In [1]:
```
# import modules
import numpy as np
import xarray as xr
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.ticker as mticker
%matplotlib inline
import cartopy.crs as ccrs
import cartopy.feature as cfeature
```

In [2]:
```
# 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....
lon	(lon)	float32	0.0 2.0 4.0 ... 354.0 356...
time	(time)	datetime64[ns]	1960-01-15 ... 2016-12...

▼ 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]:
```
# the seasonal change of temperature is calculated at (5N-5S, 170W-
group_data = SST.sst.sel(lon=slice(120,170),lat=slice(-5,5)).groupb
sst_clim = group_data.mean()
sst_clim
```

Out[3]:

xarray.DataArray 'sst' (**month**: 12, **lat**: 5, **lon**: 26)

```
array([[[29.028156, 29.124018, 29.130487, ..., 29.458986, 29.40671 ,
         29.358635],
```

```
        [29.027426, 29.153624, 29.129362, ..., 29.291643, 29.2
04933,
         29.120565],
        [28.849007, 28.912628, 28.852278, ..., 29.110067, 28.9
9955 ,
         28.881413],
        [28.612465, 28.634708, 28.546515, ..., 29.011509, 28.8
98874,
         28.79206 ],
        [28.40417 , 28.447857, 28.392477, ..., 28.926332, 28.8
47929,
         28.770119]],

       [[28.825596, 28.930664, 28.940992, ..., 29.35216 , 29.2
93056,
         29.238314],
        [28.833675, 28.988573, 28.985886, ..., 29.194006, 29.0
958  ,
         28.999252],
        [28.68234 , 28.760672, 28.715094, ..., 29.009357, 28.8
8335 ,
         28.75082 ],
        [28.4706  , 28.487507, 28.394753, ..., 28.928986, 28.8
01754,
         28.684416],
        [28.25052 , 28.287918, 28.223717, ..., 28.879599, 28.7
97909,
...
         29.634012],
        [29.52841 , 29.521248, 29.439075, ..., 29.461407, 29.4
11896,
         29.378262],
        [29.469206, 29.49123 , 29.416918, ..., 29.265162, 29.1
85635,
         29.129591],
        [29.35844 , 29.388475, 29.340836, ..., 29.25499 , 29.1
64148,
         29.110823],
        [29.258398, 29.272776, 29.248367, ..., 29.318436, 29.2
57198,
         29.215263]],

       [[29.398111, 29.451107, 29.452528, ..., 29.62688 , 29.5
98337,
         29.573372],
```

```
        [29.383438, 29.455273, 29.41713 , ..., 29.432829, 29.3
69019,
         29.315294],
        [29.23622 , 29.28212 , 29.224049, ..., 29.233976, 29.1
40806,
         29.057495],
        [29.042618, 29.06313 , 28.99859 , ..., 29.160395, 29.0
58783,
         28.97982 ],
        [28.894953, 28.918709, 28.872938, ..., 29.127762, 29.0
56019,
         28.993029]]], 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
month	(month)	int64	1 2 3 4 5 6 7 8 9 10 11 12

► 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]:

```
# deseasonalize and get outliers
sst_anom=group_data-group_data.mean(dim='time')
sst_anom.sel(lon=slice(120,170),lat=slice(-5,5))
# the data were processed to obtain outliers on a three-month scale
resample_obj = sst_anom.resample(time="3M")
ds_anom_resample = resample_obj.mean(dim="time")
ds_anom_resample
```

Out[4]:

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

```
array([[[-0.4533596 , -0.43008804, -0.3652172 , ..., -0.590425
5 ,
         -0.51613617, -0.5157356 ],
        [-0.14541245, -0.14106178, -0.20046997, ..., -0.601078
03,
         -0.5806999 , -0.5200424 ],
        [ 0.03437614, -0.01860619, -0.1291542 , ..., -0.612791
```

```
06,
         -0.5868416 , -0.55138206],
        [-0.03416824, -0.07881355, -0.139431  , ..., -0.576824
2 ,
         -0.56368065, -0.5451031 ],
        [-0.11306   , -0.14630127, -0.18651962, ..., -0.475275
04,
         -0.48386002, -0.49680328]],

       [[-0.29540953, -0.25229773, -0.21316402, ..., -0.650178
9 ,
         -0.5796814 , -0.58689374],
        [-0.18128014, -0.12417793, -0.13654137, ..., -0.690423
3 ,
         -0.68461037, -0.64244586],
        [-0.09715843, -0.08390108, -0.10546494, ..., -0.706928
9 ,
         -0.6881733 , -0.6722056 ],
        [-0.18694179, -0.16128285, -0.128987  , ..., -0.644335
45,
         -0.62889546, -0.6225446 ],
        [-0.27703476, -0.2525959 , -0.20511119, ..., -0.517519
,
...
          0.51037025,  0.44631258],
        [ 0.31214967,  0.4855779 ,  0.7164224 , ...,  0.443646
1 ,
          0.3200194 ,  0.2053426 ],
        [ 0.39565277,  0.5145791 ,  0.7320716 , ...,  0.397978
45,
          0.23362541,  0.08429018],
        [ 0.44386673,  0.44989267,  0.5983505 , ...,  0.536855
7 ,
          0.3789749 ,  0.21928024],
        [ 0.42669234,  0.40143776,  0.4725081 , ...,  0.714798
,
          0.5879669 ,  0.46769652]],

       [[ 0.32543087,  0.3451271 ,  0.4029932 , ...,  0.512637
14,
          0.4383192 ,  0.36778736],
        [ 0.42484474,  0.5078449 ,  0.57851505, ...,  0.344710
35,
          0.22703075,  0.10994244],
        [ 0.5032301 ,  0.5828867 ,  0.66394806, ...,  0.273533
```

```
82,
         0.13096333, -0.00620747],
       [ 0.46020794,  0.49208736,  0.58321095, ...,  0.378380
78,
         0.25306892,  0.11438084],
       [ 0.3544016 ,  0.36249638,  0.44186687, ...,  0.523677
8 ,
         0.4169016 ,  0.31012917]]], dtype=float32)
```

▼ Coordinates:

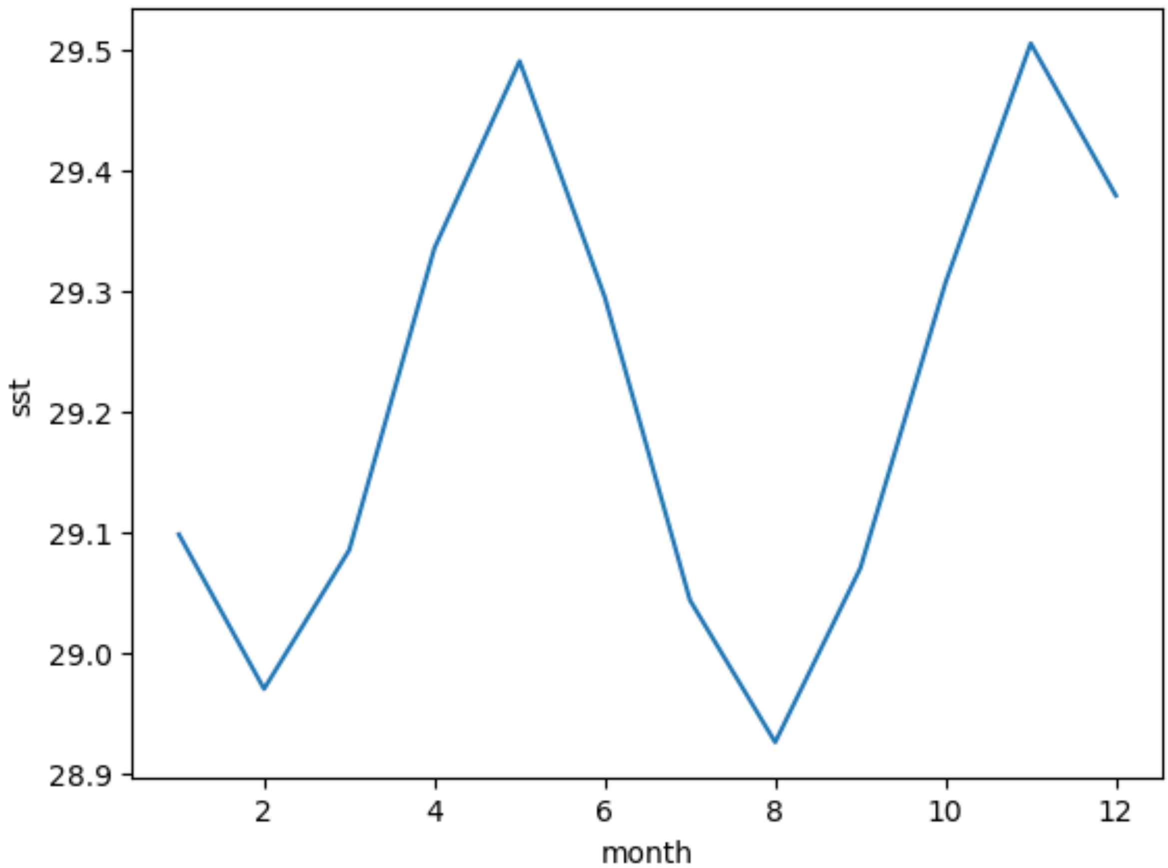
lat	(lat)	float32	-4.0 -2.0 0.0 2.0 4.0
lon	(lon)	float32	120.0 122.0 124.0 ... 168.0 170.0
time	(time)	datetime64[ns]	1960-01-31 ... 2017-01-31

