1.
1.1读取并以SST命名文件NOAA_NCDC_ERSST_v3b_SST.nc，切片出经度120~170、纬度-5~5的数据，并按照月份分组，group_data - group_data.mean(dim='time')算出数据和平均值的差值（sst_dif）。然后按照三个月的分组重新采样，并取平均值。
1.2分别按照数据和平均值的差值以及重新采样的数据绘图。
ds_anom_resample_m是重新采样值的平均值，绘制异常值大于等于0的柱状图，颜色为红色，异常值小于0的柱状图，颜色为蓝色。然后绘制了一条黑色实线，表示了SST异常值的3个月均值；添加了三条水平参考线，分别是：异常值为0.5的红色虚线，用于标识El Nino的阈值，异常值为-0.5的蓝色虚线，用于标识La Nina的阈值，异常值为0的黑色实线，用于参考。最后添加图例。

2.
2.1 读取并以TOA命名文件CERES_EBAF-TOA_200003-201701.nc，分别用变量toa_lw_all_mon、toa_sw_all_mon、solar_mon算出平均长波辐射、短波辐射和太阳辐射，分三个子图画出图形，设置标题。
total_flux是平均太阳辐射减去平均长波辐射和平均短波辐射，net_flux是变量toa_net_all_mon的平均值，分别绘图，可以发现这两个图完全一样，说明上述三种变量之间的关系就等同于net_flux。
2.2 np.deg2rad(TOA.lat)将TOA.lat中的角度值转换为弧度值，然后使用cos函数计算其余弦值。这样得到的结果作为权重，用于对接下来的数据进行加权平均。接下来分别对三个变量进行加权平均操作，并存储结果及输出。
2.3 首先，从TOA数据中获取纬度和总净辐射量的数据。然后，通过设置纬度分辨率为1.0度，并创建一个纬度范围数组，范围从-90度到90度，步长为1度。接下来，创建一个长度为纬度数组长度减一的零数组，用于存储每个纬度带的总净辐射量。
然后，使用循环遍历每个纬度带，并计算该纬度带内的总净辐射量。在每次迭代中，通过创建一个布尔掩码来选择对应纬度范围内的数据，并使用NumPy的sum函数计算总净辐射量。
最后，利用Matplotlib库绘制条形图，横轴为纬度，纵轴为总净辐射量，展示了每个1度纬度带的总净辐射量分布情况。
2.4 先表示出短波辐射、长波辐射和总的云区域。然后规定25%和75%的低云和高云阈值，分别计算低云和高云区域的短波和长波辐射通量的时间平均值，最后将计算得到的结果分别绘制成了四张子图，展示了低云和高云区域的短波和长波辐射通量的时间平均情况。
2.5 area_weights是根据纬度的余弦值计算出每个地球表面网格单元的面积权重，然后定义了低云区域和高云区域，分别计算低云区域和高云区域下的短波和长波全球平均辐射能量值。低云区域或高云区域的网格单元乘以面积权重，然后求平均值。最后绘图及添加图例。

3.
3.1 我在GES DISC官网上下载了2023年9月的气溶胶数据。通过将黑碳这一变量分组并求平均后绘图，然后求出数据于平均值的差值后绘图。
3.2 我绘制的5个图分别是黑碳的平均值变化、DMS的质量密度在特定时间以及特定经纬度范围内随时间的变化、有机碳在特定经度下随时间的变化、二氧化硫质量在一定时间序列上每隔一段时间的变化、海盐在某一经纬度上的时间变化。

In [1]:
```python
# 1. Niño 3.4 index
# Load modules
import numpy as np
import pandas as pd
import netCDF4
import xarray as xr
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec

# Show plots in the notebook
%matplotlib inline
```

In [2]:
```python
#1.1
SST = xr.open_dataset("NOAA_NCDC_ERSST_v3b_SST.nc", engine="netcdf4")
SST
```

Out[2]:

xarray.Dataset

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

▼ Coordinates:

lat	(lat)	float32	-88.0 -86.0 -84.0 ... 86.0 88.0
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 [3]:
```
SST['sst']
```

Out[3]:

xarray.DataArray 'sst' (**time**: 684, **lat**: 89, **lon**: 180)

```
[10957680 values with dtype=float32]
```

▼ Coordinates:

lat	(lat)	float32	-88.0 -86.0 -84.0 ... 86.0 88.0
lon	(lon)	float32	0.0 2.0 4.0 ... 354.0 356.0 358.0
time	(time)	datetime64[ns]	1960-01-15 ... 2016-12-15

► Indexes: (3)

▼ Attributes:

pointwidth :	1.0
valid_min :	-3.0
valid_max :	45.0
units :	degree_Celsius
long_name :	Extended reconstructed sea surface temperature
standard_name :	sea_surface_temperature
iridl:hasSemanti…	iridl:SeaSurfaceTemperature

In [4]:

```
# Compute monthly climatology for SST from Niño 3.4 region
group_data = SST.sst.sel(lon=slice(120,170),lat=slice(-5,5)).groupby('time.month')
sst_dif = group_data-group_data.mean(dim='time')

# subtract climatology from SST time series to obtain anomalies
resample_obj = sst_dif.resample(time="3M").mean(dim="time")
resample_obj
```

Out[4]:

xarray.DataArray 'sst' (**time**: 229, **lat**: 5, **lon**: 26)

```
array([[[-0.4533596 , -0.43008804, -0.3652172 , ..., -0.5904255 ,
         -0.51613617, -0.5157356 ],
        [-0.14541245, -0.14106178, -0.20046997, ..., -0.60107803,
         -0.5806999 , -0.5200424 ],
        [ 0.03437614, -0.01860619, -0.1291542 , ..., -0.61279106,
         -0.5868416 , -0.55138206],
        [-0.03416824, -0.07881355, -0.139431  , ..., -0.5768242 ,
         -0.56368065, -0.5451031 ],
        [-0.11306   , -0.14630127, -0.18651962, ..., -0.47527504,
         -0.48386002, -0.49680328]],

       [[-0.29540953, -0.25229773, -0.21316402, ..., -0.6501789 ,
         -0.5796814 , -0.58689374],
        [-0.18128014, -0.12417793, -0.13654137, ..., -0.6904233 ,
         -0.68461037, -0.64244586],
        [-0.09715843, -0.08390108, -0.10546494, ..., -0.7069289 ,
         -0.6881733 , -0.6722056 ],
        [-0.18694179, -0.16128285, -0.128987  , ..., -0.64433545,
         -0.62889546, -0.6225446 ],
        [-0.27703476, -0.2525959 , -0.20511119, ..., -0.517519  ,
...
          0.51037025,  0.44631258],
        [ 0.31214967,  0.4855779 ,  0.7164224 , ...,  0.4436461 ,
          0.3200194 ,  0.2053426 ],
        [ 0.39565277,  0.5145791 ,  0.7320716 , ...,  0.39797845,
          0.23362541,  0.08429018],
        [ 0.44386673,  0.44989267,  0.5983505 , ...,  0.5368557 ,
          0.3789749 ,  0.21928024],
        [ 0.42669234,  0.40143776,  0.4725081 , ...,  0.714798  ,
          0.5879669 ,  0.46769652]],

       [[ 0.32543087,  0.3451271 ,  0.4029932 , ...,  0.51263714,
          0.4383192 ,  0.36778736],
        [ 0.42484474,  0.5078449 ,  0.57851505, ...,  0.34471035,
          0.22703075,  0.10994244],
        [ 0.5032301 ,  0.5828867 ,  0.66394806, ...,  0.27353382,
          0.13096333, -0.00620747],
        [ 0.46020794,  0.49208736,  0.58321095, ...,  0.37838078,
          0.25306892,  0.11438084],
        [ 0.3544016 ,  0.36249638,  0.44186687, ...,  0.5236778 ,
          0.4169016 ,  0.31012917]]], dtype=float32)
```

▼ Coordinates:

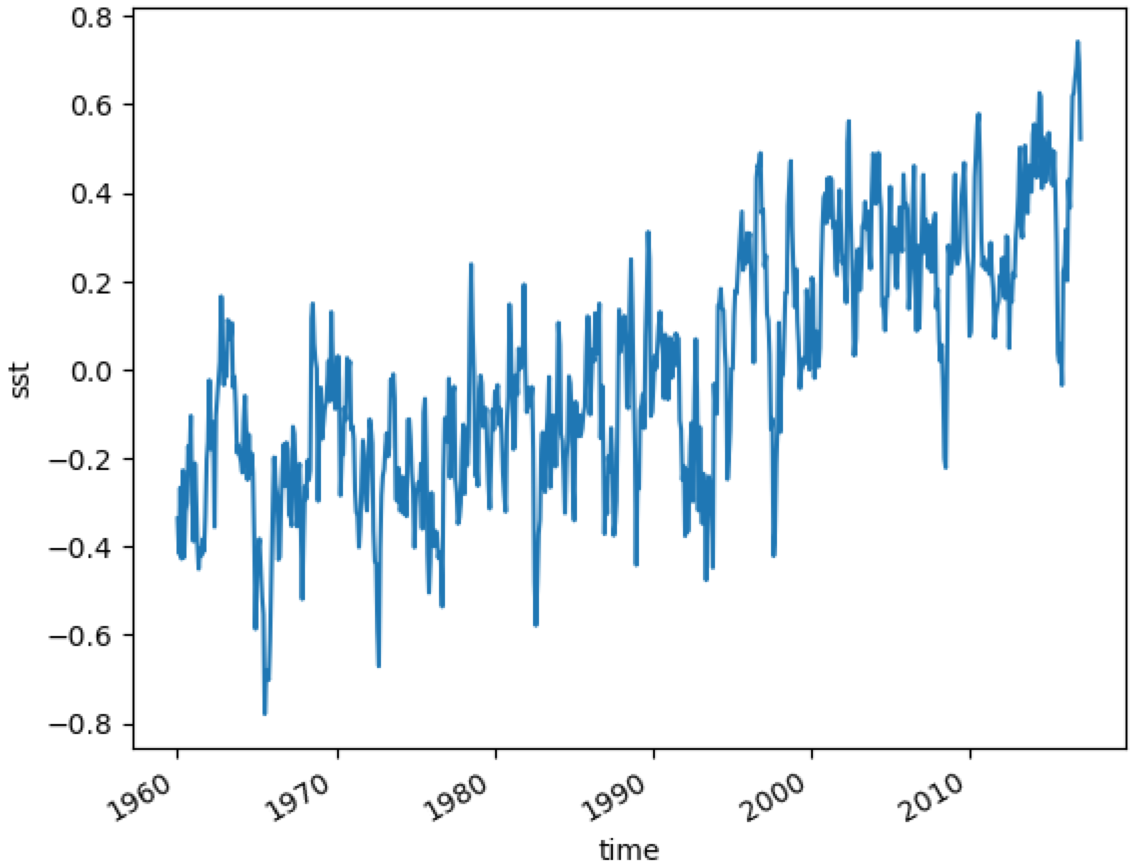
lat	(lat)	float32	-4.0 -2.0 0.0 2.0 4.0
lon	(lon)	float32	120.0 122.0 124.0 ... 168.0 170.0
time	(time)	datetime64[ns]	1960-01-31 ... 2017-01-31

► Indexes: (3)

► Attributes: (0)

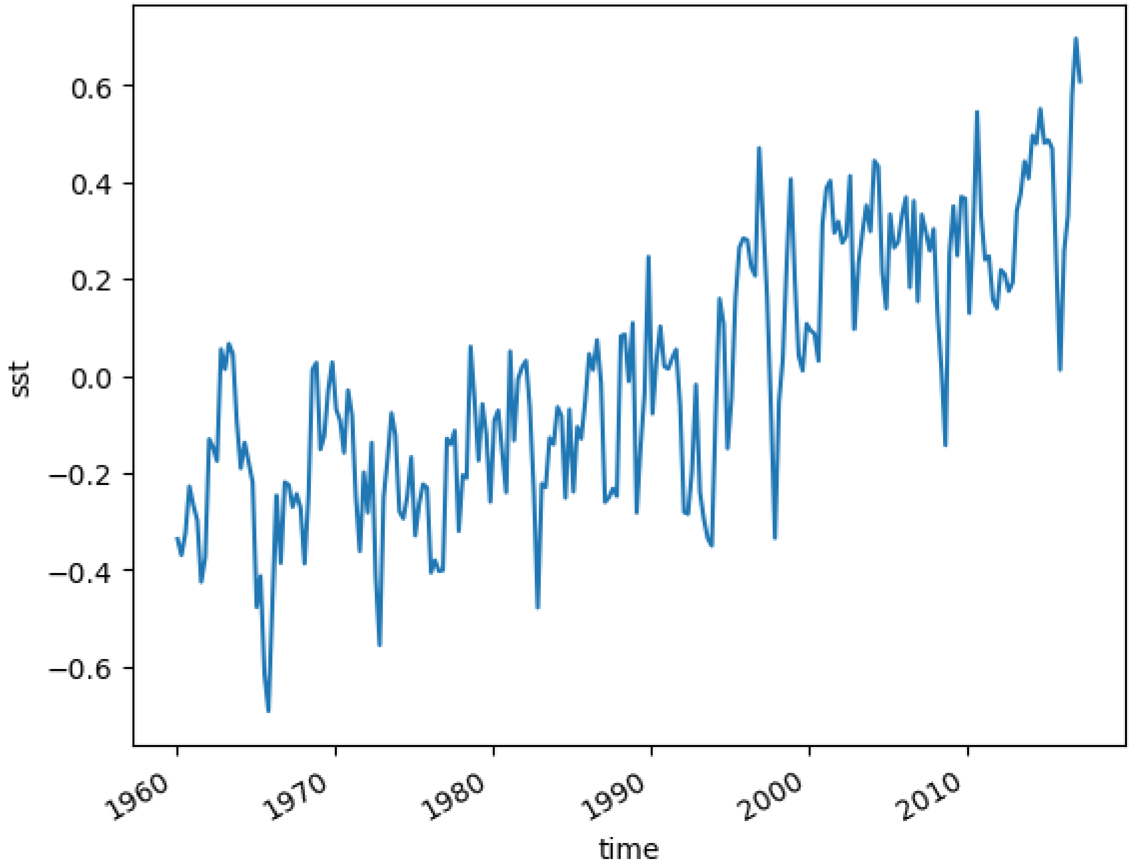
In [5]:
```
# 1.2
sst_dif.mean(dim=['lat','lon']).plot()
```

Out[5]: [<matplotlib.lines.Line2D at 0x14b06f6b6d0>]



In [6]:
```
resample_obj.mean(dim=['lat','lon']).plot()
```

Out[6]: [<matplotlib.lines.Line2D at 0x14b084f9fd0>]



In [7]:
```
ds_anom_resample_m=resample_obj.mean(dim=['lat','lon'])
ds_anom_resample_m
```

Out[7]:

xarray.DataArray 'sst' (**time**: 229)

```
array([-0.33638978, -0.37003502, -0.3239999 , -0.22765496, -0.26742154,
       -0.29706082, -0.42516705, -0.3743719 , -0.13013509, -0.14662217,
       -0.17526981,  0.05451763,  0.01313595,  0.06591826,  0.04469279,
       -0.09537051, -0.19031097, -0.13719894, -0.1779783 , -0.21954633,
       -0.47708625, -0.41306534, -0.61572886, -0.6919386 , -0.46526185,
       -0.24677637, -0.38609752, -0.21915027, -0.22480527, -0.2702479 ,
       -0.2433737 , -0.27216244, -0.38718328, -0.24891156,  0.01236948,
        0.02674307, -0.1512471 , -0.12314105, -0.02989539,  0.02746935,
       -0.06977199, -0.09244606, -0.15824564, -0.03030802, -0.08215355,
       -0.24998821, -0.36153477, -0.19859119, -0.2819085 , -0.13750277,
       -0.41236964, -0.5556232 , -0.2498695 , -0.1719188 , -0.07733187,
       -0.12359207, -0.27969757, -0.29421753, -0.2476332 , -0.16733189,
       -0.32939062, -0.26420408, -0.22348669, -0.23065028, -0.4060981 ,
       -0.38037926, -0.402714  , -0.4010484 , -0.12891535, -0.1408334 ,
       -0.11381914, -0.32007325, -0.2045178 , -0.21054327,  0.05988208,
       -0.05048161, -0.17434482, -0.05864822, -0.12214249, -0.25969198,
       -0.09298059, -0.07176815, -0.1562431 , -0.24005908,  0.05026476,
       -0.13279352, -0.00744956,  0.01719128,  0.03076849, -0.06558541,
       -0.2355391 , -0.47826445, -0.22260715, -0.22947134, -0.12784567,
       -0.14085631, -0.06479608, -0.08387943, -0.2515224 , -0.06982005,
...
       -0.19591552, -0.01864021, -0.23917682, -0.29464397, -0.33528358,
       -0.35045642, -0.07411855,  0.15897055,  0.10697694, -0.14921309,
       -0.04572915,  0.1568192 ,  0.2641609 ,  0.28375474,  0.2797301 ,
        0.22447583,  0.20625184,  0.4701414 ,  0.31612307,  0.16429943,
       -0.07111615, -0.33452275, -0.05399809,  0.03474595,  0.23891602,
        0.40586895,  0.20059861,  0.04168706,  0.01015314,  0.10702178,
        0.09294897,  0.0868701 ,  0.03048421,  0.31326863,  0.38727093,
        0.40259364,  0.29476655,  0.3183891 ,  0.27422825,  0.28749415,
        0.4125064 ,  0.09602283,  0.23268497,  0.294751  ,  0.35175908,
        0.2979943 ,  0.4437765 ,  0.4319937 ,  0.21467721,  0.13865069,
        0.33312672,  0.26419055,  0.2758488 ,  0.33165234,  0.36844757,
        0.18227148,  0.3608378 ,  0.15332824,  0.33264446,  0.2980027 ,
        0.2584041 ,  0.30271897,  0.12783696,  0.01041856, -0.14296326,
        0.25190043,  0.3500043 ,  0.2480731 ,  0.36936525,  0.36543158,
        0.12898877,  0.29491633,  0.54474586,  0.3310301 ,  0.23948544,
        0.24682468,  0.15716833,  0.13909237,  0.21837936,  0.209491  ,
        0.17454773,  0.19300571,  0.34000415,  0.3749026 ,  0.442632  ,
        0.40747023,  0.4960373 ,  0.4790274 ,  0.5508579 ,  0.48036876,
        0.48651356,  0.469067  ,  0.24312   ,  0.01210874,  0.25750467,
        0.33146283,  0.57795835,  0.6961747 ,  0.6076585 ], dtype=float32)
```

