PS3

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

1. Global methane levels from 2002

Methane ($\mathrm{CH_4}$) is a naturally occurring Greenhouse Gas (GHG), but one whose abundance has been increased substantially above its pre-industrial value by human activities, primarily because of agricultural emissions (e.g., rice production, ruminants) and fossil fuel production and use. A clear annual cycle is largely due to seasonal wetland emissions.

Atmospheric methane abundance is indirectly observed by various satellite instruments. These instruments measure spectrally resolved near-infrared and infrared radiation reflected or emitted by the Earth and its atmosphere. In the measured signal, molecular absorption signatures from methane and constituent gasses can be identified. It is through analysis of those absorption lines in these radiance observations that the averaged methane abundance in the sampled atmospheric column can be determined.

For this problem set, methane levels have been determined by applying several algorithms to different satellite instruments. Download the `netCDF4` file (`200301_202006-C3S-L3_GHG-PRODUCTS-OBS4MIPS-MERGED-v4.3.nc`) here, which contains monthly-averaged methane levels (`xch4`) in the unit of ppb at each 5° (`lon`) x 5° (`lat`) grid over the globe from `2003-01` to `2020-06` .

1.1

Compute methane climatology for each month, and plot your results in 12 panels.

In [2]:
```
ds = xr.open_dataset('data_files/200301_202006-C3S-L3_GHG-PRODUCTS-OBS4MIPS-MERGED-v4.3.nc', eng:
ds
```

Out[2]: xarray.Dataset

► Dimensions: (**time**: 210, bnds: 2, **lat**: 36, **lon**: 72, pressure: 10)

▼ Coordinates:

time	(time)	datetime64[ns]	2003-01-16T12:00:00 ... 2020-06-...
lat	(lat)	float64	-87.5 -82.5 -77.5 ... 82.5 87.5
lon	(lon)	float64	-177.5 -172.5 ... 172.5 177.5

▼ Data variables:

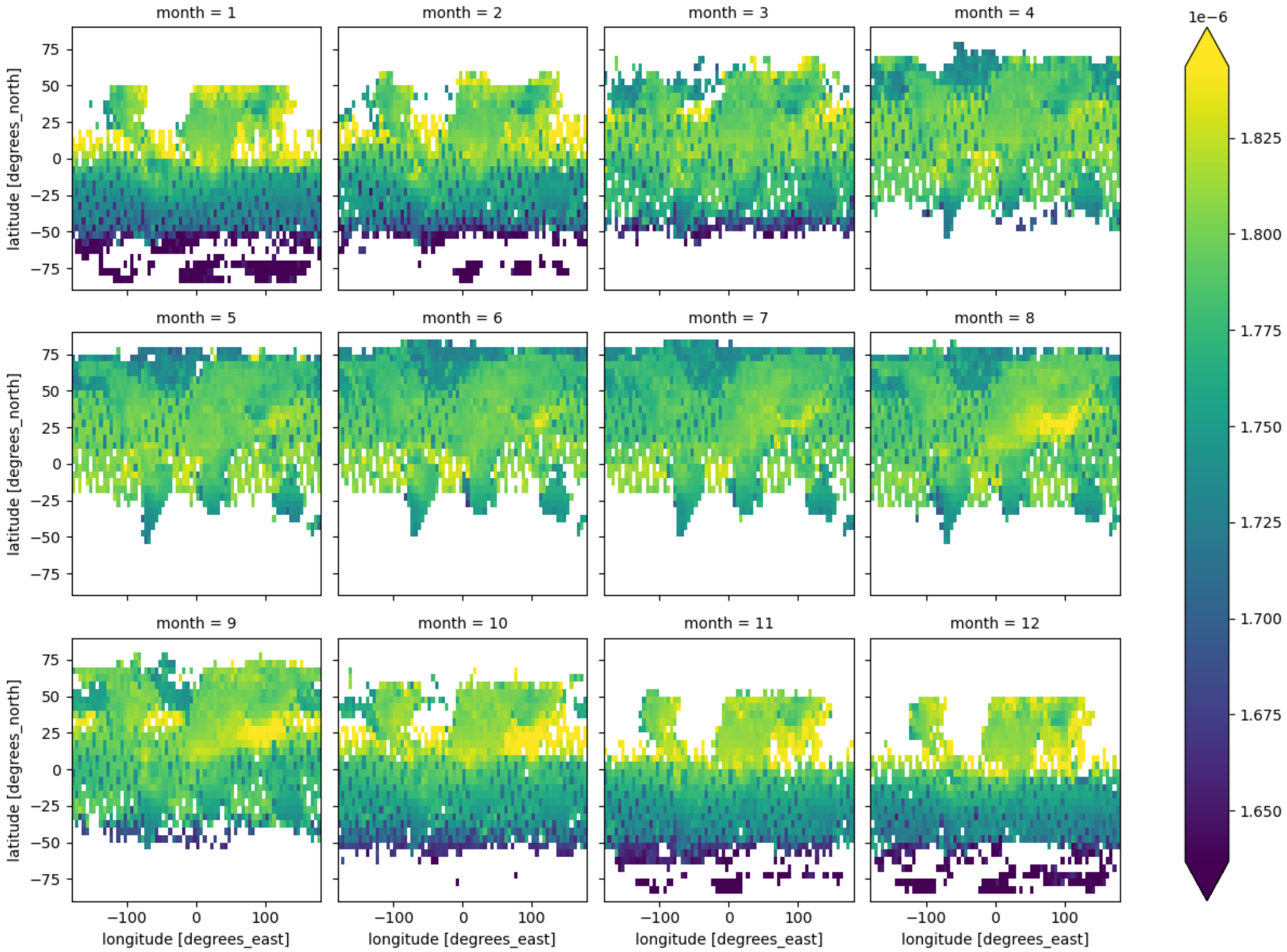
time_bnds	(time, bnds)	datetime64[ns]	...
lat_bnds	(lat, bnds)	float64	...
lon_bnds	(lon, bnds)	float64	...
pre	(pressure)	float64	...
pre_bnds	(pressure, bnds)	float64	...
land_fraction	(lat, lon)	float64	...
xch4	(time, lat, lon)	float32	...
xch4_nobs	(time, lat, lon)	float64	...
xch4_stderr	(time, lat, lon)	float32	...
xch4_stddev	(time, lat, lon)	float32	...
column_averagin...	(time, pressure, lat, lon)	float32	...
vmr_profile_ch4_...	(time, pressure, lat, lon)	float32	...

