform of ECMWF
- collecting more literature on this specific product

First requirements concerning the necessary datasets

E-OBS:

- getting familiar with dataset in general
  - spatial and temporal resolution
  - range of variables
  - how is the dataset produced
- getting familiar with technicalities surrounding the dataset
  - downloading the E-OBS manually, as it is just 5 available variables
- collecting more literature on this specific product

Acquirement of SEAS5 data with MARS

- MARS uses either the Web User Interface on the ECMWF website or can be used via a Web-API service interface which uses a python script
- Web-API client has to be installed (description and all steps until it's usable can be found in confluence wiki[1]
- to not download/overwrite already existing files script also checks for filename and variations of it
- the whole looping procedure, as well as the identification as an authorized user is done in bash commands
- all needed variables are then redirected to an outputfile (request_date_em.mars) that can be read by the mars.py script that was installed above

[1]https://confluence.ecmwf.int/display/WEBAPI/Access+MARS

SEAS5 data

- 6 hrly continuous forecast (fc)
- 51 ensemble members
- 7 months of data per initialization (ini) date
- 4 ini dates (lead times)
- global latlon grid
- variables: t2m in K, total precipitation in m

E-OBS data

- daily mean values
- ensemble mean
- data from 2011 until 2019
- european latlon grid (
- variables: air temperature, thickness of rainfall amount in mm
- no values over ocean domains

Regridding

- Both datasets were regridded according to a reference file for the EU-CORDEX domain (here called geogrid)
  - geogrid is a "generic" grid type
  - created grid file for geogrid to regrid the other datasets
  - "curvilinear" as grid type = rectangular shape, not following lon/lat lines
- regridded with the cdo command remapbil
  - bilinear interpolation remapping
  - detailed description of the interpolation scheme can be found in the SCRIP[2] description

[2] https://github.com/SCRIP-Project/SCRIP/blob/master/SCRIP/doc/SCRIPusers.pdf

Tasks of matching

- creating daily means for SEAS5
- masking SEAS5 with E-OBS data to get the same NA values at the same grid points
- inter comparing timeline of datasets and cutting them where ever the other set had no values
- changing units of E-OBS dataset to match the SEAS5 dataset
- create intuitive names to loop through for E-OBS
- creating script that sets up a directory tree from base directory

Summary of work up to meeting in Trier

Datasets were now

- on the same grid
- at the same temporal resolution
- within the same time range
- matching in terms of NA values
- matching in terms of units

First attempt at verification

- as JJA is of interes datasets were reduced to it
- creating RMSE, MAE and bias with the same scripting method
    - looping through each time step of grid points of SEAS5 ensemble mean, creating the mean, then standard deviation and then RMSE/MAE/Bias

Outcome of meeting

Reference dataset

E-OBS dataset is insufficient, as there is not enough observations and therefore the interpolated results are lacking.

ERA5 would be a reasonable choice for substitution, as it is a well described and verified reanalysis. The data can be retrieved from the Copernicus[3] server. Details of dataset on later slides.

Verification metrics

Equations should be clearly stated.

As there were problems in description of the used RMSE in the metrics it is very important to explain and document way of using different verification measures.

[3] `https://cds.climate.copernicus.eu/`

Forecast dataset

Temporal range of operational forecast not big enough, re-forecast for a bigger span would be more valuable.

The re-forecast of the SEAS5 dataset is also available on the Copernicus[4] server. It has a set of 25 ensemble members and a resolution of 1° x 1°. More details of dataset on later slides.

Literature reference

Identification of papers with similar problem of verification.

I go forward mainly but not only with the paper by Johnson et al. [12] on the verification of specifically the SEAS5 as I use the re-forecast dataset now.

[4] https://cds.climate.copernicus.eu/

Setup after meeting

Forecast
SEAS5 operational forecast

- initial dates of 01.03., 01.04., 01.05., 01.06. for different lead times (for JJA)
- 51 ensemble members
- total precipitation and 2 meter temperature
- 0.4°

Problem:
Not enough temporal cover (just 3 months of actual forecast). A span of ~30 years would be much better for a sufficient verification.

Reference
E-OBS dataset

- daily values for JJA
- ensemble mean
- precipitation and 2 meter temperature
- 0.25°

Problem:
Measurement stations are sparse, which makes the interpolation very inaccurate. A reanalysis would be better for a sufficient verification.

