In [1]:
```
import netCDF4
import xarray as xr
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec
%matplotlib inline
```

In [4]:

```
# 1. Niño 3.4 index
# 1.1
# 先将170W-120W转换为经度：190-240
ds_1 = xr.open_dataset("D:\\NOAA_NCDC_ERSST_v3b_SST.nc",engine="netcdf4")

# 选出特定区域的数据(the South American coast)
SST_SAC = ds_1.sel(lat=slice(-5,5),lon=slice(190,240))
# monthly climatology
SST_SAC_mean = SST_SAC.sst.groupby('time.month').mean(dim = 'time')
# 数据按月分组再减去对应的平均值
SST_anomalies = SST_SAC.sst.groupby("time.month")- SST_SAC_mean
SST_anomalies
```

Out[4]: xarray.DataArray 'sst' (**time**: 684, **lat**: 5, **lon**: 26)

```
array([[[[-0.43157768, -0.41846275, -0.39795303, ..., -0.2116642 ,
          -0.23776245, -0.24401474],
         [-0.41259003, -0.4067192 , -0.3875141 , ..., -0.52064896,
          -0.5346451 , -0.51997185],
         [-0.40932274, -0.39743805, -0.36237717, ..., -0.6373882 ,
          -0.6171951 , -0.583725  ],
         [-0.4140854 , -0.37909317, -0.3215618 , ..., -0.43292618,
          -0.38404274, -0.3352623 ],
         [-0.5043678 , -0.43894005, -0.3710251 , ..., -0.17453575,
          -0.11044502, -0.06918144]],

        [[-0.5374584 , -0.52739716, -0.50823593, ..., -0.40254593,
          -0.44382668, -0.45287704],
         [-0.55093956, -0.539135  , -0.51673317, ..., -0.6660595 ,
          -0.7127285 , -0.710968  ],
         [-0.61242104, -0.5959244 , -0.5572338 , ..., -0.7235069 ,
          -0.7326374 , -0.73106194],
         [-0.6798363 , -0.6483364 , -0.5889931 , ..., -0.5397434 ,
          -0.50793266, -0.49977684],
         [-0.7830448 , -0.7286701 , -0.6683655 , ..., -0.33967972,
...
          -0.2555828 , -0.13972664],
         [-0.989378  , -1.0497723 , -1.0954857 , ..., -0.86087227,
          -0.7690697 , -0.65498734],
         [-1.1887245 , -1.252285  , -1.3029232 , ..., -1.0460625 ,
          -0.9661274 , -0.8785801 ],
         [-1.002367  , -1.0756893 , -1.1325111 , ..., -0.7207298 ,
          -0.6597252 , -0.5900669 ],
         [-0.5770798 , -0.65514374, -0.72174263, ..., -0.4353485 ,
          -0.36265945, -0.28103828]],

        [[-0.3578701 , -0.41542053, -0.47110367, ..., -0.2400589 ,
          -0.1464405 , -0.03788376],
         [-0.7678585 , -0.83501625, -0.9024124 , ..., -0.727829  ,
          -0.61603355, -0.48027992],
         [-0.96187973, -1.0445309 , -1.1224213 , ..., -0.9327831 ,
          -0.81235695, -0.6655674 ],
         [-0.82112694, -0.9206734 , -1.0085506 , ..., -0.6531601 ,
          -0.5626869 , -0.4374504 ],
         [-0.4864292 , -0.5823746 , -0.6702862 , ..., -0.36221695,
          -0.30041504, -0.1987915 ]]], dtype=float32)
```

▼ Coordinates:

lat	(lat)	float32	-4.0 -2.0 0.0 2.0 4.0
lon	(lon)	float32	190.0 192.0 194.0 ... 238.0 240.0
time	(time)	datetime64[ns]	1960-01-15 ... 2016-12-15
month	(time)	int64	1 2 3 4 5 6 7 ... 6 7 8 9 10 11 12

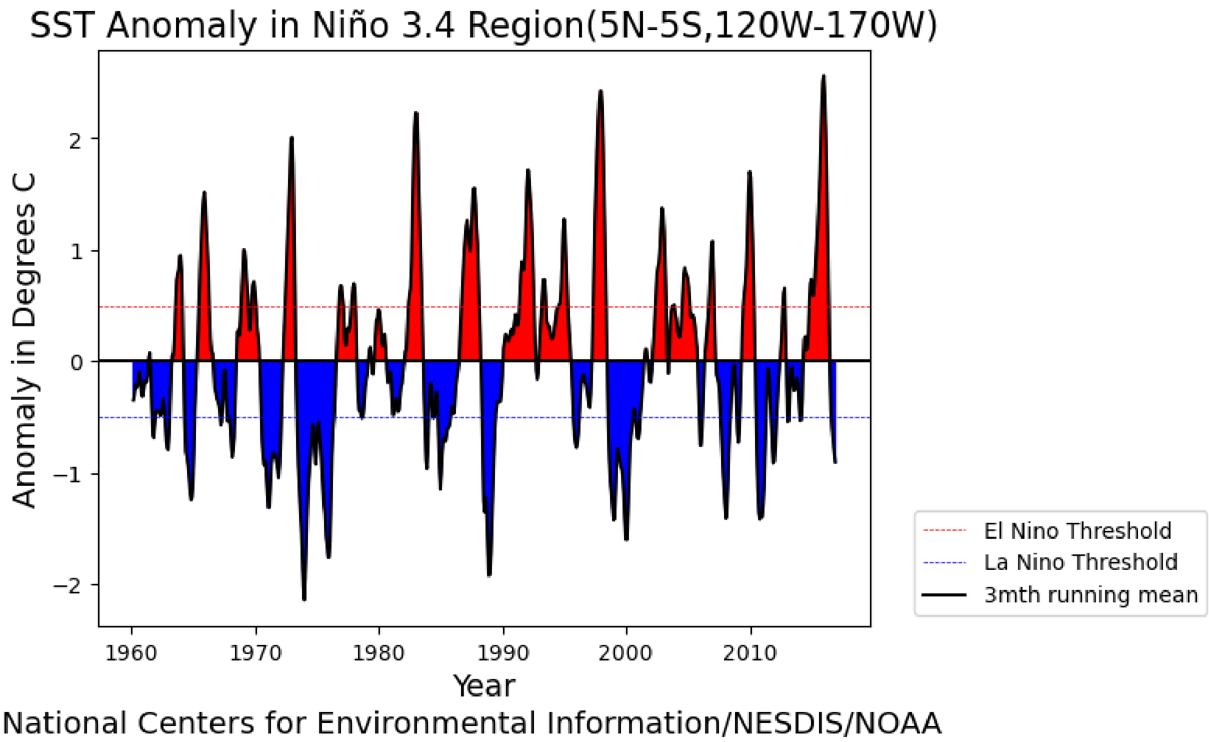
▶ Indexes: (3)