▼ Coordinates:

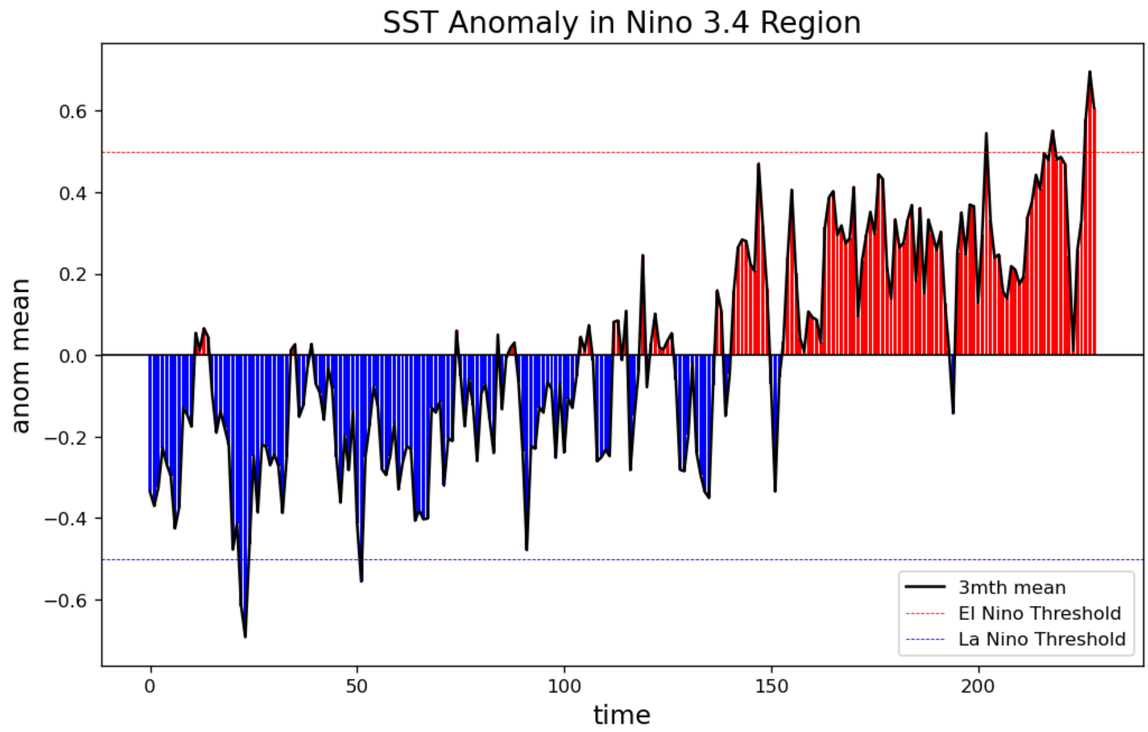
time	(time)	datetime64[ns]	1960-01-31 ... 2017-01-31

► Indexes: (1)

► Attributes: (0)

In [8]:
```
# draw the plot
df=pd.DataFrame(ds_anom_resample_m.where(ds_anom_resample_m>=0),columns=['anom>=0'])
df['anom<0']=pd.DataFrame(ds_anom_resample_m.where(ds_anom_resample_m<0))
df['date'] = pd.DataFrame(ds_anom_resample_m.time)
df.set_index('date',inplace=True)

plt.figure(figsize=(10,6),dpi=120)
plt.bar(np.arange(len(df['anom>=0'])),df['anom>=0'],color="red")
plt.bar(np.arange(len(df['anom<0'])),df['anom<0'],color="blue")
plt.plot(ds_anom_resample_m,'k-')

plt.axhline(y=0.5,color="red",linestyle='--',linewidth=0.5)
plt.axhline(y=-0.5,color="blue",linestyle='--',linewidth=0.5)
plt.axhline(y=0,color="black",linestyle='-',linewidth=1)
plt.legend(labels=['3mth mean','EI Nino Threshold','La Nino Threshold'],loc=4)
plt.ylabel('anom mean',fontsize=14)
plt.xlabel('time',fontsize=14)
plt.title('SST Anomaly in Nino 3.4 Region',fontsize=16)
```

Out[8]:
```
Text(0.5, 1.0, 'SST Anomaly in Nino 3.4 Region')
```



In [9]:
```
#2 Earth' s energy budget
#2.1
TOA = xr.open_dataset("CERES_EBAF-TOA_200003-201701.nc", engine="netcdf4")
TOA
```

Out[9]:

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 89.5

▾ 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_d…	(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.

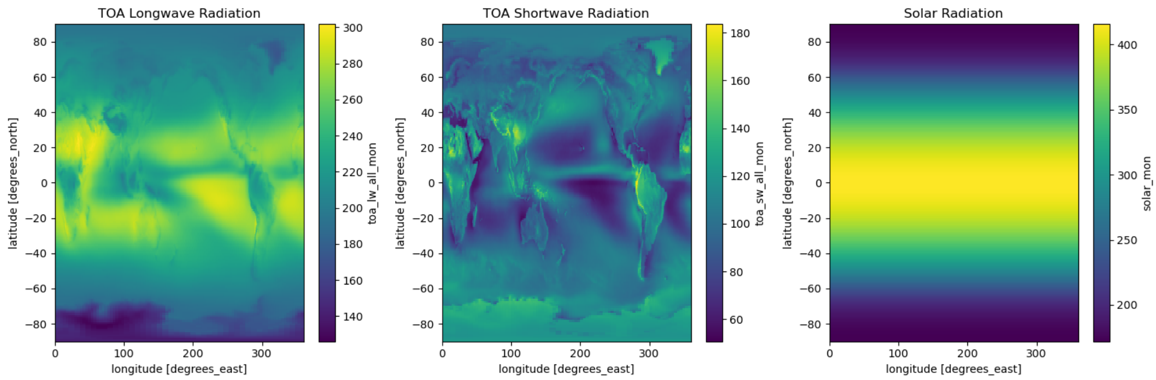
Version : Edition 4.0; Release Date March 7, 2017

Fill_Value : Fill Value is -999.0

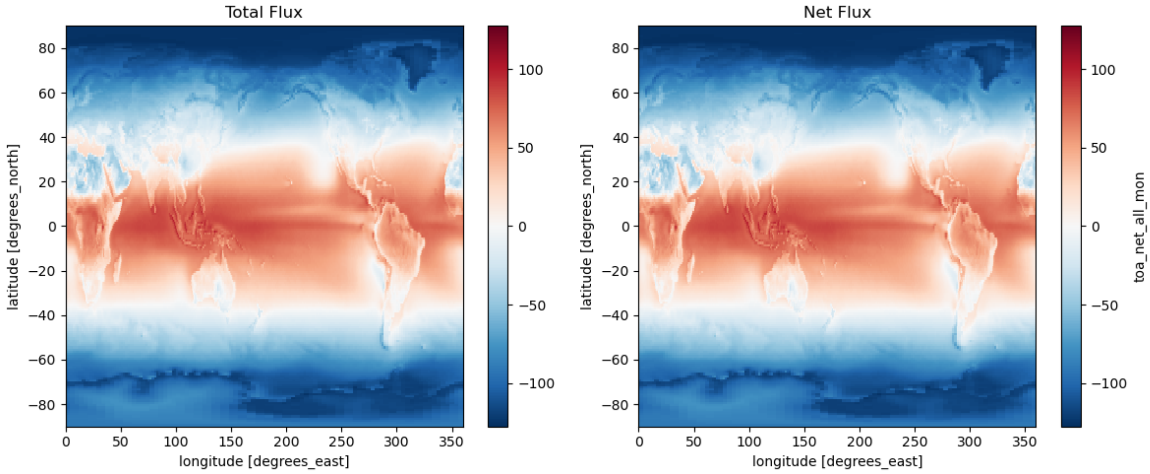
DOI : 10.5067/TERRA+AQUA/CERES/EBAF-TOA_L3B.004.0

