In [465…

```
import warnings
warnings.filterwarnings("ignore")
import xarray as xr
import cartopy.crs as ccrs
from cartopy.mpl.ticker import LongitudeFormatter, LatitudeFormatter
import matplotlib.pyplot as plt
import numpy as np
```

1. Niño 3.4 index

1.1 Compute monthly climatology for SST from Niño 3.4 region, and subtract climatology from SST time series to obtain anomalies.

In [466…

```
ncfile = 'NOAA_NCDC_ERSST_v3b_SST.nc'
ds = xr.open_dataset(ncfile)
ds
```

Out[466…

xarray.Dataset

▶ Dimensions: (**lat**: 89, **lon**: 180, **time**: 684)

▼ Coordinates:

lat	(lat)	float32	-88.0 -86.0 -84.0 ... 86.0 ...
lon	(lon)	float32	0.0 2.0 4.0 ... 354.0 356.0 ...
time	(time)	datetime64[ns]	1960-01-15 ... 2016-12-15

▼ Data variables:

sst	(time, lat, lon)	float32	...

▶ Indexes: (3)

▼ Attributes:

Conventions : IRIDL

source : https://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCDC/.ERSST/.version3b/.sst/

history : extracted and cleaned by Ryan Abernathey for Research Computing in Earth Science

In [467…

```
# Read variables
time = ds['time'][:]
lat  = ds['lat'][:]
lon  = ds['lon'][:]
sst  = ds['sst'][:,:,:]
```

In [468…

```
# Set up the map.
def plotmap():
    plt.figure(figsize=(15,10))
    plt.rcParams['figure.figsize'] = (15, 10)

    #Set the projection information
```

```
    proj = ccrs.PlateCarree(central_longitude=180)
    #Create a figure with an axes object and ass the projection to that axes.
    fig,ax = plt.subplots(subplot_kw=dict(projection=proj))

    # Set X and Y axes
    ax.set_xticks([0,60,120,180,240,300,360],crs=ccrs.PlateCarree())
    ax.set_yticks([-90,-60,-30,0,30,60,90],crs=ccrs.PlateCarree())
    lon_formatter = LongitudeFormatter()
    lat_formatter = LatitudeFormatter()
    ax.xaxis.set_major_formatter(lon_formatter)
    ax.yaxis.set_major_formatter(lat_formatter)
    ax.tick_params(axis='both',labelsize=13)

    # Add coastlines
    ax.coastlines(zorder=10)

    # Add gridlines
    ax.gridlines(xlocs=np.arange(0,361,30), ylocs=np.arange(-90,91,30))

    return fig,ax
```

In [471…

```
# Calculate the monthly mean SST
sstmean = np.zeros((12,89,180))
for i in range(0,12):
    month = sst.isel(time=slice(i,180,12)).values
    monthmean = np.mean(month,axis=0)
    sstmean[i,:,:] = monthmean[:,:]
```

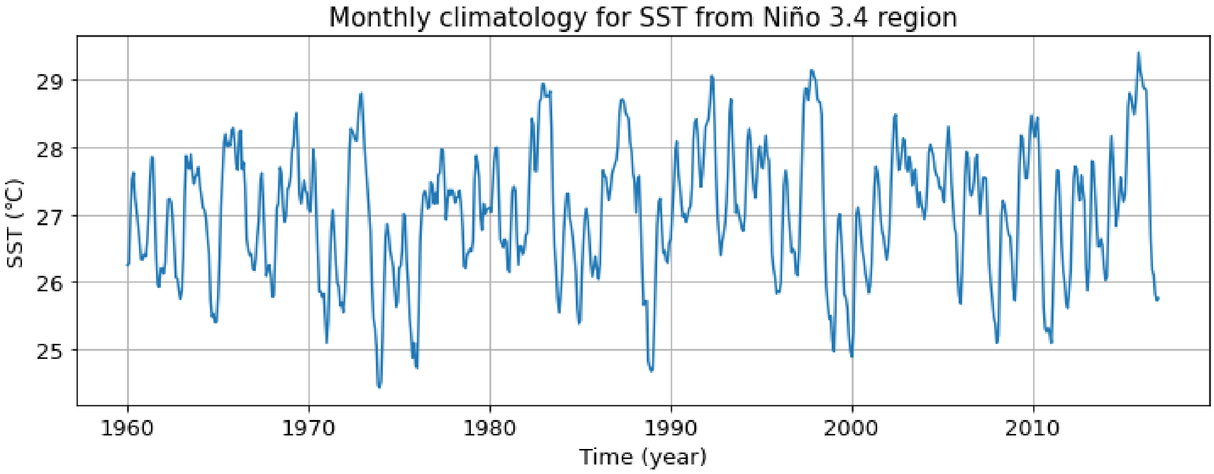
In [475…

```
# Select the Niño 3.4 region
# Niño 3.4 (5N-5S, 170W-120W)
region34 = sst.sel(lat=slice(-5,5)).sel(lon=slice(190,240))
#ctime = time.sel(time=slice('1982','2018'))
region34_mean = np.mean(region34,axis=(1,2))
```

In [476…

```
fig = plt.figure(figsize=(12,4))
plt.rcParams['figure.figsize'] = (12,4)

fig, ax = plt.subplots()

ax.plot(time,region34_mean)
ax.tick_params(axis='both',labelsize=13)
ax.set_xlabel('Time (year)',fontsize=13)
ax.set_ylabel('SST (℃)',fontsize=13)
ax.set_title('Monthly climatology for SST from Niño 3.4 region',fontsize=15)
ax.grid()

plt.show()
```

```
<Figure size 864x288 with 0 Axes>
```

