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In [249]:

```
import numpy as np
import pandas as pd
import xarray as xr
from matplotlib import pyplot as plt
%matplotlib inline
import cartopy.crs as ccrs
```

Nino 3.4 index

In [2]:

```
sst_file = xr.open_dataset('Data/NOAA_NCDC_ERSST_v3b_SST.nc')
sst_file
```

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 ... 354.0 356.0 358.0
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 [3]:

```
sst = sst_file.sst
```

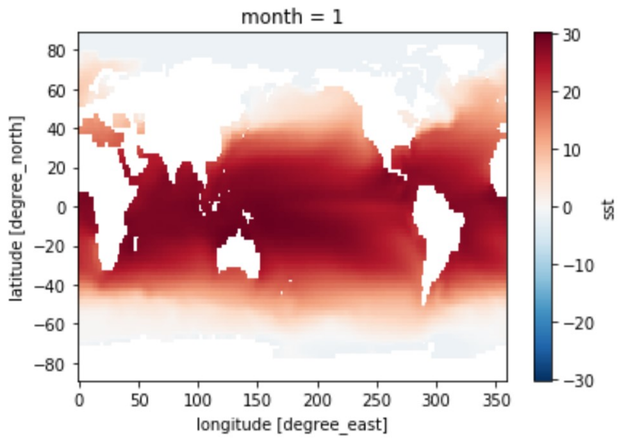
Climatology: 1986-2015 30 year

In [4]:

```
sst_30clim = sst.groupby(sst.time.dt.month).mean()
```

In [5]:
```
sst_30clim[0].plot()
```

Out[5]: <matplotlib.collections.QuadMesh at 0x7f8fbdae23d0>



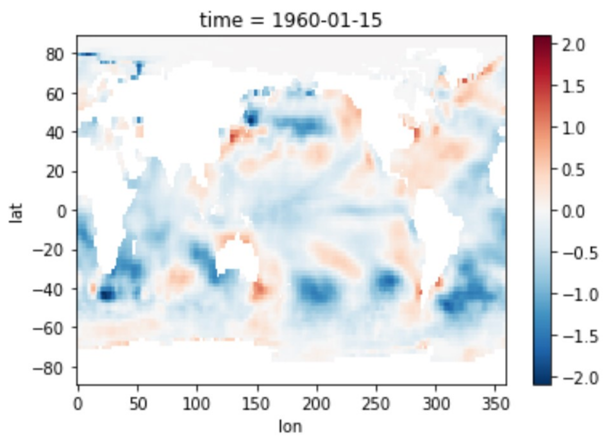
Extract anomaly

In [43]:
```
def get_anom(data,data_clim):
    data_anom=xr.DataArray(
    np.zeros(data.shape),
    [('time',data.time),('lat',data.lat),('lon',data.lon)])

    for i in range(len(data)):
        data_anom[i]=data[i]-data_clim.where((data_clim.month.isin(data[i].time.dt.month))
                                              ,drop=True).squeeze().values
    return data_anom
```

In [226]:
```
sst_anom=get_anom(sst,sst_30clim)
```

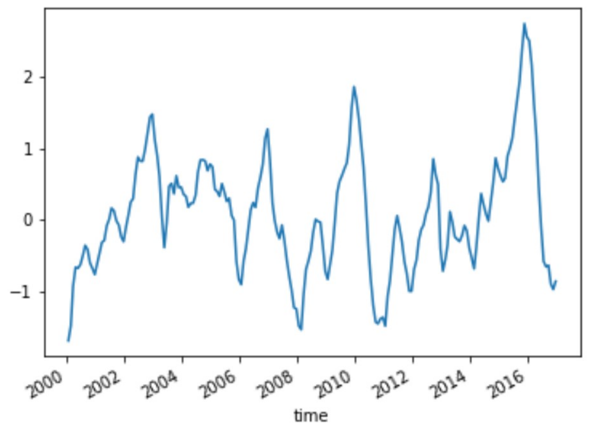
In [227]:
```
sst_anom[0].plot()
```

Out[227]: <matplotlib.collections.QuadMesh at 0x7f8f7eccb450>



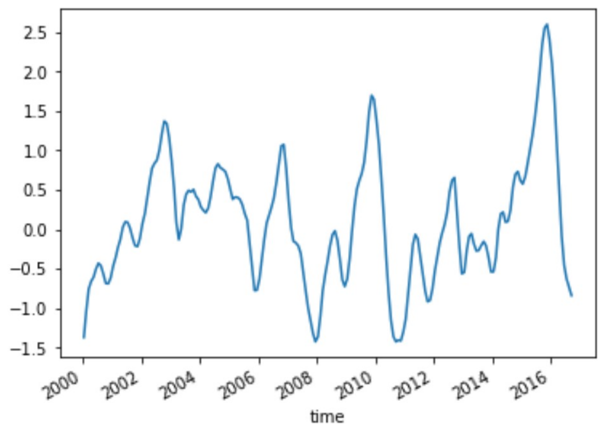
In [10]:
```
# Select the Niño 3.4 region
# Niño 3.4 (5N-5S, 170W-120W)
region34_anom = sst_anom.sel(time=slice('2000','2016')).sel(lat=slice(-5.5,4.5),lon=slice(190.5,240.5))
region34_anom_mean = np.mean(region34_anom,axis=(1,2))
```