▶ Attributes: (0)

In [47]:

```
# 1.2
# 先求anomalies的三个月滑动平均，时间是从1960.01.15到2016.12.15共684个月
# 参考：https://blog.csdn.net/weixin_43343144/article/details/102823058
SST_anomalies_rolling = SST_anomalies.rolling(time=3, center=True).mean()
# 下面开始作图并对图进行调整
x = pd.date_range(start = '1960-01',periods = 684, freq = 'm')
y = np.nanmean(SST_anomalies_rolling,axis = (1,2))
plt.plot(x,y,'k-')
# 颜色填充参考：https://blog.csdn.net/HHG20171226/article/details/101650909
plt.fill_between(x,y,where=(y<0),color='blue')
plt.fill_between(x,y,where=(y>0),color='red')
plt.title('SST Anomaly in Niño 3.4 Region(5N-5S,120W-170W)',fontsize=16)
plt.suptitle('National Centers for Environmental Information/NESDIS/NOAA',y = 0,fontsize=14)
plt.xlabel('Year',fontsize=14)
plt.ylabel('Anomaly in Degrees C',fontsize=14)
plt.axhline(y=0.5,color ="red", linestyle ="--",linewidth=0.5, label='El Nino Threshold')
plt.axhline(y=-0.5,color ="blue", linestyle ="--",linewidth=0.5,label='La Nino Threshold')
plt.axhline(y=0,color ="black", linestyle ="-",linewidth=1.5,label='3mth running mean')
# 图例的位置参考：https://blog.csdn.net/john_xyz/article/details/54754937
plt.legend(fontsize=10,loc=4, bbox_to_anchor=(1.45,0))
plt.show()
```

```
C:\Users\lenovo\AppData\Local\Temp\ipykernel_13900\2070765726.py:7: RuntimeWarning: Mean of empty slice
  y = np.nanmean(SST_anomalies_rolling,axis = (1,2))
```



In [9]:
```python
# 2. Earth’ s energy budget
# 先读取数据
ds_2 = xr.open_dataset("D:\\CERES_EBAF-TOA_200003-201701.nc",engine="netcdf4")
ds_2
```

Out[9]:

xarray.Dataset

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

▾ Coordinates:

lon	(lon)	float32	0.5 1.5 2.5 ... 357.5 358.5 359.5
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	...

long_name : Top of The Atmosphere Cloud Radiative Effects Shortwave Flux, Monthly Means
standard_name : TOA CRE Shortwave Flux
CF_name : toa_shortwave_cloud_radiative_effect
units : W m-2
valid_min : -400.000
valid_max : 100.000

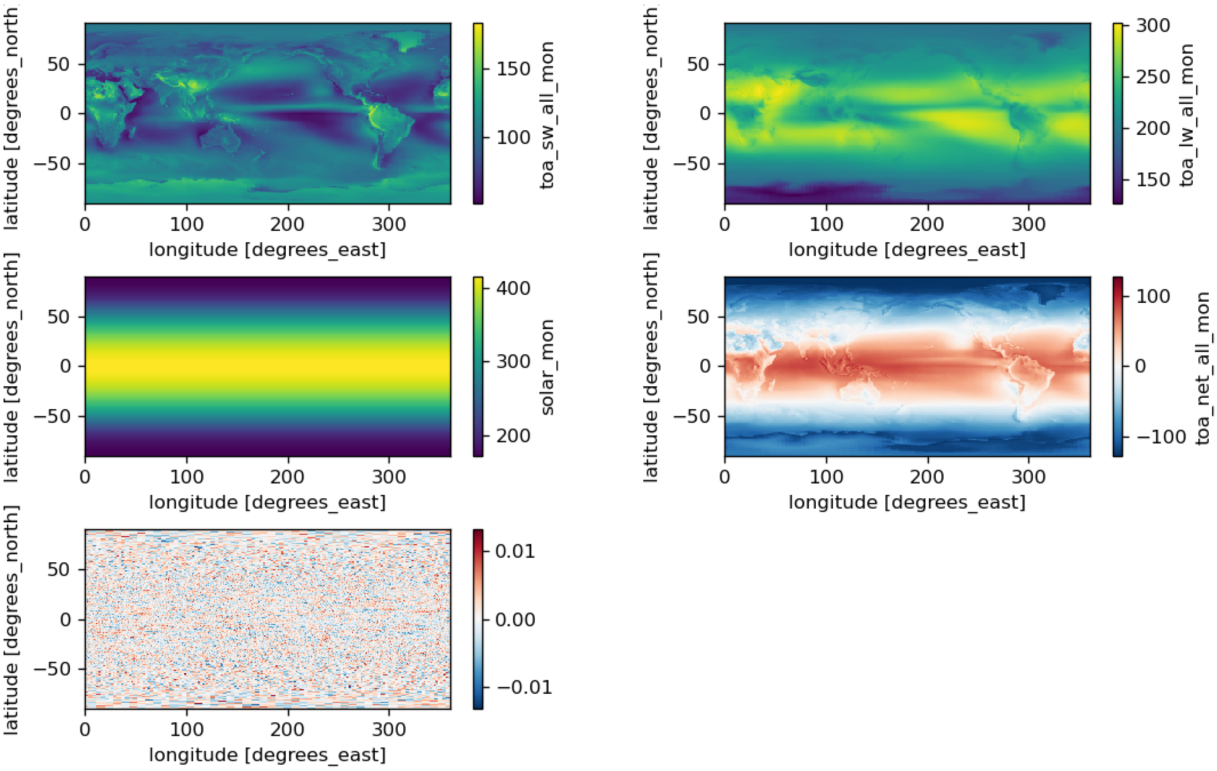
toa_cre_lw_mon	(time, lat, lon)	float32	...
toa_cre_net_mon	(time, lat, lon)	float32	...
solar_mon	(time, lat, lon)	float32	...
cldarea_total_d...	(time, lat, lon)	float32	...
cldpress_total_...	(time, lat, lon)	float32	...
cldtemp_total_d...	(time, lat, lon)	float32	...
cldtau_total_da...	(time, lat, 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 [5]:
```python
# 2.1
plt.figure(figsize = (8,5), dpi = 120)
# the time-mean TOA shortwave
plt.subplot(3,2,1)
sw = ds_2.toa_sw_all_mon.mean(dim = 'time')
sw.plot()

# the time-mean TOA longwave
plt.subplot(3,2,2)
lw = ds_2.toa_lw_all_mon.mean(dim = 'time')
lw.plot()

# the time-mean solar radiation
plt.subplot(3,2,3)
solar = ds_2.solar_mon.mean(dim = 'time')
solar.plot()

# the time-mean TOA net flux
plt.subplot(3,2,4)
net = ds_2.toa_net_all_mon.mean(dim = 'time')
net.plot()

# 计算得到的平均净通量
plt.subplot(3,2,5)
# cal_net为计算得到的TOA净通量
cal_net = solar - sw - lw
# cal为TOA净通量的计算值减去实际值
cal = cal_net - net
cal.plot()

plt.tight_layout()
# 子图间距调整参考：https://blog.csdn.net/qq_35240689/article/details/131361568#
plt.subplots_adjust(left = 0, right = 1, top = 1, bottom = 0, wspace = 0.4, hspace = 0.4)
plt.show()
# 从图5可以看出TOA净通量与计算值并不完全相等，因为除了长波和短波辐射，对流和蒸发过程也会改变能量（所以实际计算应
```



