

How to work with RZSM products: From download to visualization

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Table of current products

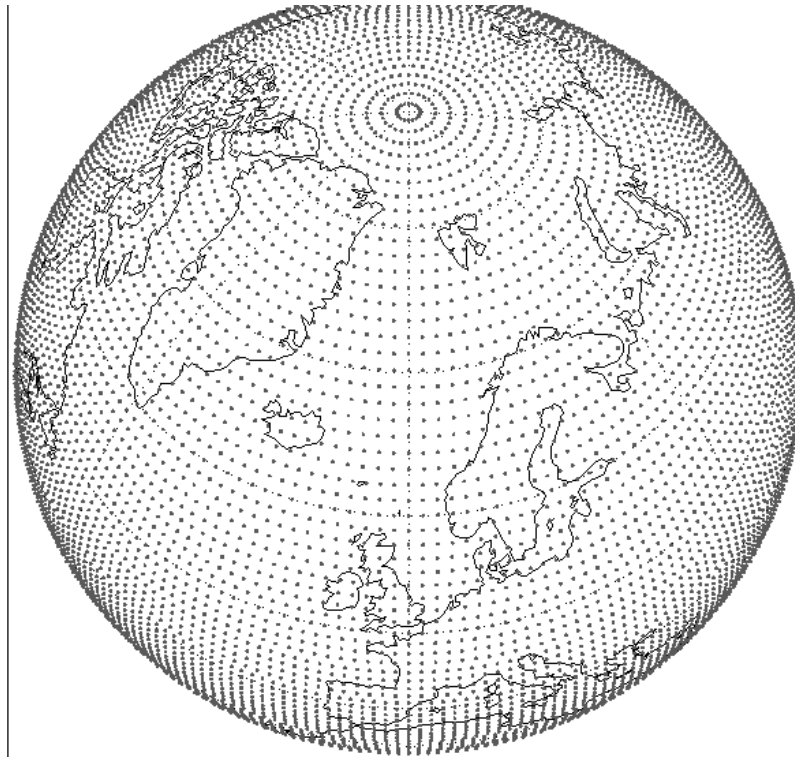
NRT and data record RSM products

Product name	Type	Period	Obs assimilated	DA system	Resolution	QC flags
H14	NRT	2012 onwards	25 km sampled ASCAT-A/B SSM products (H102/H103)	Regular updates of ECMWF LDAS (38R1- 46R1)	25 km	Yes since 4/10/18 (1=normal, 2=frozen risk, 3=outside nominal range)
H27	Data record	1992-2014	ERS 1/2 (1992-2006) and ASCAT-A (2007- 2014) reprocessed SSM	41R1 of ECMWF LDAS	16 km	None
H140	Data record	2015-2016	ASCAT-A (2015-2016) reprocessed SSM	43R3 of ECMWF LDAS	16 km	None

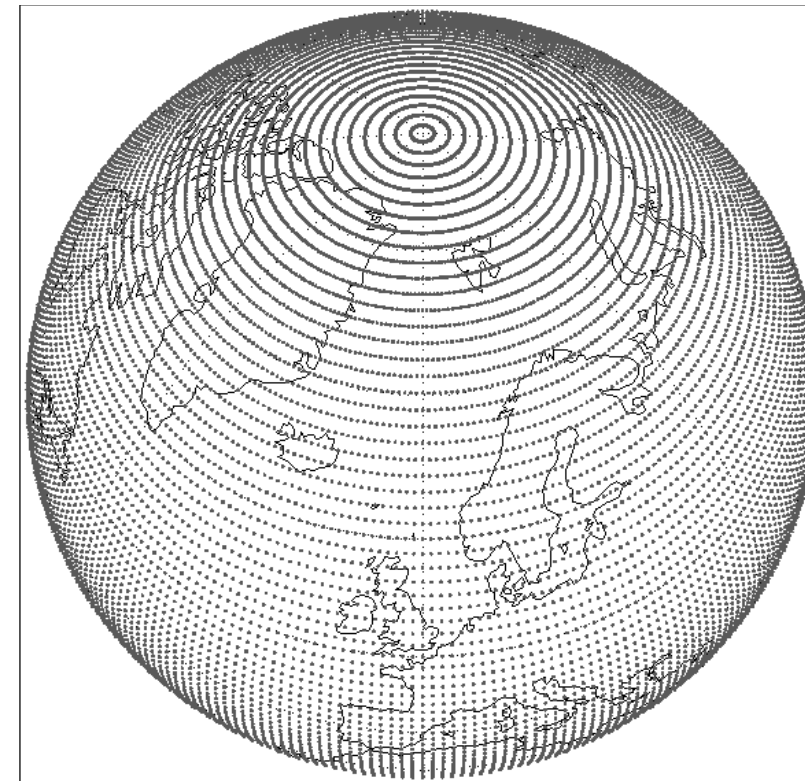
Format

- H14 is available in grib format on a linear reduced Gaussian grid (T799~25 km resolution);
- H27/H140 are available in grib format at (T1279~16 km resolution).
- The reduced Gaussian grid maintains approximately equidistant grid-point distances between the poles and the equator (unlike regular lat/lon grid):

Reduced Gaussian grid:



Regular lat/lon grid:



For more info, see <https://confluence.ecmwf.int/display/FCST/Gaussian+grids>

Requirements for examples

- python version 3.6
- The following libraries: *metview*, *pandas*, *pylab*, *matplotlib*, *numpy*, *cartopy*
- A miniconda script for linux/mac will be provided on github, which sets up a local environment and downloads the relevant libraries for all the soil moisture examples:
https://github.com/H-SAF/eumetrain_sm_week_2019
- The following examples can be run in jupyter notebook (Exercise_2 from github above)
- More information about metview-python:
<https://github.com/ecmwf/metview-python>

Documentation

The documentation can be found via <http://hsaf.meteoam.it/user-documents.php>:

- Product user manual
- Algorithm theoretical baseline document
- Product validation report
- If you have any queries, please contact the H SAF helpdesk: us_hsaf@meteoam.it

Downloading the data from ftp

- H14, H27 and H140 daily grib files can be downloaded via the H-SAF ftp: <ftp://ftphsaf.meteoam.it/products>
- First register with H SAF: <http://hsaf.meteoam.it/user-registration.php> to obtain username and password
- Easy to download data from ftp using software such as filezilla <https://filezilla-project.org/> .
- Alternatively, to download example file (H14 for 30/05/2018) from the terminal type:

```
ftp user@ftphsaf.meteoam.it
```

```
password: (type your password)
```

```
cd /products/h14/h14_cur_mon_grib
```

```
get h14_20190530_0000.grib.bz2
```

```
exit
```

```
bzip2 -d h14_20190530_0000.grib.bz2
```

Reading grib data in metview-python

```
import metview as mv #for reading and plotting grib files
import numpy as np #for grid/data manipulation
import matplotlib.pyplot as plt #For plotting
```

```
SM =mv.read("h14_2019053000.grib") #Read in grib data for 30/5/2019:

SWI1=mv.read(data=SM,param="40.228") #1st layer (0-7 cm depth)
SWI2=mv.read(data=SM,param="41.228") #2nd layer (7-28 cm depth)
SWI3=mv.read(data=SM,param="42.228") #3rd layer (28-100 cm depth)
SWI4=mv.read(data=SM,param="43.228") #4th layer (100-289 cm)
qc=mv.read(data=SM,param="200.228") #Quality control flag (1=normal, 2=risk of frozen conditions,
#3=outside nominal range)

RZSM = SWI1
#Extract root-zone SM values from depth integrating the 4 layers
RZSM = RZSM.set_values(SWI1.values()*0.07 + SWI2.values()*0.21 + SWI3.values()*0.72)
```


Plotting grib data in metview-python

```
#Create contouring for metview plot
cont_pc = mv.mcont(contour = "off",
    legend = "on",
    contour_shade = "on",
    contour_level_selection_type = "level_list",
    contour_level_list = [0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0],
    contour_label_format = "(F4.1)",
    contour_label = "off",
    contour_label_height = 0.40,
    contour_label_colour = "charcoal",
    contour_label_frequency = 10,
    contour_highlight = "off",
    contour_shade_method = "area_fill",
    contour_shade_colour_method = "gradients",
    contour_gradients_colour_list = ['burgundy', 'red', 'orange', 'yellow', 'green', 'cyan', 'sky', 'blue', 'navy'],
    contour_gradients_step_list = [20, 20, 20, 20, 20, 20, 20, 20, 20])
```

```
#Create legend:
my_legend = mv.mlegend(legend_display_type = "continuous",
    legend_entry_border='off',
    legend_text_colour = "charcoal",
    legend_values_list=[0.0, 0.2, 0.4, 0.6, 0.8, 1.0],
    legend_text_composition = 'user_text_only',
    legend_text_font_size = 1,
    legend_user_maximum = "on",
)
```