In [11]:
```
region34_anom_mean.plot()
```
Out[11]:
```
[<matplotlib.lines.Line2D at 0x7f8fbf64e0d0>]
```



In [12]:
```
# Smooth the anomalies with a 3-month running mean
nstep = len(region34_anom)-3
index_oni = xr.DataArray(
    np.zeros(nstep),[('time',region34_anom.time[:-3])])
for i in range(0,nstep):
    index_oni[i] = np.mean(region34_anom[i:i+3])
```

In [13]:
```
index_oni.plot()
```
Out[13]:
```
[<matplotlib.lines.Line2D at 0x7f8fb8532210>]
```



Calculate index: running mean

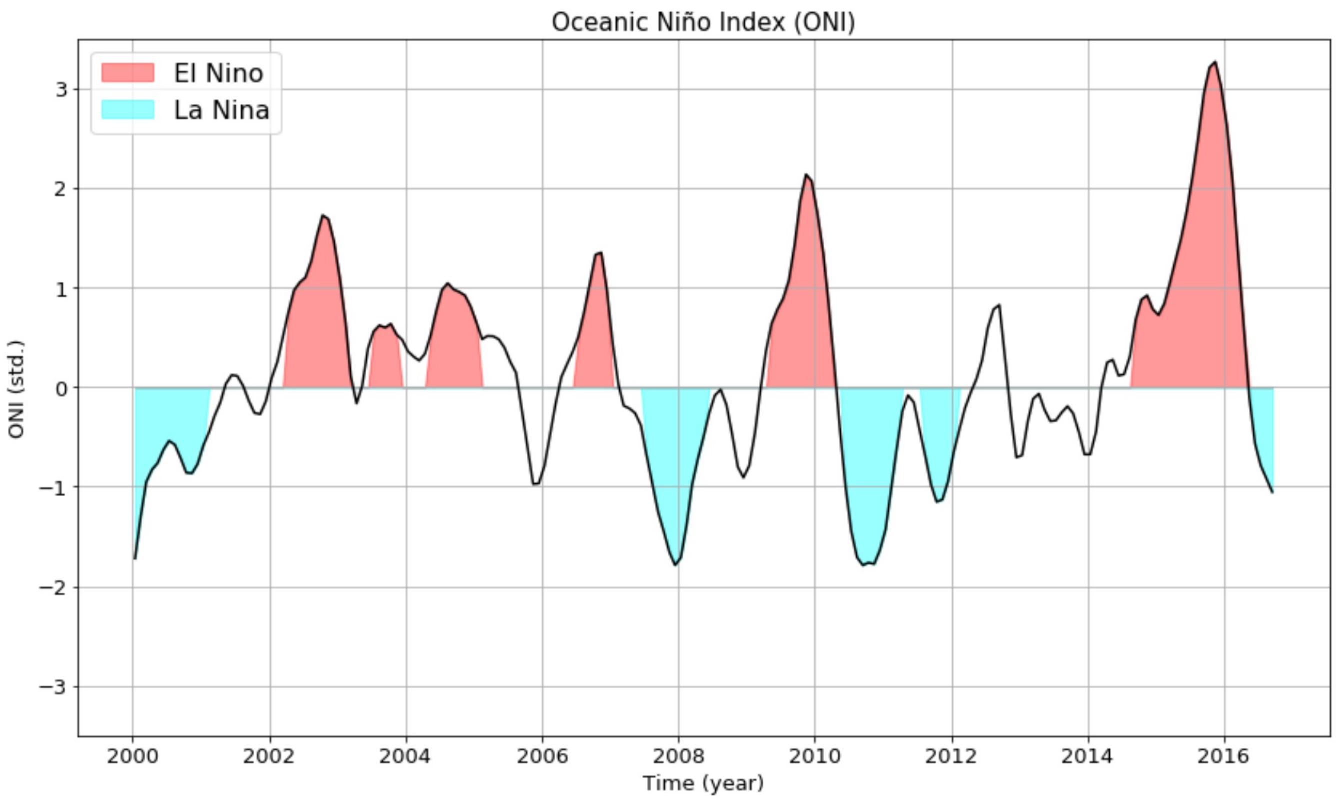
In [14]:
```
# Mark the El Nino events and La Nina events
# The ONI uses a 3-month running mean, and to be classified as a full-fledged El Niño or La Niña
# The anomalies must exceed +0.5C or -0.5C for at least five consecutive months.
# This is the operational definition used by NOAA.https://origin.cpc.ncep.noaa.gov/

# Normalize the smoothed values by its standard deviation over the period.
n_index_oni = index_oni / np.std(index_oni)

El_index = np.zeros(len(n_index_oni))
La_index = np.zeros(len(n_index_oni))
for i in range(len(index_oni-5)):
    if (n_index_oni[i:i+5]>0.5).all() == True:
        El_index[i:i+5] = n_index_oni[i:i+5]
    if (n_index_oni[i:i+5]<-0.5).all() == True:
        La_index[i:i+5] = n_index_oni[i:i+5]
```