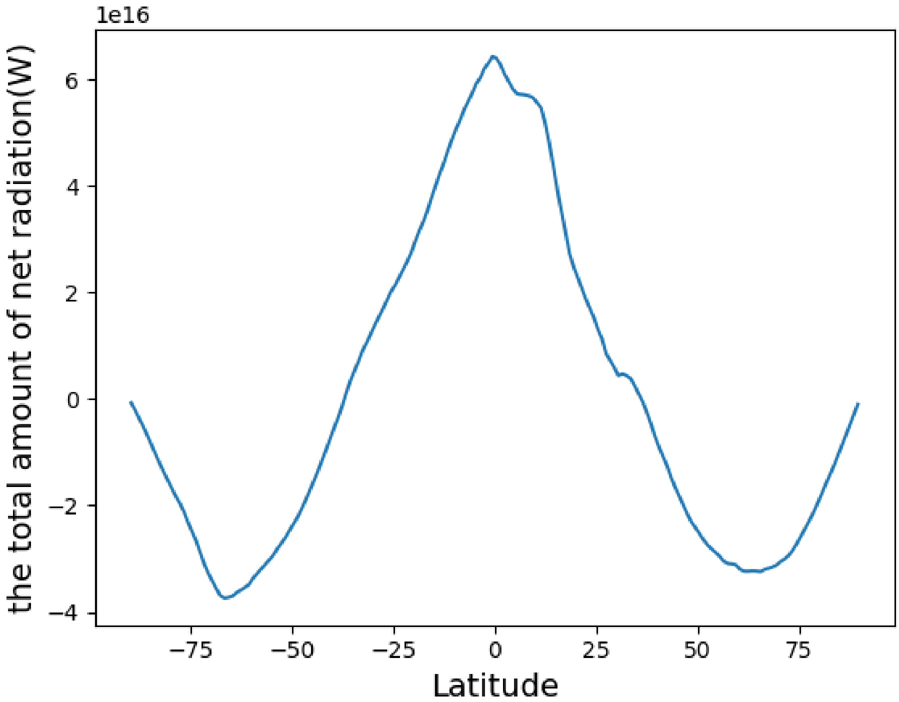
In [26]:
```
# 2.2 (1.先求TOA incoming solar,三个数值计算步骤相同，这里分开计算)
import math
val = math.pi
# 将地球视为圆球，半径为6371 km，由于经度1° 对应的长度都相同等于ΠR/180 = 111
# 而纬度1° 对应的长度等于2ΠR×cosσ/360 = 111*cosσ （其中σ为纬度）
# 若将经度×纬度（1° ×1° ）视为一个网格，每个网格是梯形，为了简化计算将其视为矩形
# 每个网格面积为（ΠR/180）×（2ΠR×cosσ/360）= 12321*cosσ （平方千米）,即1.2321*(10**10)*cosσ 平方米

# 对每个位置的值取时间平均，2.1中已经已求过，为solar
solar = ds_2.solar_mon.mean(dim = 'time')
# 再对每个纬度位置取经度平均
solar_lat_mean = solar.mean(dim='lon')
# 新建DataFrame
df = pd.DataFrame()
df['lat_1']=solar_lat_mean['lat']
df['solar_lat_mean']=np.array(solar_lat_mean)
# 纬度制换算成弧度制
df['lat_radian_1']=np.deg2rad(df['lat_1'])
df['cosσ_1']= np.cos(df['lat_radian_1'])
# 每个纬度带所对应的总能量
df['solar_lat_total']= 1.2321*(10**10)*(df['cosσ_1'])*(df['solar_lat_mean'])*360
# 地球表面入射的总太阳能(W)
solar_total = df['solar_lat_total'].sum()
# 总太阳能除以地球表面积，即入射太阳通量
solar_mean = solar_total /(4*val*6371*6371*(10**6))
solar_mean
# 得到的值339.097约等于Poster中的340.4，误差可能由“为了简化计算，将网格近似于矩形”#或“实际地球为椭圆形，而非玎
```
Out[26]: 339.0974520882081