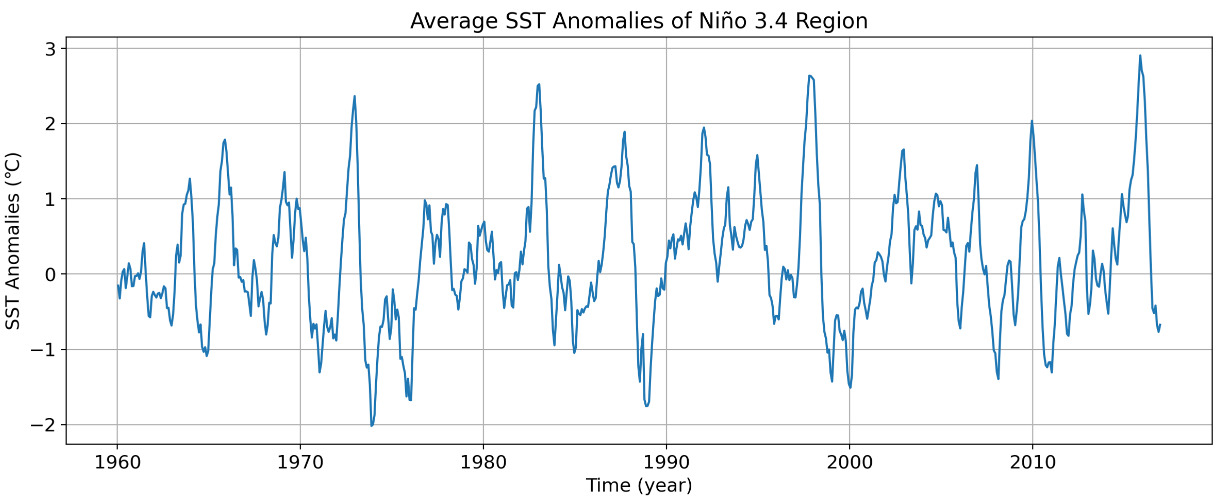


In [477…

```
# Calculate the monthly mean SST of Niño 3.4 region
region34_m_mean = np.zeros(12)
for i in range(0,12):
    region34_m_mean[i] = np.mean(region34_mean.isel(time=np.arange(i,180,12)))

# Calculate the anomalies
# Subtract the monthly mean SST to detrend the seasonal variation
region34_anoma = np.zeros(57*12)
for i in range(0,57*12):
    k = i % 12
    region34_anoma[i] = region34_mean.values[i] - region34_m_mean[k]
```

In [478…

```
fig, ax = plt.subplots(figsize=(12,5),dpi=200)

ax.plot(time,region34_anoma)
ax.tick_params(axis='both',labelsize=13)
#ax.set_ylim(-3.5,3.5)
ax.set_xlabel('Time (year)',fontsize=13)
ax.set_ylabel('SST Anomalies (℃)',fontsize=13)
ax.set_title('Average SST Anomalies of Niño 3.4 Region',fontsize=15)
ax.grid()
plt.tight_layout()
plt.show()
```

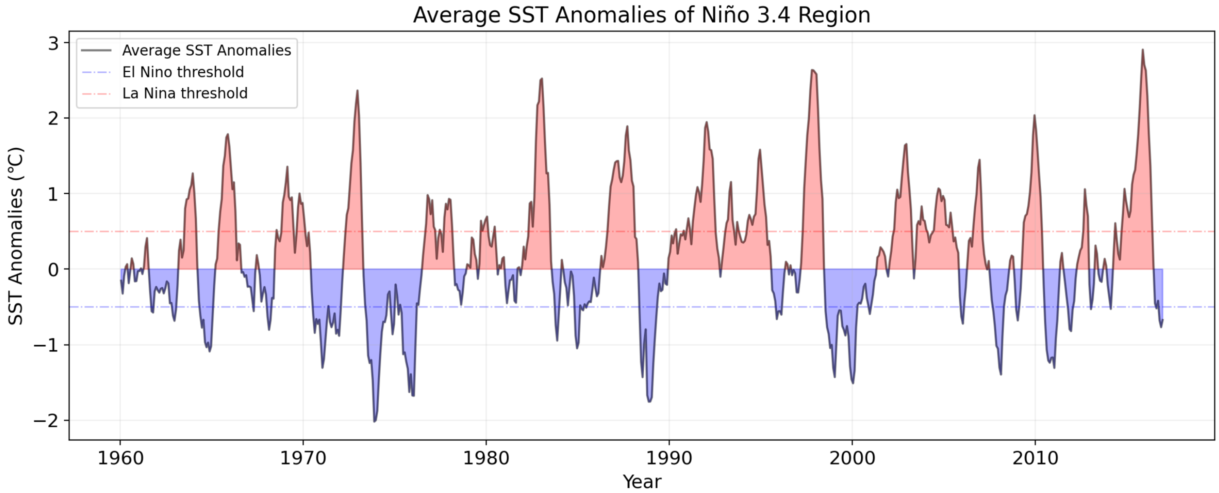


1.2 Visualize the computed Niño 3.4.

In [479…

```
fig, ax = plt.subplots(figsize=(12,5),dpi=200)
```

```
ax.plot(time,region34_anoma, label = 'Average SST Anomalies',color='black', a
ax.fill_between(time, region34_anoma, where=(region34_anoma > 0), interpolate
ax.fill_between(time, region34_anoma, where=(region34_anoma < 0), interpolate

ax.axhline(y=-0.5, color='blue', linestyle='-.', label='El Nino threshold', l
ax.axhline(y=0.5, color='red', linestyle='-.',  label='La Nina threshold', li

ax.tick_params(axis='both',labelsize=13)
#ax.set_ylim(-3.5,3.5)
ax.set_xlabel('Year',fontsize=13)
ax.set_ylabel('SST Anomalies (℃)',fontsize=13)
ax.set_title('Average SST Anomalies of Niño 3.4 Region',fontsize=15)
ax.grid(alpha=0.2)

plt.tight_layout()
plt.legend()
plt.show()
```



2. Earth's energy budget

2.1 Make a 2D plot of the time-mean TOA longwave, shortwave, and solar radiation for all-sky conditions. Add up the three variables above and verify (visually) that they are equivalent to the TOA net flux.

In [480…

```
ncfile2 = 'CERES_EBAF-TOA_200003-201701.nc'
ds2 = xr.open_dataset(ncfile2)
ds2
```

Out[480…

xarray.Dataset

▸ Dimensions: (**lon**: 360, **time**: 203, **lat**: 180)

▾ Coordinates:

lon	(lon)	float32	0.5 1.5 2.5 ... 357.5 358.5 ...
time	(time)	datetime64[ns]	2000-03-15 ... 2017-01-15
lat	(lat)	float32	-89.5 -88.5 -87.5 ... 88.5 ...

▾ Data variables:

toa_sw_all_mon	(time, lat, lon)	float32	...
toa_lw_all_mon	(time, lat, lon)	float32	...

toa_net_all_mon	(time, lat, lon)	float32	...
toa_sw_clr_mon	(time, lat, lon)	float32	...
toa_lw_clr_mon	(time, lat, lon)	float32	...
toa_net_clr_mon	(time, lat, lon)	float32	...
toa_cre_sw_mon	(time, lat, lon)	float32	...
toa_cre_lw_mon	(time, lat, lon)	float32	...
toa_cre_net_mon	(time, lat, lon)	float32	...
solar_mon	(time, lat, lon)	float32	...
cldarea_total_d...	(time, lat, lon)	float32	...
cldpress_total_...	(time, lat, lon)	float32	...
cldtemp_total_...	(time, lat, lon)	float32	...
cldtau_total_da...	(time, lat, lon)	float32	...