In [15]:
```
El_index.shape,La_index.shape
```
Out[15]:
```
((201,), (201,))
```

Visualize the Nino 3.4

In [16]:
```python
def enso_plot(n_index_oni,El_index,La_index):
    xtime = n_index_oni.time.values

    fig, ax = plt.subplots(figsize=(14,8))

    ax.plot(xtime,n_index_oni,'k')
    ax.tick_params(axis='both',labelsize=13)
    ax.set_ylim(-3.5,3.5)
    ax.set_xlabel('Time (year)',fontsize=13)
    ax.set_ylabel('ONI (std.)',fontsize=13)
    ax.set_title('Oceanic Niño Index (ONI)',fontsize=15)
    ax.grid()

    # Mark the El Nino events and La Nina events
    fil1 = ax.fill_between(xtime,0,El_index,color='r',alpha=0.4)
    fil2 = ax.fill_between(xtime,0,La_index,color='cyan',alpha=0.4)
    # Add legend
    ax.legend([fil1,fil2],['El Nino','La Nina'],fontsize=16)
    plt.show()
    return fig,ax
```

In [17]:
```python
enso_plot(n_index_oni,El_index,La_index)
```

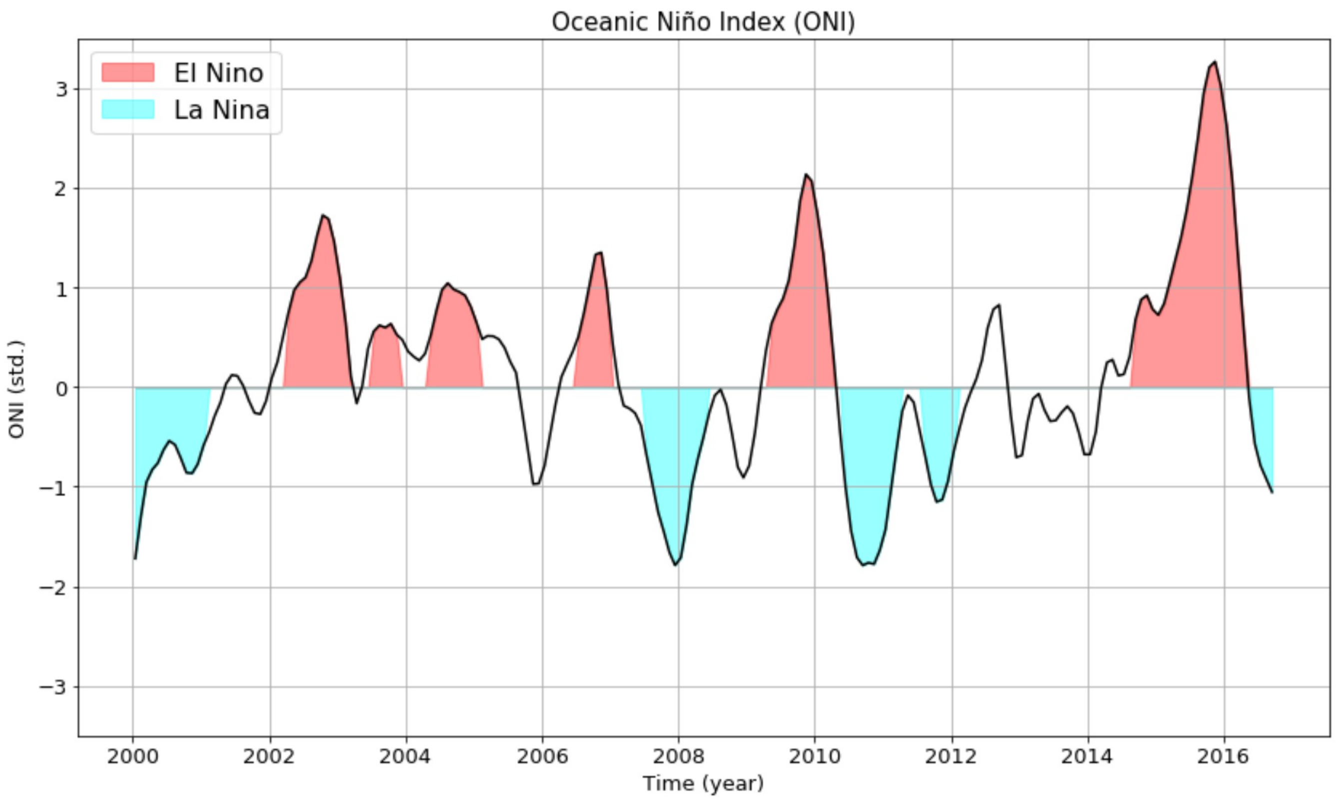


Out[17]:
```
(<Figure size 1008x576 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f8fb837ef10>)
```