Production_Files : 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 [10]:
```python
# Calculate the time-mean of the variables
mean_longwave = TOA['toa_lw_all_mon'].mean(dim='time')
mean_shortwave = TOA['toa_sw_all_mon'].mean(dim='time')
mean_solar = TOA['solar_mon'].mean(dim='time')

# Create a 2D plot for the time-mean TOA longwave, shortwave, and solar radiation
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(15, 5))
mean_longwave.plot(ax=ax1)
ax1.set_title('TOA Longwave Radiation')

mean_shortwave.plot(ax=ax2)
ax2.set_title('TOA Shortwave Radiation')

mean_solar.plot(ax=ax3)
ax3.set_title('Solar Radiation')

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



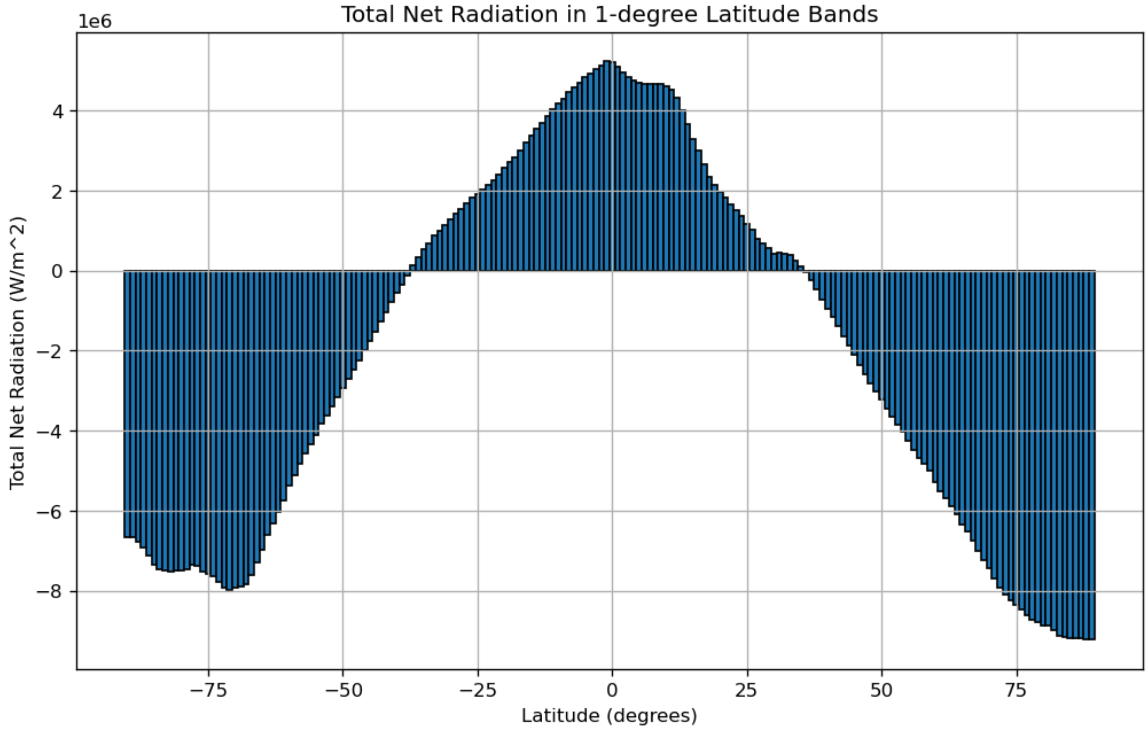
In [11]:
```python
# Add up the three variables and verify visually that they are equivalent to the TOA
total_flux = mean_solar - mean_longwave - mean_shortwave
net_flux = TOA['toa_net_all_mon'].mean(dim='time')

fig, (ax4, ax5) = plt.subplots(1, 2, figsize=(12, 5))
total_flux.plot(ax=ax4)
ax4.set_title('Total Flux')

net_flux.plot(ax=ax5)
ax5.set_title('Net Flux')

plt.tight_layout()
plt.show()

# We can see that these two axes have the totally same shape, which means that the th
```



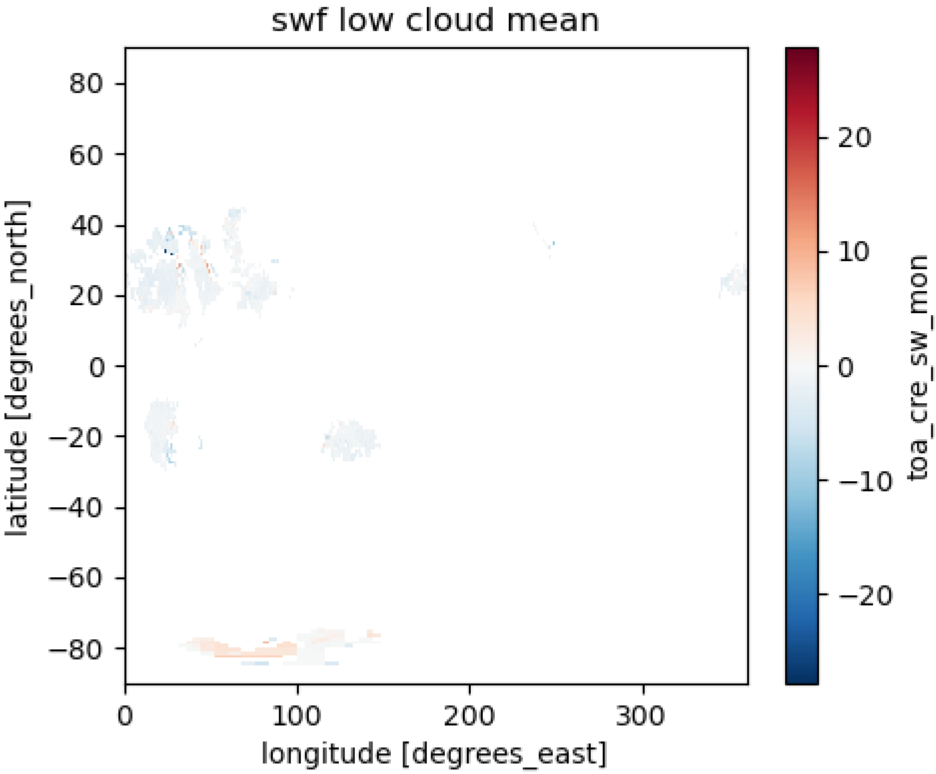
In [12]:
```python
# 2.2
weights = np.cos(np.deg2rad(TOA.lat))
#weights.dims

toa_lw_all_mon_gr = TOA.toa_lw_all_mon.weighted(weights).mean(dim=['time','lon','lat'
toa_sw_all_mon_gr = TOA.toa_sw_all_mon.weighted(weights).mean(dim=['time','lon','lat'
solar_mon_gr = TOA.solar_mon.weighted(weights).mean(dim=['time','lon','lat'])