► Attributes: (28)

In [3]:
```
xch4_clim = ds.xch4.groupby('time.month').mean()
```

In [4]:
```
xch4_clim.plot(col="month", col_wrap=4, robust=True)
```

Out[4]:
```
<xarray.plot.facetgrid.FacetGrid at 0x2bb0065ba90>
```

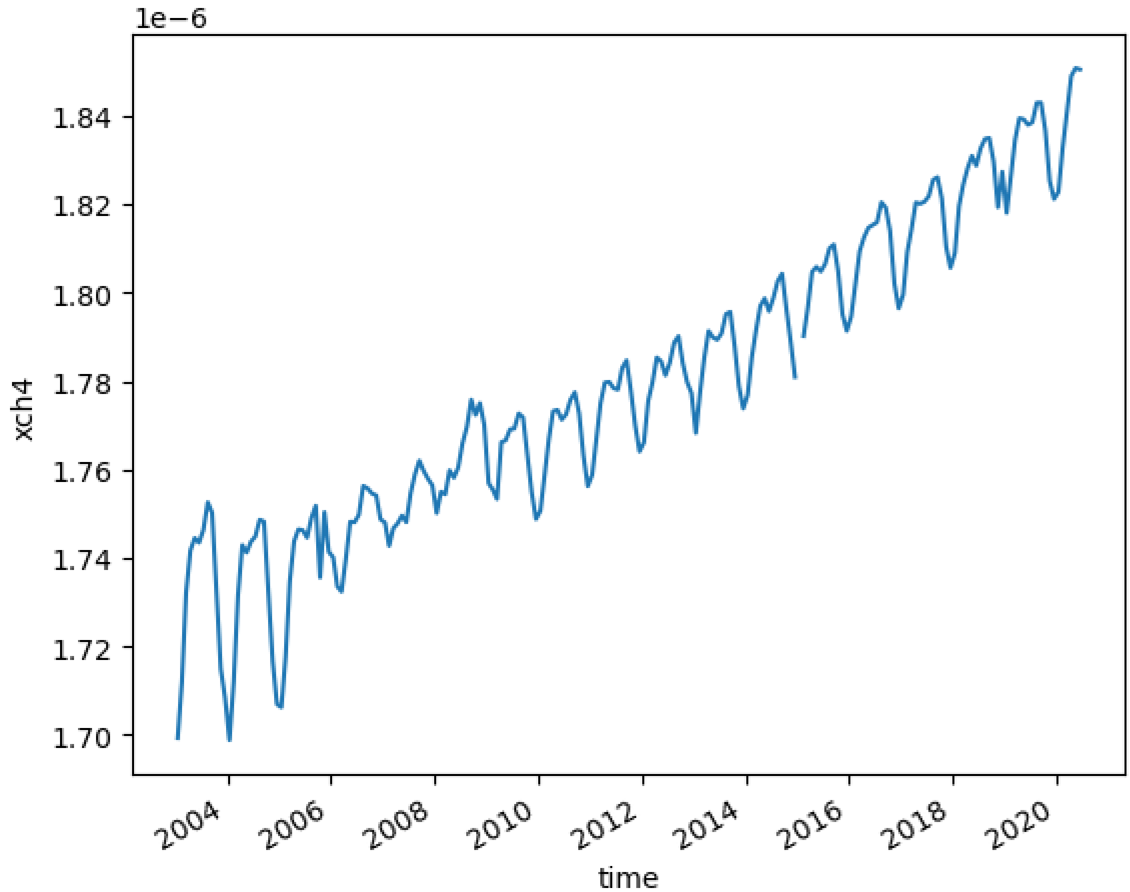


1.2

Plot globally-averaged methane from `2003-01` to `2020-06` as a time series. Describe your results. Check your plot with this one.

In [5]:
```
ds.xch4.sel(time=slice('2003-01','2020-06')).mean(dim='lat').mean(dim='lon').plot()
```

Out[5]:
```
[<matplotlib.lines.Line2D at 0x2bb01fb9e50>]
```



The golbally-averaged methane shows a steady increase trend despite periodic cycle within each year.

