

part-2

December 5, 2019

1 Using Python with Earth Science Datasets: Cartopy, xarray, and pyresample

1.1 Objective: working with Earth science datasets

- You will learn to:
 - Plot data on a map
 - Read netCDF datasets
 - Perform re-gridding, averaging, filtering, and out-of-memory operations
-

2 Recap on packages

Packages give us additional functionality, saving us the trouble of writing procedures ourselves.

Primary libraries from the last part... * [NumPy](#): Fast mathematical operations on arrays * [Pandas](#): Operations and easy read/write of tabular data. Builds extra functionality on top of NumPy. * [Matplotlib](#): Primary Python plotting/visualization package. You can generate line plots, histograms, scatter plots, etc., with just a few lines of code.

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

[2]: # Bring back our list of aeronet stations...
filename = 'data/aeronet_locations_v3.txt'
station_list = pd.read_csv(filename, skiprows=1)
station_list.columns = ['site', 'lon', 'lat', 'elev']
```

2.1 Cartopy

- Cartopy is not included in Anaconda, need to install yourself.

Open the terminal (Mac/Linux) or Anaconda Prompt (Windows) and type:

```
conda install -c conda-forge cartopy
```

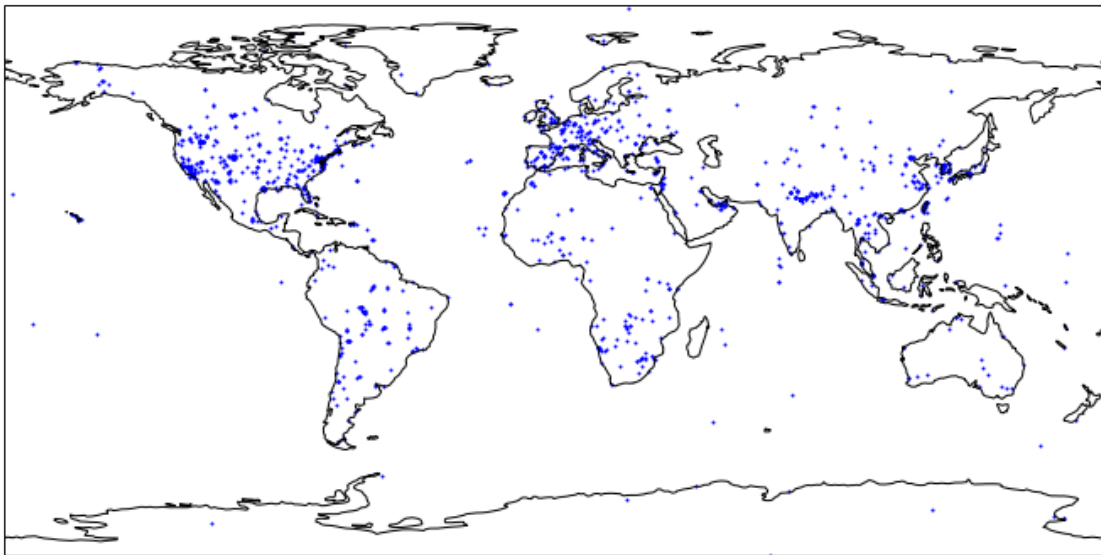
- Rather than import all of Cartopy, we just want the projection classes to pair with matplotlib.
- More [map projections](#).

```
[3]: # Options to increase figure size
plt.rcParams['figure.figsize'] = [12, 6]
plt.rcParams.update({'font.size': 16})

from cartopy import crs as ccrs

[4]: from_proj = ccrs.PlateCarree()
to_proj = ccrs.PlateCarree()