▶ Indexes: (3)

▶ Attributes: (0)

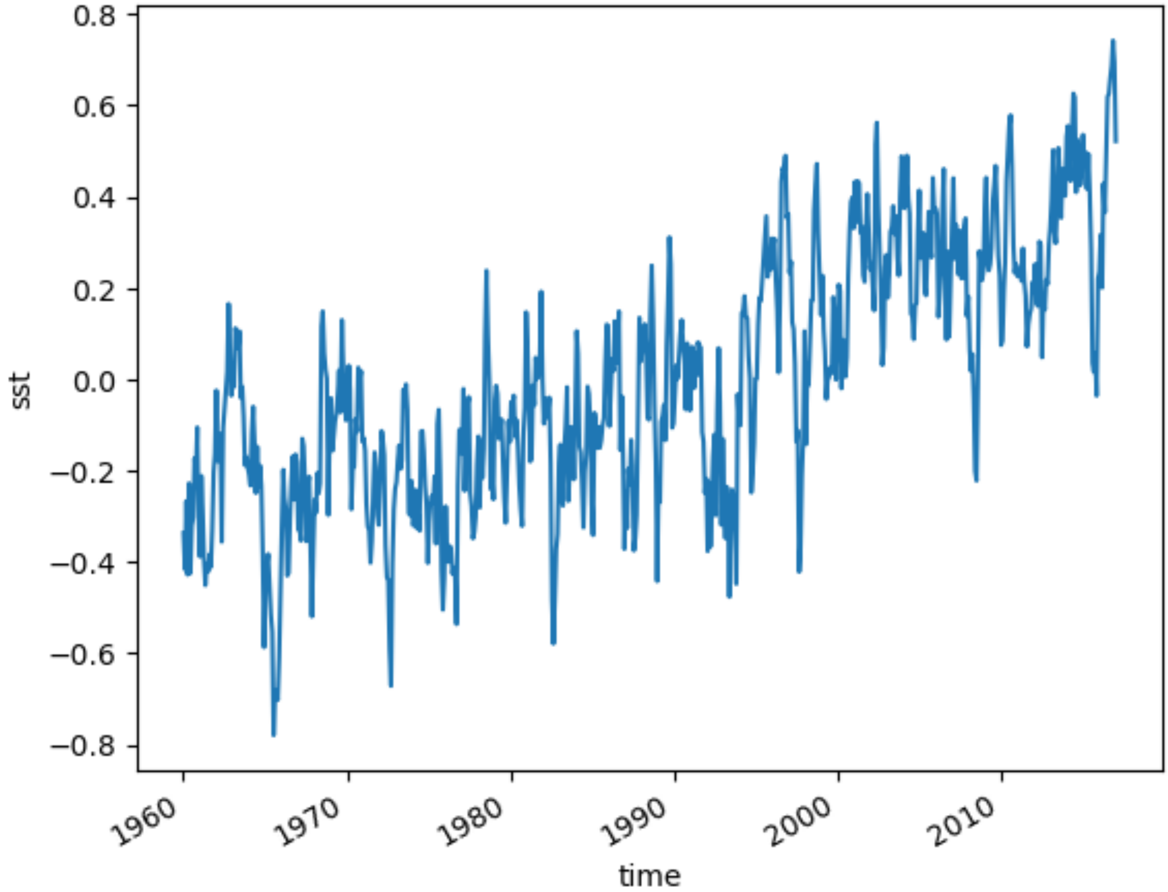
In [5]:
```
# 1.2
# visualize seasonal changes
sst_clim.mean(dim=['lat','lon']).plot()
```

Out[5]: [<matplotlib.lines.Line2D at 0x140accdd0>]



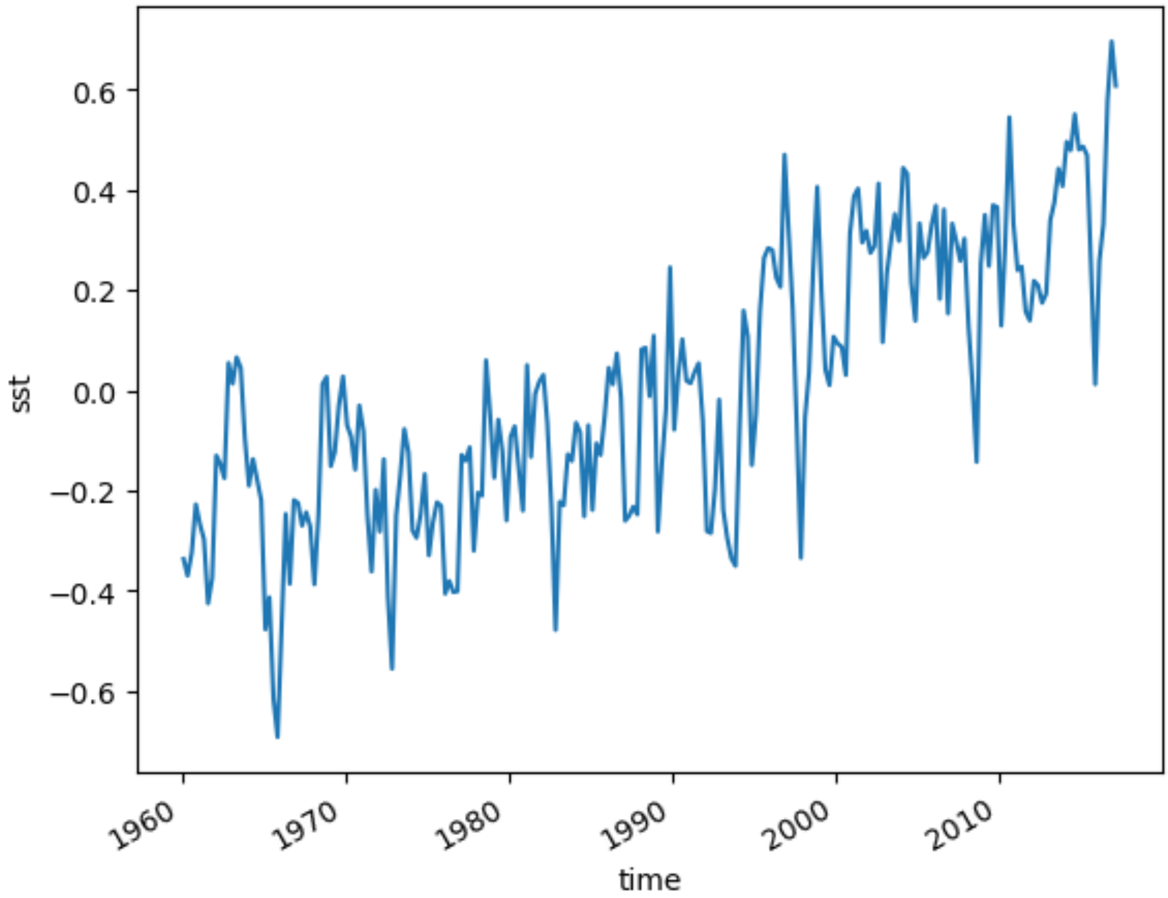
In [6]:
```
# visualize the de-seasonality change
sst_anom.mean(dim=['lat','lon']).plot()
```

Out[6]: [<matplotlib.lines.Line2D at 0x1419301d0>]



In [7]:
```
# visualization of outliers on a three-month scale
ds_anom_resample.mean(dim=['lat','lon']).plot()
```

Out[7]: [<matplotlib.lines.Line2D at 0x141acded0>]



In [8]:
```
ds_anom_resample_m=ds_anom_resample.mean(dim=['lat','lon'])
ds_anom_resample_m
```