Plotting grib data in metview-python

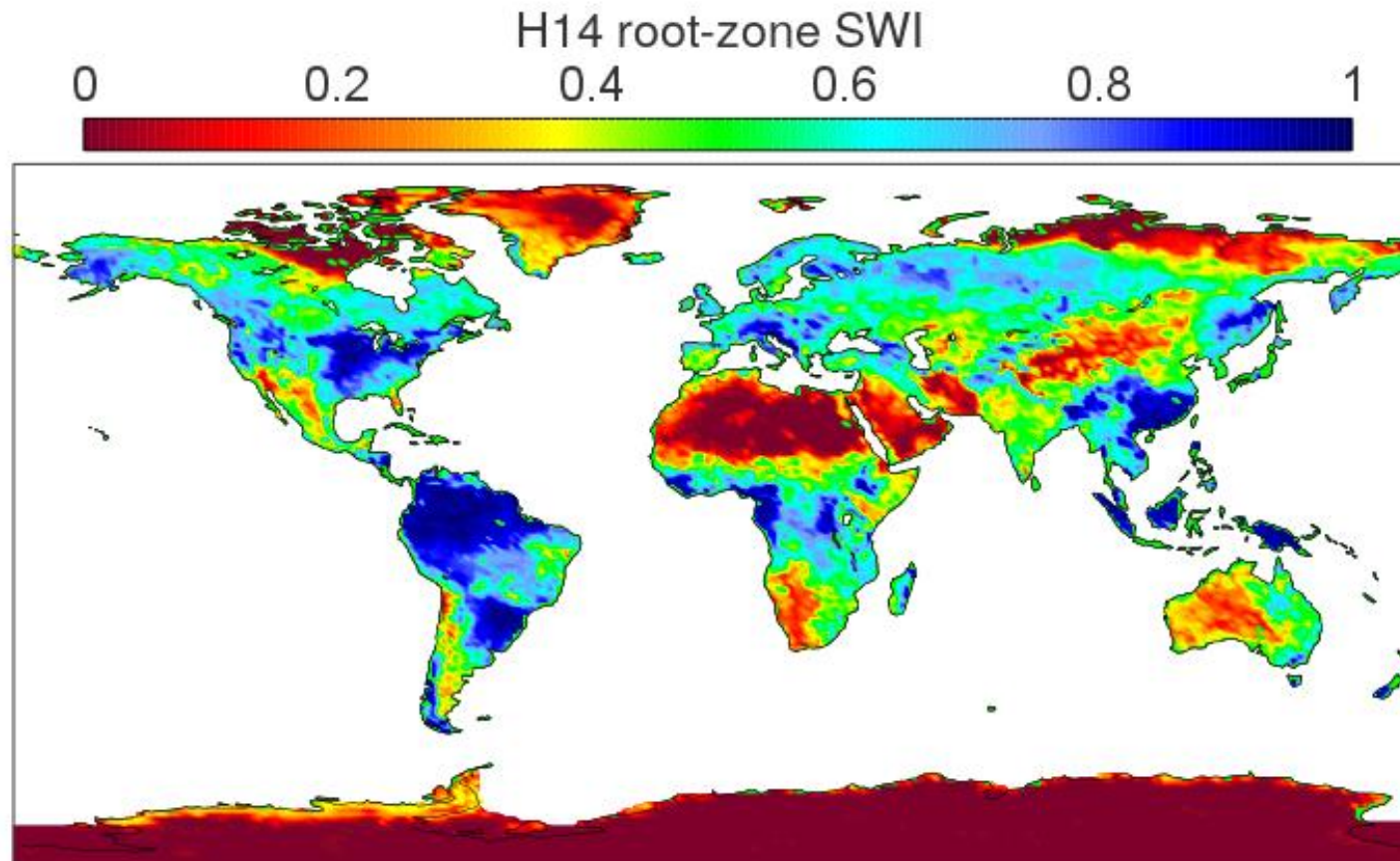
```
# shaded land to make the points stand out more
grey_land_shading = mv.mcoast(
    map_coastline_land_shade      = "on",
    map_coastline_land_shade_colour = "grey",
    map_grid_latitude_increment    = 40,
    map_grid_longitude_increment   = 80,
    map_grid_colour                = "charcoal",
    map_grid = "off",
    map_label = "off")
```

```
#Extract global domain [upper lon, lower lon, upper lat, lower lat]
area_view = mv.geoview(
    map_area_definition = 'corners',