Progress since meeting

Creation of automated script to download SEAS5 re-forecast dataset from Copernicus server.

```python
#!/usr/bin/env python
import cdsapi
import os.path

c = cdsapi.Client()

pwd    = os.getcwd()
dirout = [str(pwd) + '/reforecast/']
if not os.path.exists(dirout[0]):
        os.mkdir(dirout[0])

os.chdir(dirout[0])

mon=["%.2d" % i for i in range(3,7)]

steps = []
for i in range(6,5161,6):
        steps.append(i)

for y in range(1993, 2017):
    for m in mon:
                if not
                os.path.exists('refc_{year}_{month}.grib'.format(year=y,month=m))
                and
                os.path.exists('refc_{year}_{month}.nc'.format(year=y,month=m))
                and
                os.path.exists('EU_refc_{year}_{month}_JJA.nc'.format(year=y,month=m
                )) and
                os.path.exists('refc_{year}_{month}_JJA.nc'.format(year=y,month=m)):
            c.retrieve('seasonal-original-single-levels',
            {
                'originating_centre':'ecmwf',
                'system':'5',
                'variable':'2m_temperature',
                'year':y,
                'month':m,
                'day':'01',
                'leadtime_hour':steps,
                'format':'grib'
            },
            'refc_{year}_{month}.grib'.format(year=y,month=m)
                    )
```

Re-forecast download script

- creates output directory, if not yet created
- loops over months for ini dates (03/04/05/06) for years from 1993 until 2017
- 25 ensemble members
- 6 hourly temporal resolution
- 1° spatial resolution
- works similar to first retrieval script but retrieves directly, not creating a temporal file (request.mars above)

Columns

Creation of automated script to download ERA5 dataset from Copernicus server.

```python
#!/usr/bin/env python
import cdsapi
from datetime import datetime, timedelta
from dateutil.relativedelta import relativedelta
import os.path

c = cdsapi.Client()

pwd    = os.getcwd()
dirout = [str(pwd) + '/ERA5/']
if not os.path.exists(dirout[0]):
        os.mkdir(dirout[0])

os.chdir(dirout[0])

def days_of_month(y, m):
    d0 = datetime(y, m, 1)
    d1 = d0 + relativedelta(months=1)
    out = list()
    while d0 < d1:
        out.append(d0.strftime('%Y-%m-%d'))
        d0 += timedelta(days=1)
    return out

year=range(1993, 2019)
mon=range(6,9)

for y in year:
    for m in mon:
        timerange=days_of_month(y, m)
    file=[str(dirout[0]+'ERA5_{yyyy}_0{mm}.grib'.format(yyyy=y,mm=m))]
    if not os.path.exists(file[0]):
            c.retrieve('reanalysis-era5-single-levels',
            {
        'product_type':'reanalysis',
        'format':'grib',
        'variable':['2m_temperature','total_precipitation'],
        'date':timerange,
        'time':['00:00','06:00','12:00','18:00']
        },
               file[0]
                      )
```

ERA5 download script

- creates output directory, if not yet created
- loops over months JJA for years from 1993 until 2017
- reanalysis without members (HRES reference data)
- 6 hourly temporal resolution
- 0.28° spatial resolution
- works similar to first retrieval script but retrieves directly, not creating a temporal file (request.mars above)

Tasks of matching

- split SEAS5 re-forecast into ensemble members, as they are not treated as a 4th dimension in raw dataset but integrated into "timeline"
- the remapping procedure remains the same as with previous datsets
- reducing SEAS5 to JJA only (ERA5 was already downloaded matching only these months)
- as they are forced by the same atmospheric model matching is much easier to do
- both are also downloaded in GRIB format and have to be transformed

Mainly after Johnson et al. (2019) [12], Jolliffe (2012) [13] and Wilks (2011) [31]

- Deterministic measures (ensemble mean)
  - RMSE
  - MAE
  - ME
- Probabilistic measures (ensemble members)
  - Reliability diagrams
  - ACC
  - CRPSS
  - Brier score

Equations after which determinitsic metrics is calculated:

- Root Mean Squared Error (RMSE)[13]

$$RMSE = \frac{1}{N}\sum_{t=1}^{N}\sqrt{\frac{1}{M}\sum_{i=1}^{M}(f_{i,t} - o_{i,t})^2}$$

where M is the number of points in the grid, N the years over which values are taken for JJA, f/$o_{i,t}$ the value at time t and location i and answers the question "What is the mean grid-based RMSE, averaged across all times (JJA)?"

Equations after which determinitsic metrics is calculated:

- Mean Absolute Error (MAE)[13]

- Mean Error (ME) - Bias

Equations after which probabilistic metrics is calculated:

- Anomaly correlation coefficient (ACC) [13]

$$ACC_t = \frac{\sum_{i=1}^{M}(f'_i - \bar{f'_i})(o'_i - \bar{o'_i})}{M s_{f'} s_{o'}}$$

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To Do next:

Implementing of verification metrics on new dataset

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