In [27]:
```
# 2.2 (2.再求outgoing longwave)
# 对每个位置的值取时间平均
lw = ds_2.toa_lw_all_mon.mean(dim = 'time')
# 再对每个纬度位置取经度平均
lw_lat_mean = lw.mean(dim='lon')
# 新建DataFrame
df_1 = pd.DataFrame()
df_1['lat_1']=lw_lat_mean['lat']
df_1['lw_lat_mean']=np.array(lw_lat_mean)
df_1['lat_radian_1']=np.deg2rad(df_1['lat_1'])
df_1['cosσ_1']= np.cos(df_1['lat_radian_1'])
# 每个纬度带所对应的总长波辐射
df_1['lw_lat_total']= 1.2321*(10**10)*(df_1['cosσ_1'])*(df_1['lw_lat_mean'])*360
# 地球表面的总长波辐射(W)
lw_total = df_1['lw_lat_total'].sum()
# 总短波辐射除以地球表面积，即长波辐射通量
lw_mean = lw_total /(4*val*6371*6371*(10**6))
lw_mean
# 得到的值239.429约等于Poster中的239.9，误差可能由“为了简化计算，将网格近似于矩形”或“实际地球为椭圆形，而非球
```
Out[27]: 239.42938524444125

In [28]:
```
# 2.2 (3.再求outgoing shortwave)
# 对每个位置的值取时间平均
sw = ds_2.toa_sw_all_mon.mean(dim = 'time')
# 再对每个纬度位置取经度平均
sw_lat_mean = sw.mean(dim='lon')
# 新建DataFrame
df_2 = pd.DataFrame()
df_2['lat_1']=sw_lat_mean['lat']
df_2['sw_lat_mean']=np.array(sw_lat_mean)
df_2['lat_radian_1']=np.deg2rad(df_2['lat_1'])
df_2['cosσ_1']= np.cos(df_2['lat_radian_1'])
# 每个纬度带所对应的总短波辐射
df_2['sw_lat_total']= 1.2321*(10**10)*(df_2['cosσ_1'])*(df_2['sw_lat_mean'])*360
# 地球表面的总短波辐射(W)
sw_total = df_2['sw_lat_total'].sum()
# 总短波辐射除以地球表面积，即短波辐射通量
sw_mean = sw_total /(4*val*6371*6371*(10**6))
sw_mean
# 得到的值98.793约等于Poster中的99.9，误差可能由“为了简化计算，将网格近似于矩形”或“实际地球为椭圆形，而非球形
```
Out[28]: 98.7930231365236

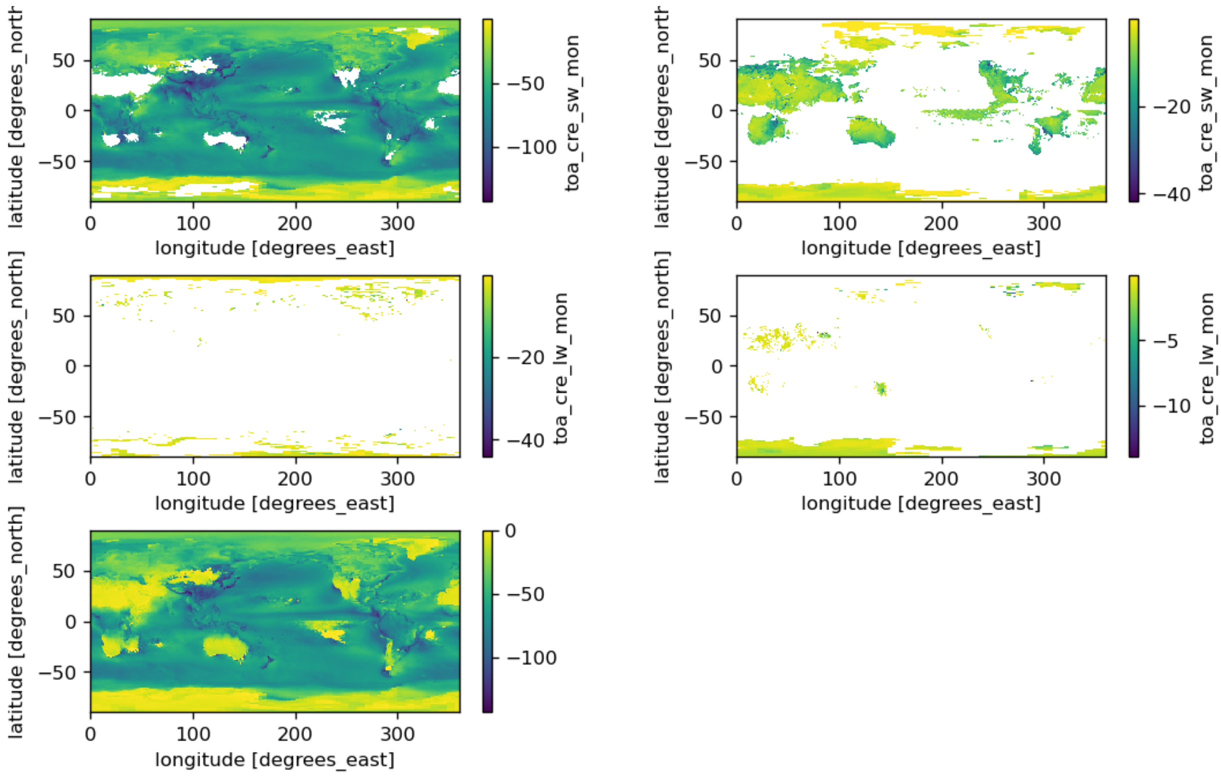
In [29]:

```
# 2.3
# 对于同一纬度上的网格，面积大小都相等，因此先将同一纬度上的净通量相加
lat_1 = ds_2.toa_net_all_mon.groupby('lat').sum(dim=('time','lon'))
df_3 = pd.DataFrame()
df_3['lat']=ds_2['lat']
df_3['amount']=np.array(lat_1)
df_3['radian']=np.deg2rad(df_3['lat'])
df_3['cosσ']= np.cos(df_3['radian'])
# 同一纬度的净通量×面积 = 同一纬度上的净辐射总量
df_3['Total_amount']= 1.2321*(10**10)*(df_3['cosσ'])*(df_3['amount'])
# 作图
x = df_3['lat']
y = df_3['Total_amount']
plt.ylabel('the total amount of net radiation(W)',fontsize=14)
plt.xlabel('Latitude',fontsize=14)
plt.plot(x,y)
plt.show()
```