    area = [-89,-179,89,179],
    coastlines = grey_land_shading
)
```

```
#Create title
title = mv.mtext(text_lines = ["<font size='1'>H14 root-zone SWI</font>"],
    text_justification = "centre",
    text_font_size = 0.5,
    text_colour = "charcoal")
```

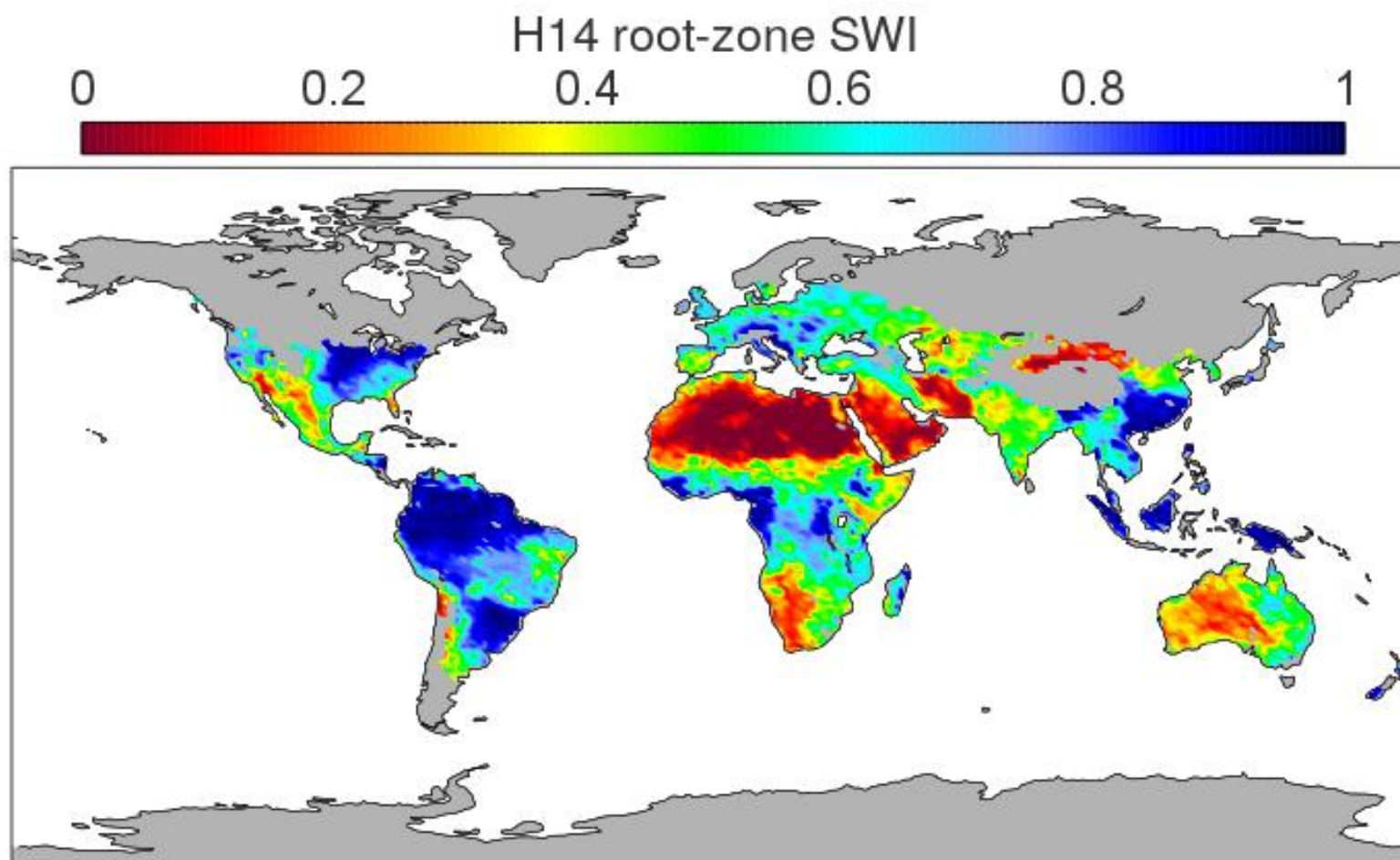
```
#Create plot
mv.setoutput('jupyter')
#mv.setoutput(mv.png_output(output_name = 'H14_SWI_20181231')) # To save as png image
dw = mv.plot_superpage(pages = mv.mvl_regular_layout(area_view,1,1,1,1))
mv.plot(dw[0], RZSM, cont_pc, my_legend,title)
```