print("outgoing longwave:",toa_lw_all_mon_gr.values,'W•m^-2')
print("outgoing shortwave:",toa_sw_all_mon_gr.values,'W•m^-2')
print("TOA incoming solar:",solar_mon_gr.values,'W•m^-2')
```

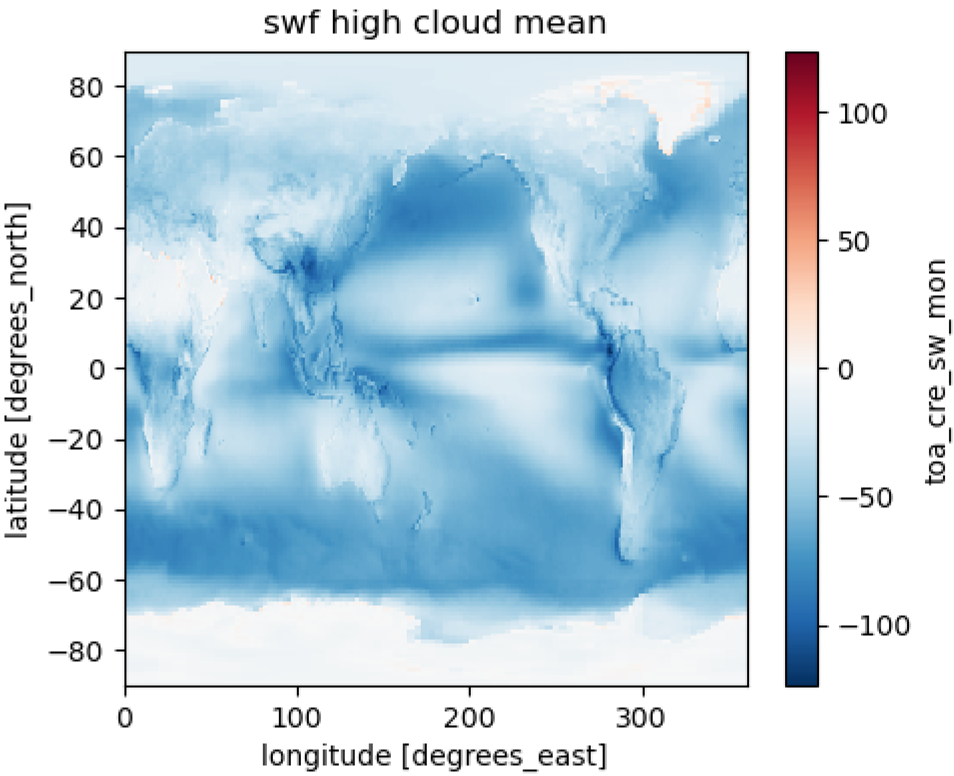
```
outgoing longwave: 240.26692 W•m^-2
outgoing shortwave: 99.13806 W•m^-2
TOA incoming solar: 340.28326 W•m^-2
```

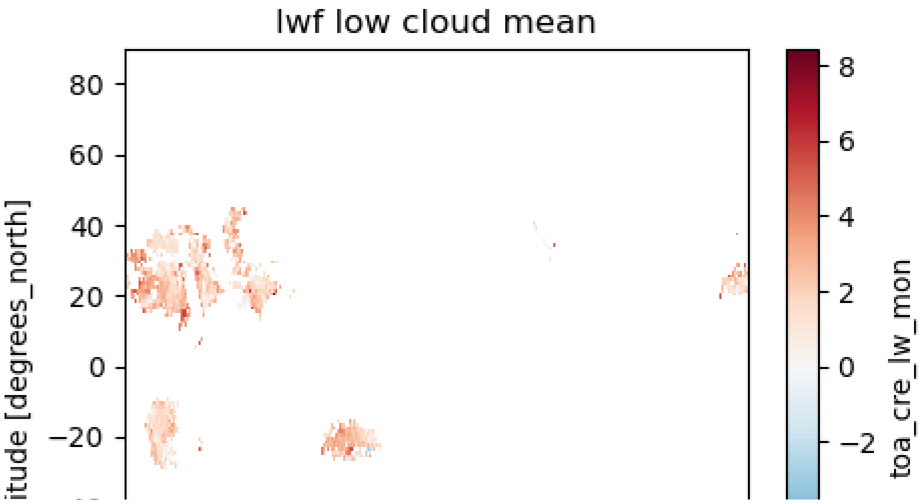
In [13]:
```
# 2.3

latitude = TOA.variables['lat'][:]
net_radiation = TOA.variables['toa_net_all_mon'][:]

# Calculate total net radiation in each 1-degree latitude band
lat_resolution = 1.0
lat_bands = np.arange(-90, 91, lat_resolution)
net_radiation_total = np.zeros(len(lat_bands) - 1)

for i in range(len(lat_bands) - 1):
    lat_min, lat_max = lat_bands[i], lat_bands[i + 1]
    lat_mask = (latitude >= lat_min) & (latitude < lat_max)
    net_radiation_total[i] = np.sum(net_radiation[:, lat_mask])

# Plot the results
plt.figure(figsize=(10, 6), dpi=120)
plt.bar(lat_bands[:-1], net_radiation_total, width=lat_resolution, edgecolor='black')
plt.title('Total Net Radiation in 1-degree Latitude Bands')
plt.xlabel('Latitude (degrees)')
plt.ylabel('Total Net Radiation (W/m^2)')
plt.grid(True)
plt.show()
```

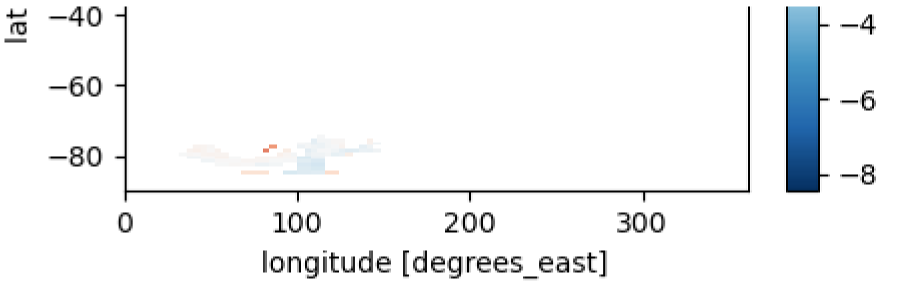


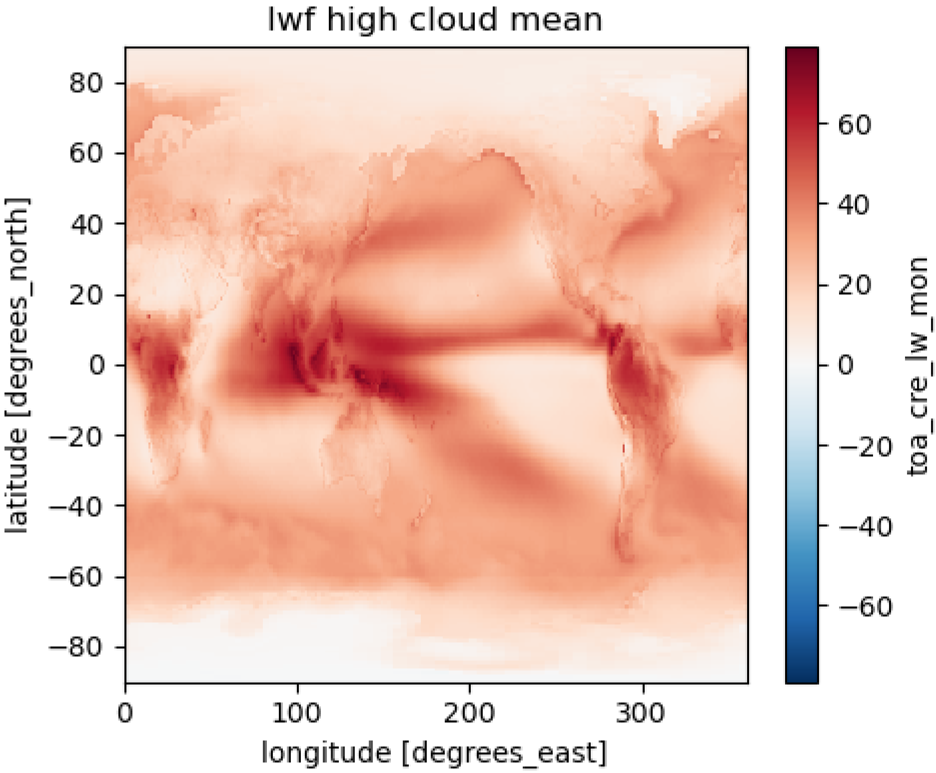
In [14]:
```
# 2.4
swf = TOA['toa_cre_sw_mon']  # Shortwave radiation flux
lwf = TOA['toa_cre_lw_mon']  # Longwave radiation flux
cld = TOA['cldarea_total_daynight_mon']  # Total cloud area fraction

# Define low and high cloud thresholds
low_cloud_threshold = TOA['cldtau_total_day_mon'].quantile(0.25)
high_cloud_threshold = TOA['cldtau_total_day_mon'].quantile(0.75)

# Calculate time-mean for low and high cloud areas
swf_low_cloud_mean = swf.where(cld<low_cloud_threshold).mean(dim='time')
swf_high_cloud_mean = swf.where(cld>high_cloud_threshold).mean(dim='time')
lwf_low_cloud_mean = lwf.where(cld<low_cloud_threshold).mean(dim='time')
lwf_high_cloud_mean = lwf.where(cld>high_cloud_threshold).mean(dim='time')

# Plot
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(5, 16))
swf_low_cloud_mean.plot(ax=ax1)
ax1.set_title('swf low cloud mean')

swf_high_cloud_mean.plot(ax=ax2)
ax2.set_title('swf high cloud mean')

lwf_low_cloud_mean.plot(ax=ax3)
ax3.set_title('lwf low cloud mean')

lwf_high_cloud_mean.plot(ax=ax4)
ax4.set_title('lwf high cloud mean')