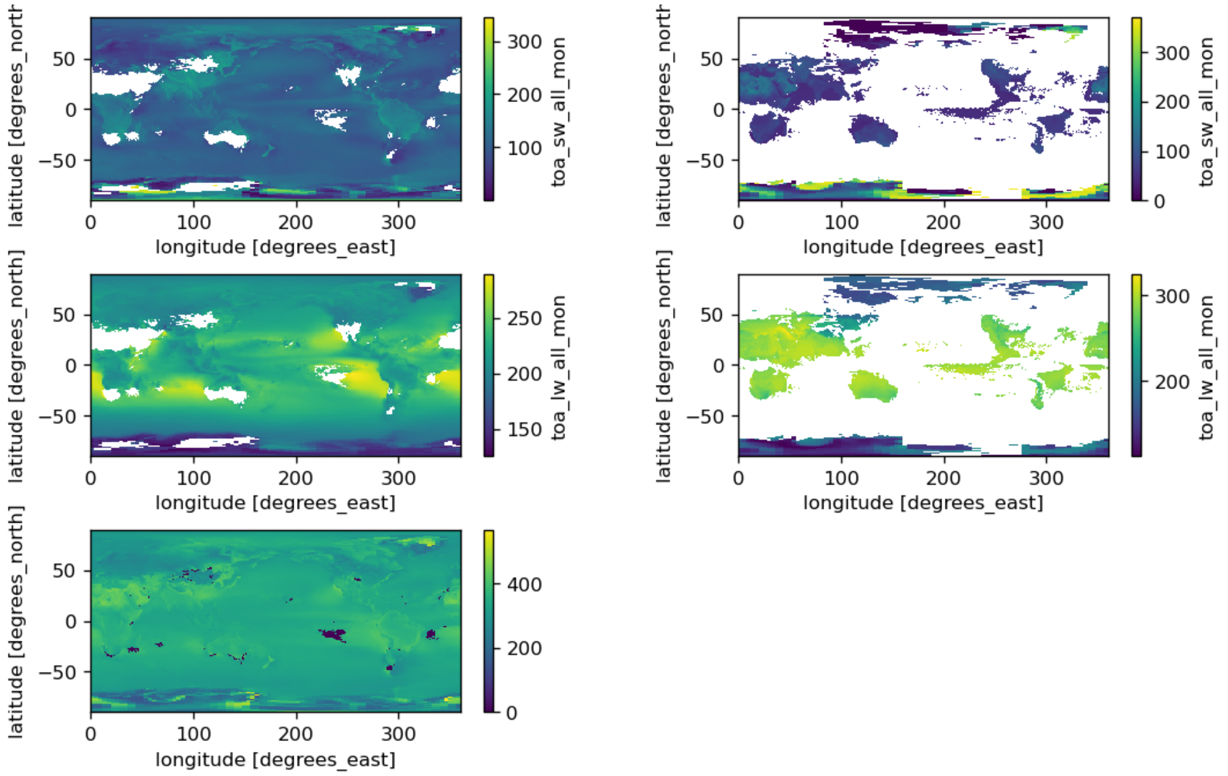


In [18]:

```
# 2.4（一种想法：涉及高云低云，数据用Cloud Radiative的数据：toa_cre_sw_mon和toa_cre_lw_mon）
plt.figure(figsize = (8,5), dpi = 120)

# 这里计算高云和低云地区的短波辐射和长波辐射
# 因此使用toa_cre_sw_mon（Top of The Atmosphere Cloud Radiative Effects Shortwave Flux）和toa_cre_lw_mon数据
# outgoing表示云效应中反射出去的那部分（+表示吸收，-表示反射）

# 1.短波辐射在高云区域
sw_high = ds_2.toa_cre_sw_mon.where((ds_2['cldarea_total_daynight_mon']>=75)&(ds_2['toa_cre_sw_mon']<0)).mean(d
plt.subplot(3,2,1)
sw_high.plot()

# 2.短波辐射在低云区域
sw_low = ds_2.toa_cre_sw_mon.where((ds_2['cldarea_total_daynight_mon']<=25)&(ds_2['toa_cre_sw_mon']<0)).mean(di
plt.subplot(3,2,2)
sw_low.plot()

# 3.长波辐射在高云区域
lw_high = ds_2.toa_cre_lw_mon.where((ds_2['cldarea_total_daynight_mon']>=75)&(ds_2['toa_cre_lw_mon']<0)).mean(d
plt.subplot(3,2,3)
lw_high.plot()

# 4.长波辐射在低云区域
lw_low = ds_2.toa_cre_lw_mon.where((ds_2['cldarea_total_daynight_mon']<=25)&(ds_2['toa_cre_lw_mon']<0)).mean(di
plt.subplot(3,2,4)
lw_low.plot()

# 5.在高云和低云区域的短波和长波辐射总效应复合图
out_sw = ds_2.toa_cre_sw_mon.where(((ds_2['cldarea_total_daynight_mon']<=25)|(ds_2['cldarea_total_daynight_mon']
                                  &(ds_2['toa_cre_sw_mon']<0)).mean(dim='time')
out_lw = ds_2.toa_cre_lw_mon.where(((ds_2['cldarea_total_daynight_mon']<=25)|(ds_2['cldarea_total_daynight_mon']
                                   &(ds_2['toa_cre_lw_mon']<0)).mean(dim='time')
# 将空值填充为0
out_sw = out_sw .fillna(0)
out_lw = out_lw.fillna(0)
out_total = out_sw + out_lw
plt.subplot(3,2,5)
out_total.plot()

plt.tight_layout()
plt.subplots_adjust(left = 0, right = 1, top = 1, bottom = 0, wspace = 0.4, hspace = 0.4)
plt.show()
```