Plotting grib data in metview-python



Masking suspect data

```
#Mask suspect data  
masked_data=RZSM.values(); masked_data[qc.values()>1.0]=np.nan  
RZSM = RZSM.set_values(masked_data)
```



Conversion to regular grid

```
import matplotlib.pyplot as plt
import cartopy.crs as ccrs
import metview as mv

filename='h14_2019053000.grib'
SM = mv.read(filename)

SM1 = mv.read(data=SM,param='40.228') #1st layer (0-7 cm depth)
SM2 = mv.read(data=SM,param='41.228') #2nd layer (7-28 cm depth)
SM3 = mv.read(data=SM,param='42.228') #3rd layer (28-100 cm depth)

RZSM = SM1
RZSM = RZSM.set_values(SM1.values()*0.07 + SM2.values()*0.21 + SM3.values()*0.72) #Depth integration for RZSM

RZSM_ll = mv.read(data=RZSM,grid=[0.25,0.25]) #Convert grid to regular lat-lon of 0.25 degrees by 0.25 degrees
```

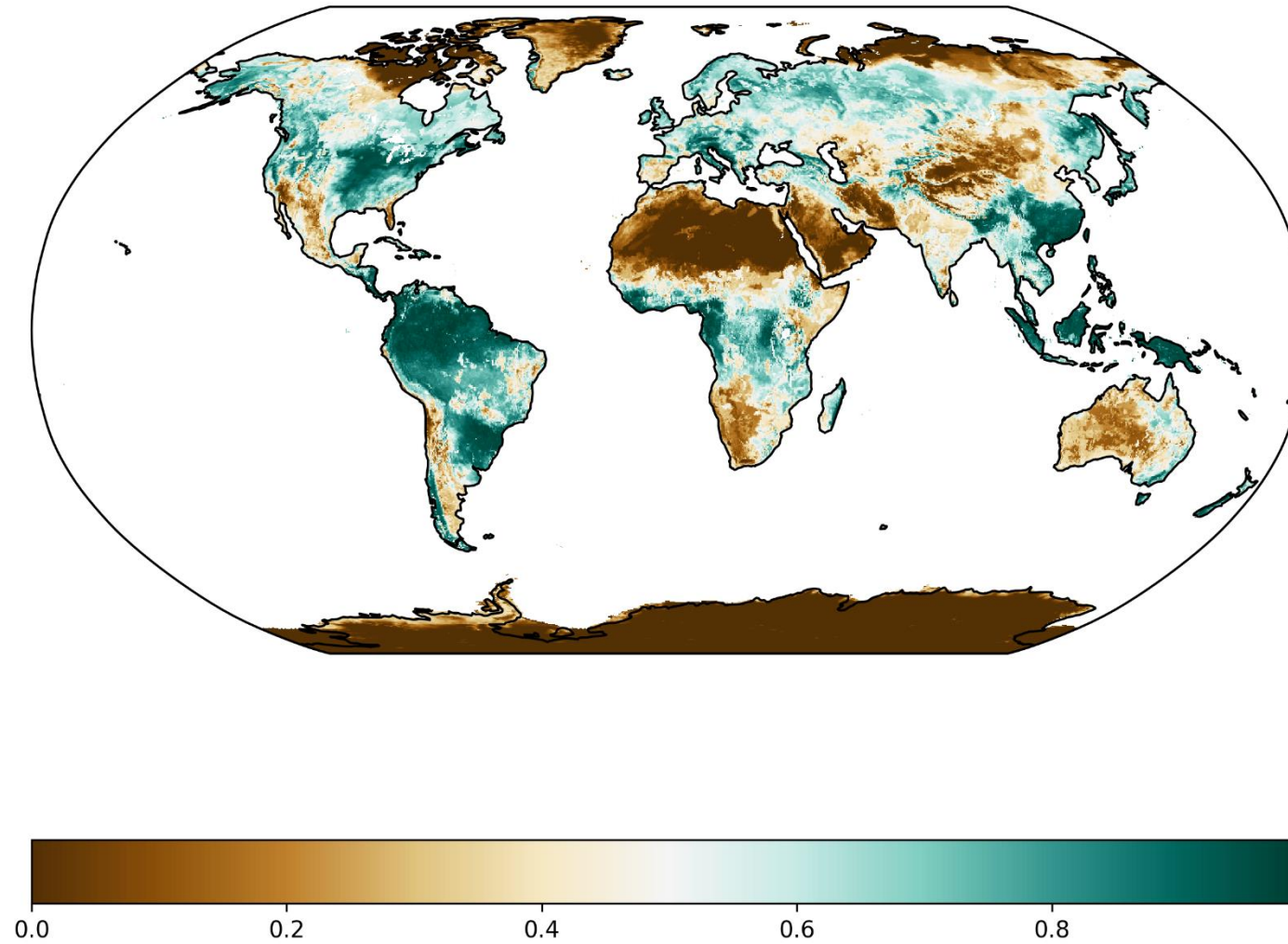
Plot with cartopy

```
[[Nj,Ni]] = mv.grib_get(RZSM_ll,['Nj','Ni']) #Extract number of points in lat/lon
Nj=int(Nj)
Ni=int(Ni)

fig = plt.figure(figsize=(10, 10))
cmap=plt.cm.get_cmap('BrBG') #Choose colour map type
RZSM_np = RZSM_ll.values().reshape(Nj,Ni)
ax = plt.axes(projection=ccrs.Robinson()) #Choose projection
ax.coastlines()
#Plot image with cartopy:
im = ax.imshow(RZSM_np,origin='upper',cmap=cmap,extent=[0.00001,360.,-90,90],transform=ccrs.PlateCarree())
plt.gcf().colorbar(im,ax=ax,orientation='horizontal'); plt.title("H14 root-zone SWI",fontsize=20)
#plt.savefig('Cartopy_plot.png',dpi=300,layout='tight') #To save in png format
plt.show()
plt.close()
```


Plot with cartopy

H14 root-zone SWI



Plot time series over Europe

```
import metview as mv #for reading and plotting grib files
import numpy as np #for grid/data manipulation
import pandas as pd #Needed for time series
import pylab as pl #mainly for plotting

analysis_period = ['2001-01-01', '2010-12-31']

data_range = pd.date_range(analysis_period[0], analysis_period[1])

area = [30, -10.87, 60, 30] #Europe domain with which to integrate [upper lon, lower lon, upper lat, lower lat]

SM_df_layer=pd.DataFrame(pl.empty((data_range.size),data_range)) #Pandas dataframe for time series
```