Out[8]: 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 ], dt
ype=float32)
```

▼ Coordinates:

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

▶ Indexes: (1)

▶ Attributes: (0)

In [9]:
```
df=pd.DataFrame(ds_anom_resample_m.where(ds_anom_resample_m>=0),colu
df['anom<0']=pd.DataFrame(ds_anom_resample_m.where(ds_anom_resample_
df['date'] = pd.DataFrame(ds_anom_resample_m.time)
df.set_index('date',inplace=True)
df
```

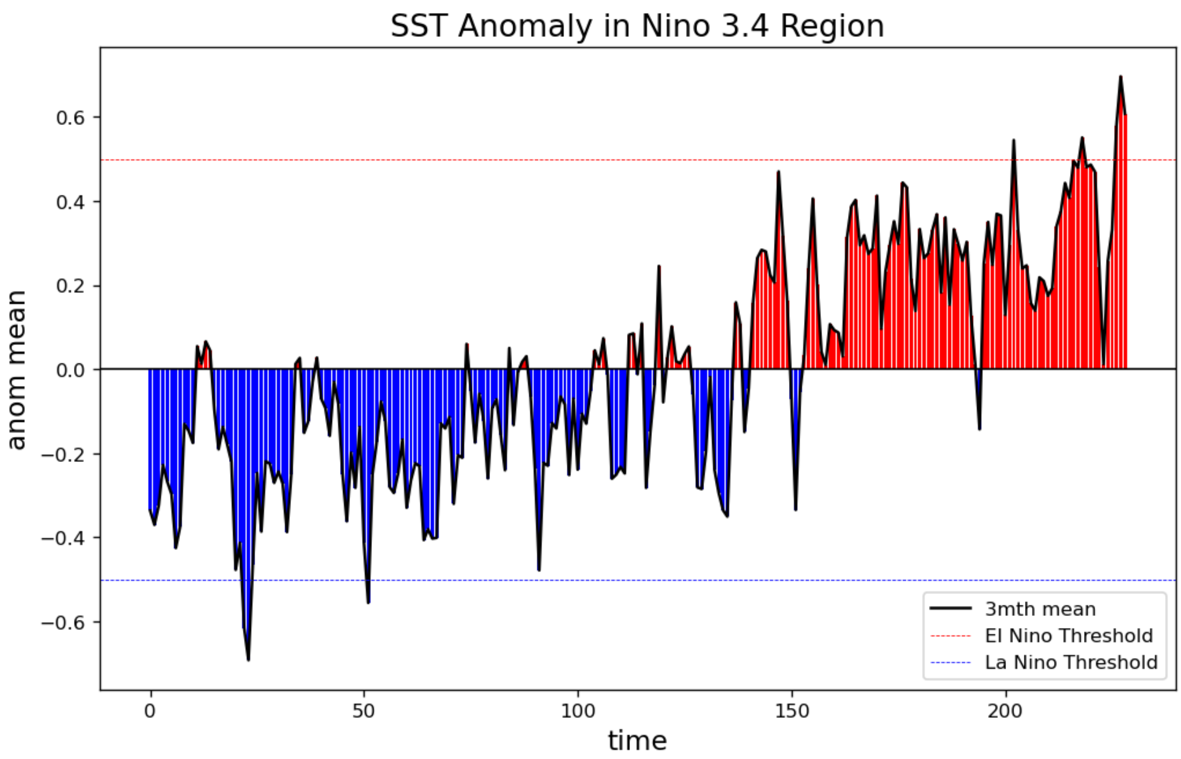
Out[9]:

	anom>=0	anom<0
date		
1960-01-31	NaN	-0.336390
1960-04-30	NaN	-0.370035
1960-07-31	NaN	-0.324000
1960-10-31	NaN	-0.227655
1961-01-31	NaN	-0.267422
...	...	...
2016-01-31	0.257505	NaN
2016-04-30	0.331463	NaN
2016-07-31	0.577958	NaN
2016-10-31	0.696175	NaN
2017-01-31	0.607659	NaN

229 rows × 2 columns

In [10]:
```
# color according to positive and negative
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 Thresho
plt.ylabel('anom mean',fontsize=14)
plt.xlabel('time',fontsize=14)
plt.title('SST Anomaly in Nino 3.4 Region',fontsize=16)
```

Out[10]:
```
Text(0.5, 1.0, 'SST Anomaly in Nino 3.4 Region')
```



In [ ]:

In [11]:
```
# 2
TOA = xr.open_dataset("CERES_EBAF-TOA_200003-201701.nc",engine='net
TOA
```

Out[11]:

xarray.Dataset

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

▼ Coordinates:

lon	(lon)	float32	0.5 1.5 2.5 ... 357.5 358...
time	(time)	datetime64[ns]	2000-03-15 ... 2017-01...

lat	(lat)	float32	-89.5 -88.5 -87.5 ... 88....

▼ Data variables:

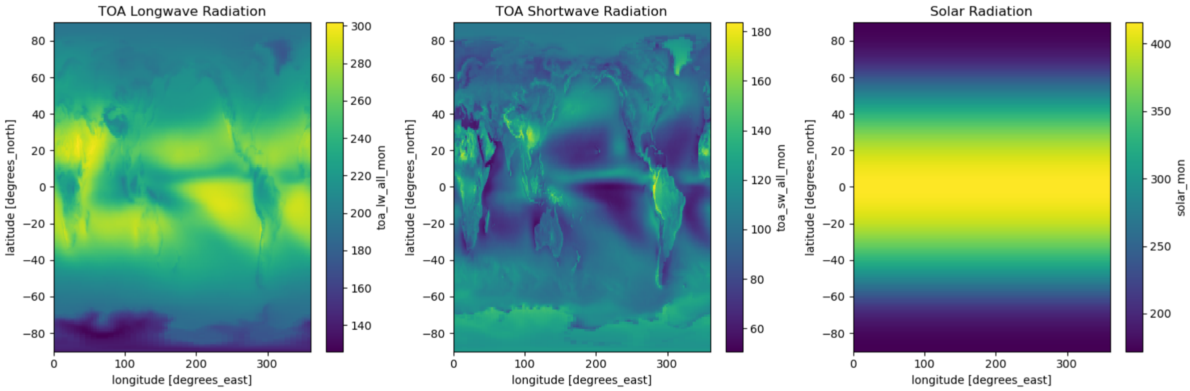
toa_sw_all_mon	(time, lat, lon)	float32	...
toa_lw_all_mon	(time, lat, lon)	float32	...
toa_net_all_mon	(time, lat, lon)	float32	...
toa_sw_clr_mon	(time, lat, lon)	float32	...
toa_lw_clr_mon	(time, lat, lon)	float32	...
toa_net_clr_mon	(time, lat, lon)	float32	...
toa_cre_sw_mon	(time, lat, lon)	float32	...
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)

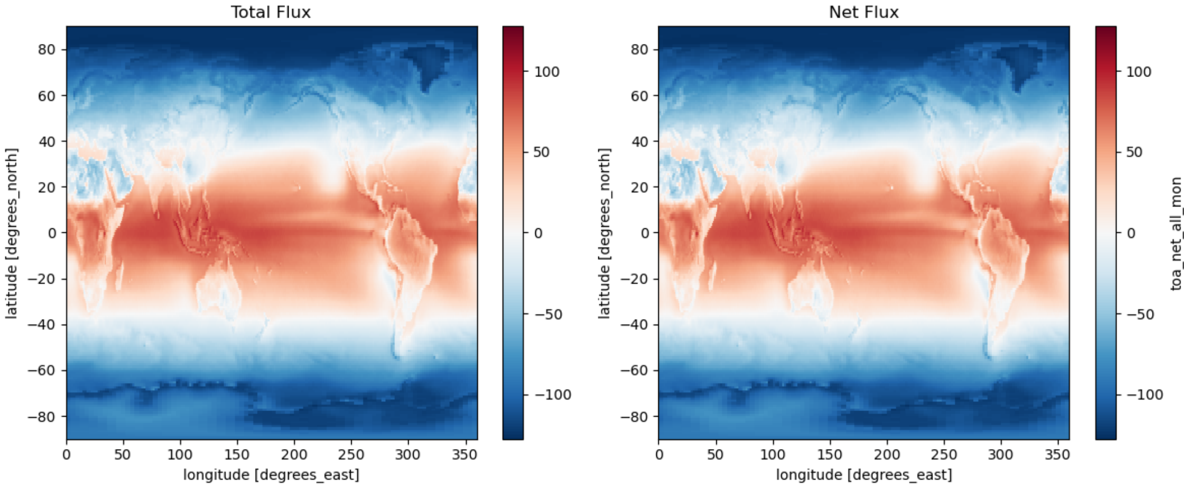
▼ Attributes:

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 [12]:
```
# 2.1
toa_sw_mean = TOA['toa_sw_all_mon'].mean(dim='time')
toa_lw_mean = TOA['toa_lw_all_mon'].mean(dim='time')
solar_mean = TOA['solar_mon'].mean(dim='time')


fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(15, 5))
toa_lw_mean.plot(ax=ax1)
ax1.set_title('TOA Longwave Radiation')