In [54]:
```
# 2.4（另一种想法：如果不是用数据用Cloud Radiative的数据，还是用All-Sky conditions的数据:toa_sw_all_mon和toa_lw_
plt.figure(figsize = (8,5), dpi = 120)

# 这里计算高云和低云地区的短波辐射和长波辐射
# 因此使用toa_cre_sw_mon（Top of The Atmosphere Cloud Radiative Effects Shortwave Flux）和toa_cre_lw_mon数据
# outgoing表示云效应中反射出去的那部分（+表示吸收，-表示反射）

# 1.短波辐射在高云区域
sw_high_1= ds_2.toa_sw_all_mon.where(ds_2['cldarea_total_daynight_mon']>=75).mean(dim='time')
plt.subplot(3,2,1)
sw_high_1.plot()

# 2.短波辐射在低云区域
sw_low_1= ds_2.toa_sw_all_mon.where(ds_2['cldarea_total_daynight_mon']<=25).mean(dim='time')
plt.subplot(3,2,2)
sw_low_1.plot()

# 3.长波辐射在高云区域
lw_high_1= ds_2.toa_lw_all_mon.where(ds_2['cldarea_total_daynight_mon']>=75).mean(dim='time')
plt.subplot(3,2,3)
lw_high_1.plot()

# 4.长波辐射在低云区域
lw_low_1= ds_2.toa_lw_all_mon.where(ds_2['cldarea_total_daynight_mon']<=25).mean(dim='time')
plt.subplot(3,2,4)
lw_low_1.plot()

# 5.在高云和低云区域的短波和长波辐射总效应复合图
out_sw_1 = ds_2.toa_sw_all_mon.where((ds_2['cldarea_total_daynight_mon']<=25)|(ds_2['cldarea_total_daynight_mon'
out_lw_1 = ds_2.toa_lw_all_mon.where((ds_2['cldarea_total_daynight_mon']<=25)|(ds_2['cldarea_total_daynight_mon'

# 将空值填充为0
out_sw_1 = out_sw_1.fillna(0)
out_lw_1 = out_lw_1.fillna(0)
out_total_1 = out_sw_1 + out_lw_1
plt.subplot(3,2,5)
out_total_1.plot()

plt.tight_layout()
plt.subplots_adjust(left = 0, right = 1, top = 1, bottom = 0, wspace = 0.4, hspace = 0.4)
plt.show()
```



In [22]:
```python
# 2.5
# 选择高云区域的长波和短波辐射通量（云辐射效应的长波和短波辐射）
sw_flux = ds_2.toa_cre_sw_mon.where(((ds_2['cldarea_total_daynight_mon']<=25)|
                                     (ds_2['cldarea_total_daynight_mon']>=75))).mean(dim=('time','lon'))
lw_flux = ds_2.toa_cre_lw_mon.where(((ds_2['cldarea_total_daynight_mon']<=25)|
                                     (ds_2['cldarea_total_daynight_mon']>=75))).mean(dim=('time','lon'))

df_4 = pd.DataFrame()
df_4['lat_1']=sw_flux['lat']
df_4['lat_2']=lw_flux['lat']
df_4['sw_mean']=np.array(sw_flux)
df_4['lw_mean']=np.array(lw_flux)
# 纬度制换算成弧度制
df_4['lat_radian_1']=np.deg2rad(df_4['lat_1'])
df_4['lat_radian_2']=np.deg2rad(df_4['lat_2'])
df_4['cosσ_1']= np.cos(df_4['lat_radian_1'])
df_4['cosσ_2']= np.cos(df_4['lat_radian_2'])
# 每个纬度带所对应的总短波辐射
df_4['sw_aolar_mean']= 1.2321*(10**10)*(df_4['cosσ_1'])*(df_4['sw_mean'])*360
df_4['lw_aolar_mean']= 1.2321*(10**10)*(df_4['cosσ_2'])*(df_4['lw_mean'])*360
# 地球表面的总短波辐射(W)
sw_total = df_4['sw_aolar_mean'].sum()
lw_total = df_4['lw_aolar_mean'].sum()
# 总短波辐射除以地球表面积，即短波辐射通量
sw_mean = sw_total /(4*val*6371*6371*(10**6))
lw_mean = lw_total /(4*val*6371*6371*(10**6))
# 输出云层短波辐射和长波辐射的总效应
global_mean_values = sw_mean + lw_mean
print(global_mean_values)

# TOA Cloud Radiative Shortwave Effects:-56.726
# TOA Cloud Radiative Longwave Effects:34.312
# The global mean values of shortwave and longwave radiation, composited in high and low cloud regions is -22.41
```

```
-22.415337660458675
```

In [36]:
```python
# 3. Explore a netCDF dataset
# 打开文件，数据是关于全球陆地每日的最高温度( CPC Global Unified Temperature_maximum temperature，经度和纬度分辨
ds_3 = xr.open_dataset("D:\\tmax.2021.nc",engine="netcdf4")
ds_3
```

Out[36]:

xarray.Dataset

▶ Dimensions: (**lat**: 360, **lon**: 720, **time**: 365)