▶ Indexes: (3)

▼ Attributes:

title :	CERES EBAF (Energy Balanced and Filled) TOA Fluxes. Monthly Averages and 07/2005 to 06/2015 Climatology.
institution :	NASA/LaRC (Langley Research Center) Hampton, Va
Conventions :	CF-1.4
comment :	Data is from East to West and South to North.
Version :	Edition 4.0; Release Date March 7, 2017
Fill_Value :	Fill Value is -999.0
DOI :	10.5067/TERRA+AQUA/CERES/EBAF-TOA_L3B.004.0
Production_File...	List of files used in creating the present Master netCDF file: /homedir/nloeb/ebaf/monthly_means/adj_fluxes/deliverable/sw*.gz /homedir/nloeb/ebaf/monthly_means/adj_fluxes/deliverable/lw*.gz /homedir/nloeb/ebaf/monthly_means/adj_fluxes/deliverable/net*.gz /homedir/nloeb/ebaf/monthly_means/adj_fluxes/deliverable/solflx*.gz /homedir/nloeb/ebaf/monthly_means/out_glob.dat

In [481…

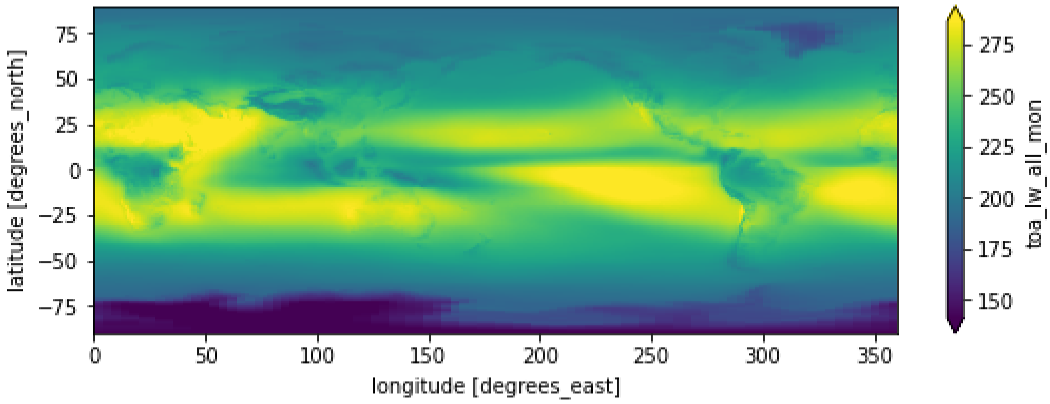
```
lw = ds2['toa_lw_all_mon']
sw = ds2['toa_sw_all_mon']
rad = ds2['solar_mon']
net = ds2['toa_net_all_mon']
```

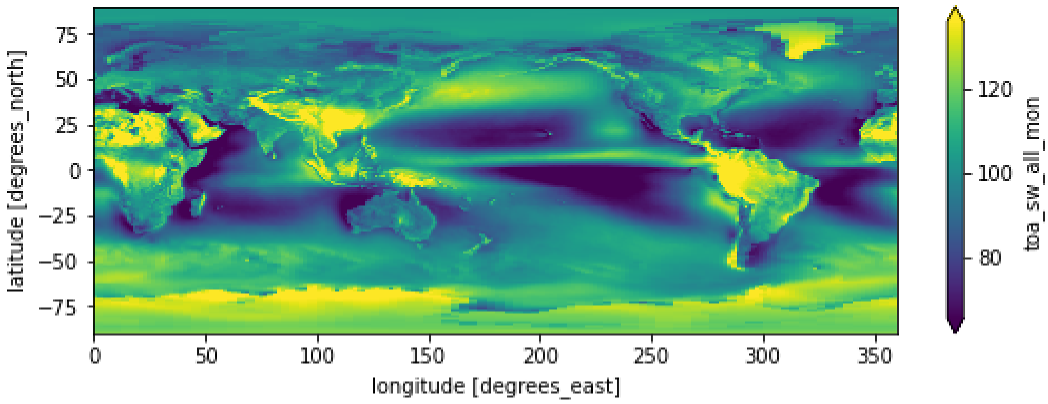
In [483…

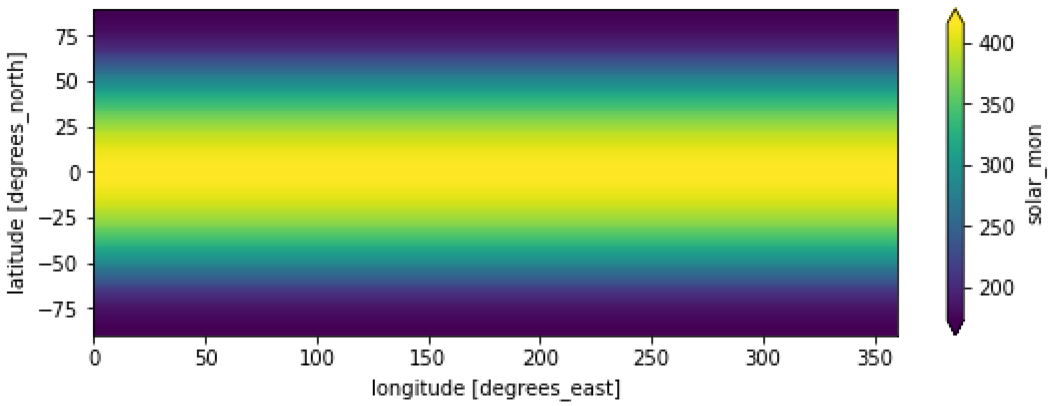
```
# Make a 2D plot of the time-mean TOA longwave, shortwave, and solar radiatio
lw.mean(dim='time').plot(size=3,robust=True)
sw.mean(dim='time').plot(size=3,robust=True)
rad.mean(dim='time').plot(size=3,robust=True)
```

Out[483…

```
<matplotlib.collections.QuadMesh at 0x157c82520>
```





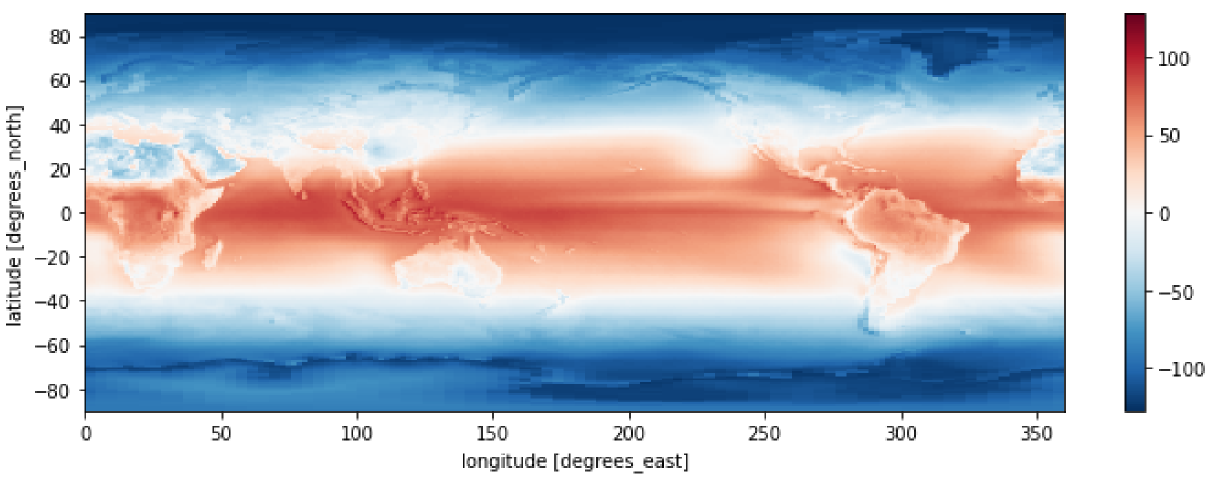


In [484…

```
# Visualise the three variables above
(rad.mean(dim='time')-lw.mean(dim='time')-sw.mean(dim='time')).plot()
```