Plot time series over Europe

```
for days, d in zip(data_range, range(len(data_range))): #Loop over days in time series:

    SM = mv.read("/h27_"+str(days.year)+'%02d'%(days.month)+'%02d'%(days.day)+'00.grib')

    SM1 = mv.read(data=SM, param='40.228') #1st layer (0-7 cm depth)
    SM2 = mv.read(data=SM, param='41.228') #2nd layer (7-28 cm depth)
    SM3 = mv.read(data=SM, param='42.228') #3rd layer (28-100 cm depth)

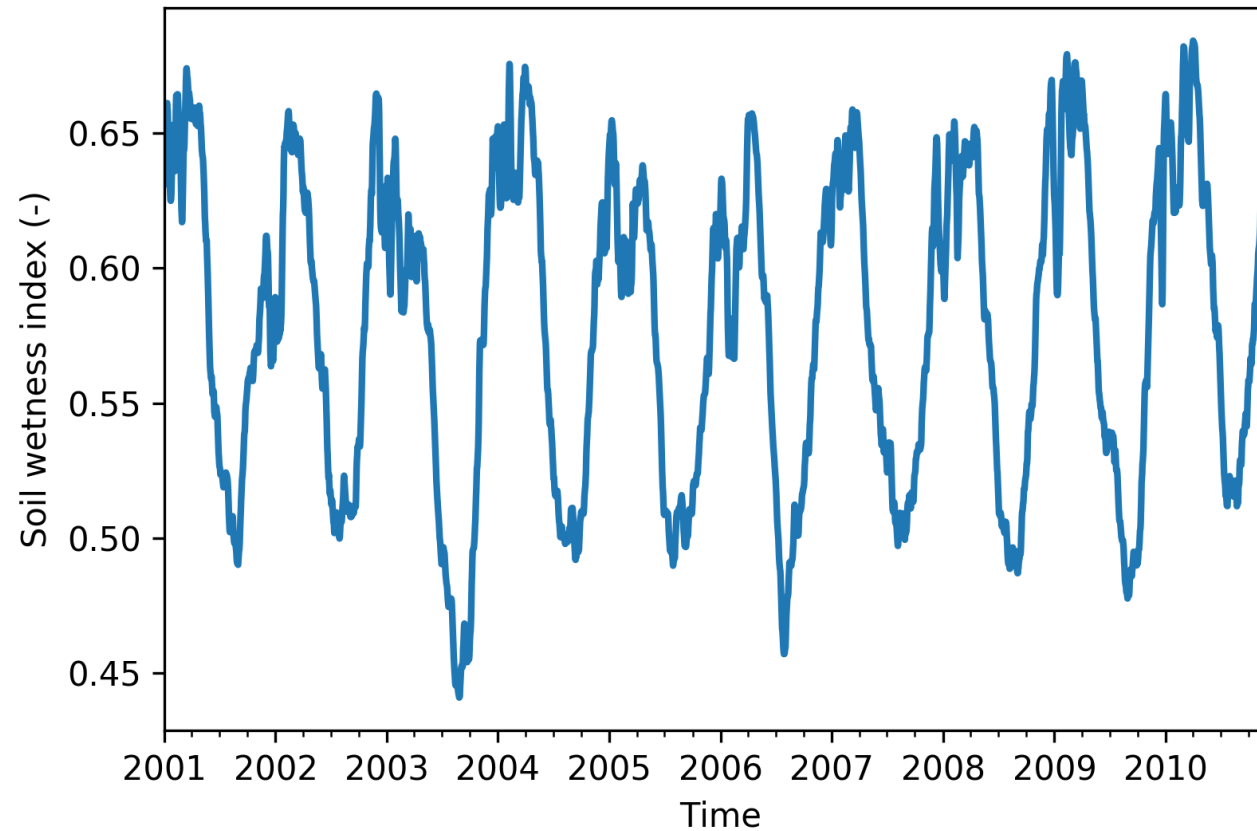
    SM1_layer = mv.integrate(SM1, area) #Average soil moisture over European domain
    SM2_layer = mv.integrate(SM2, area)
    SM3_layer = mv.integrate(SM3, area)

    SM_df_layer.iloc[d] = (SM1_layer*0.07)+(SM2_layer*0.21)+(SM3_layer*0.72) #Depth integrated SWI

#Plot time series
SM_df_layer.index=data_range
SM_df_layer.iloc[:].plot(legend=False, linewidth=2.0)
pl.gca().get_legend().remove()
pl.xlabel('Time'); pl.ylabel('Soil wetness index (-)'); pl.title('H27 Root-zone SWI over Europe');
pl.savefig('H27_time_series.png', dpi=300, layout='tight')
```

Plot time series over Europe

H27 Root-zone SWI over Europe

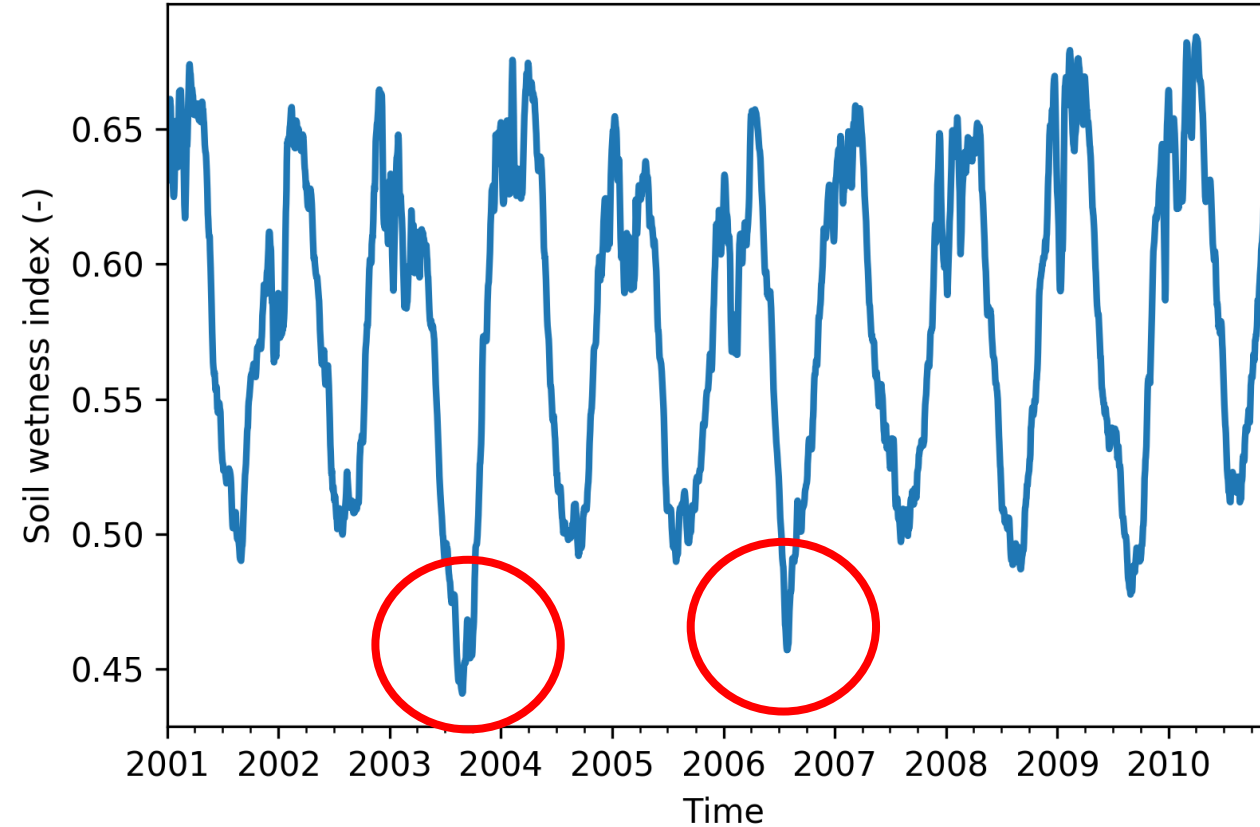


```
#To plot a time series for a particular gridpoint, simply use the "nearest_gridpoint" function  
SM1_point = mv.nearest_gridpoint(SWI1, [60, 16]) #Value of SM1 at nearest point to 60 degrees East, 16 North  
print(SM_1_point)
```