An enclosed function: 1 step

In [18]:
```
def oni_index_plot(sst):
    #Step1. 30 year climatology mean
    sst_30clim = sst.groupby(sst.time.dt.month).mean()

    #Step2. sst anomalies
    sst_anom=get_anom(sst)

    #Step3. Select the Niño 3.4 region (5N-5S, 170W-120W)
    region34_anom = sst_anom.sel(time=slice('2000','2016')).sel(lat=slice(-5.5,4.5),lon=slice(190.5,24
0.5))
    region34_anom_mean = np.mean(region34_anom,axis=(1,2))

    #Step4. Smooth the anomalies with a 3-month running mean
    nstep = len(region34_anom)-3
    index_oni = xr.DataArray(
    np.zeros(nstep),[('time',region34_anom.time[:-3])])
    for i in range(0,nstep):
        index_oni[i] = np.mean(region34_anom[i:i+3])

    #Step 5 Mark the El Nino events and La Nina events
    n_index_oni = index_oni / np.std(index_oni)

    El_index = np.zeros(len(n_index_oni))
    La_index = np.zeros(len(n_index_oni))

    for i in range(len(index_oni-5)):
        if (n_index_oni[i:i+5]>0.5).all() == True:
            El_index[i:i+5] = n_index_oni[i:i+5]
        if (n_index_oni[i:i+5]<-0.5).all() == True:
            La_index[i:i+5] = n_index_oni[i:i+5]
    fig,ax=enso_plot(n_index_oni,El_index,La_index)
    return fig,ax
```

In [20]:
```
oni_index_plot(sst)
```



Out[20]:
```
(<Figure size 1008x576 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f8fb830a690>)
```

Earth's energy budget

In [2]:
```
ds = xr.open_dataset('Data/CERES_EBAF-TOA_200003-201701.nc')
ds
```

Out[2]:

xarray.Dataset

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

▼ 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	...
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	...

▼ 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

Make a 2D plot

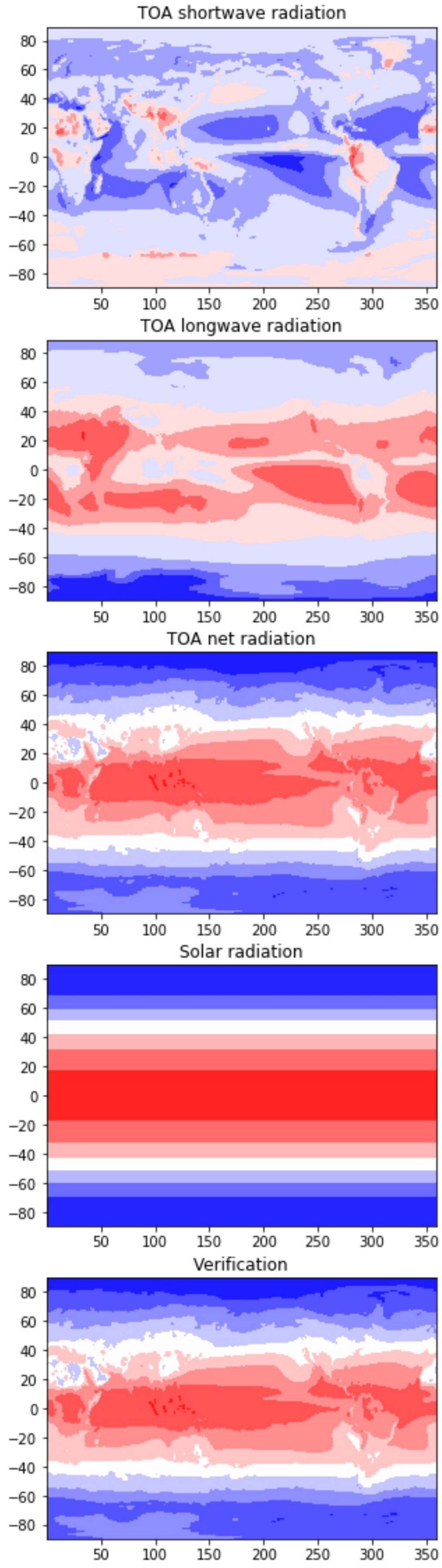
1. time-mean TOA longwave
2. shortwave
3. solar radiation for all-sky conditions.
4. Add up the three variables above and verify (visually) that they are equivalent to the TOA net flux.