Out[484…

```
<matplotlib.collections.QuadMesh at 0x157e16b20>
```

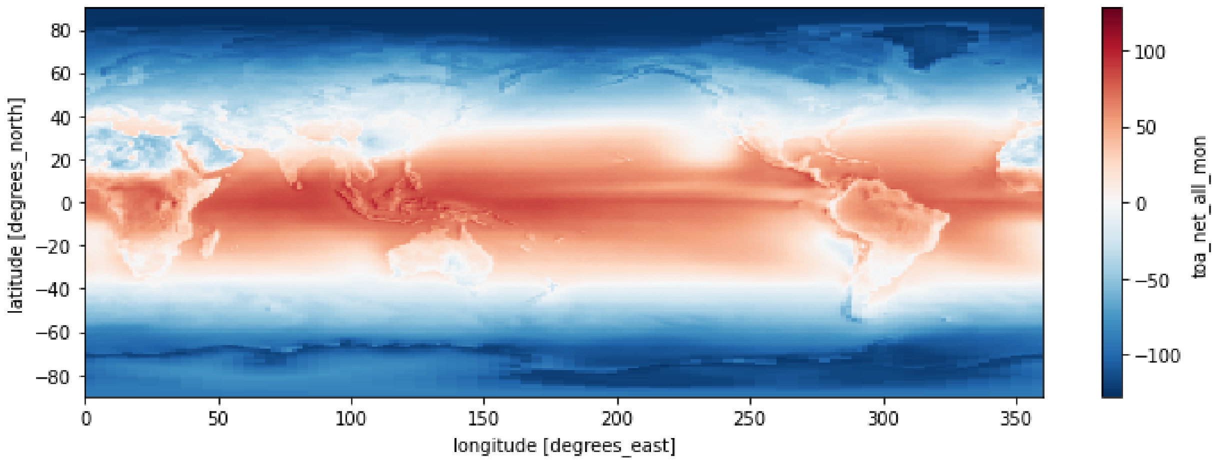


In [485…

```
# Visualise the TOA net flux
net.mean(dim='time').plot()
```

Out [485…

```
<matplotlib.collections.QuadMesh at 0x157ee77c0>
```



By Comparing the figure of the above two flux, we can know that the incoming solar radiation substract the outcoming longwave and shortwave radiation equals to the net TOA flux.

2.2 Calculate and verify that the TOA incoming solar, outgoing longwave, and outgoing shortwave approximately match up with the cartoon above.

In [486…

```
in_solar = rad.mean()
out_lw = lw.mean()
out_sw = sw.mean()
print("incoming solar: ", in_solar.values)
print("outgoing longwave: ", out_lw.values)
print("outgoing shortwave: ", out_sw.values)
```

```
incoming solar:  298.33038
outgoing longwave:  224.7552
outgoing shortwave:  102.30436
```

In [487…

```
(in_solar.values-out_lw.values-out_sw.values)
```

Out [487…

```
-28.72918
```

In [488…

```
net.mean().values
```

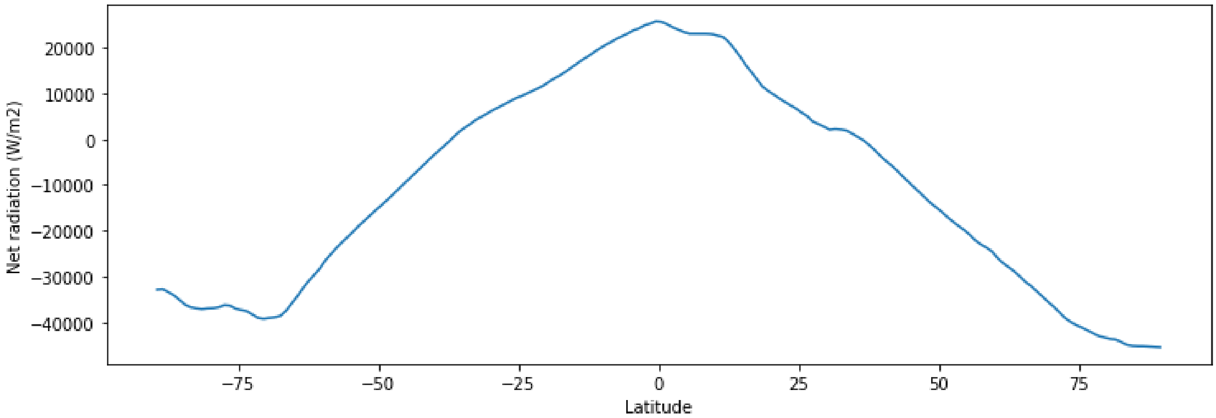
Out [488…

```
array(-28.729034, dtype=float32)
```

2.3 Calculate and plot the total amount of net radiation in each 1-degree latitude band. Label with correct units.

In [489…

```
net.sum(dim='lon').mean(dim='time').plot()
plt.xlabel('Latitude')
plt.ylabel('Net radiation (W/m2)')
plt.show()
```



2.4 Calculate and plot composites of time-mean outgoing shortwave and longwave radiation for low and high cloud area regions.

In [490…

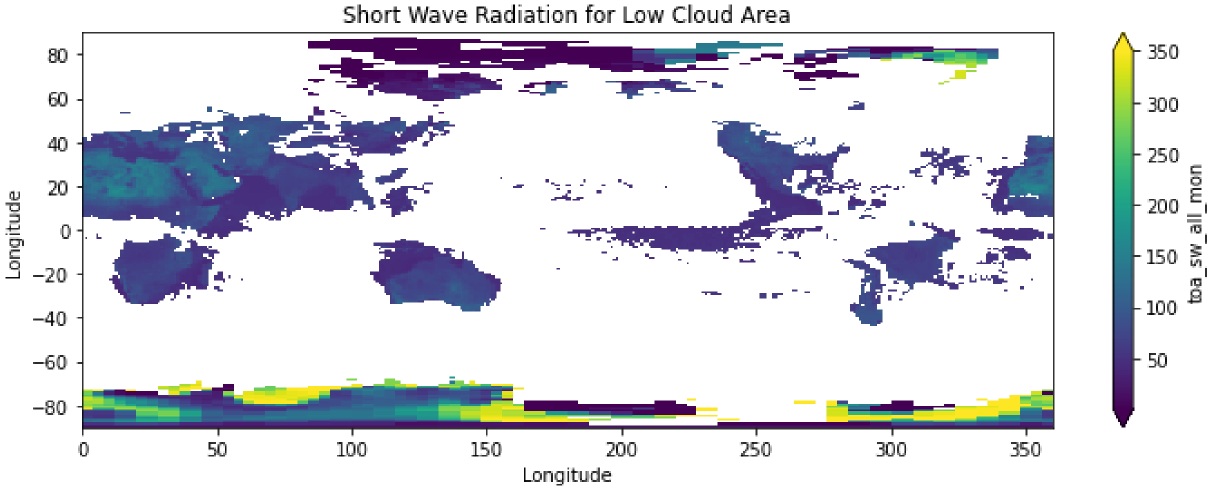
```
cloud_frac = ds2['cldarea_total_daynight_mon']
```