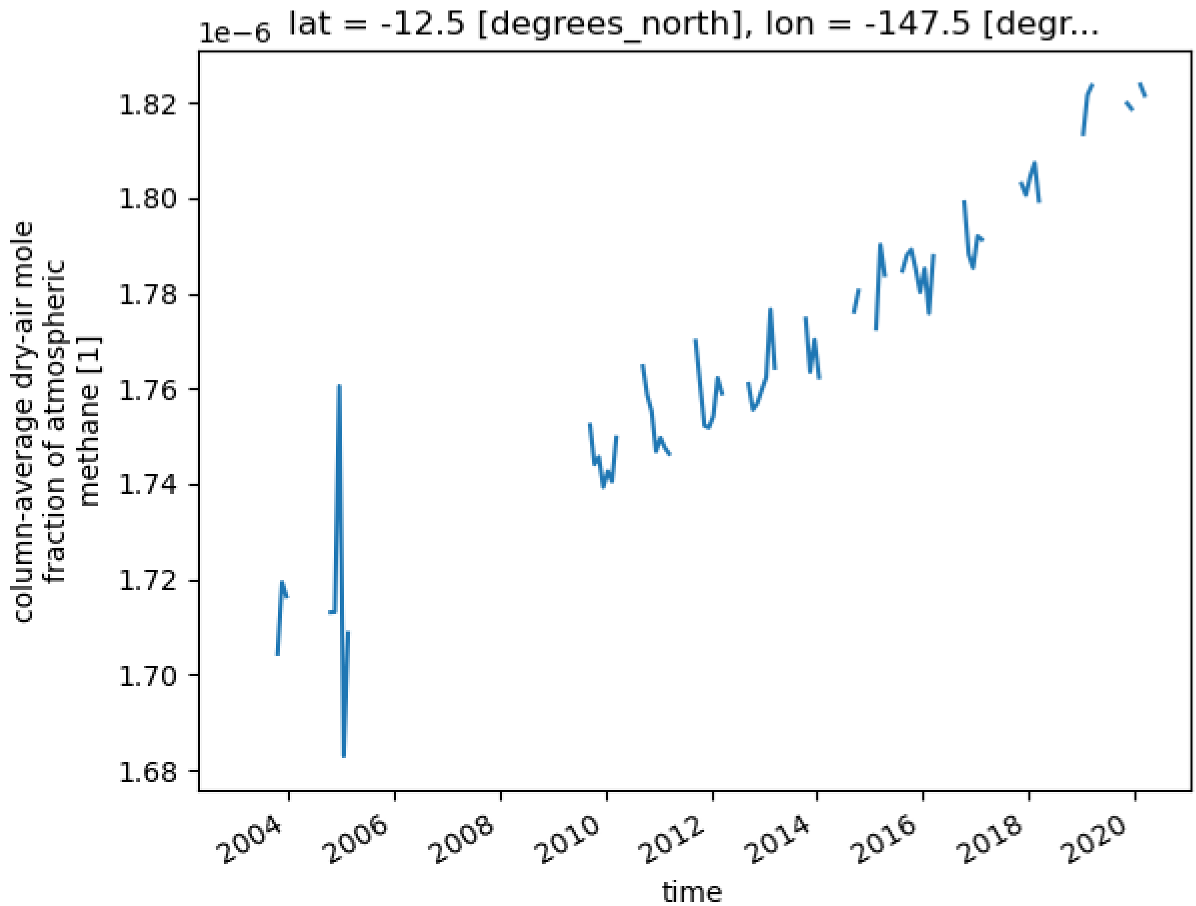
1.3

Plot deseasonalized methane levels at point `[15°S, 150°W]` from `2003-01` to `2020-06` as a time series. Describe your results.

In [6]:
```
pnt = ds.xch4.sel(time=slice('2003-01','2020-06'))
pnt.sel(lon=-150, lat=-15, method='nearest').plot()
```

```
E:\Programmes\anaconda3\lib\site-packages\xarray\core\indexes.py:234: FutureWarning: Passing met
hod to Float64Index.get_loc is deprecated and will raise in a future version. Use index.get_inde
xer([item], method=...) instead.
  indexer = self.index.get_loc(
E:\Programmes\anaconda3\lib\site-packages\xarray\core\indexes.py:234: FutureWarning: Passing met
hod to Float64Index.get_loc is deprecated and will raise in a future version. Use index.get_inde
xer([item], method=...) instead.
  indexer = self.index.get_loc(
```

Out[6]:
```
[<matplotlib.lines.Line2D at 0x2bb0112e4c0>]
```



There are lots of missing data within the observation range. But it can be observed a growing trend during the past two decades.

2. Niño 3.4 index

The *Niño 3.4 anomalies* may be thought of as representing the average equatorial sea surface temperatures (SSTs) across the Pacific from about the dateline to the South American coast (`5N-5S` , `170W-120W`). The Niño 3.4 index typically uses a 3-month running mean, and El Niño or La Niña events are defined when the Niño 3.4 SSTs exceed `+/- 0.5°C` for a period of `5` months or more. Check Equatorial Pacific Sea Surface Temperatures for more about the Niño 3.4 index.

In this problem set, you will use the sea surface temperature (SST) data from NOAA. Download the `netCDF4` file (`NOAA_NCDC_ERSST_v3b_SST.nc`) here.

2.1

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

In [7]:
```
ds2 = xr.open_dataset('data_files/NOAA_NCDC_ERSST_v3b_SST.nc', engine='netcdf4')
ds2
```

Out[7]: 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 ... 354.0 356.0 358.0
time	(time)	datetime64[ns]	1960-01-15 ... 2016-12-15

▼ Data variables:

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

▼ 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 [8]:
```
ds2 = ds2.sst.sel(lon=['190','240'],lat=['-6','6'])
```

In [9]:
```
overall_mean = ds2.mean()
overall_mean
```

Out[9]: xarray.DataArray 'sst'

array(27.786516, dtype=float32)

► Coordinates: (0)

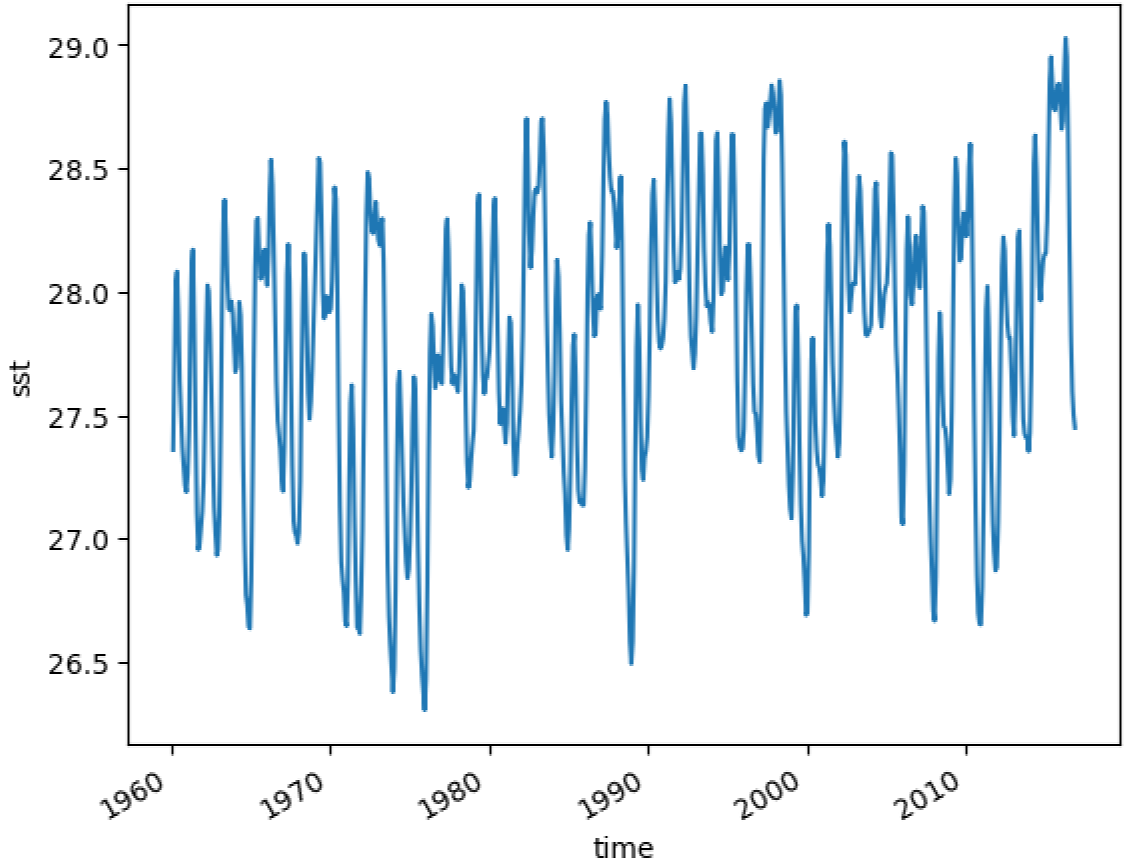
► Attributes: (0)