# Center on the Atlantic
ax = plt.axes(projection=to_proj)
ax.coastlines()
plt.scatter(station_list['lon'], station_list['lat'], color='blue', s=1,
            →transform=from_proj)
plt.show()
```

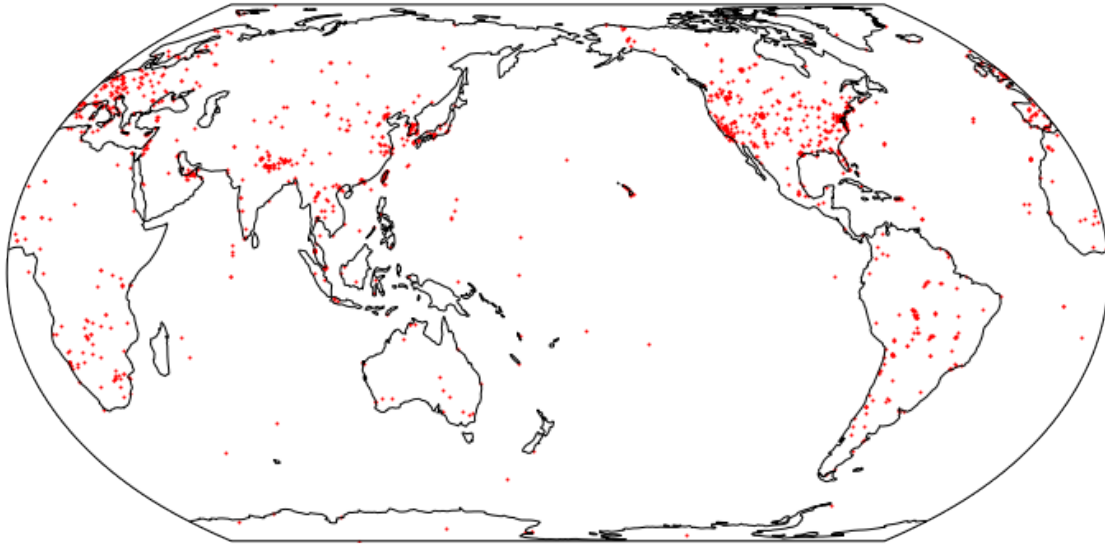


Exercise 1

- Import aeronet_locations_v3.txt with read_csv
- Define the map axes using with option projection=ccrs.PlateCarree()
- Add coastlines
- Make a scatter plot of the station locations
- Challenge: Change the projection to Equal Earth and shift the plot to center on -180 using ccrs.EqualEarth(central_longitude=-180)

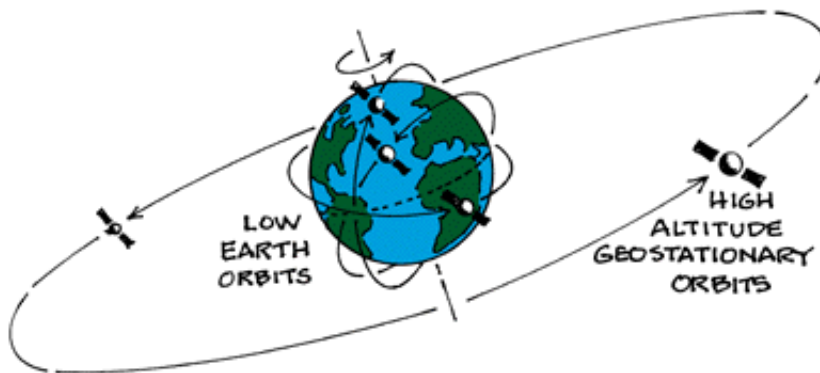
```
[5]: # Solution: Center on the Pacific
from_proj = ccrs.PlateCarree()
to_proj = ccrs.EqualEarth(central_longitude=-180)