0.5507599115371704

Plot time series over Europe

H27 Root-zone SWI over Europe



**Hot and dry
summers of 2003
and 2006**

```
#To plot a time series for a particular gridpoint, simply use the "nearest_gridpoint" function  
SM1_point = mv.nearest_gridpoint(SWI1, [60, 16]) #Value of SM1 at nearest point to 60 degrees East, 16 North  
print(SM_1_point)
```

0.5507599115371704

Convert grib to netCDF with regional data

- The following examples use the CDO tool, which is free to download from:
<https://code.mpimet.mpg.de/projects/cdo>
- Information about latitude and longitude points for reduced Gaussian grid:
https://www.ecmwf.int/en/forecasts/documentation-and-support/gaussian_n400
- For our grid (T799), there are 1600 regular latitude points (and 800 longitude points). We can now convert our reduced Gaussian grid to regular lat/lon:

module load cdo

#To convert to regular lat/lon

```
cdo -R remapcon,r1600x800 -setgridtype,regular h14_2019053000.grib h14_2019053000_r.grib
```

#Then convert the file from grib to netcdf:

```
cdo -f nc copy h14_2019053000_r.grib h14_2019053000.nc
```

#Then extract the Italian domain from the global netcdf file (lon0=5, lon1=19, lat0=36, lat1=48):

```
cdo -sellonlatbox,5,19,36,48 h14_2019053000.nc h14_2019053000_Italy.nc
```

#File is vastly reduced (h14_2019053000.nc ~ 25 mb, h14_2019053000_Italy.nc ~ 70 kb)!

Regional plot of netCDF

```
import matplotlib.pyplot as plt
import cartopy.crs as ccrs
import metview as mv
from netCDF4 import Dataset # For reading netCDF
```

```
SM="h14_2019053000_Italy.nc"
SM_data=Dataset(SM) #Read netCDF data

lon=SM_data.variables["lon"][:] #Read in lon coordinates
lat=SM_data.variables["lat"][:] #Read in lat coordinates

SWI_11=SM_data.variables["var40"][:] #1st layer (0-7 cm depth)
SWI_12=SM_data.variables["var41"][:] #2nd layer (7-28 cm depth)
SWI_13=SM_data.variables["var42"][:] #3rd layer (28-100 cm depth)
SWI_14=SM_data.variables["var43"][:] #4th layer (100-289 cm)

SWI_RZ=(SWI_11*0.07) + (SWI_12*0.21) + (SWI_13*0.72) #Depth integrated SWI
print (np.shape(SWI_RZ))

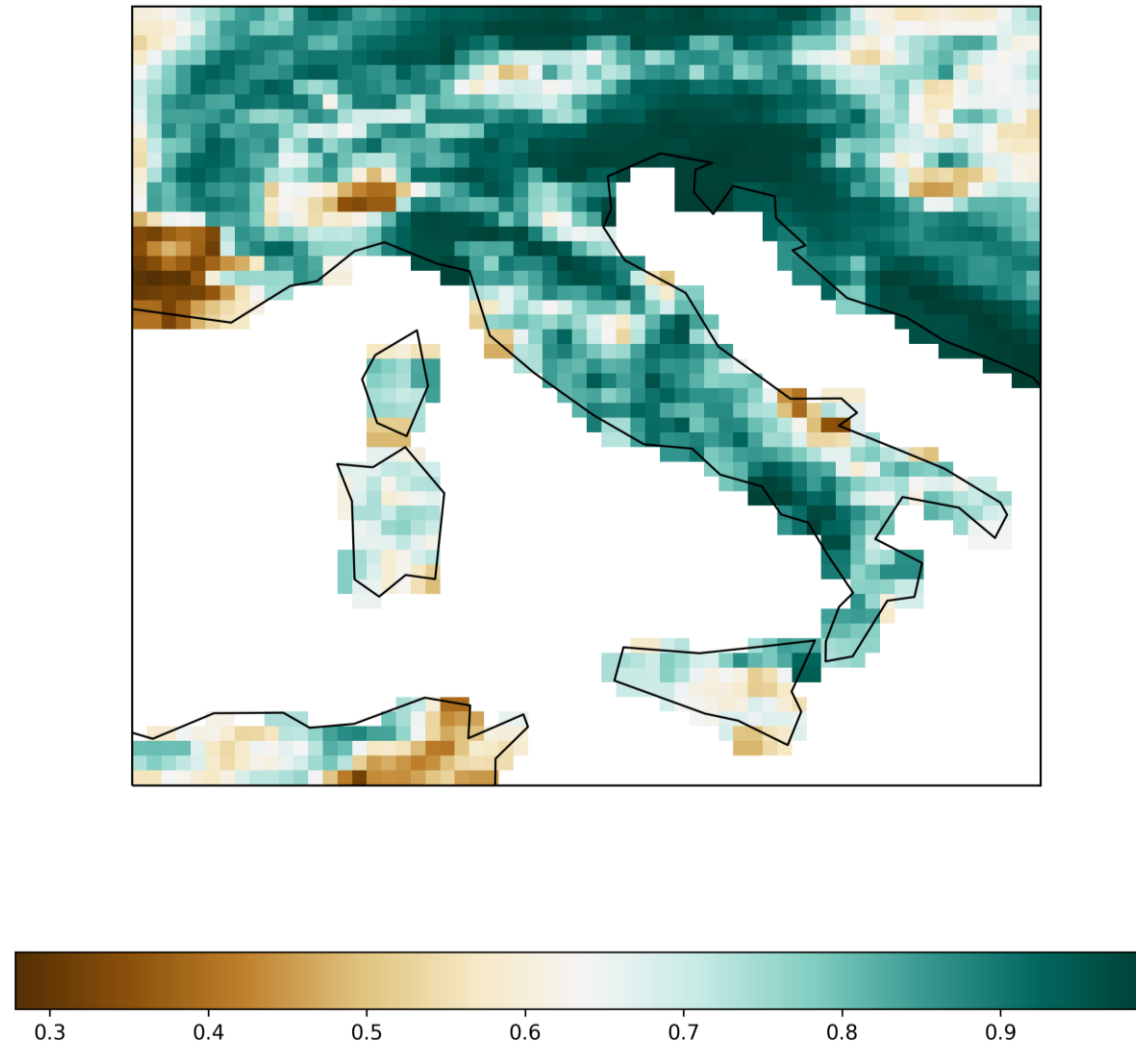
fig = plt.figure(figsize=(10, 10))

cmap=plt.cm.get_cmap('BrBG')

ax = plt.axes(projection=ccrs.PlateCarree())
im = ax.imshow(SWI_RZ[0],cmap=cmap,extent=[5,19,36,48])
plt.gcf().colorbar(im,ax=ax,orientation='horizontal'); plt.title("H14 root-zone SWI",fontsize=20)
ax.coastlines()
plt.savefig('regional_netCDF.png',dpi=300,layout='tight')
```