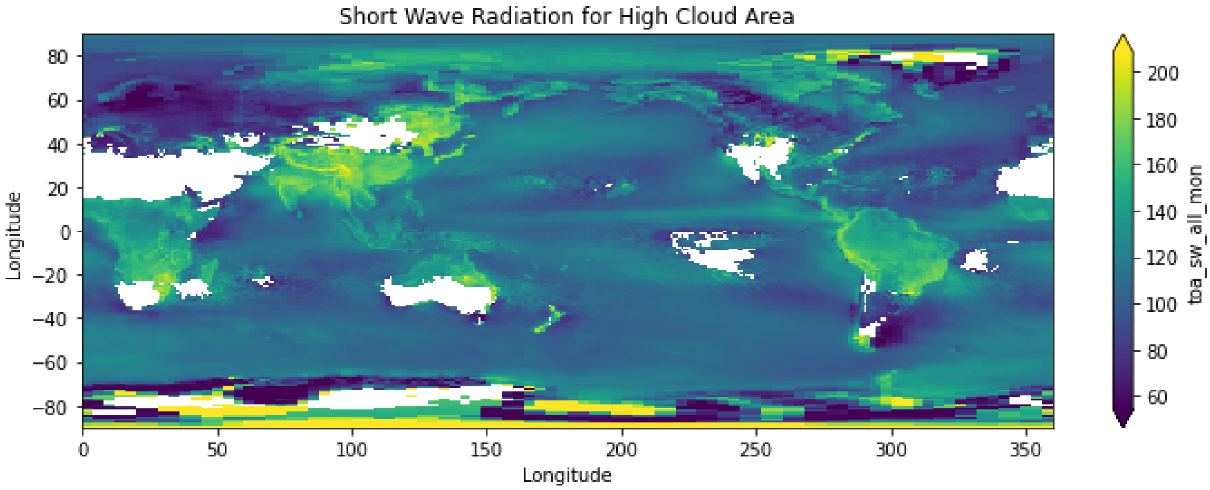
In [491…

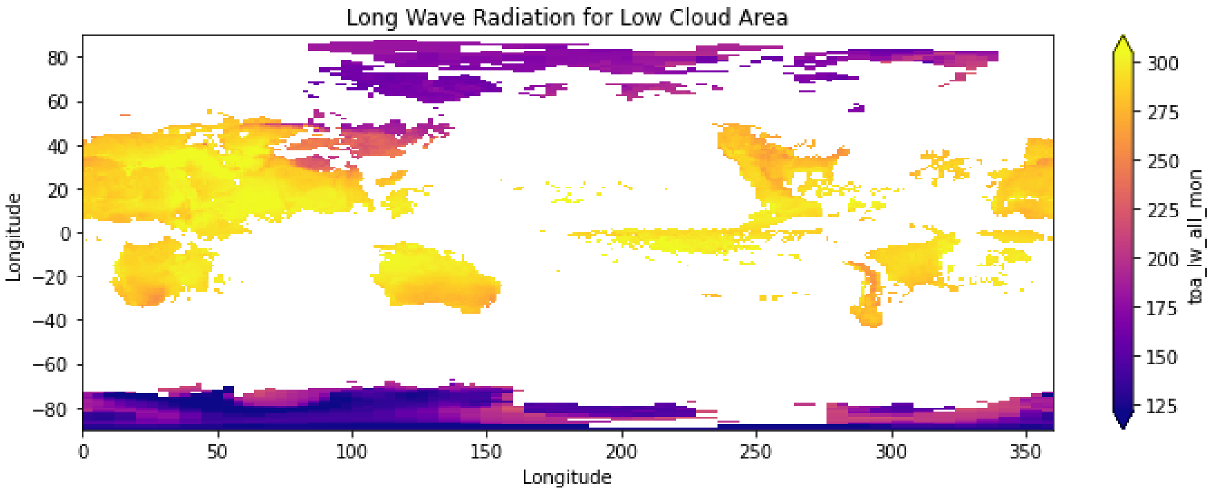
```
low_sw_mean = sw.where(cloud_frac <= 25).mean(dim='time')
high_sw_mean = sw.where(cloud_frac >= 75).mean(dim='time')

low_lw_mean = lw.where(cloud_frac <= 25).mean(dim='time')
high_lw_mean = lw.where(cloud_frac >= 75).mean(dim='time')
```

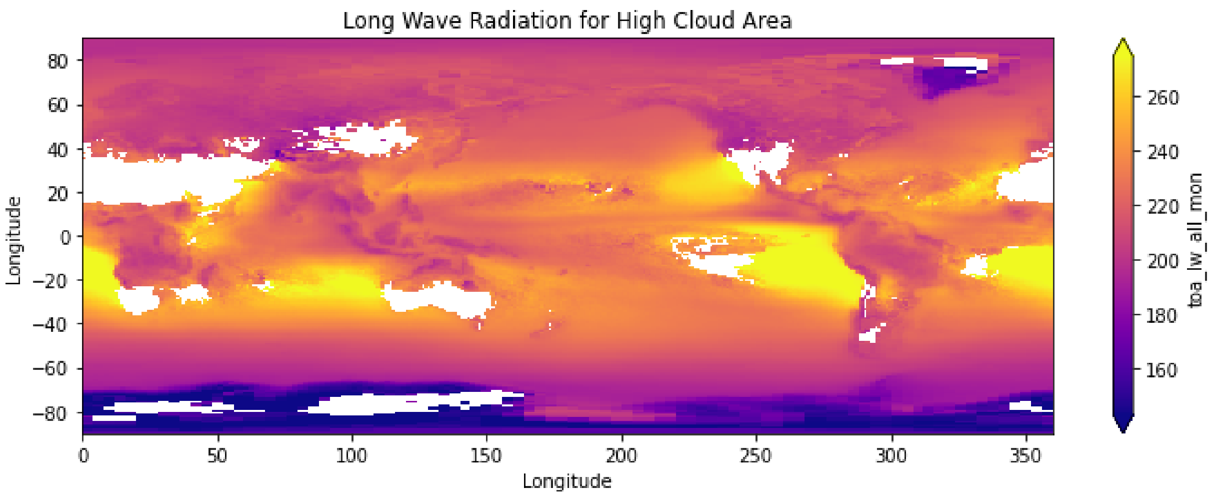
In [492…

```
low_sw_mean.plot(cmap='viridis',size=4,robust=True)
plt.title('Short Wave Radiation for Low Cloud Area')
plt.xlabel('Longitude')
plt.ylabel('Longitude')
plt.show()

high_sw_mean.plot(cmap='viridis',size=4,robust=True)
plt.title('Short Wave Radiation for High Cloud Area')
plt.xlabel('Longitude')
plt.ylabel('Longitude')
plt.show()

low_lw_mean.plot(cmap='plasma',size=4,robust=True)
plt.title('Long Wave Radiation for Low Cloud Area')
plt.xlabel('Longitude')
plt.ylabel('Longitude')
plt.show()

high_lw_mean.plot(cmap='plasma',size=4,robust=True)
plt.title('Long Wave Radiation for High Cloud Area')
plt.xlabel('Longitude')
plt.ylabel('Longitude')
plt.show()
```