ax = plt.axes(projection=to_proj)
ax.coastlines()
plt.scatter(station_list['lon'], station_list['lat'], color='red', s=1,
            ↪transform=from_proj)
plt.show()
```



2.2 Examining the 2018 California Wildfires from Space

- 6,870 fires had burned over a 6,000 km² area.
- The smoke from the wildfires also had an impact on air quality both in proximity of the fires as well as across the country.
- We'll look at satellite observations from **Suomi-NPP** and **GOES-17** to show the impact of the California wildfires on AOD.



We're in the golden age of satellite datasets, which is a blessing and a curse:

- Inundated with datasets, don't know which ones to use
- No single repository for access of the data
- Inconsistent formatting and filetypes

netCDF4 and HDF5 are the dominant formats used in satellite remote sensing (but others do exist)

2.3 xarray

- xarray is like pandas, but for N-dimensional arrays.
- Can read and write NetCDF, HDF5, and GRIB (with the additional cfgrib package) files.
- Can perform efficient operations on these datasets, including out-of-memory and parallel operations.

2.3.1 LEO Example: Suomi-NPP

LEO Satellites orbit the Earth many times a day, data are organized in 1 minute swaths per file. We'll be looking at aerosol optical depth data over California.

```
[6]: import xarray
```

```
[7]: # Import your data...
filename = 'data/
→JRR-AOD_v1r2_npp_s201811082130296_e201811082131537_c201811082228260.nc'
npp = xarray.open_dataset(filename)

# Print a list of variables
list(npp.variables)
```

```
[7]: ['Latitude', 'Longitude', 'QCA11', 'AOD550']
```

```
[8]: AOD_NPP = npp['AOD550']
lat_NPP = npp['Latitude']
lon_NPP = npp['Longitude']
```

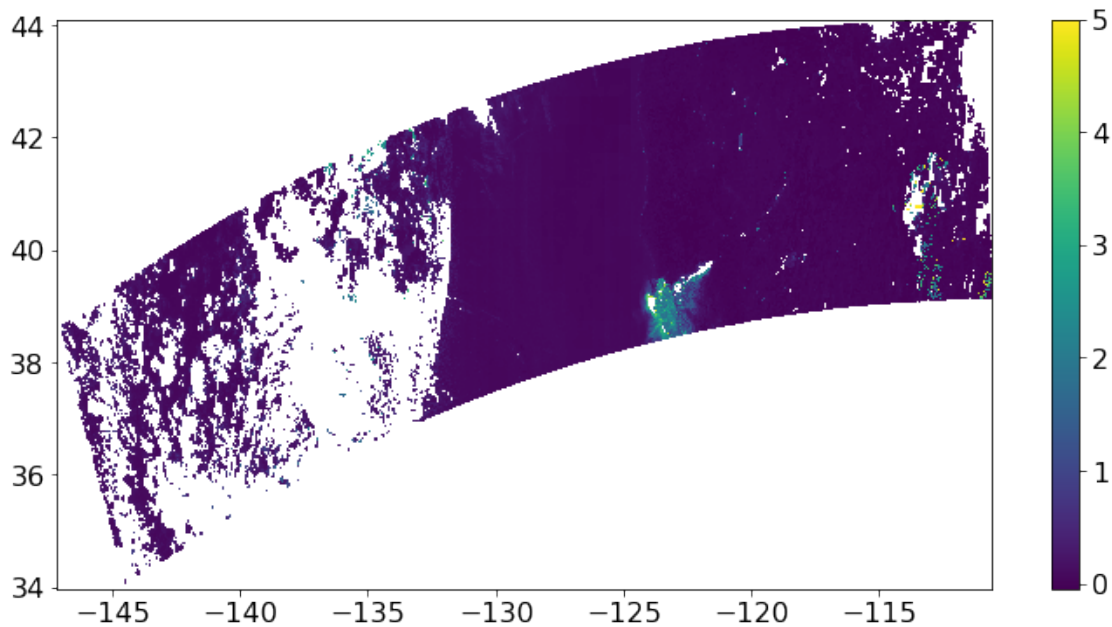
```
[9]: # xarray has automatically read in the missing values as nan
AOD_NPP
```

```
[9]: <xarray.DataArray 'AOD550' (Rows: 768, Columns: 3200)>
[2457600 values with dtype=float32]
Coordinates:
  Latitude   (Rows, Columns) float32 ...
  Longitude  (Rows, Columns) float32 ...
Dimensions without coordinates: Rows, Columns
Attributes:
  long_name:    Aerosol optical depth at 550 nm
  units:        1
  valid_range:  [-0.05  5.  ]
```