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

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

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



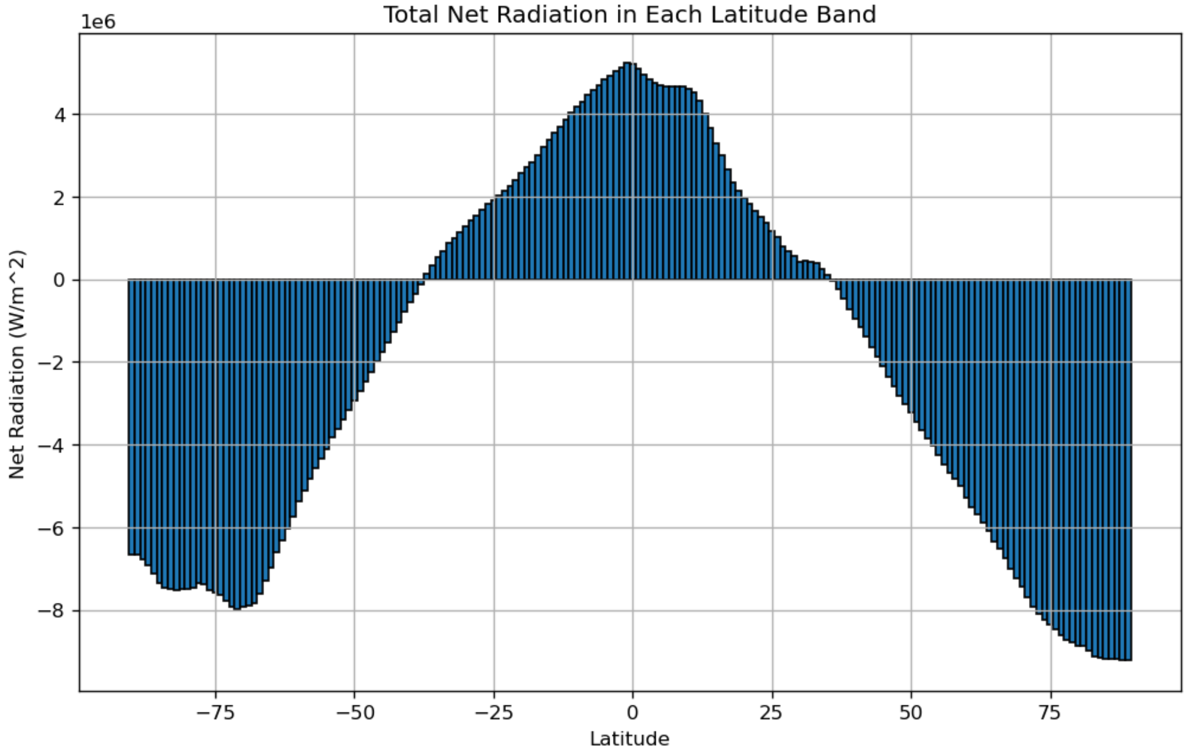
In [13]:
```
#Add up the three variables and verify visually that they are equiva
total_flux = solar_mean - toa_lw_mean - toa_sw_mean
toa_net = TOA['toa_net_all_mon'].mean(dim='time')

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

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

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



In [14]:
```
# 2.2
# Calculate and verify TOA incoming solar, outgoing longwave, and ou

weights = np.cos(np.deg2rad(TOA.lat))

toa_incoming_solar = TOA['solar_mon'].weighted(weights).mean(dim=['
toa_outgoing_lw = TOA['toa_lw_all_mon'].weighted(weights).mean(dim=
toa_outgoing_sw = TOA['toa_sw_all_mon'].weighted(weights).mean(dim=

print("outgoing longwave:",toa_outgoing_lw.values,'W·m^-2')
print("outgoing shortwave:",toa_outgoing_sw.values,'W·m^-2')
print("incoming solar:",toa_incoming_solar.values,'W·m^-2')
```

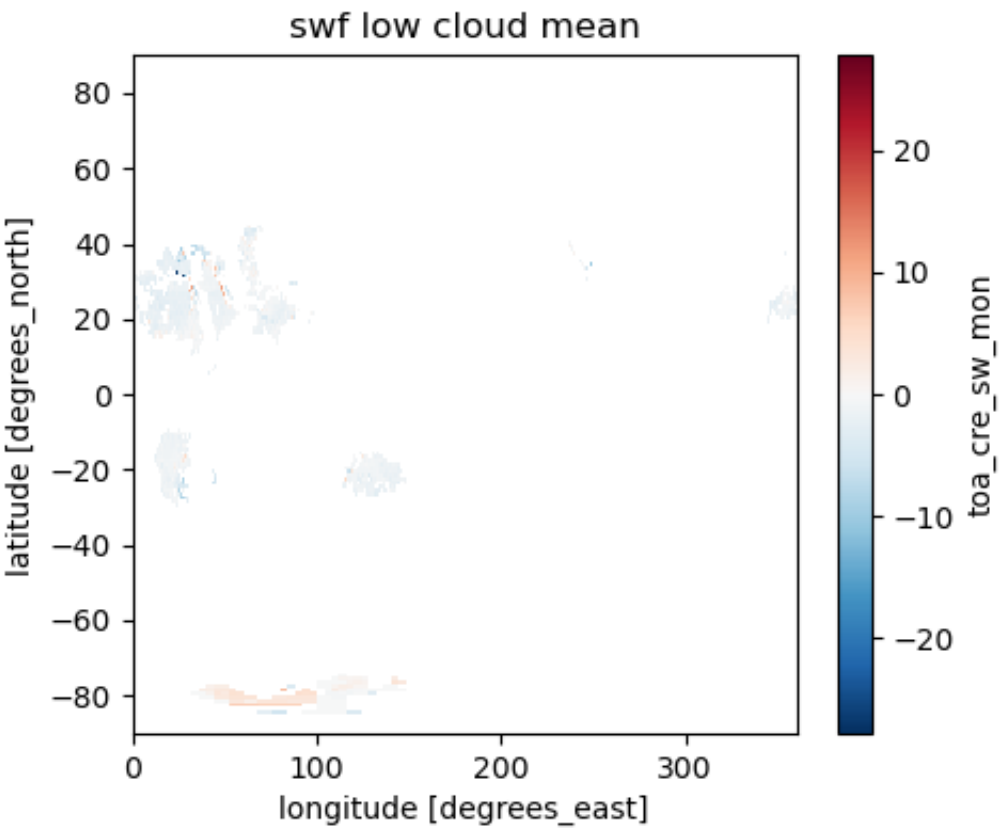
```
outgoing longwave: 240.26692 W·m^-2
outgoing shortwave: 99.13806 W·m^-2
incoming solar: 340.28326 W·m^-2
```

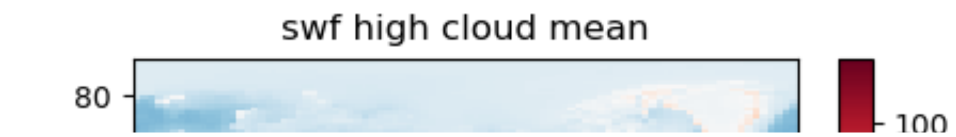
In [15]:
```
# 2.3
#I could't handle the questions below, so i asked my academic sibli