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


swf low cloud mean
latitude [degrees_north]
80
60
40
20
0
−20
−40
−60
−80
0
100
200
300
longitude [degrees_east]
20
10
0
−10
−20
toa_cre_sw_mon


swf high cloud mean
latitude [degrees_north]
80
60
40
20
0
−20
−40
−60
−80
0
100
200
300
longitude [degrees_east]
100
50
0
−50
−100
toa_cre_sw_mon

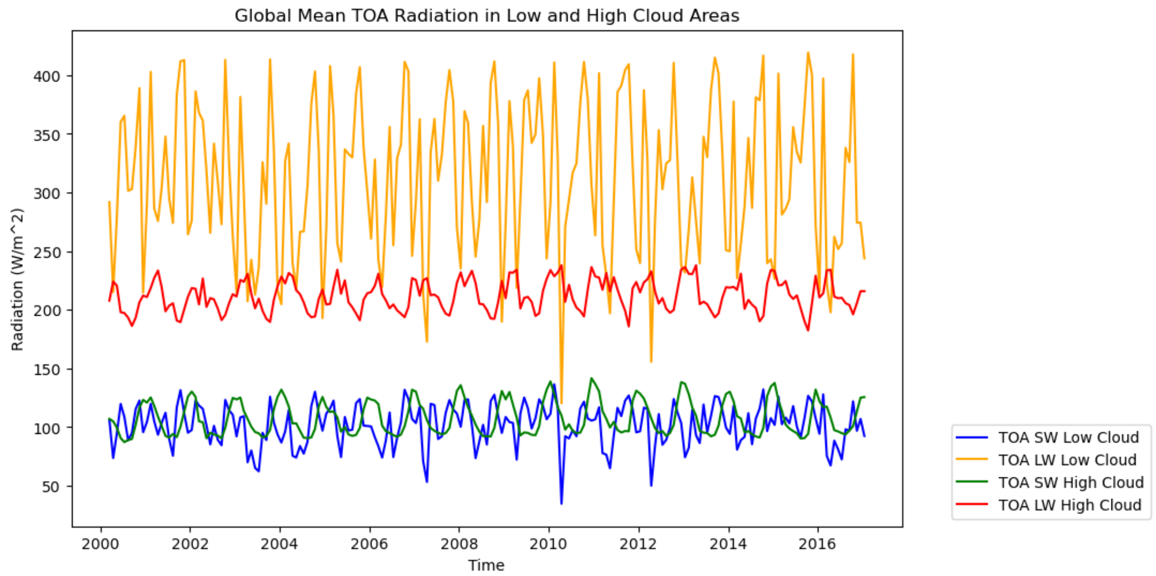

lwf low cloud mean
itude [degrees_north]
80
60
40
20
0
−20
8
6
4
2
0
−2
toa_cre_lw_mon


lat
−40
−60
−80
0
100
200
300
longitude [degrees_east]
−4
−6
−8


lwf high cloud mean
80
60
40
20
0
−20
−40
−60
−80
latitude [degrees_north]
0
100
200
300
longitude [degrees_east]
60
40
20
0
−20
−40
−60
toa_cre_lw_mon

In [18]:

```
# 2.5
# Extract relevant variables and coordinates
toa_sw_all = TOA['toa_sw_all_mon']
toa_lw_all = TOA['toa_lw_all_mon']
lat = np.radians(toa_sw_all['lat'])
lon = np.radians(toa_sw_all['lon'])

# Calculate area-weighted global mean values for shortwave and longwave radiation in
cos_lat = np.cos(lat)
area_weights = cos_lat / cos_lat.mean()

# Define cloud area
cf = TOA['cldarea_total_daynight_mon'] / 100
low_cloud_area = cf <= 0.25
high_cloud_area = cf >= 0.75

global_sw_low_cloud = (toa_sw_all *  area_weights).where(low_cloud_area).mean(dim=['l
global_lw_low_cloud = (toa_lw_all *  area_weights).where(low_cloud_area).mean(dim=['l

global_sw_high_cloud = (toa_sw_all * area_weights).where(high_cloud_area).mean(dim=['
global_lw_high_cloud = (toa_lw_all * area_weights).where(high_cloud_area).mean(dim=['

# Plot the four time series on a single graph
plt.figure(figsize=(10, 6))

plt.plot(global_sw_low_cloud['time'], global_sw_low_cloud, label='TOA SW Low Cloud',
plt.plot(global_lw_low_cloud['time'], global_lw_low_cloud, label='TOA LW Low Cloud',
plt.plot(global_sw_high_cloud['time'], global_sw_high_cloud, label='TOA SW High Cloud
plt.plot(global_lw_high_cloud['time'], global_lw_high_cloud, label='TOA LW High Cloud

# Set plot title and labels
plt.title('Global Mean TOA Radiation in Low and High Cloud Areas')
plt.xlabel('Time')
plt.ylabel('Radiation (W/m^2)')

plt.legend(loc='lower left',bbox_to_anchor=(1.05, 0))
plt.show()
```



In [19]:
```
# 3
data = xr.open_dataset("MERRA2_400.tavgU_2d_aer_Nx.202309.nc4", engine="netcdf4")
data
```

Out[19]:

xarray.Dataset

▶ Dimensions: (**lon**: 576, **lat**: 361, **time**: 24)

▼ Coordinates:

lon	(lon)	float64	-180.0 -179.4 ... 178.8 179.4
lat	(lat)	float64	-90.0 -89.5 -89.0 ... 89.5 90.0
time	(time)	datetime64[ns]	2023-09-01T00:30:00 ... 2023-09-...

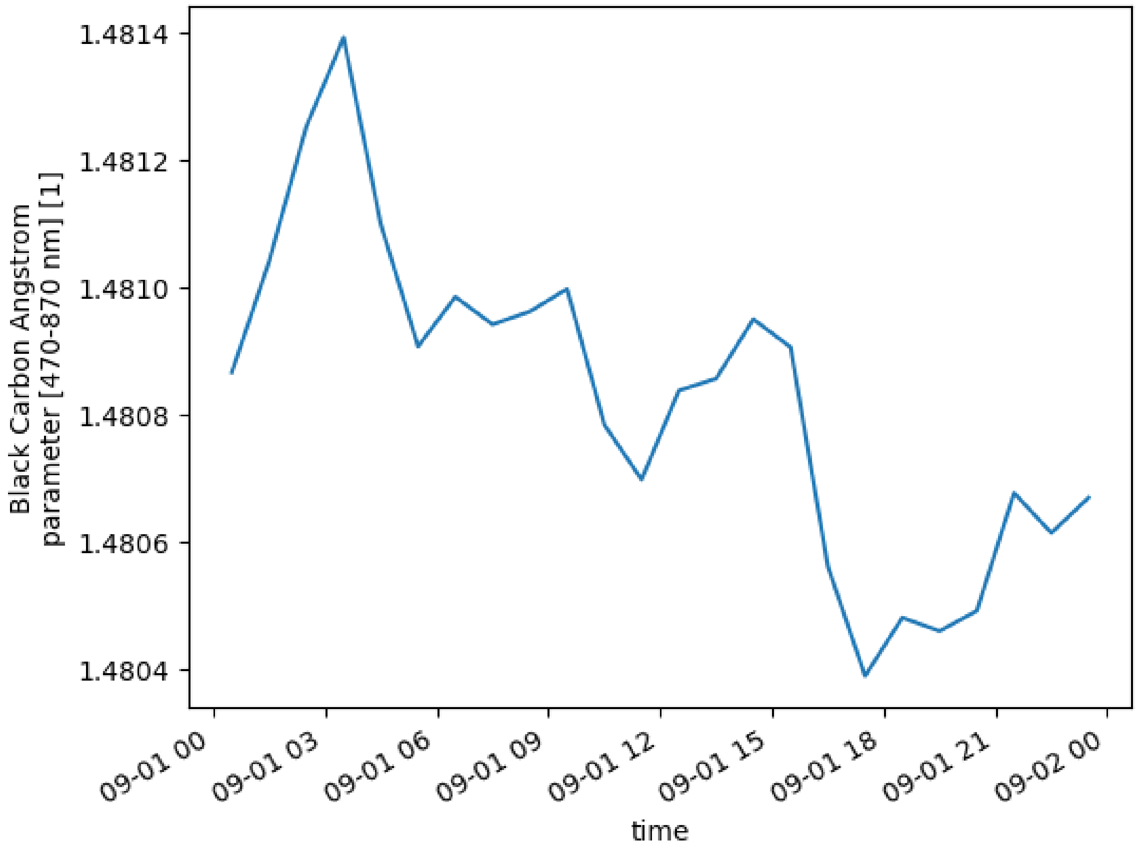
▶ Data variables: (50)

▶ Indexes: (3)

▶ Attributes: (30)