In [10]:
```
ds_rolling = ds2.rolling(time=3, center=True)
ds_rolling
```

Out[10]: DataArrayRolling [time->3(center)]

In [11]:
```
ds_rolling.mean().mean(dim=['lon','lat']).plot()
```

Out[11]: [<matplotlib.lines.Line2D at 0x2bb011a3fd0>]



In [12]:
```
sst_anom = ds_rolling.mean() - overall_mean
sst_anom
```

Out[12]: xarray.DataArray 'sst' (**time**: 684, **lat**: 2, **lon**: 2)

```
array([[[       nan,        nan],
        [       nan,        nan]],

       [[ 0.8321419 , -1.4950333 ],
        [-0.40036774, -0.64657974]],

       [[ 0.9872036 , -0.79281235],
        [-0.36144066, -0.16091347]],

       ...,

       [[ 1.2324429 , -2.6276512 ],
        [ 1.1617756 , -0.912426  ]],

       [[ 1.2956429 , -2.4825268 ],
        [ 0.8325443 , -0.99769783]],

       [[       nan,        nan],
        [       nan,        nan]]], dtype=float32)
```

▼ Coordinates:

lat	(lat)	float32	-6.0 6.0
lon	(lon)	float32	190.0 240.0
time	(time)	datetime64[ns]	1960-01-15 ... 2016-12-15

► Attributes: (0)

2.2

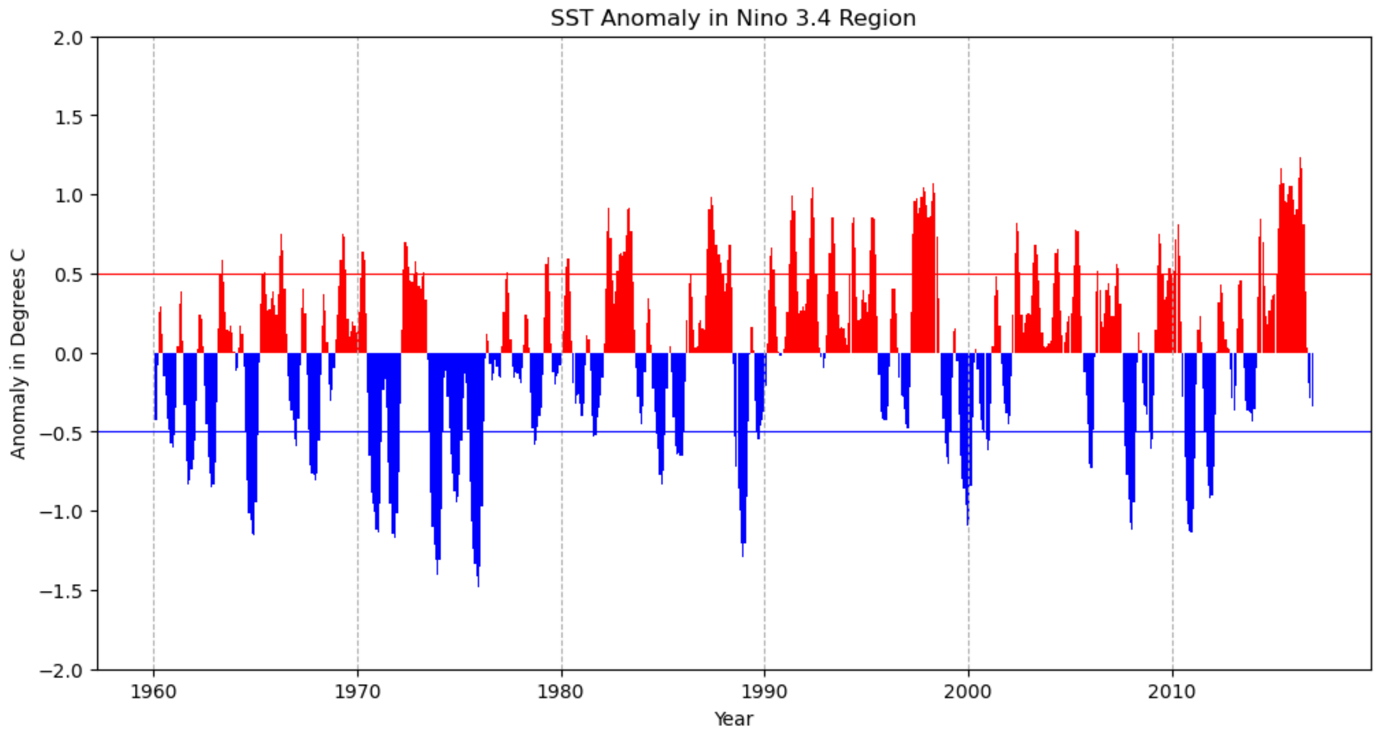
Visualize the computed Niño 3.4. Your plot should look similar to this one.