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])


plt.figure(figsize=(10, 6), dpi=120)
plt.bar(lat_bands[:-1], net_radiation_total, width=lat_resolution, 
plt.title('Total Net Radiation in Each Latitude Band')
plt.xlabel('Latitude')
plt.ylabel('Net Radiation (W/m^2)')
plt.grid(True)
plt.show()
```

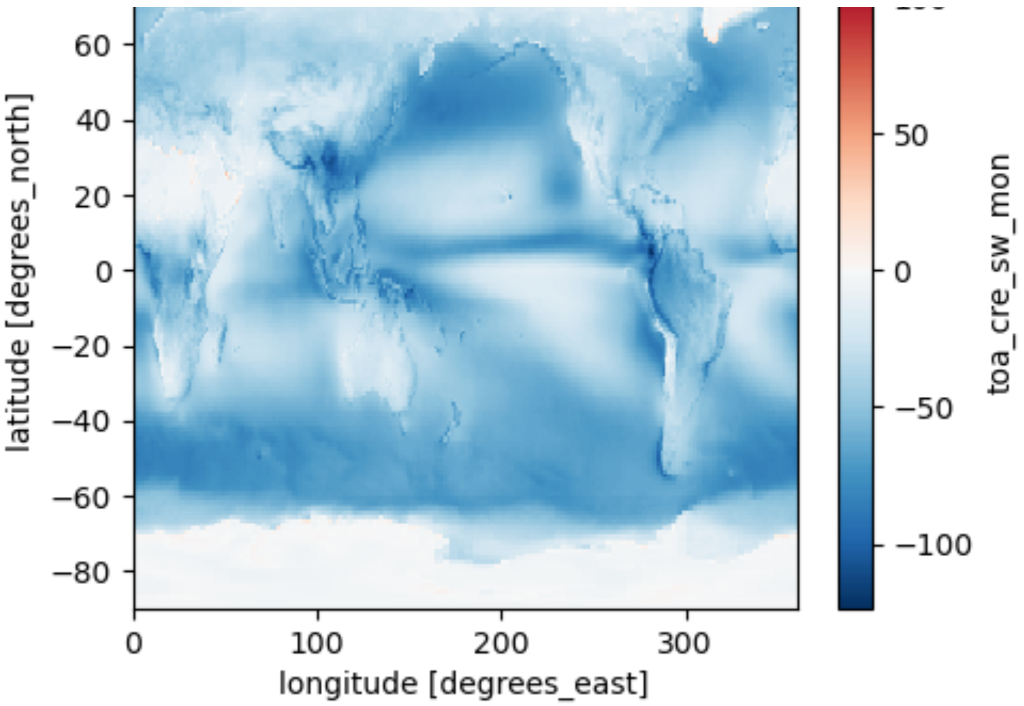


In [16]:
```
# 2.4
swf = TOA['toa_cre_sw_mon']  # Shortwave radiation flux
lwf = TOA['toa_cre_lw_mon']  # Longwave radiation flux
cld = TOA['cldarea_total_daynight_mon']  # Total cloud area fractio

# Define low and high cloud thresholds
```

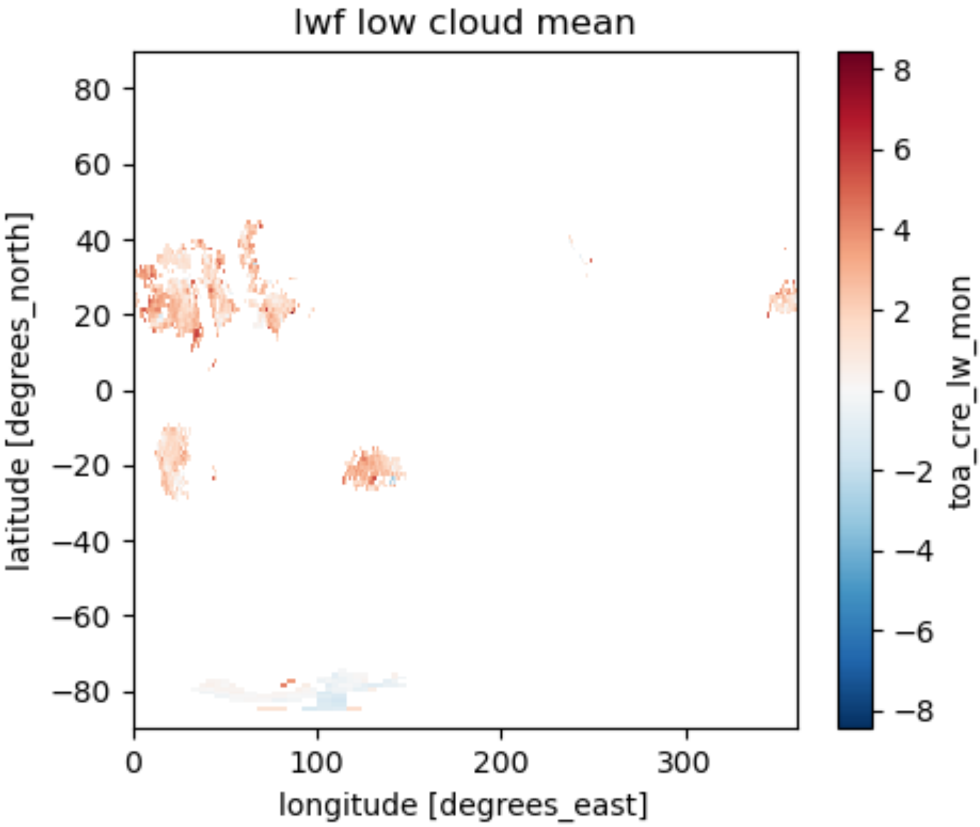
```
low_cloud_threshold = TOA['cldtau_total_day_mon'].quantile(0.25)
high_cloud_threshold = TOA['cldtau_total_day_mon'].quantile(0.75)

# Calculate time-mean for low and high cloud areas
swf_low_cloud_mean = swf.where(cld<low_cloud_threshold).mean(dim='t
swf_high_cloud_mean = swf.where(cld>high_cloud_threshold).mean(dim=
lwf_low_cloud_mean = lwf.where(cld<low_cloud_threshold).mean(dim='t
lwf_high_cloud_mean = lwf.where(cld>high_cloud_threshold).mean(dim=

# 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()
```



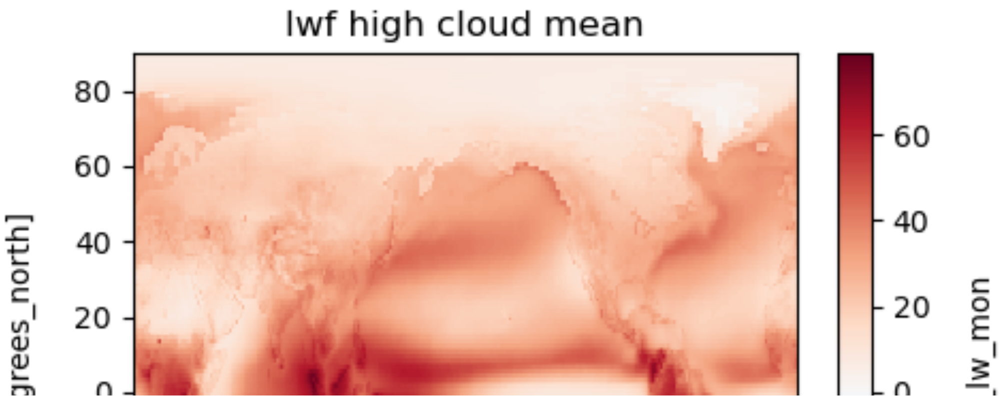




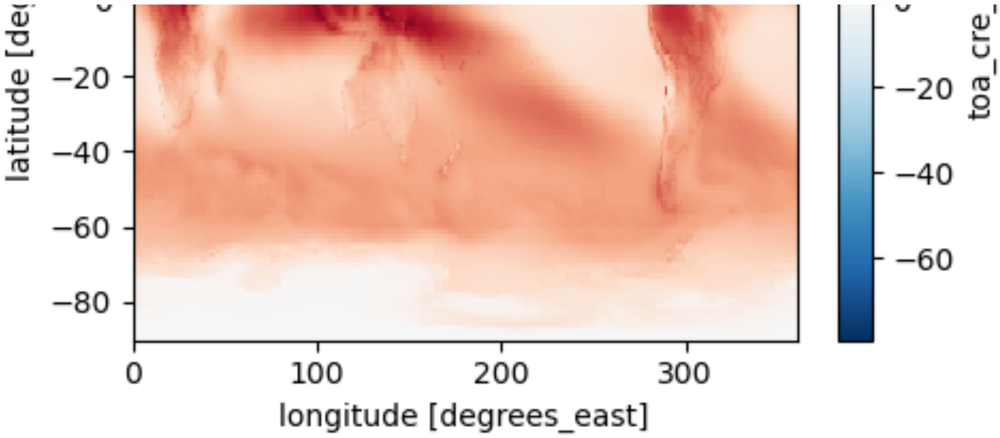
60
40
20
0
−20
−40
−60
−80
latitude [degrees_north]
0
100
200
300
longitude [degrees_east]
50
0
−50
−100
toa_cre_sw_mon



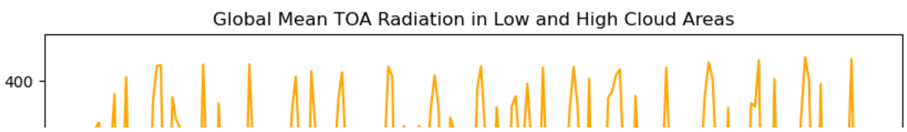
lwf low cloud mean
80
60
40
20
0
−20
−40
−60
−80
latitude [degrees_north]
0
100
200
300
longitude [degrees_east]
8
6
4
2
0
−2
−4
−6
−8
toa_cre_lw_mon

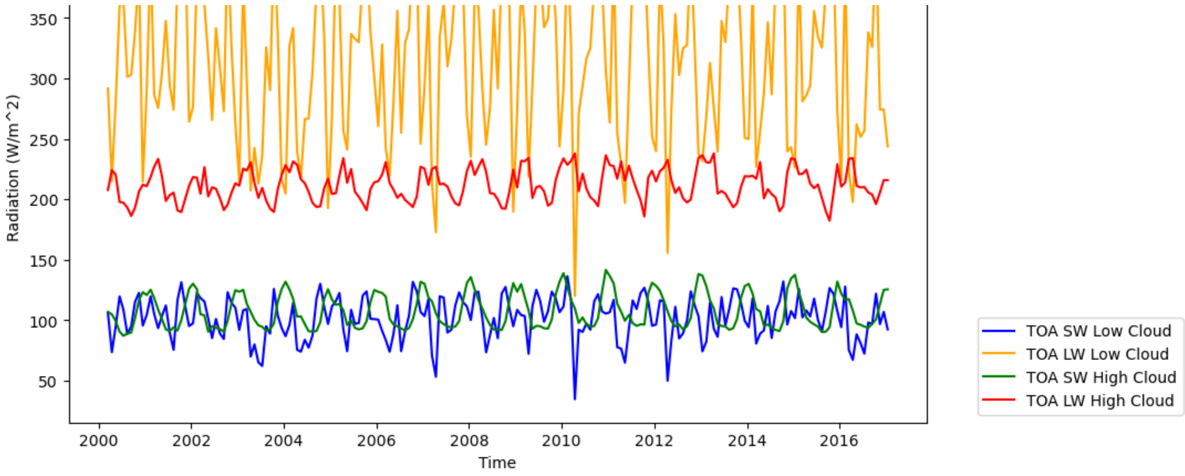


lwf high cloud mean
80
60
40
20
0
60
40
20
0



In [19]:
```
# 2.5
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 longi
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_a
global_lw_low_cloud = (toa_lw_all *  area_weights).where(low_cloud_a