```
[10]: AOD_NPP.mean()
```

```
[10]: <xarray.DataArray 'AOD550' ()>  
array(0.082712, dtype=float32)
```

```
[11]: plt.pcolormesh(lon_NPP, lat_NPP, AOD_NPP)  
plt.colorbar()  
plt.show()
```

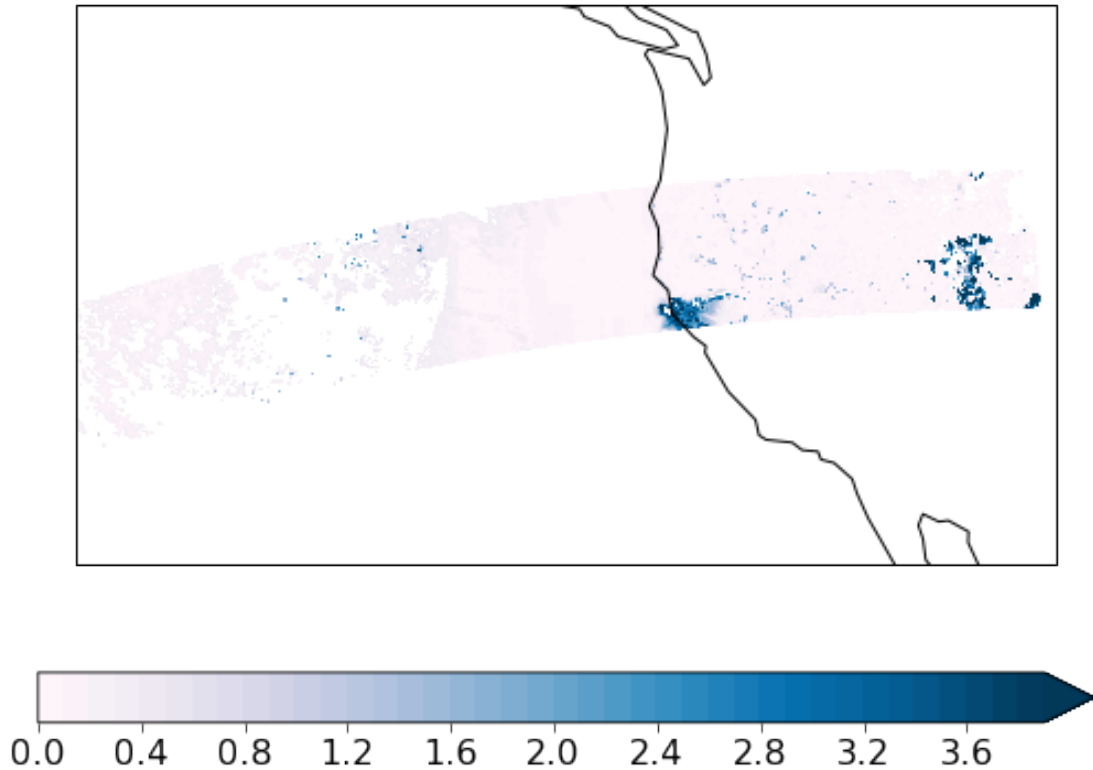


In the next plot, we'll * Add in the cartopy map * Change the color scheme * See the [matplotlib color schemes](#) and [ColorBrewer schemes](#). * Recommend [cmocean](#), a collection of colormaps for oceanography but great for other purposes too. * There is an option to zoom in on the data using `plt.xlim` and `plt.ylim`

```
[12]: from_proj = ccrs.PlateCarree()  
to_proj = ccrs.PlateCarree()  
  
levs = np.arange(0, 4, 0.1)  
  