Regional plot of netCDF

H14 root-zone SWI



Summary

- There are 3 different root-zone SWI products:
 - H14: Global near-real-time 25 km resolution
 - H27: Global data record (1992-2014)
 - H140: Global data record (2015-2016)
- The metview library directly reads and plots grib data from its original non-Gaussian grid
- Metview has other features, including conversion to regular grid, nearest gridpoint extraction and integrating over geographical region
- The CDO tool can convert grib files to regular grids in netCDF format and extract local regions
- Cartopy is a good alternative to metview for regular grids

References

- Albergel, C., 2011 Product Validation Report (PVR-14). URL: http://hsaf.meteoam.it/documents/PVR/SAF_HSAF_PVR-14.pdf. Last accessed April 2018.
- E. Artinyan, 2012: Assimilation of small-scale surface soil moisture (H-SAF H08) into a coupled SVAT and hydrological model system. 2012 Eumetsat Meteorological satellite conference, 3-7 September, 2012, Sopot, Poland***** poster presentation
- Baguis, P. and Roulin, E., 2017. Soil Moisture Data Assimilation in a Hydrological Model: A Case Study in Belgium Using Large-Scale Satellite Data. *Remote Sensing*, 9(8), p.820.
- Dorigo, W. A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., Gruber, A., Drusch, M., Mecklenburg, S., van Oevelen, P., Robock, A., and Jackson, T.: The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements, *Hydrol. Earth Syst. Sci.*, 15, 1675-1698, <https://doi.org/10.5194/hess-15-1675-2011>, 2011.
- D. Fairbairn, P. de Ronsay, and P. Browne, "The new stand-alone surface analysis at ECMWF: Implications for land-atmosphere DA coupling," *J. Hydrometeorol.*, 2019. <https://doi.org/10.1175/JHM-D-19-0074.1>
- Koster, R.D., Sud, Y.C., Guo, Z., Dirmeyer, P.A., Bonan, G., Oleson, K.W., Chan, E., Versegny, D., Cox, P., Davies, H. and Kowalczyk, E., 2006. GLACE: the global land-atmosphere coupling experiment. Part I: overview. *Journal of Hydrometeorology*, 7(4), pp.590-610.
- Massari, C., Brocca, L., Ciabatta, L., Moramarco, T., Gabellani, S., Albergel, C., De Rosnay, P., Puca, S. and Wagner, W., 2015. The use of H-SAF soil moisture products for operational hydrology: flood modelling over Italy. *Hydrology*, 2(1), pp.2-22.
- Struzik, P. and Kępińska-Kasprzak, M., 2016. Use of conventional and satellite data for estimation of evapotranspiration spatial and temporal pattern. *Meteorology Hydrology and Water Management. Research and Operational Applications*, 4.