Short Wave Radiation for Low Cloud Area
Longitude
Longitude
toa_sw_all_mon


Short Wave Radiation for High Cloud Area
Longitude
Longitude
toa_sw_all_mon


Long Wave Radiation for Low Cloud Area
Longitude
Longitude
toa_lw_all_mon


Long Wave Radiation for High Cloud Area
Longitude
Longitude
toa_lw_all_mon

2.5 Calculate the global mean values of shortwave and longwave radiation, composited in high and low cloud regions. What is the overall effect of clouds on shortwave and longwave radiation?

In [493…

```
global_low_sw_mean = low_sw_mean.mean(dim=['lat','lon'])
global_high_sw_mean = high_sw_mean.mean(dim=['lat','lon'])

global_low_lw_mean = low_lw_mean.mean(dim=['lat','lon'])
global_high_lw_mean = high_lw_mean.mean(dim=['lat','lon'])
```

In [494…

```
# Print results
print("Global Mean Shortwave Radiation in Low Cloud Regions:", global_low_sw_
print("Global Mean Shortwave Radiation in High Cloud Regions:", global_high_s

print("Global Mean Longwave Radiation in Low Cloud Regions:", global_low_lw_m
print("Global Mean Longwave Radiation in High Cloud Regions:", global_high_lw
```

```
Global Mean Shortwave Radiation in Low Cloud Regions: 88.81645
Global Mean Shortwave Radiation in High Cloud Regions: 114.74328
Global Mean Longwave Radiation in Low Cloud Regions: 233.06702
Global Mean Longwave Radiation in High Cloud Regions: 215.37349
```

Based on the result, the high cloud tends to lead the increasing shortwave radiation and lower the longwave radiation.

3. Explore a netCDF dataset

The NetCDF dataset I chose is ERA5 reanalysis data, which contains surface 2-meter temperature and 10-meter U/V speed monthly mean from 2017 to 2021. I only use the temperature variable to do some analysis below:

3.1 Plot a time series of a certain variable with monthly seasonal cycle removed.

In [495…

```
ds3 = xr.open_dataset('/Users/xujiayu/Desktop/Course/RS/Kuangdong/monthly17-2
ds3
```

Out[495…

xarray.Dataset

▶ Dimensions: (**longitude**: 3600, **latitude**: 1801, **time**: 60)

▼ Coordinates:

longitude	(longitude)	float32	0.0 0.1 0.2 ... 3...
latitude	(latitude)	float32	90.0 89.9 89.8...
time	(time)	datetime64[ns]	2017-01-01 ... ...

▼ Data variables:

u10	(time, latitude, longitude)	float32	...
v10	(time, latitude, longitude)	float32	...
t2m	(time, latitude, longitude)	float32	...

▶ Indexes: (3)

▾ Attributes:

Conventions : CF-1.6

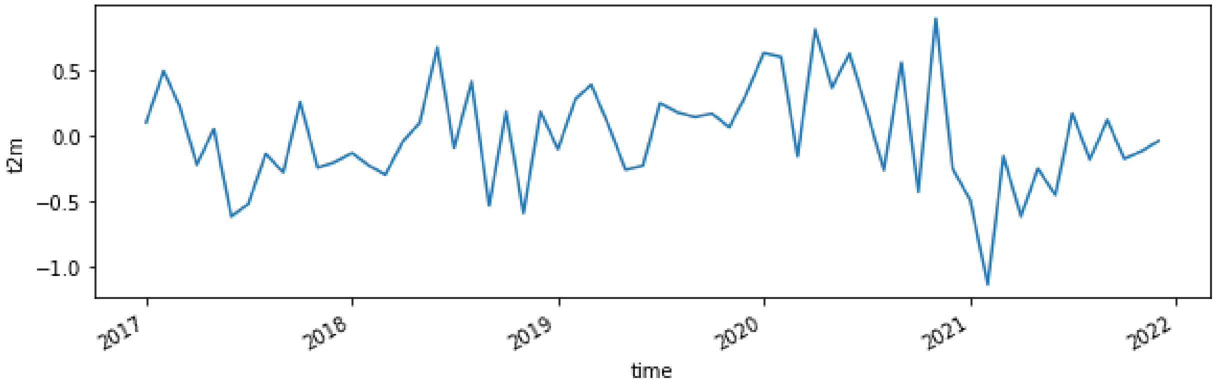
history : 2022-10-24 17:12:02 GMT by grib_to_netcdf-2.25.1: /opt/ecmwf/mars-client/bin/grib_to_netcdf.bin -S param -o /cache/data4/adaptor.mars.internal-1666631480.7186973-9489-5-454c49c1-fcd0-4b9e-835f-561319dc6bcf.nc /cache/tmp/454c49c1-fcd0-4b9e-835f-561319dc6bcf-adaptor.mars.internal-1666631450.529024-9489-9-tmp.grib

In [337…

```
temp = ds3['t2m'] # 2m temperature
```

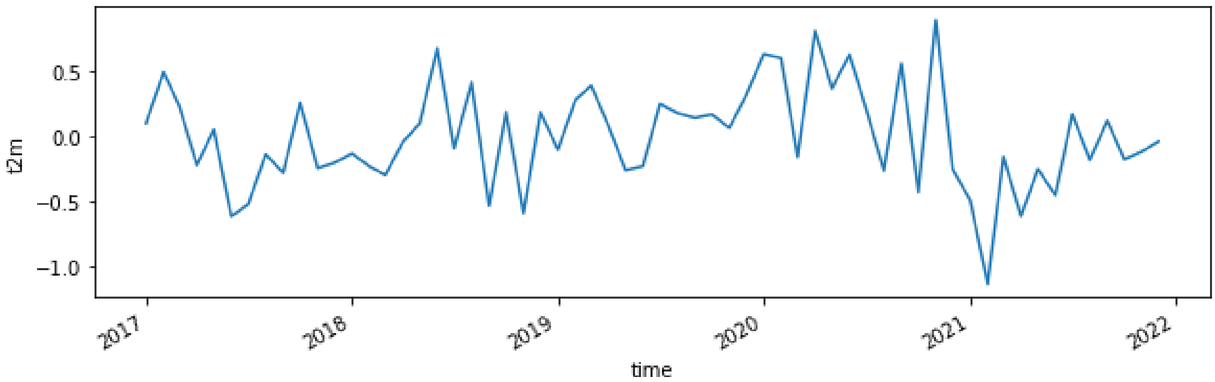
In [496…

```
# time series of temperature
time_ser = temp.mean(dim=['latitude','longitude'])

# monthly seasonal cycle
m_season = temp.groupby('time.month').mean(dim='time').mean(['latitude','long

# removed the seasonal cycle
(time_ser - np.tile(m_season.values,5)).plot(size=3)
plt.tight_layout()
plt.show()
```