# Using cartopy, create the map projection and plot the data  
ax = plt.axes(projection=to_proj)  
ax.coastlines()  
  
# Can change color scheme using the cmap argument  
plt.contourf(lon_NPP, lat_NPP, AOD_NPP, levs, transform=from_proj, extend='max',  
             cmap="PuBu")  
  
plt.colorbar(orientation="horizontal", fraction=0.07)  
  
plt.xlim(-145, -110)
```

```
plt.ylim(30, 50)

# To zoom in on data:
#plt.xlim(-125, -120)
#plt.ylim(38, 44)
plt.show()
```



Exercise 2

??? = Fill in the blanks!

Import from netCDF files

- Import JRR-AOD_v1r1_npp_s201808091957192_e201808091958434_c201808092051240.nc using the `xarray.open_dataset` command.
- Inspect the available variables.
- Save the latitude, longitude, and AOD to arrays.

Create a cartopy plot

- Define the axes, including the projection.
 - Challenge: Make an orthographic plot using: `ccrs.Orthographic(central_longitude=-75.0, central_latitude=0.0)`
- Create a plot using `plt.contourf(???, ???, ???, transform=???)`

- Challenge: Change the data scale from the default to 0.0-1.6
- Remember to `plt.show()` at the end to display!

2.4 Common tasks

1. Regridding
2. Masking datasets
3. Filtering with Quality Flags

2.4.1 Regridding

Regridding is the process of interpolating from one grid resolution to a different grid resolution and [UCAR's website has a good discussion](#).

There are a few options:

- Interpolate using `griddata` from SciPy package (2D interpolate too slow/limited number of points)
- Regridding in `iris` package (autodetection of GRIB and NC fileformats... if they follow the conventions!)
- `xESMF`, a Python package for regridding for gridded datasets (not designed for satellite data)
- **Pyresample**: the syntax can be fairly complex, but very fast

Pyresample also is not included in Anaconda, so install using:

```
conda install -c conda-forge pyresample
```

Steps: 1. Define the new grid (either in Python or import an irregular array) 2. Define the swath/satellite grid 3. Resample to get the new values for the updated grid

```
[13]: from pyresample import geometry
      from pyresample.kd_tree import resample_nearest

[14]: # Create a new grid at 0.1 degree resolution
      x = np.arange(lon_NPP.min(), lon_NPP.max(), 0.1)
      y = np.arange(lat_NPP.min(), lat_NPP.max(), 0.1)
      new_lon, new_lat = np.meshgrid(x,y)

      # define the new grid using
      new_lonlat = geometry.GridDefinition(lons=new_lon, lats=new_lat)

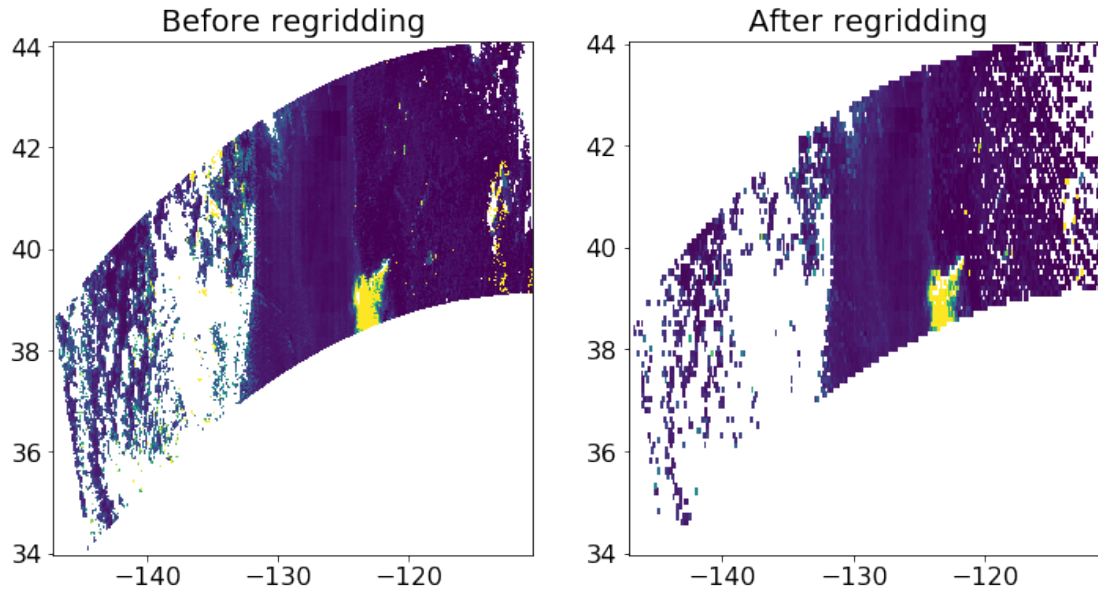
[15]: # Input list of swath points
      old_lonlat = geometry.SwathDefinition(lons=lon_NPP, lats=lat_NPP)