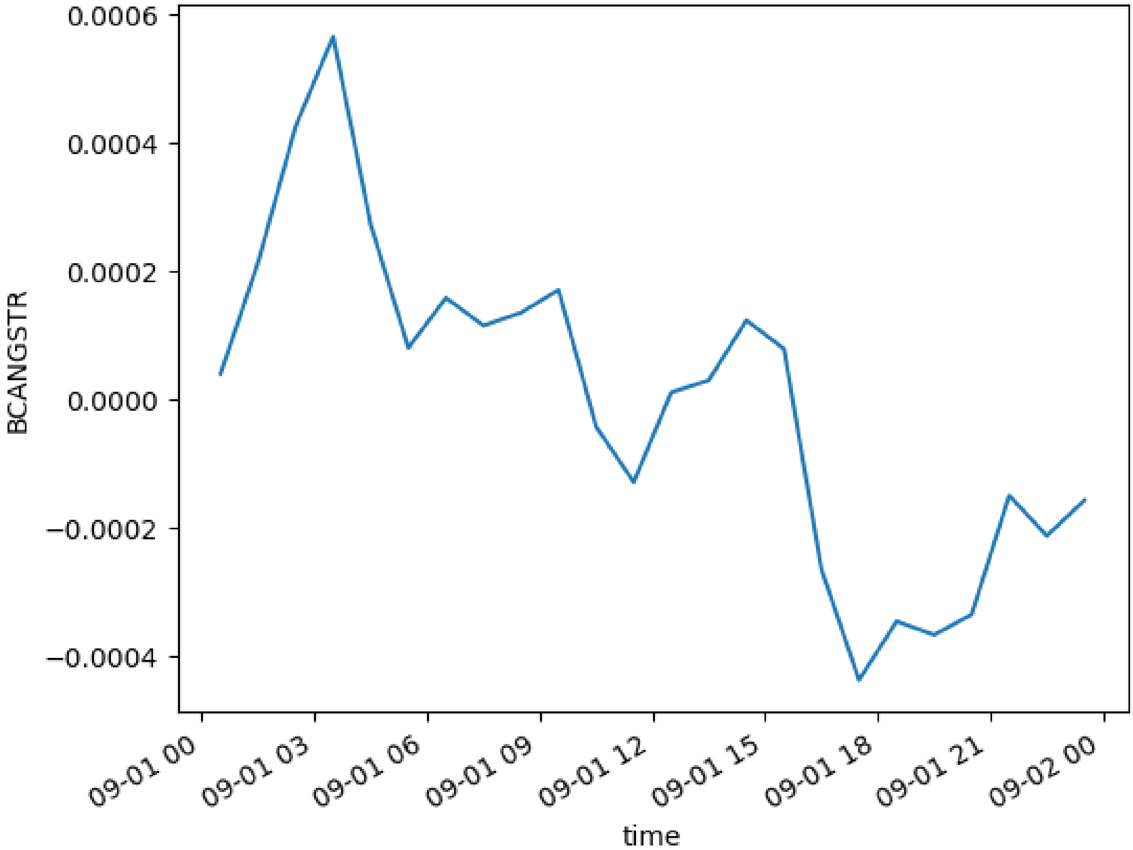
In [20]:
```
# 3.1
data_clim=data.BCANGSTR.groupby("time.month")
data_clim.mean(dim=['lon','lat']).plot()
```

Out[20]: [<matplotlib.lines.Line2D at 0x14b0f2a1210>]



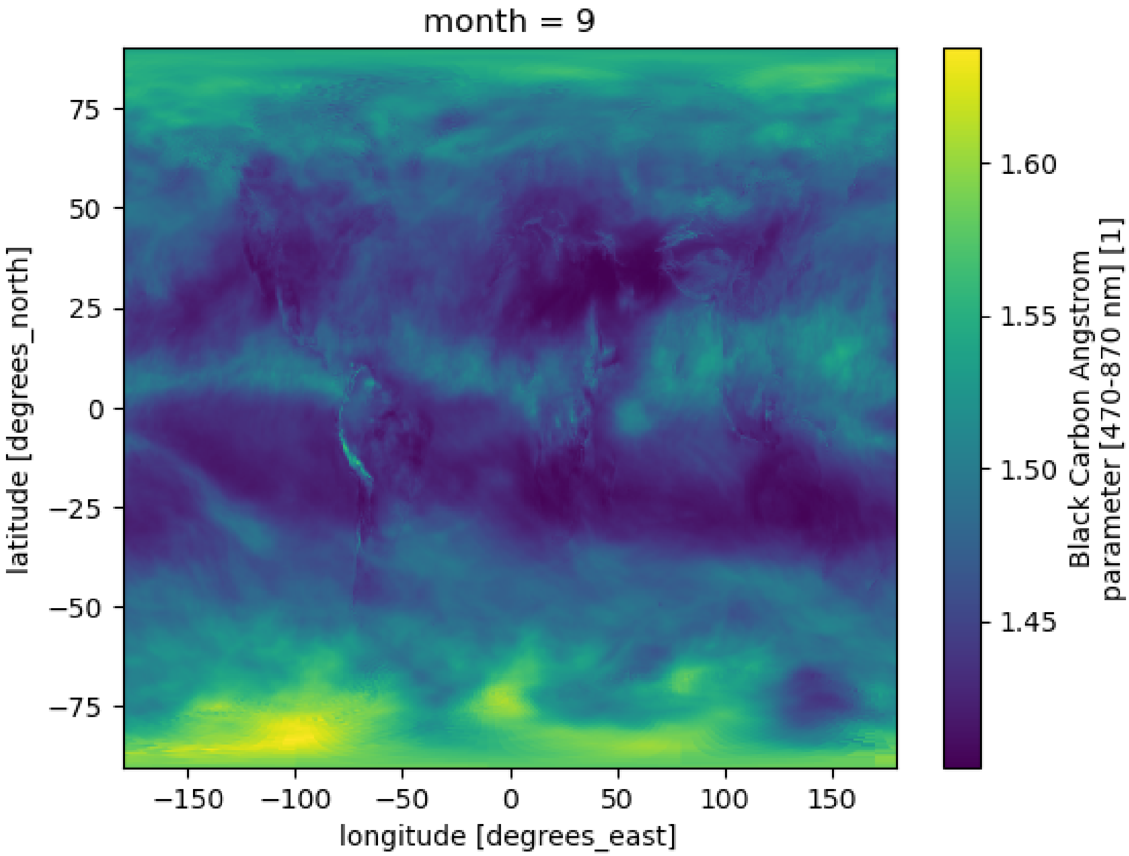
In [21]:
```
data_dif=data_clim-data_clim.mean(dim='time')
data_dif.mean(dim=['lon','lat']).plot()
```

Out[21]: [<matplotlib.lines.Line2D at 0x14b0be136d0>]



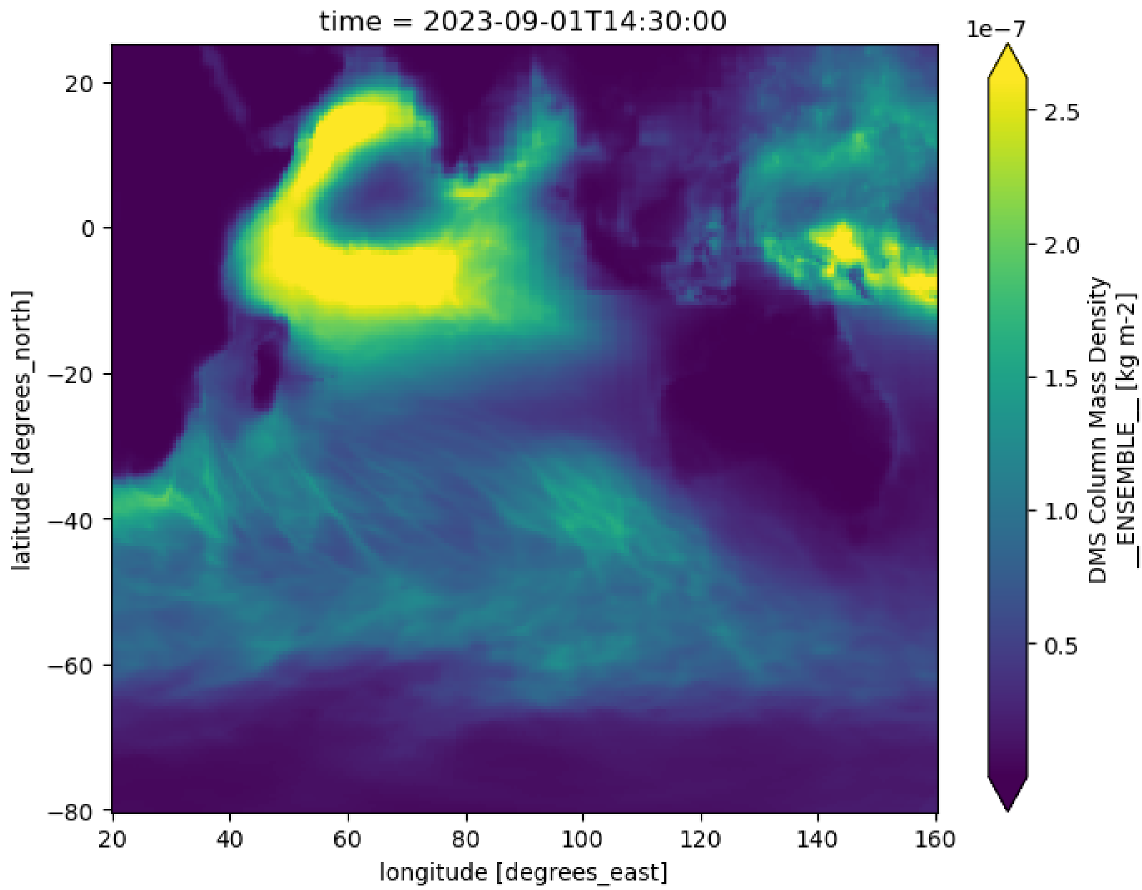
In [22]:
```
# 3.2
# 3.2.1
data1=data.BCANGSTR.groupby("time.month").mean()
data1.plot()
```