global_sw_high_cloud = (toa_sw_all * area_weights).where(high_cloud_
global_lw_high_cloud = (toa_lw_all * area_weights).where(high_cloud_


plt.figure(figsize=(10, 6))

plt.plot(global_sw_low_cloud['time'], global_sw_low_cloud, label='T
plt.plot(global_lw_low_cloud['time'], global_lw_low_cloud, label='T
plt.plot(global_sw_high_cloud['time'], global_sw_high_cloud, label=
plt.plot(global_lw_high_cloud['time'], global_lw_high_cloud, label=

# 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 [22]:
```
# 3
#Load the netCDF dataset
ds = xr.open_dataset('MERRA2_200.tavgU_2d_aer_Nx.200008.nc4', engin
ds
```

Out[22]:

xarray.Dataset

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

▼ Coordinates:

lon	(lon)	float64	-180.0 -179.4 ... 178.8 ...
lat	(lat)	float64	-90.0 -89.5 -89.0 ... 89....
time	(time)	datetime64[ns]	2000-08-01T00:30:00 .....

▼ Data variables:

BCANGSTR	(time, lat, lon)	float32	...
BCCMASS	(time, lat, lon)	float32	...
BCEXTTAU	(time, lat, lon)	float32	...
BCFLUXU	(time, lat, lon)	float32	...
BCFLUXV	(time, lat, lon)	float32	...
BCSCATAU	(time, lat, lon)	float32	...
BCSMASS	(time, lat, lon)	float32	...
DMSCMASS	(time, lat, lon)	float32	...
DMSSMASS	(time, lat, lon)	float32	...
DUANGSTR	(time, lat, lon)	float32	...
DUCMASS	(time, lat, lon)	float32	...
DUCMASS25	(time, lat, lon)	float32	...
DUEXTT25	(time, lat, lon)	float32	...
DUEXTTAU	(time, lat, lon)	float32	...
DUFLUXU	(time, lat, lon)	float32	...
DUFLUXV	(time, lat, lon)	float32	...
DUSCAT25	(time, lat, lon)	float32	...

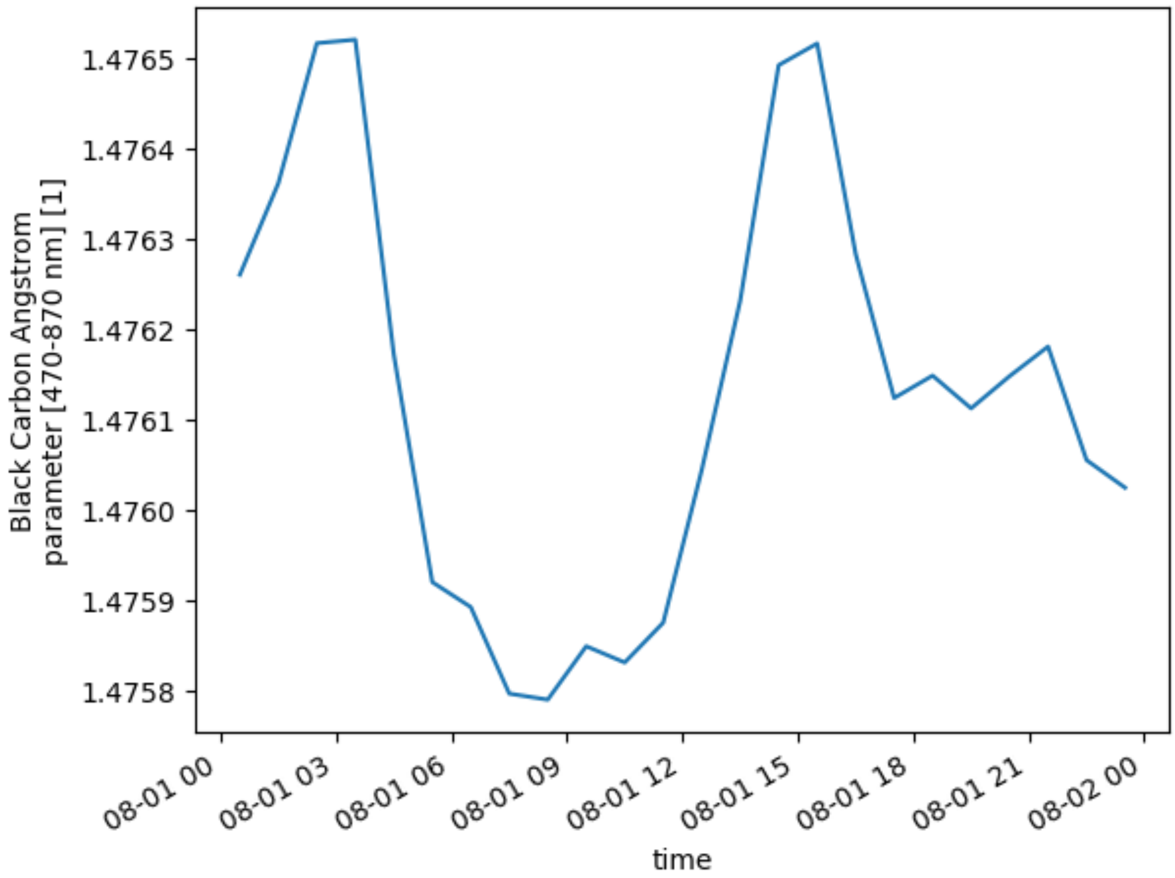
DUSCATAU	(time, lat, lon)	float32	...
DUSMASS	(time, lat, lon)	float32	...
DUSMASS25	(time, lat, lon)	float32	...
OCANGSTR	(time, lat, lon)	float32	...
OCCMASS	(time, lat, lon)	float32	...
OCEXTTAU	(time, lat, lon)	float32	...
OCFLUXU	(time, lat, lon)	float32	...
OCFLUXV	(time, lat, lon)	float32	...
OCSCATAU	(time, lat, lon)	float32	...
OCSMASS	(time, lat, lon)	float32	...
SO2CMASS	(time, lat, lon)	float32	...
SO2SMASS	(time, lat, lon)	float32	...
SO4CMASS	(time, lat, lon)	float32	...
SO4SMASS	(time, lat, lon)	float32	...
SSANGSTR	(time, lat, lon)	float32	...
SSCMASS	(time, lat, lon)	float32	...
SSCMASS25	(time, lat, lon)	float32	...
SSEXTT25	(time, lat, lon)	float32	...
SSEXTTAU	(time, lat, lon)	float32	...
SSFLUXU	(time, lat, lon)	float32	...
SSFLUXV	(time, lat, lon)	float32	...
SSSCAT25	(time, lat, lon)	float32	...
SSSCATAU	(time, lat, lon)	float32	...
SSSMASS	(time, lat, lon)	float32	...
SSSMASS25	(time, lat, lon)	float32	...
SUANGSTR	(time, lat, lon)	float32	...
SUEXTTAU	(time, lat, lon)	float32	...
SUFLUXU	(time, lat, lon)	float32	...
SUFLUXV	(time, lat, lon)	float32	...
SUSCATAU	(time, lat, lon)	float32	...
TOTANGSTR	(time, lat, lon)	float32	...
TOTEXTTAU	(time, lat, lon)	float32	...
TOTSCATAU	(time, lat, lon)	float32	...