In [3]:
```
plt_data=[ds.toa_sw_all_mon.mean(dim='time'),
     ds.toa_lw_all_mon.mean(dim='time'),
     ds.toa_net_all_mon.mean(dim='time'),
     ds.solar_mon.mean(dim='time'),]
labels=['TOA shortwave radiation','TOA longwave radiation',
       'TOA net radiation','Solar radiation']
```

TOA net radiation = Solar radiation - (TOA shortwave_out + TOA longwave_out)

In [61]:
```python
fig,axs=plt.subplots(5,1,figsize=(5,20))
lon=plt_data[0].lon
lat=plt_data[0].lat

for data,ax,label in zip(plt_data[:4],axs[:4],labels[:4]):
    ax.contourf(lon,lat,data,cmap='bwr',)
    ax.set_title(label)
axs[4].contourf(lon,lat,plt_data[3]-(plt_data[0]+plt_data[1]),cmap='bwr')
axs[4].set_title('Verification')
```

Out[61]: Text(0.5, 1.0, 'Verification')

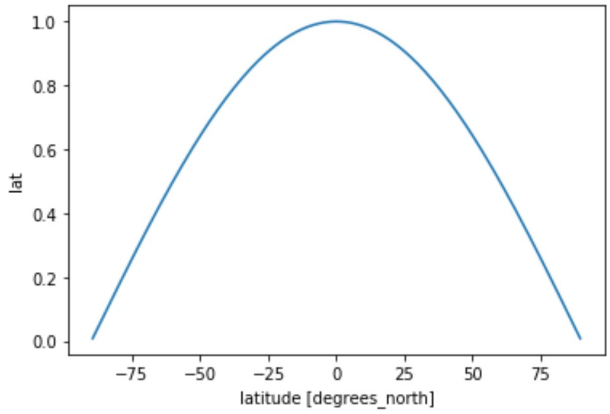


Calculate and verify

The TOA incoming solar, outgoing longwave, and outgoing shortwave approximately match up with the cartoon above.