In [13]:
```
nino = sst_anom.mean(dim=['lat', 'lon'])
nino = nino.to_dataframe()
```

In [14]:
```
nino['sign'] = nino['sst'] > 0
```

In [15]:
```
fig, ax = plt.subplots(figsize=(12, 6))
ax.yaxis.set_ticks_position('left')
ax.set(title = 'SST Anomaly in Nino 3.4 Region',
       xlabel = 'Year',
       ylabel = 'Anomaly in Degrees C')
ax.bar(nino.index, nino['sst'],width=30,
       color = nino.sign.map({True: 'r', False: 'b'}))
ax.grid(ls = 'dashed', axis = 'x')
ax.set_ylim(-2.0,2.0)
ax.axhline(0.5,linewidth=0.8,color='red')
ax.axhline(-0.5,linewidth=0.8,color='blue')
```

Out[15]: <matplotlib.lines.Line2D at 0x2bb012203a0>



3. Explore a netCDF dataset

Browse the NASA's Goddard Earth Sciences Data and Information Services Center (GES DISC) website. Search and download a dataset you are interested in. You are also welcome to use data from your group in this problem set. But the dataset should be in `netCDF` format, and have temporal information.

3.1

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

I use here a global monthly precipitation data for analysis.

In [16]:
```
# Read the dataset
ds3 = xr.open_dataset('data_files/precip.mon.mean.nc', engine='netcdf4')
ds3
```

Out[16]: xarray.Dataset

► Dimensions: (**lat**: 72, **lon**: 144, **time**: 518, nv: 2)

▼ Coordinates:

lat	(lat)	float32	-88.75 -86.25 ... 86.25 88.75
lon	(lon)	float32	1.25 3.75 6.25 ... 356.2 358.8
time	(time)	datetime64[ns]	1979-01-01 ... 2022-02-01

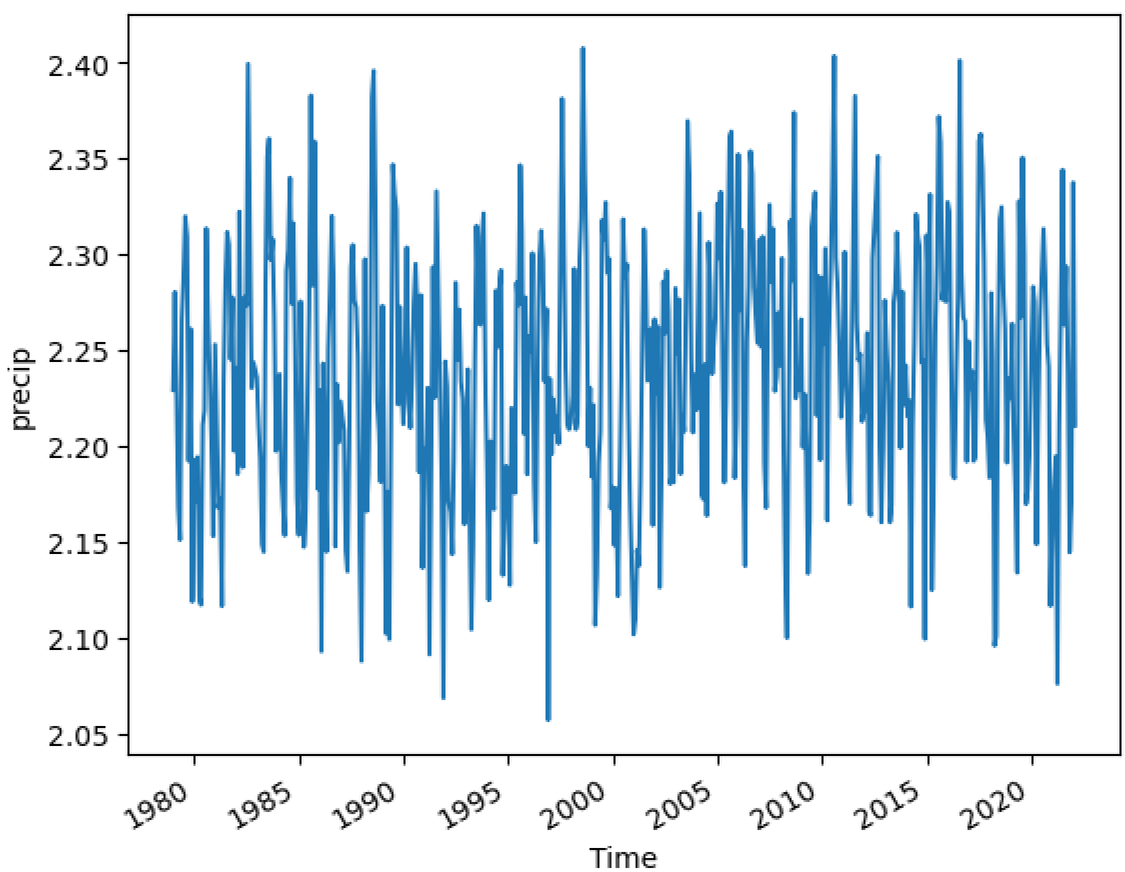
▼ Data variables:

time_bnds	(time, nv)	datetime64[ns]	...
lat_bnds	(lat, nv)	float32	...
lon_bnds	(lon, nv)	float32	...
precip	(time, lat, lon)	float32	...