In [497…

```
# removed the seasonal cycle
(time_ser - np.tile(m_season.values,5)).plot(size=3)
plt.tight_layout()
plt.show()
```

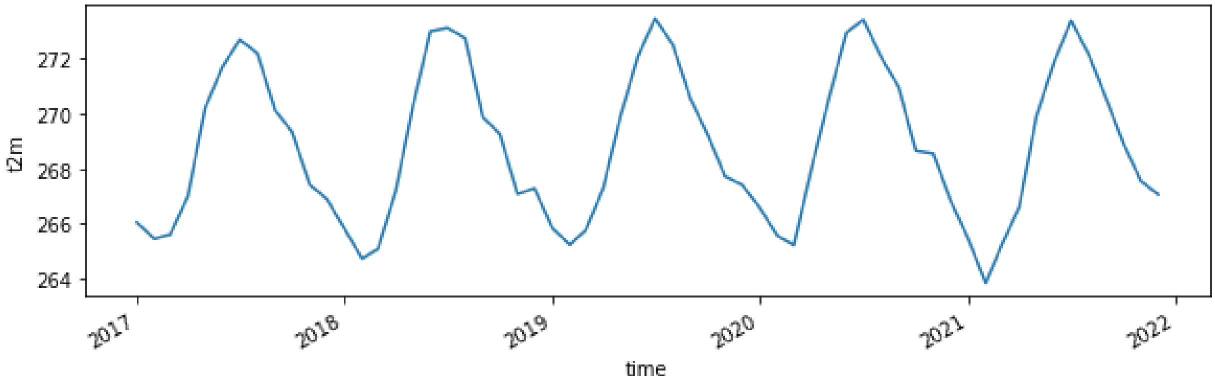


3.2 Make 5 different plots using the dataset.

In [453…

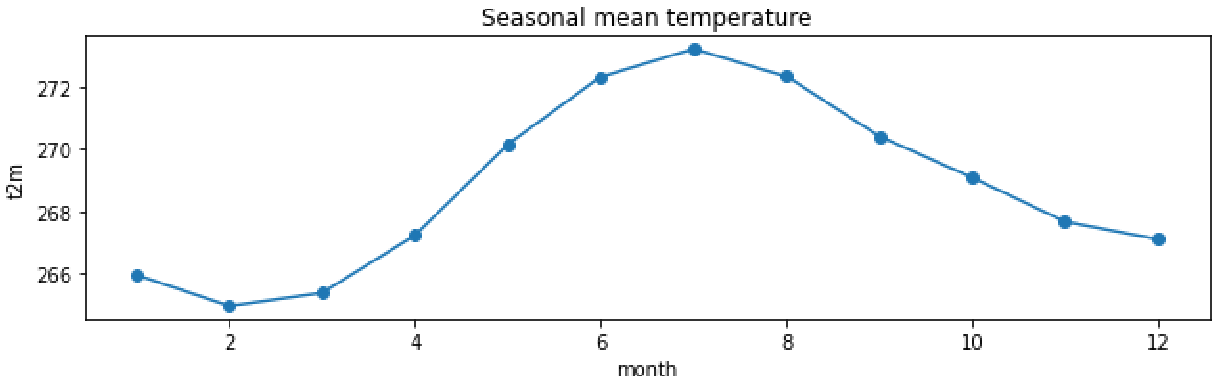
```
# 1. Time series of mean temperature
time_ser.plot(size=3)
```

```
plt.tight_layout()
plt.show()
```



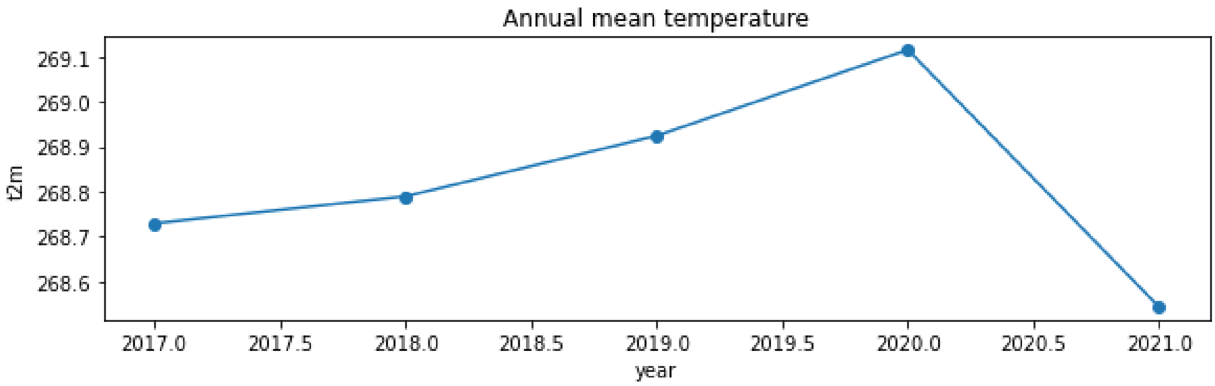
In [454…

```
# 2. Seasonal and annual mean of temperature
m_season.plot(marker='o',size=3)
plt.title('Seasonal mean temperature')
plt.tight_layout()
plt.show()
```