In [4]:
```
weights=np.cos(np.deg2rad(ds.lat))
weights.plot()
```

Out[4]: `[<matplotlib.lines.Line2D at 0x7f2221824950>]`

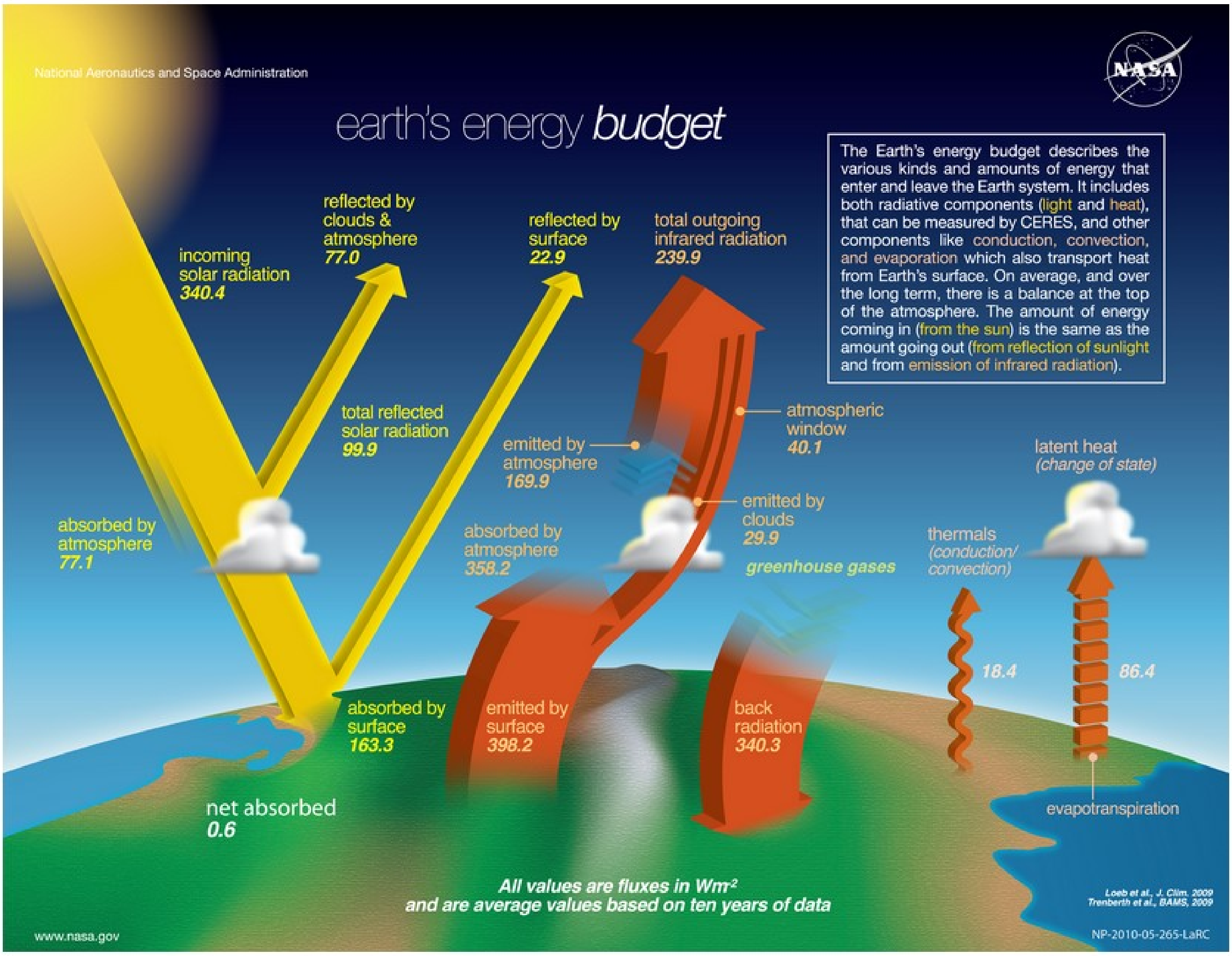


In [6]:
```
data_list=[ds.solar_mon,ds.toa_sw_all_mon,ds.toa_lw_all_mon]
```

In [12]:
```
list(map(lambda data: data.sel(time=slice('2006','2016')).weighted(weights).mean(), data_list))
```

Out[12]:
```
[<xarray.DataArray ()>
 array(340.29804625),
 <xarray.DataArray ()>
 array(99.00475716),
 <xarray.DataArray ()>
 array(240.26727502)]
```

1. TOA incoming solar radiation: $340.4 W m^2$ in cartoon
2. TOA outgoing shortwave radiation : $99.9 W m^2$
3. TOA outgoing longwave radiation is $240.3 W m^2$, close to $239.9 W m^2$ in cartoon



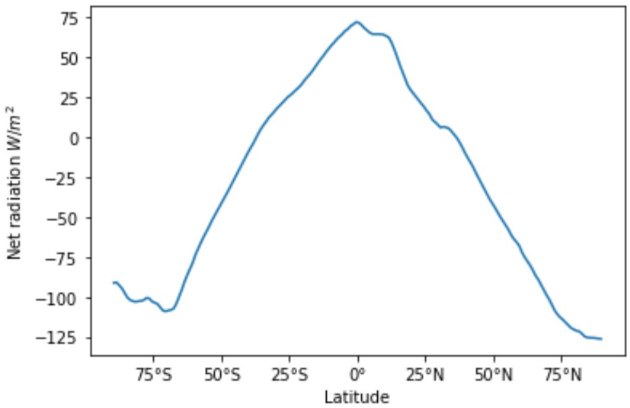
Calculate and plot

Total amount of net radiation in each 1-degree latitude band. Label with correct units.

In [14]:
```
from cartopy.mpl.ticker import LongitudeFormatter, LatitudeFormatter
```

In [21]:
```
fig,ax=plt.subplots()
ax.plot(ds.lat,ds.toa_net_all_mon.weighted(weights).mean(dim=['time','lon']))
ax.set_ylabel('Net radiation $W/m^2$')
ax.xaxis.set_major_formatter(LatitudeFormatter())
ax.set_xlabel('Latitude')
```

Out[21]: Text(0.5, 0, 'Latitude')



Calculate and plot

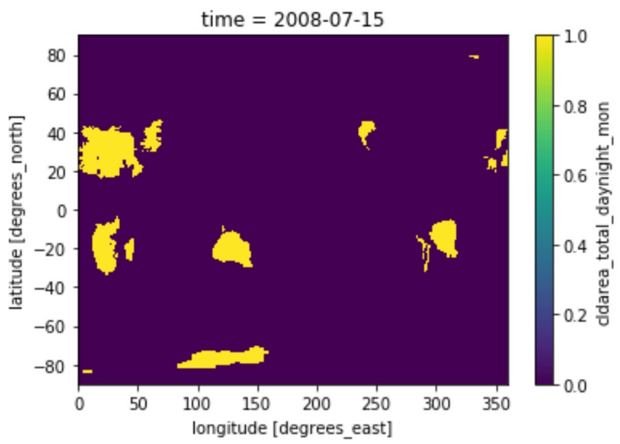
Composites of time-mean outgoing shortwave and longwave radiation for low and high cloud area regions. Here we define low cloud area as ≤25% and high cloud area as ≥75%. Your results should be 2D maps.