      # Resample the data
      new_AOD = resample_nearest(old_lonlat, AOD_NPP.values, new_lonlat,
      ↪radius_of_influence=5000, fill_value=None)

[16]: # To compare: Putting two plots together using plt.subplot
      plt.subplot(1, 2, 1)
      plt.title("Before regridding")
```

```
plt.pcolormesh(lon_NPP, lat_NPP, AOD_NPP, vmin=0, vmax=1)

plt.subplot(1, 2, 2)
plt.pcolormesh(new_lon, new_lat, new_AOD, vmin=0, vmax=1)
plt.title("After regridding")
plt.show()
```



2.4.2 Masking datasets

May want to add a land/ocean mask to our datasets

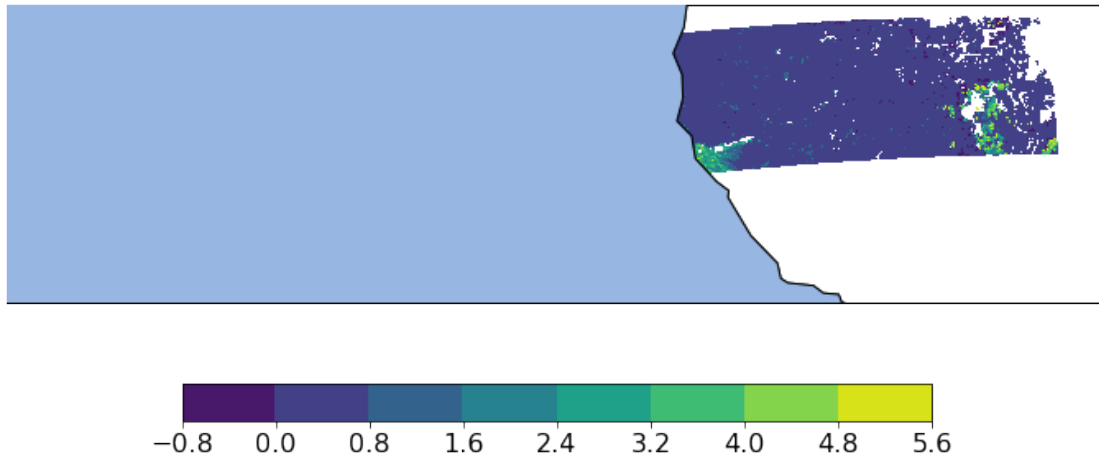
```
[17]: import cartopy.feature as feature

[18]: from_proj = ccrs.PlateCarree()
      to_proj = ccrs.PlateCarree()

      ax = plt.axes(projection=to_proj)
      ax.coastlines()
      plot = ax.contourf(lon_NPP, lat_NPP, AOD_NPP, transform=from_proj)

      # Mask out the ocean: zorder places it on top of the existing data
      ax.add_feature(feature.OCEAN, zorder=100, edgecolor='black')

      cb = plt.colorbar(plot, orientation="horizontal", fraction=0.07)
      plt.show()
```

Exercise 3

- Filter your plot in Exercise 2 (using NPP data) by data quality using the variable 'QCAL1'
- Import QCAL1 into a variable
- Create a mask for medium/low quality data or pixels with no retrieval
- Make a new map with the filtered data