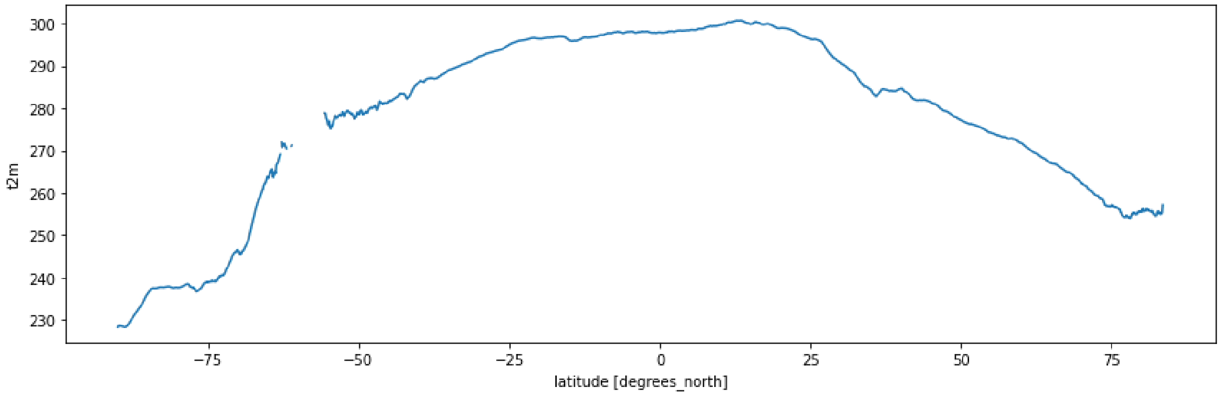
In [455…

```
ann_mean = temp.groupby('time.year').mean(dim='time').mean(dim = ['latitude',
ann_mean.plot(marker='o',size=3)
plt.title('Annual mean temperature')
plt.tight_layout()
plt.show()
```



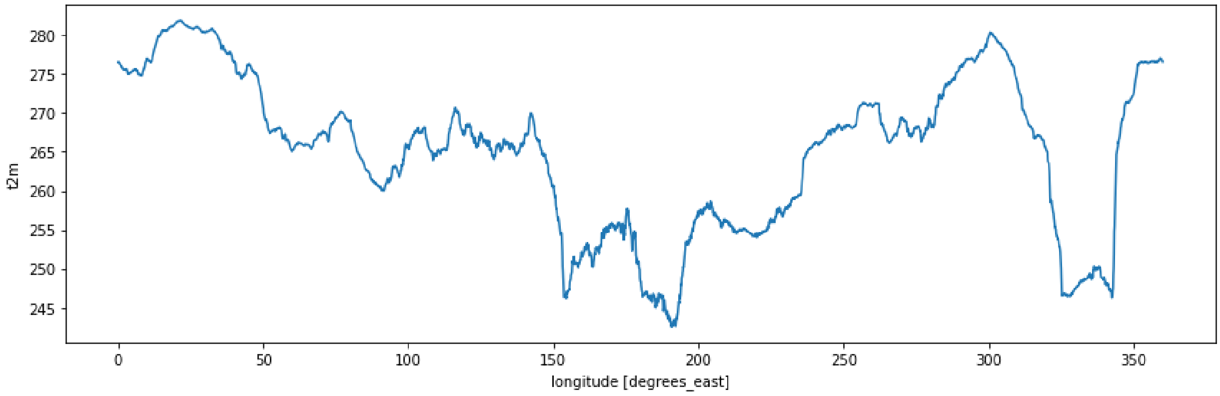
In [460…

```
# 3. Time series of mean temperature in different latitude/longitude directio
temp.mean(dim=['longitude','time']).plot()
plt.tight_layout()
plt.show()
```



In [459…

```
temp.mean(dim=['latitude','time']).plot()
plt.tight_layout()
plt.show()
```

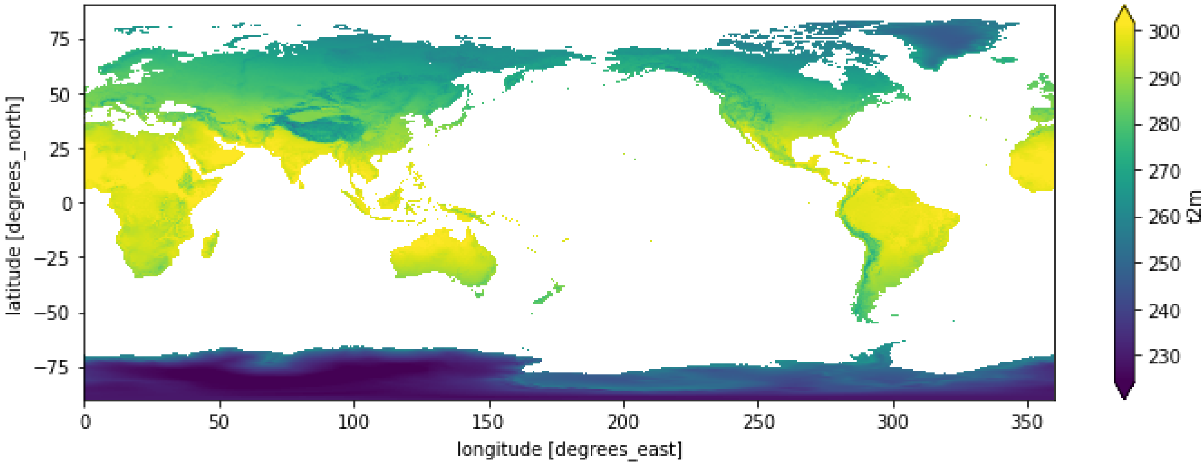


In [463…

```
# 4. Mean temperature during the 5 years
temp.mean(dim='time').plot(robust=True)
```

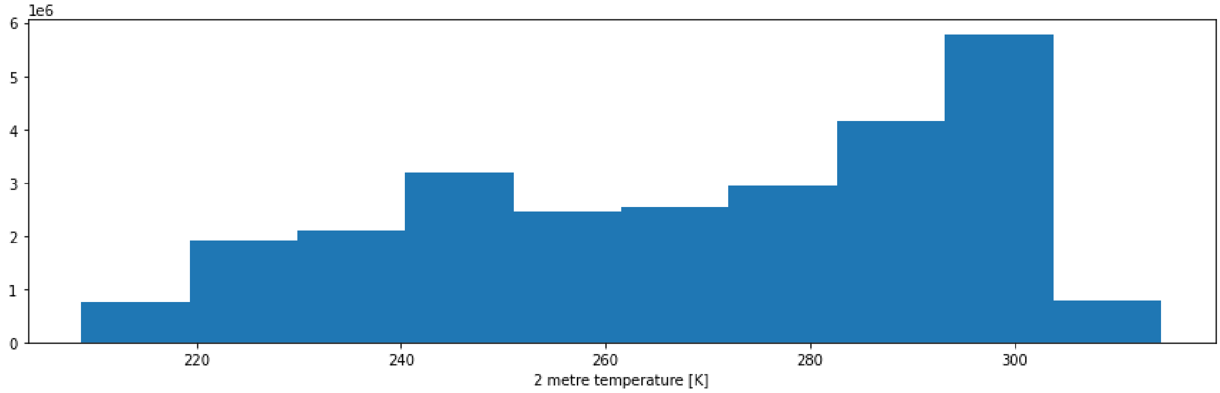
Out[463…

```
<matplotlib.collections.QuadMesh at 0x157617f40>
```



In [464…

```
# 5. Histogram of mean temperature over 5 years
temp.groupby('time.month').mean().plot()
plt.tight_layout()
plt.show()
```


1e6
6
5
4
3
2
1
0
220
240
260
280
300
2 metre temperature [K]