▼ Coordinates:

lat	(lat)	float32	89.75 89.25 88.75 ... -89.25 -89.75
lon	(lon)	float32	0.25 0.75 1.25 ... 359.2 359.8
time	(time)	datetime64[ns]	2021-01-01 ... 2021-12-31

▼ Data variables:

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

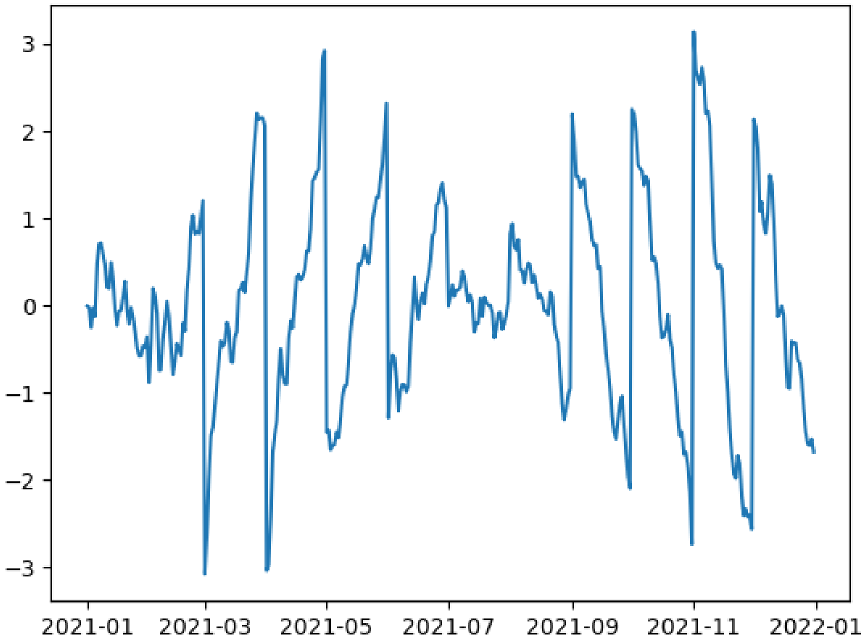
```
[94608000 values with dtype=float32]
```

▶ Indexes: (3)

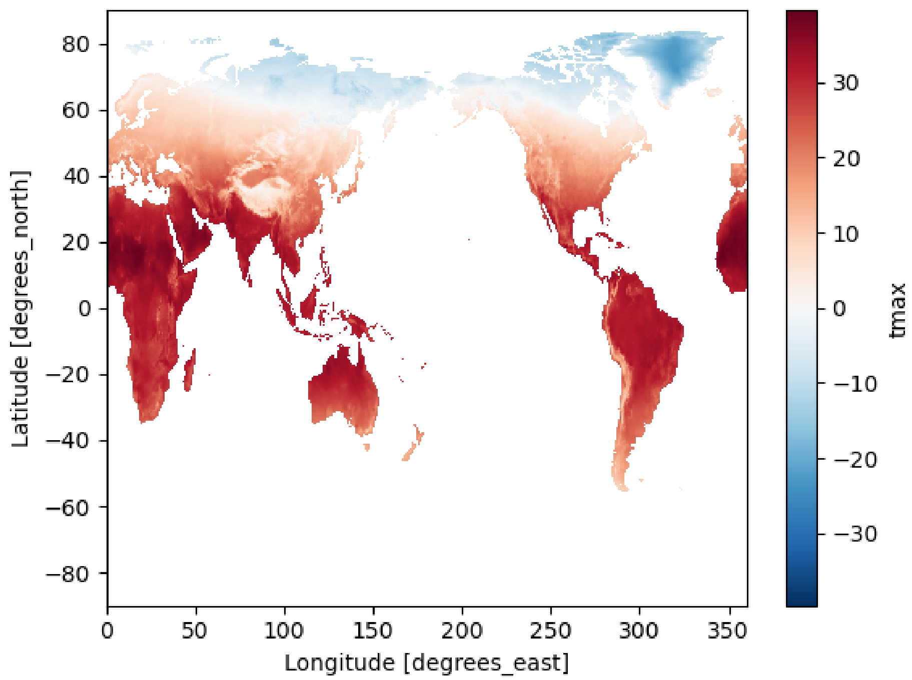
▼ Attributes:

Conventions :	CF-1.0
Source :	ftp://ftp.cpc.ncep.noaa.gov/precip/wd52ws/global_temp/
References :	https://www.psl.noaa.gov/data/gridded/data.cpc.globaltemp.html
version :	V1.0
title :	CPC GLOBAL TEMP V1.0
dataset_title :	CPC GLOBAL TEMP
history :	Updated 2022-01-01 16:55:57

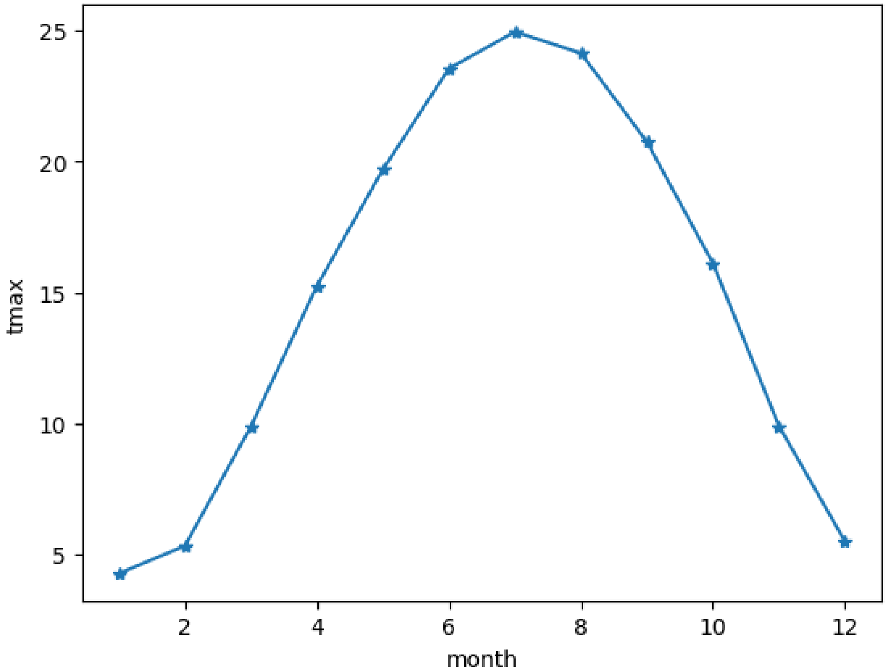
In [45]:
```
# 3.1
# 先将数据按月分组，减去月度变化之后
aT = ds_3.tmax.groupby('time.month')
aT_anomalies = aT - aT.mean(dim='time')
# 再对其经纬度求平均(调过不是陆地区域的空值)
y = np.nanmean(aT_anomalies,axis = (1,2))
x = pd.date_range(start = '2021-01-01',periods = 365, freq = 'd')
plt.plot(x,y)
plt.show()
```