```
[19]: qc_flag = npp['QCAL1']

mask_HQ = (qc_flag != 0)
AOD_NPP_HQ = np.ma.masked_where(mask_HQ, qc_flag)
```

2.5 Saving images

- Create the plot, then use plt.savefig

```
[20]: from_proj = ccrs.PlateCarree()
to_proj = ccrs.PlateCarree()

levs = np.arange(0, 1.8, 0.1)

ax = plt.axes(projection=to_proj)
plt.contourf(lon_NPP, lat_NPP, AOD_NPP_HQ, levs, transform=from_proj)
ax.coastlines()
plt.colorbar(orientation="horizontal", fraction=0.07)

# Add DPI option to change resolution of the plot (maintains the same aspect_
→ratio)
plt.savefig('Wildfires_AOD_2018221_1612.png', dpi=500)

# TIP: If you want to suppress the output (runs faster!), use the following:
```

```
plt.close()
```

2.6 Out-of-memory processing

- Some datasets are so big that it is not a good idea to load them all into memory.
- xarray operations can be run on successive pieces of datasets so the entire data is never in memory. Operations will be run in parallel! [See more details](#).
- We'll use the MERRA-2 reanalysis of AOD.

```
[21]: filename = 'data/MERRA2_400.inst3_2d_gas_Nx.20181109.nc4.nc'  
merra = xarray.open_dataset(filename, chunks={'time': 1})
```

```
[22]: merra['AODANA']
```

```
[22]: <xarray.DataArray 'AODANA' (time: 8, lat: 361, lon: 576)>  
dask.array<shape=(8, 361, 576), dtype=float32, chunksize=(1, 361, 576)>  
Coordinates:  
  * lat      (lat) float64 -90.0 -89.5 -89.0 -88.5 -88.0 ... 88.5 89.0 89.5 90.0  
  * lon      (lon) float64 -180.0 -179.4 -178.8 -178.1 ... 178.1 178.8 179.4  
  * time      (time) datetime64[ns] 2018-11-09 ... 2018-11-09T21:00:00  
Attributes:  
    long_name:      Aerosol Optical Depth Analysis  
    units:          1  
    fmissing_value: 1000000000000000.0  
    standard_name:   Aerosol Optical Depth Analysis  
    vmax:           1000000000000000.0  
    vmin:           -1000000000000000.0  
    valid_range:     [-1.e+15  1.e+15]  
    origname:        AODANA  
    fullnamepath:    /AODANA
```

```
[23]: # Let's do a time-mean  
  
merra['AODANA'].mean(dim='time')
```

```
[23]: <xarray.DataArray 'AODANA' (lat: 361, lon: 576)>  
dask.array<shape=(361, 576), dtype=float32, chunksize=(361, 576)>  
Coordinates:  
  * lat      (lat) float64 -90.0 -89.5 -89.0 -88.5 -88.0 ... 88.5 89.0 89.5 90.0  
  * lon      (lon) float64 -180.0 -179.4 -178.8 -178.1 ... 178.1 178.8 179.4
```

The mean does not compute! xarray will avoid doing the computation with out-of-memory datasets until you tell it to.