► Attributes: (18)

In [17]:
```
# Plot an overall time series
ds3.precip.mean(dim=['lat','lon']).plot()
```

Out[17]: [<matplotlib.lines.Line2D at 0x2bb0337ffa0>]

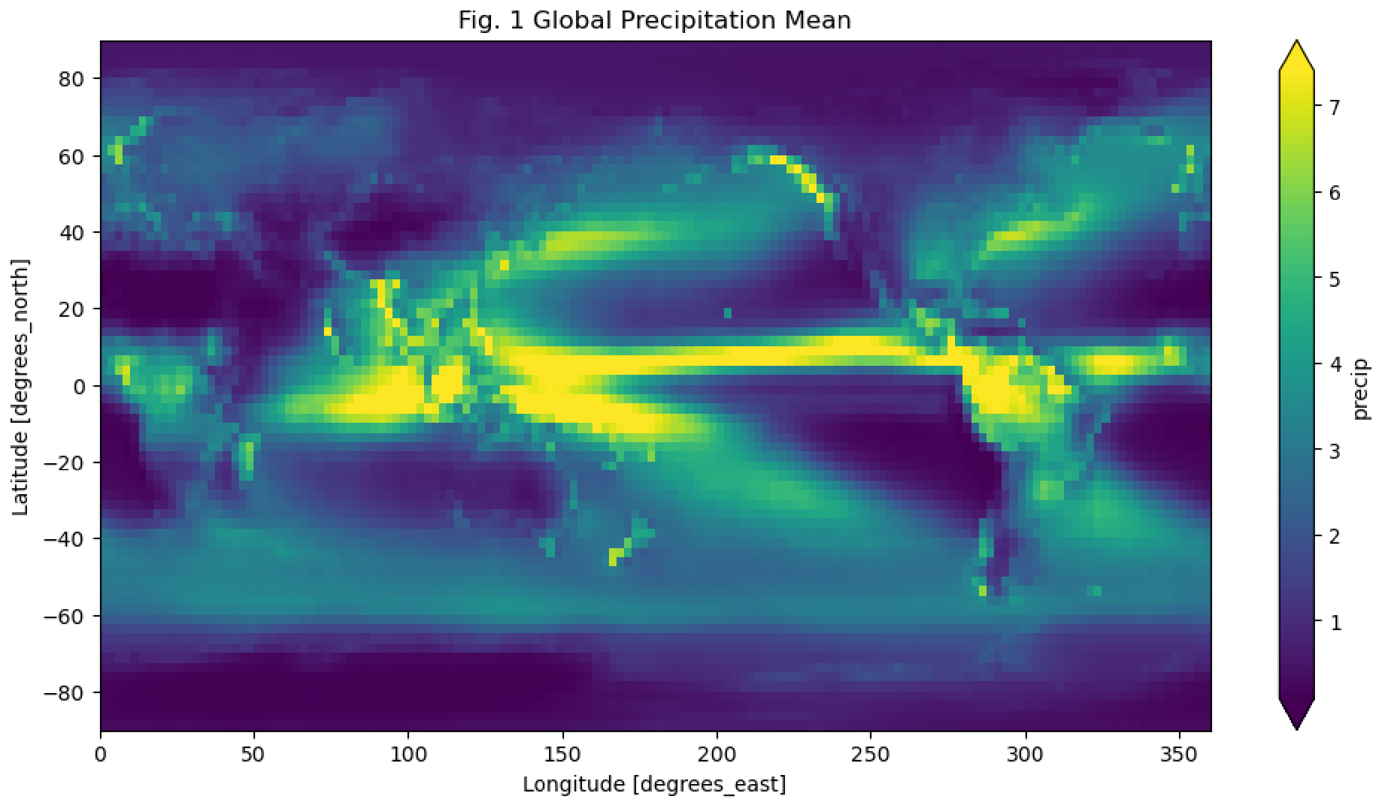


3.2

Make at least 5 different plots using the dataset.

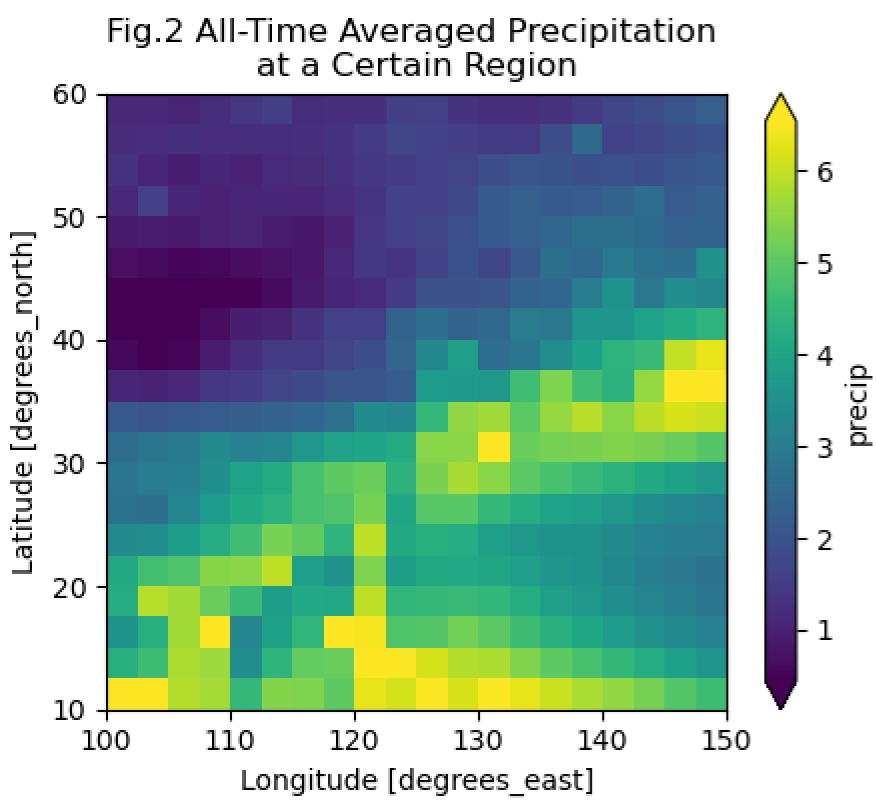
In [18]:
```
ds3.precip.mean(dim=['time']).plot(robust=True, figsize=(12, 6))
plt.title('Fig. 1 Global Precipitation Mean')
```

Out[18]: Text(0.5, 1.0, 'Fig. 1 Global Precipitation Mean')



In [19]:
```
ds3.precip.mean(dim=['time']).sel(lon=slice(100,150),lat=slice(10,60)).plot(robust=True, figsize=
plt.title('Fig.2 All-Time Averaged Precipitation \nat a Certain Region')
```

Out[19]: Text(0.5, 1.0, 'Fig.2 All-Time Averaged Precipitation \nat a Certain Region')