▶ Indexes: (3)

▶ Attributes: (30)

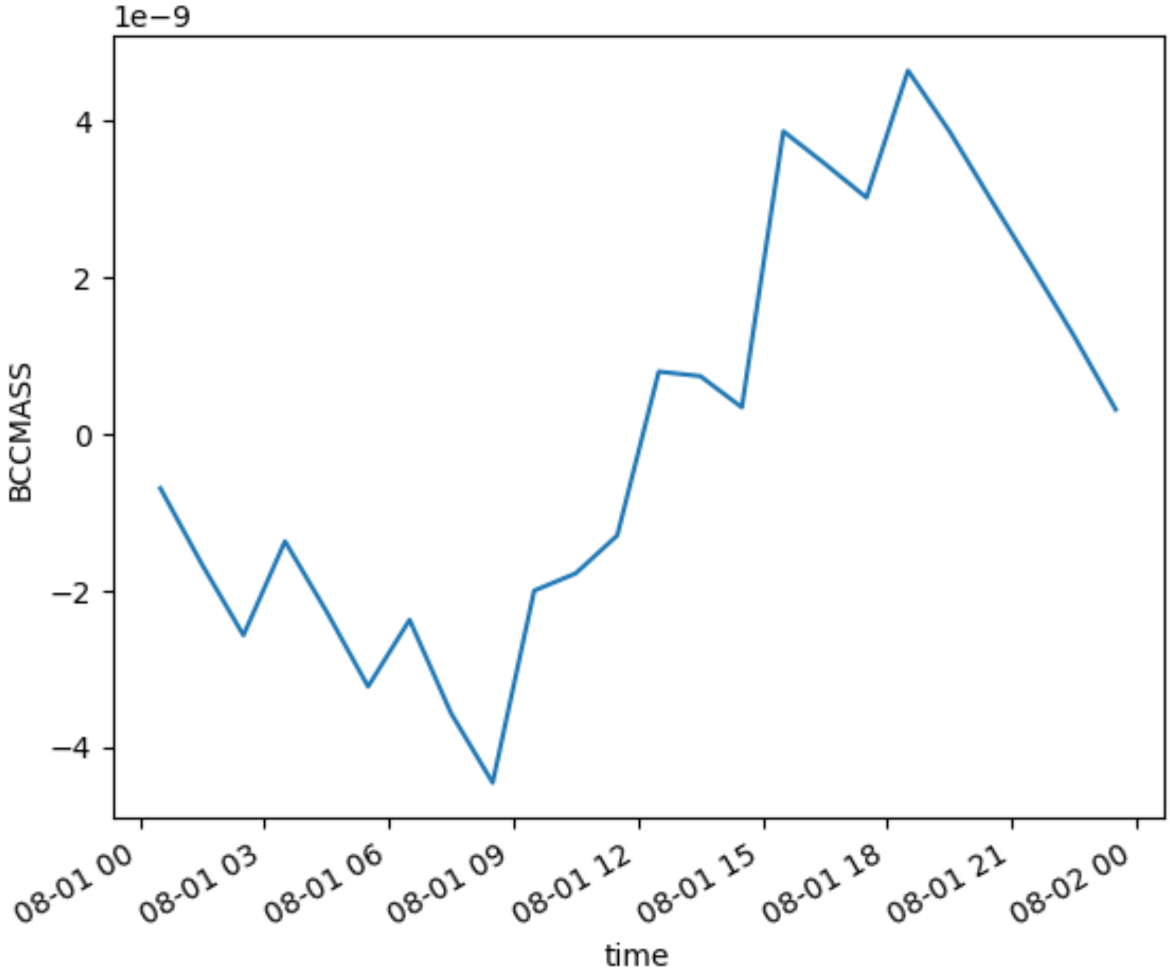
In [33]:
```
ds_clim=ds.BCANGSTR.groupby("time.month")
ds_clim.mean(dim=['lon','lat']).plot()
```

Out[33]:
```
[<matplotlib.lines.Line2D at 0x1420a9050>]
```



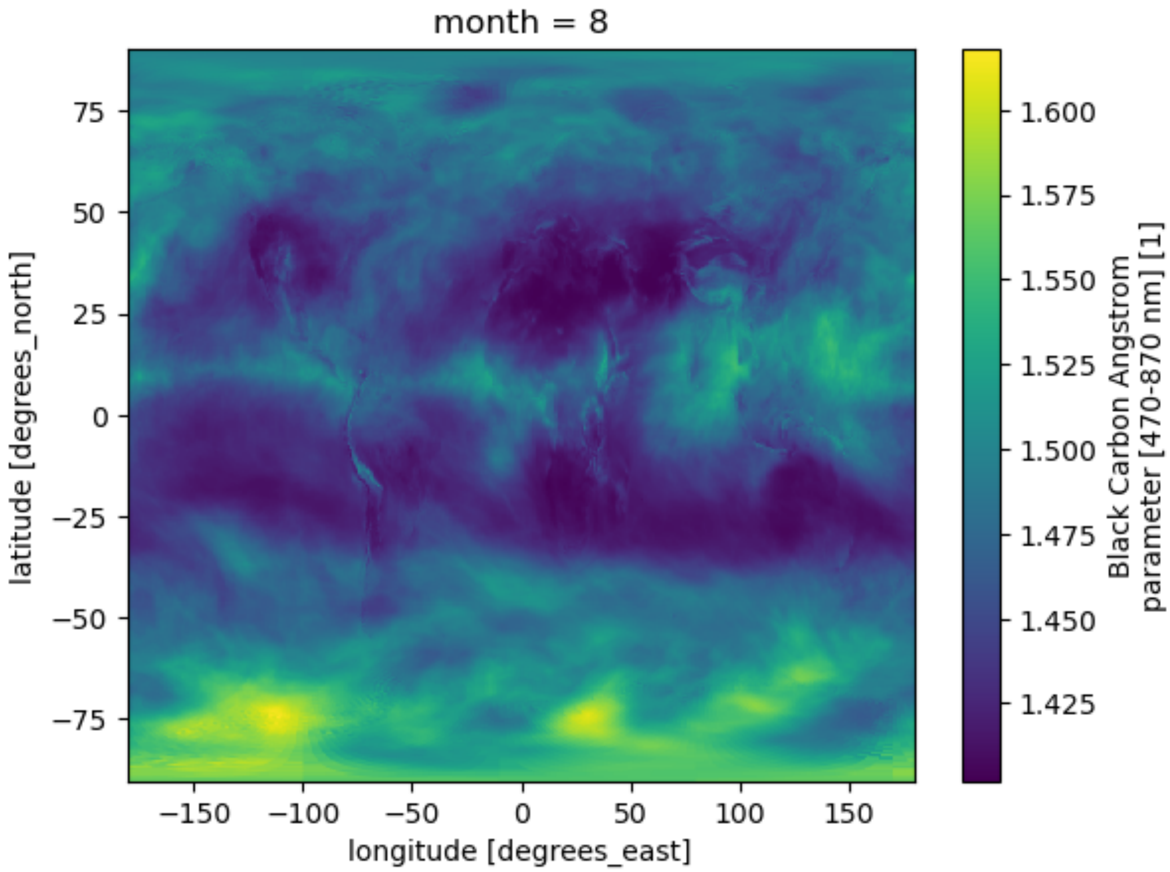
In [31]:
```
ds_dif=ds_clim-ds_clim.mean(dim='time')
ds_dif.mean(dim=['lon','lat']).plot()
```

Out[31]: [<matplotlib.lines.Line2D at 0x1438d3a50>]