Out[22]: <matplotlib.collections.QuadMesh at 0x14b0f37d490>

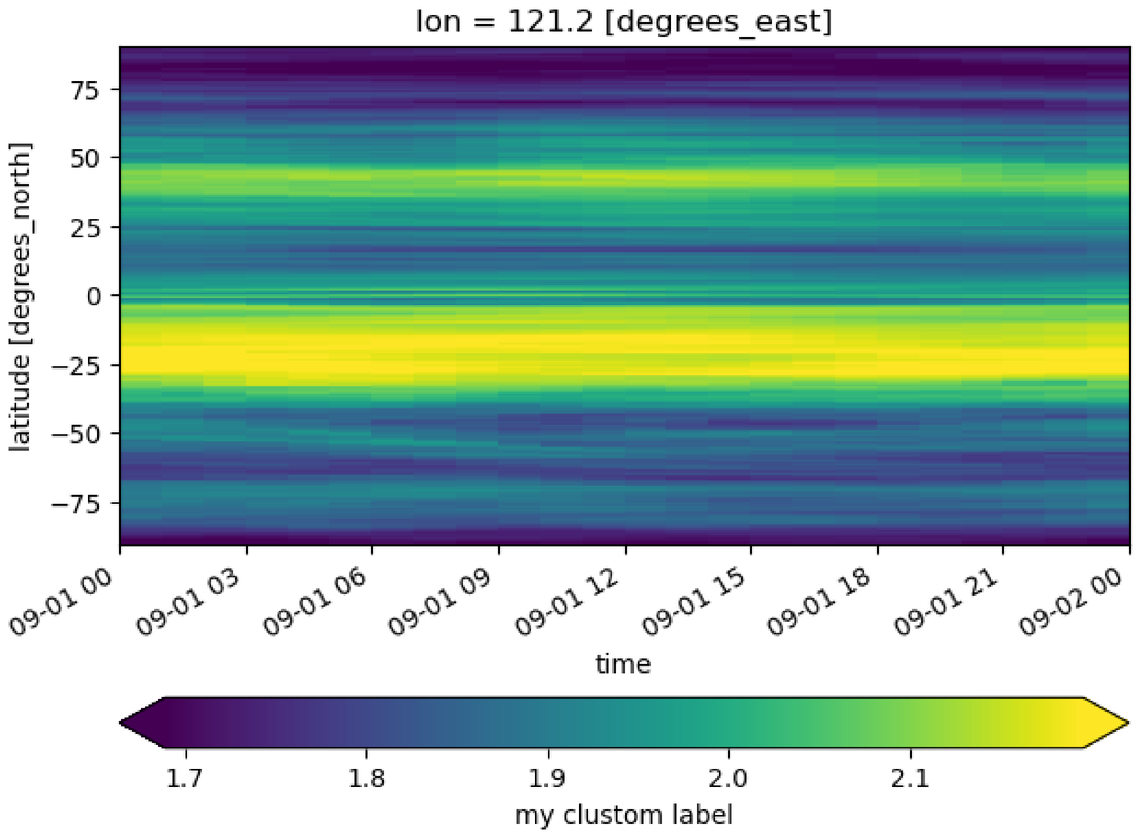


In [23]:
```python
# 3.2.2
data.DMSCMASS.isel(time=-10).sel(lon=slice(20, 160),
                                 lat=slice(-80, 25)).plot(robust=True, figsize=(8, 6))
```

Out[23]:
```
<matplotlib.collections.QuadMesh at 0x14b099e6550>
```

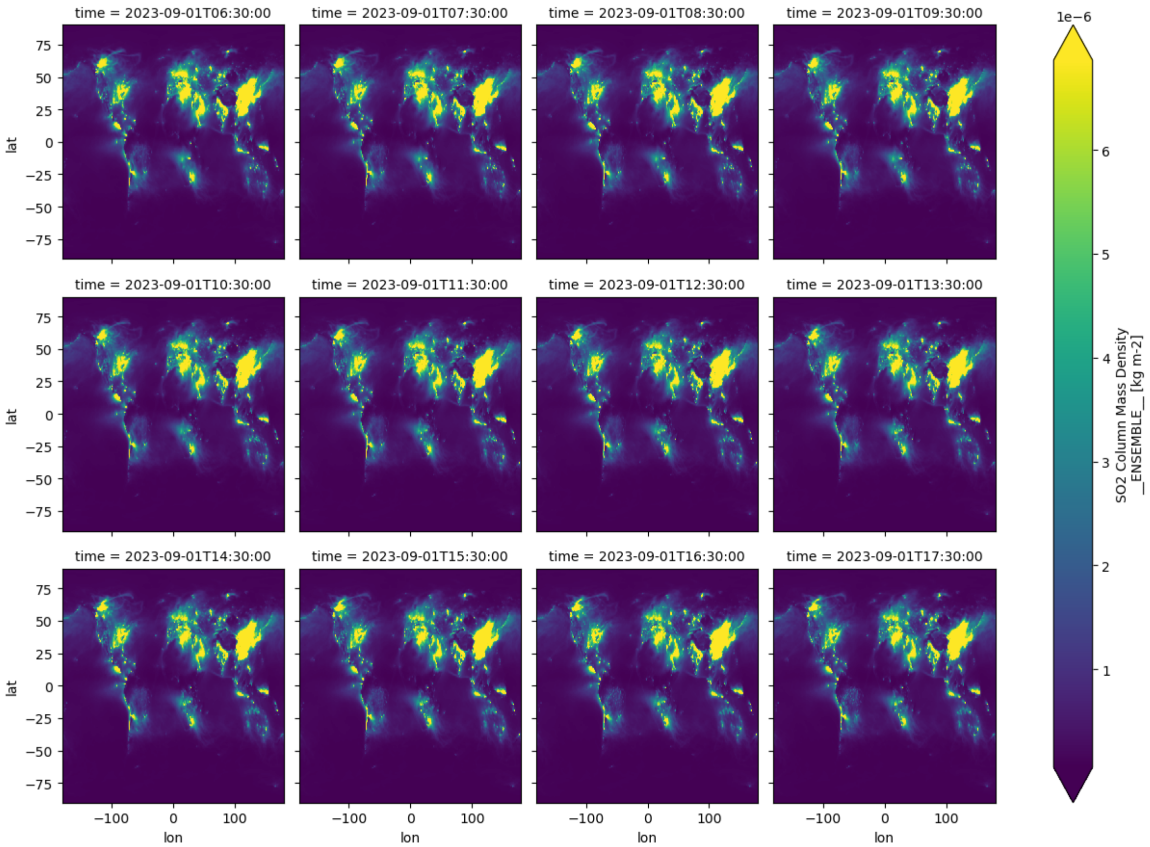


In [24]:
```
# 3.2.3
colorbar_kwargs = {
    "orientation": "horizontal",
    "label": "my clustom label",
    "pad": 0.2,
}

data.OCANGSTR.sel(lon=121.5, method='nearest').plot(
    x="time",
    robust=True,
    cbar_kwargs=colorbar_kwargs,
)

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



In [25]:
```
# 3.2.4
data.SO2CMASS.sel(time=slice("2023-09-01T06:30:00", "2023-09-01T17:30:00")).plot(col=
```

Out[25]: <xarray.plot.facetgrid.FacetGrid at 0x14b1ebf83d0>



In [26]:
```
# 3.2.5
data.SSANGSTR.sel(lon=120, lat=22.5, method='nearest').plot(marker="o", size=6)
```

Out[26]:
```
[<matplotlib.lines.Line2D at 0x14b0983f0d0>]
```