In [16]:
```
cloud_frac=ds.cldarea_total_daynight_mon
low_cloud=cloud_frac.where(cloud_frac<= 25)
high_cloud=cloud_frac.where(cloud_frac>=75)
```

In [17]:
```
low_cloud_mask=xr.where(np.isnan(low_cloud)==False,1,0)
high_cloud_mask=xr.where(np.isnan(high_cloud)==False,1,0)
```

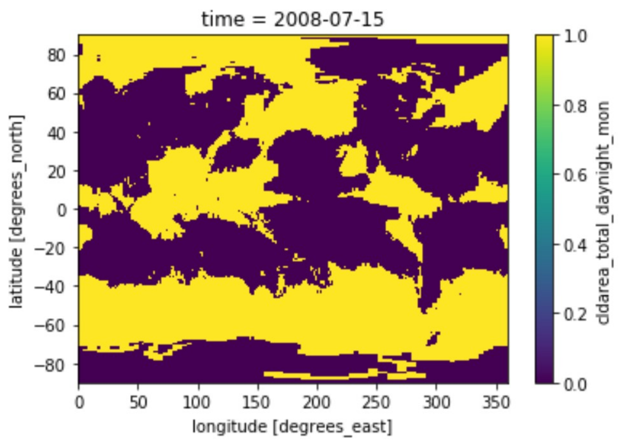
In [194]:
```
low_cloud_mask[100].plot()
```

Out[194]: <matplotlib.collections.QuadMesh at 0x7f8f93589750>



In [195]:
```
high_cloud_mask[100].plot()
```

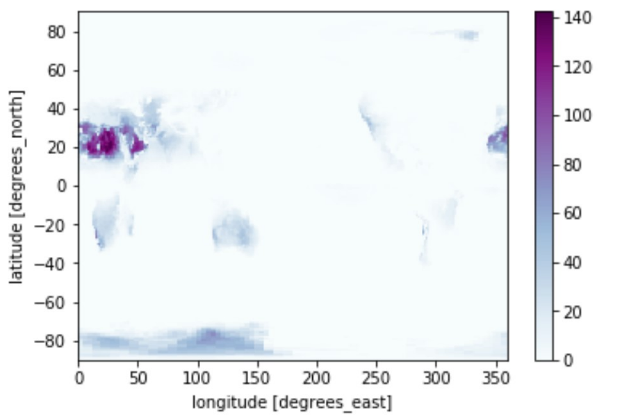
Out[195]: <matplotlib.collections.QuadMesh at 0x7f8f93250a10>



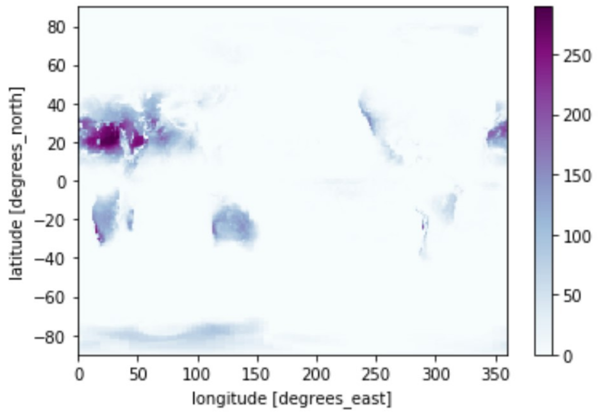
In [18]:
```
low_cloud_sw=ds.toa_sw_all_mon*low_cloud_mask
low_cloud_lw=ds.toa_lw_all_mon*low_cloud_mask
```

In [208]:
```
low_cloud_sw.mean(dim='time').plot(cmap='BuPu')
```

Out[208]: <matplotlib.collections.QuadMesh at 0x7f8f803ed4d0>

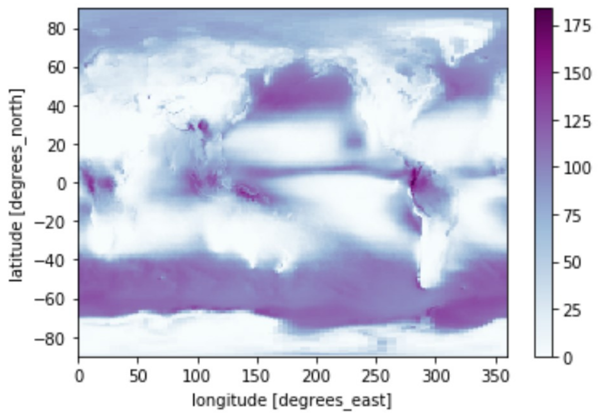


In [214]:
```
low_cloud_lw.mean(dim='time').plot(cmap='BuPu')
```
Out[214]: <matplotlib.collections.QuadMesh at 0x7f8f7f3c79d0>