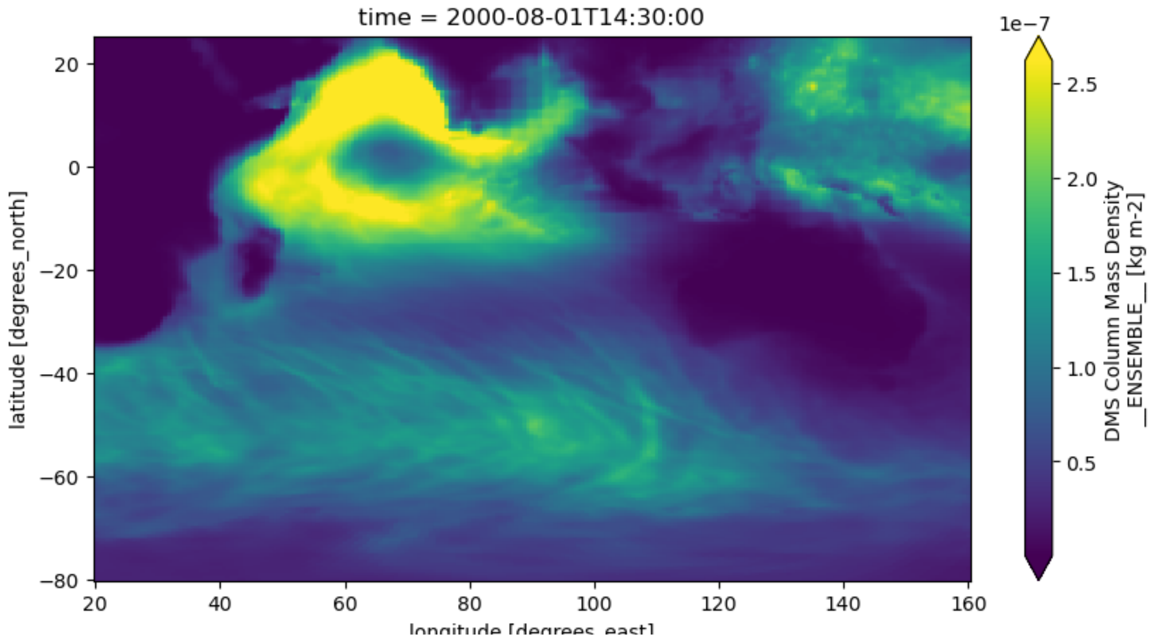
In [25]:
```
# 3.2
ds1=ds.BCANGSTR.groupby("time.month").mean()
ds1.plot()
```

Out[25]: <matplotlib.collections.QuadMesh at 0x14206df50>

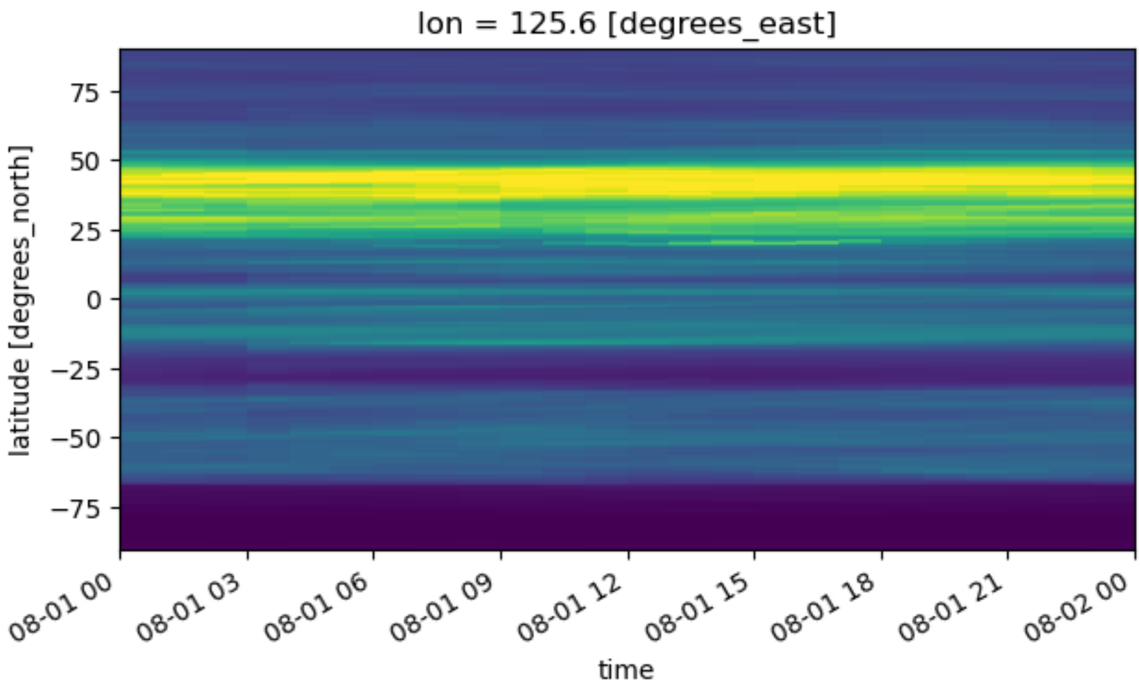


In [26]:
```
ds.DMSCMASS.isel(time=-10).sel(lon=slice(20, 160),
                                   lat=slice(-80, 25)).plot(robust=True, fig
```

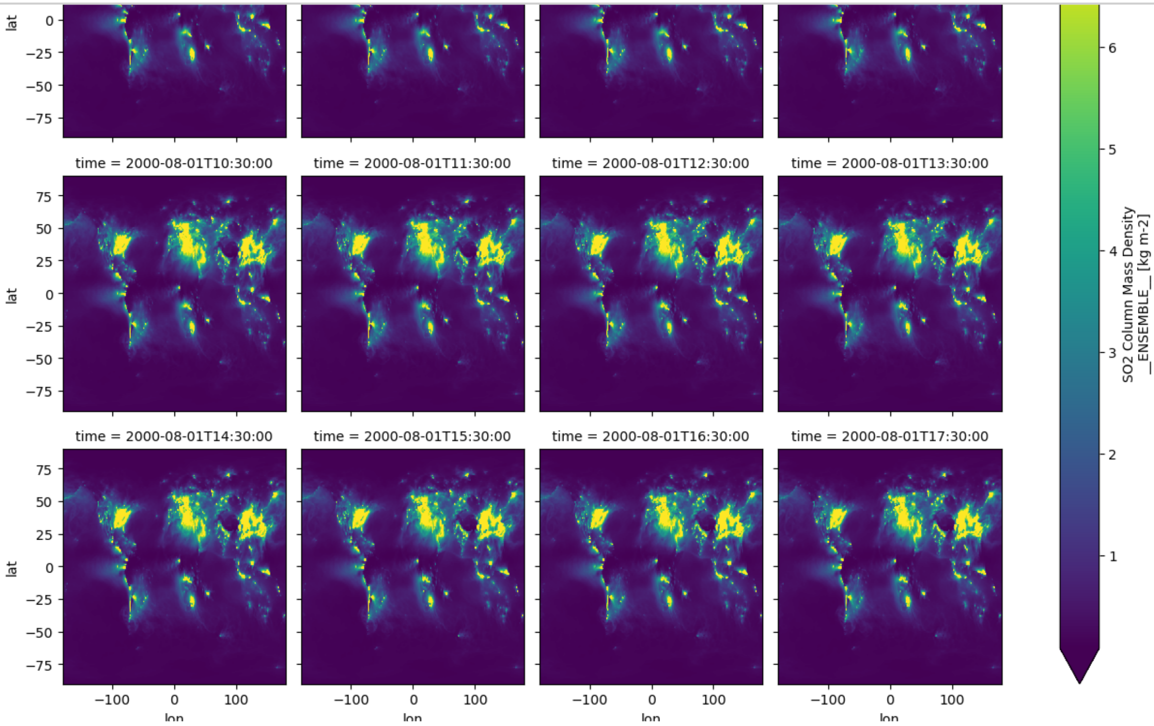
Out[26]: <matplotlib.collections.QuadMesh at 0x142127550>



In [27]:
```
colorbar_kwargs = {
    "orientation": "horizontal",
    "label": "my clustom label",
    "pad": 0.2,
}

ds.TOTSCATAU.sel(lon=125.35, method='nearest').plot(
    x="time",
    robust=True,
    cbar_kwargs=colorbar_kwargs,
)

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



In [28]:
```
ds.SO2CMASS.sel(time=slice("2000-08-01T06:30:00", "2000-08-01T17:30
```



In [29]:
```
ds.BCFLUXU.sel(lon=125.35, lat=43.88, method='nearest').plot(marker=
```

Out[29]: [<matplotlib.lines.Line2D at 0x1439fda10>]