In [48]:
```
# 3.2 (1) 2021年全球陆地最高气温的年平均值
ds_3.tmax.mean(dim='time').plot()
plt.show()
```

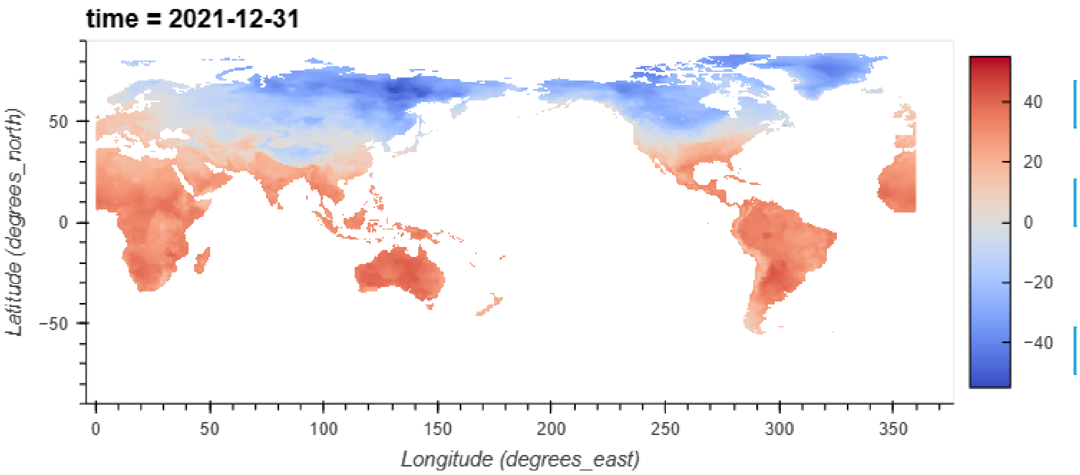


In [53]:
```
# 3.2 (2) 全球最高温度的月平均值
group_data.mean().mean(dim=('lat','lon')).plot(marker='*')
plt.show()
```

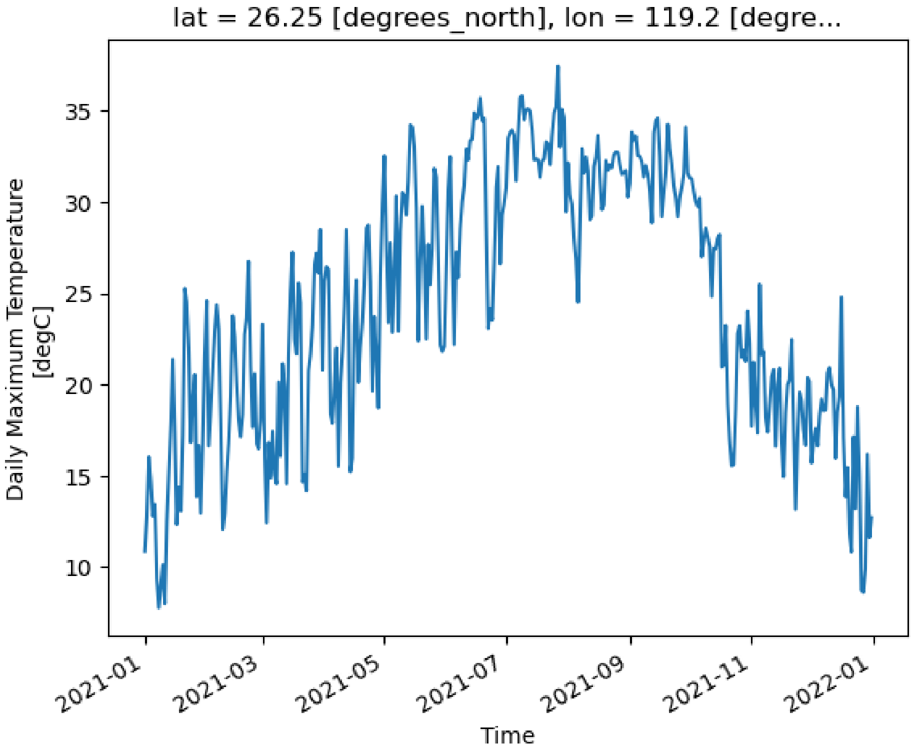


In [50]:
```
# 3.2 (3) 2021-12-31日的全球最高气温分布
import hvplot.xarray
ds_3.tmax.isel(time=-1).hvplot()
```

Out[50]:



In [51]:
```
# 3.2 (4) 对指定地区（东经：119.28，北纬：26.08）的最高温度画时间序列图
ds_3.tmax.sel(lat=26.08,lon=119.28,method='nearest').plot()
plt.show()
```



In [52]:
```
# 3.2 (5) 不同纬度的年平均最高温度(南半球高纬度地区没有陆地，因此没有数据)
ds_3.tmax.mean(dim=('lon','time')).plot()
plt.show()
# 可以看出，赤道地区的年平均最高温度是比较高的，而两级地区的年平均最高温度随着纬度升高而下降
```