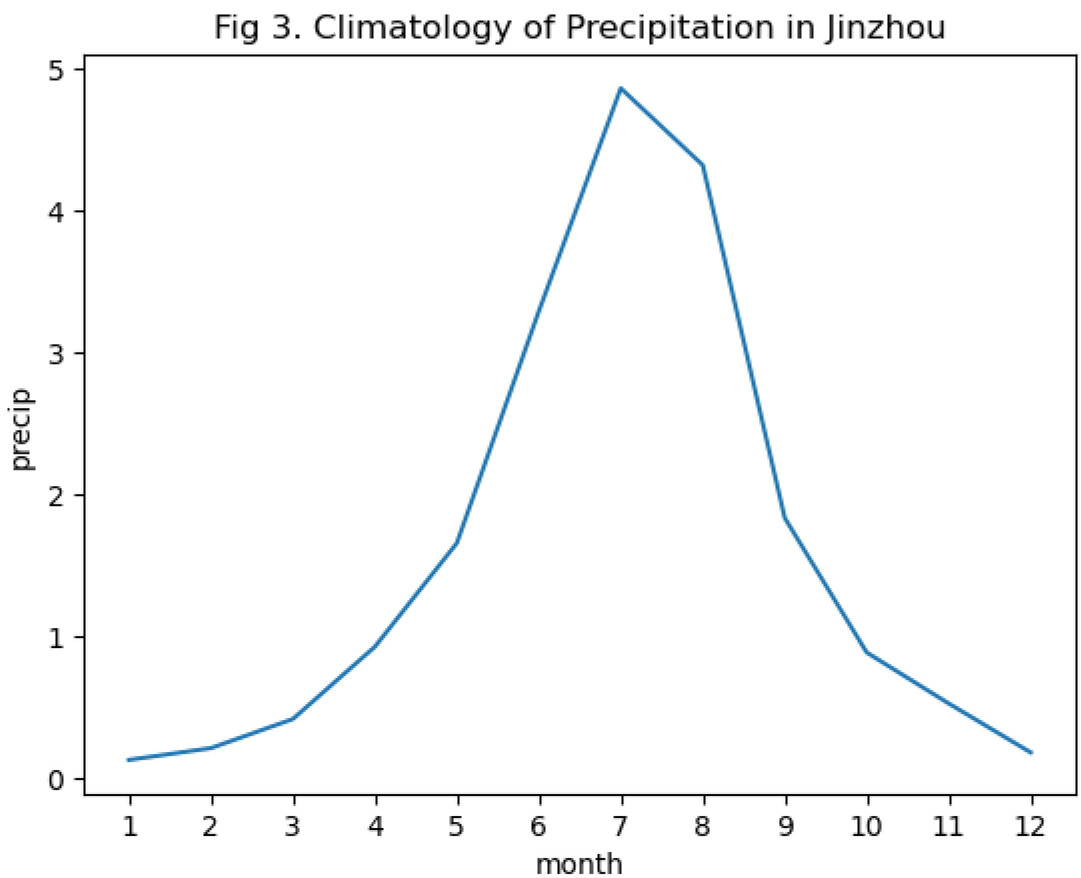


In [20]:
```
# Calculate the climatology
precip_clim = ds3.precip.groupby('time.month').mean()
precip_clim

# Plot climatology at a specific point (Jinzhou, Liaoning)
```

```
precip_clim.sel(lon=121.13, lat=41.10, method='nearest').plot()
plt.xticks(np.arange(1,13))
plt.title('Fig 3. Climatology of Precipitation in Jinzhou')
plt.show()
```

```
E:\Programmes\anaconda3\lib\site-packages\xarray\core\indexes.py:234: FutureWarning: Passing met
hod to Float64Index.get_loc is deprecated and will raise in a future version. Use index.get_inde
xer([item], method=...) instead.
  indexer = self.index.get_loc(
E:\Programmes\anaconda3\lib\site-packages\xarray\core\indexes.py:234: FutureWarning: Passing met
hod to Float64Index.get_loc is deprecated and will raise in a future version. Use index.get_inde
xer([item], method=...) instead.
  indexer = self.index.get_loc(
```