```
[24]: mean_AOD = merra['AODANA'].mean(dim='time').compute()  
mean_AOD
```

```
[24]: <xarray.DataArray 'AODANA' (lat: 361, lon: 576)>  
array([[0.045397, 0.045397, 0.045397, ..., 0.045397, 0.045397, 0.045397],  
       [0.047764, 0.047781, 0.047797, ..., 0.047711, 0.047729, 0.047746],  
       [0.049648, 0.049689, 0.049729, ..., 0.049524, 0.049565, 0.049607],  
       ...,  
       [0.045397, 0.045397, 0.045397, ..., 0.045397, 0.045397, 0.045397],  
       [0.047764, 0.047781, 0.047797, ..., 0.047711, 0.047729, 0.047746],  
       [0.049648, 0.049689, 0.049729, ..., 0.049524, 0.049565, 0.049607],  
       ...,  
       [0.045397, 0.045397, 0.045397, ..., 0.045397, 0.045397, 0.045397],  
       [0.047764, 0.047781, 0.047797, ..., 0.047711, 0.047729, 0.047746],  
       [0.049648, 0.049689, 0.049729, ..., 0.049524, 0.049565, 0.049607]])
```

```

...,
[0.050253, 0.05023 , 0.050207, ..., 0.050324, 0.0503 , 0.050277],
[0.052478, 0.052453, 0.052429, ..., 0.052554, 0.052529, 0.052503],
[0.054713, 0.054713, 0.054713, ..., 0.054713, 0.054713, 0.054713]],
dtype=float32)
Coordinates:
* lat      (lat) float64 -90.0 -89.5 -89.0 -88.5 -88.0 ... 88.5 89.0 89.5 90.0
* lon      (lon) float64 -180.0 -179.4 -178.8 -178.1 ... 178.1 178.8 179.4

```

```

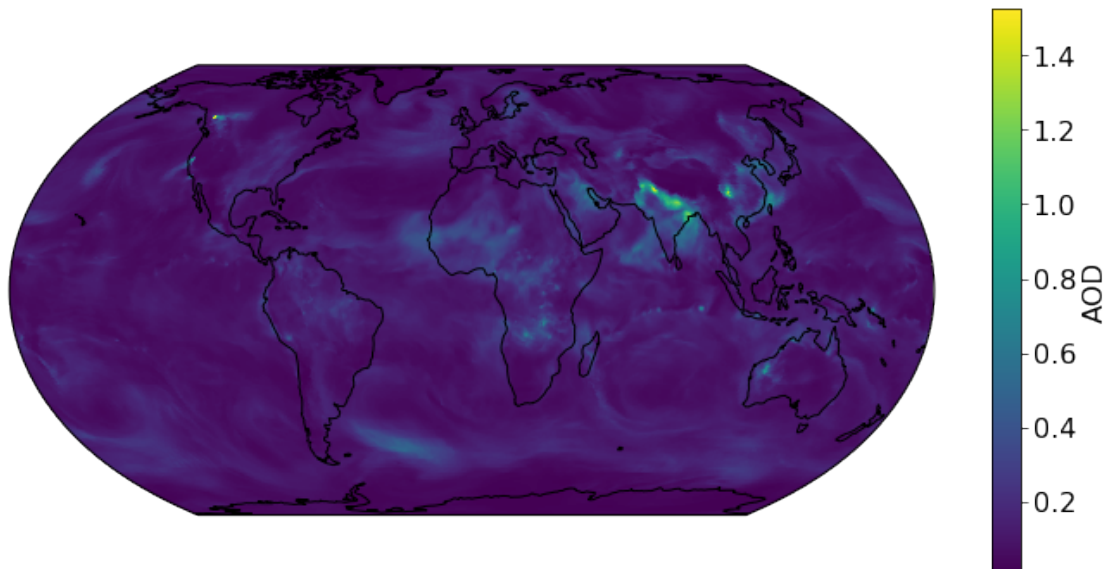
[25]: from_proj = ccrs.PlateCarree()
to_proj = ccrs.EqualEarth()

# Using cartopy, create the map projection and plot the data
ax = plt.axes(projection=to_proj)
ax.coastlines()

# Can change color scheme using the cmap argument
plt.pcolormesh(merra['lon'], merra['lat'], mean_AOD, transform=from_proj)
plt.colorbar(label='AOD')

plt.show()

```



2.7 Scripting

- Notebooks are nice for sharing results with others, but scripts are useful for automating tasks.
- You can export a script from Jupyter Notebook directly: File Download As Python (.py)