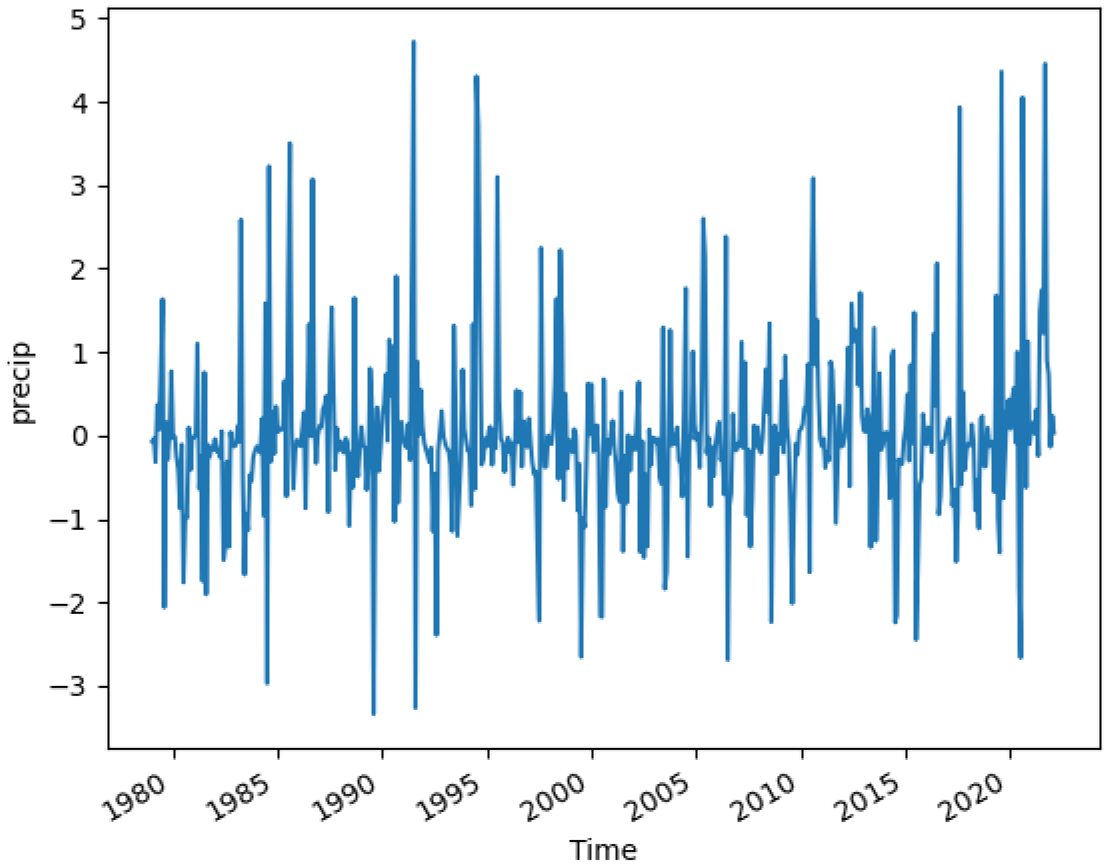


In [21]:
```
precip_anom = ds3.precip.groupby('time.month') - precip_clim
precip_anom.sel(lon=121.13, lat=41.10, method='nearest').plot()
plt.title('Fig. 4 Anomalies of Precipitation in Jinzhou')
```

```
E:\Programmes\anaconda3\lib\site-packages\xarray\core\indexes.py:234: FutureWarning: Passing met
hod to Float64Index.get_loc is deprecated and will raise in a future version. Use index.get_inde
xer([item], method=...) instead.
  indexer = self.index.get_loc(
E:\Programmes\anaconda3\lib\site-packages\xarray\core\indexes.py:234: FutureWarning: Passing met
hod to Float64Index.get_loc is deprecated and will raise in a future version. Use index.get_inde
xer([item], method=...) instead.
  indexer = self.index.get_loc(
```

Out[21]:
```
Text(0.5, 1.0, 'Fig. 4 Anomalies of Precipitation in Jinzhou')
```

Fig. 4 Anomalies of Precipitation in Jinzhou



In [22]:
```
precip_clim.plot(col="month", col_wrap=4, robust=True)
```

Out[22]:
```
<xarray.plot.facetgrid.FacetGrid at 0x2bb05dd5820>
```

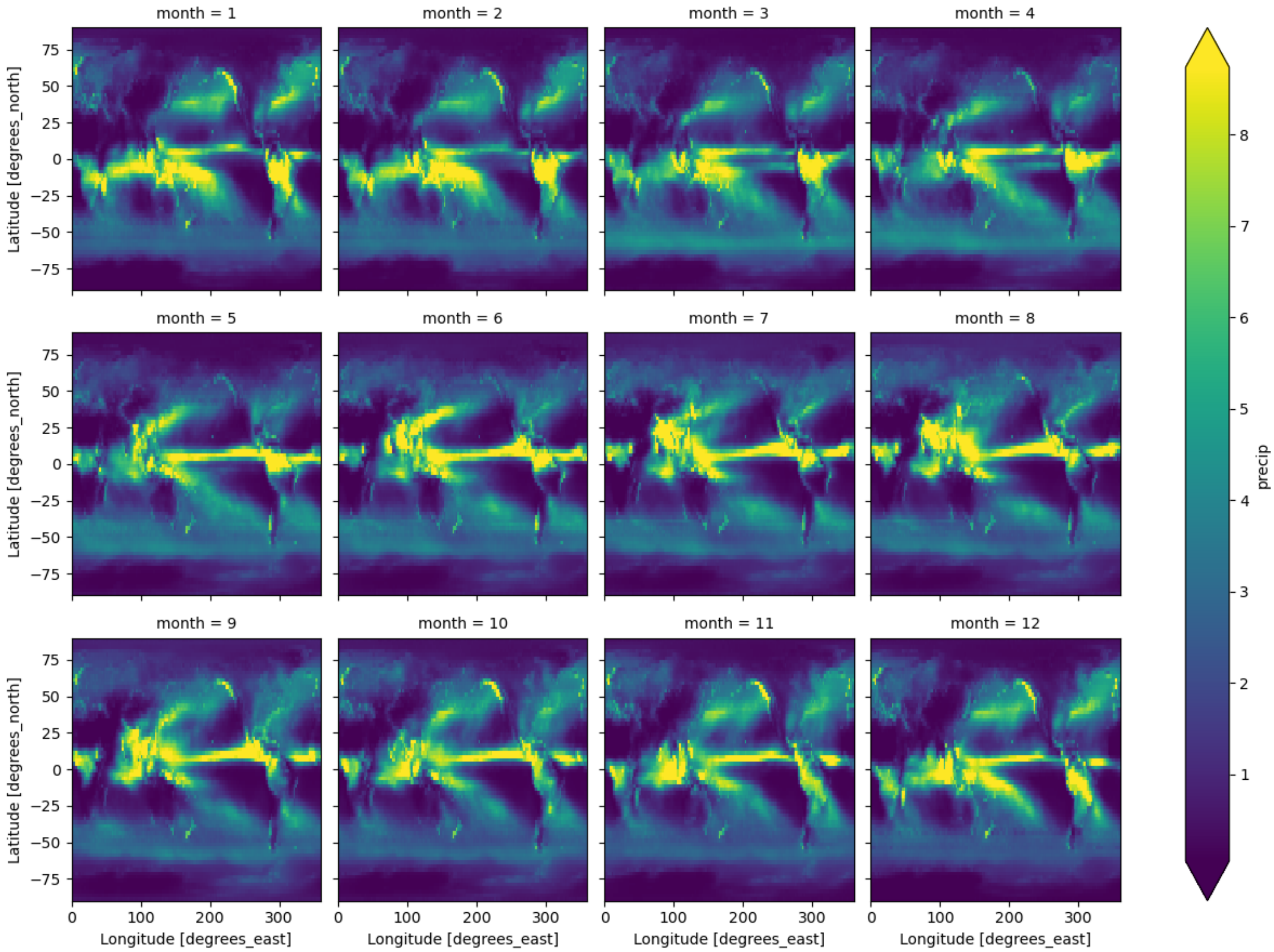


Fig. 5 Global Precipitation Mean in Each Month