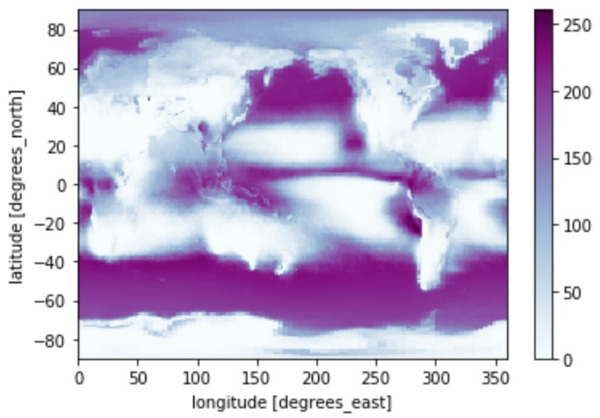


In [19]:
```
high_cloud_sw=ds.toa_sw_all_mon*high_cloud_mask
high_cloud_lw=ds.toa_lw_all_mon*high_cloud_mask
```

In [211]:
```
high_cloud_sw.mean(dim='time').plot(cmap='BuPu')
```
Out[211]: <matplotlib.collections.QuadMesh at 0x7f8f7f540ed0>



In [212]:
```
high_cloud_lw.mean(dim='time').plot(cmap='BuPu')
```
Out[212]: <matplotlib.collections.QuadMesh at 0x7f8f7f493290>



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?

1. Clouds reflect more shortwave radiation.
2. Part of longwave radiation is diretly emitted by clouds.
3. Regions with high cloud cover possibly emit more latent heat and contributes to the outgoing longwave radiation.

In [23]:
```
print('Low cloud area global mean shortwave radiation %.2f W/m^2'%low_cloud_sw.weighted(weights).mean
())
print('Low cloud area global mean longwave radiation %.2f W/m^2'%low_cloud_lw.weighted(weights).mean())
print('High cloud area global mean shortwave radiation %.2f W/m^2'%high_cloud_sw.weighted(weights).mean
())
print('High cloud area global mean longwave radiation %.2f W/m^2'%high_cloud_lw.weighted(weights).mean
())
```

```
Low cloud area global mean shortwave radiation 3.97 W/m^2
Low cloud area global mean longwave radiation 12.19 W/m^2
High cloud area global mean shortwave radiation 48.82 W/m^2
High cloud area global mean longwave radiation 96.13 W/m^2
```

Explore a netCDF dataset

Dataset: CESM CMIP6 Experiment CESM2_amip-4xCO2_r1i1p1f1
case name: f.e21.FHIST_BGC.f09_f09_mg17.CFMIP-amip-4xCO2.001
description: the same as the amip experiment within DECK, except that the CO2 concentration seen by the radiation scheme is quadrupled. AMIP SSTs with 4xCO2
more information: https://csegweb.cgd.ucar.edu/experiments/public/ (https://csegweb.cgd.ucar.edu/experiments/public/)

File download path http://esgf-data.ucar.edu/thredds/fileServer/esg_dataroot/CMIP6/CFMIP/NCAR/CESM2/amip-4xCO2/r1i1p1f1/Amon/pr/gn/v20190408/pr_Amon_CESM2_amip-4xCO2_r1i1p1f1_gn_197901-201412.nc (http://esgf-data.ucar.edu/thredds/fileServer/esg_dataroot/CMIP6/CFMIP/NCAR/CESM2/amip-4xCO2/r1i1p1f1/Amon/pr/gn/v20190408/pr_Amon_CESM2_amip-4xCO2_r1i1p1f1_gn_197901-201412.nc)

In [40]:
```
cesm_pr=xr.open_dataset('Data/pr_Amon_CESM2_amip-4xCO2_r1i1p1f1_gn_197901-201412.nc')
```

```
/home/andrea/anaconda3/lib/python3.7/site-packages/xarray/conventions.py:500: SerializationWarning: v
ariable 'pr' has multiple fill values {1e+20, 1e+20}, decoding all values to NaN.
  decode_timedelta=decode_timedelta,
```

In [41]:
```
pr=cesm_pr.pr
pr
```

Out[41]:

xarray.DataArray 'pr' (**time**: 432, **lat**: 192, **lon**: 288)

[23887872 values with dtype=float32]

▼Coordinates:

lat	(lat)	float64	-90.0 -89.06 -88.12 ... 89.06 90.0
lon	(lon)	float64	0.0 1.25 2.5 ... 356.2 357.5 358.8
time	(time)	object	1979-01-15 12:00:00 ... 2014-12-...

▶Attributes: (19)

In [42]:
```
pr_clim_sel=pr.sel(time=slice('1979','1998'))
pr_clim_30y=pr_clim_sel.groupby(pr_clim_sel.time.dt.month).mean()
```

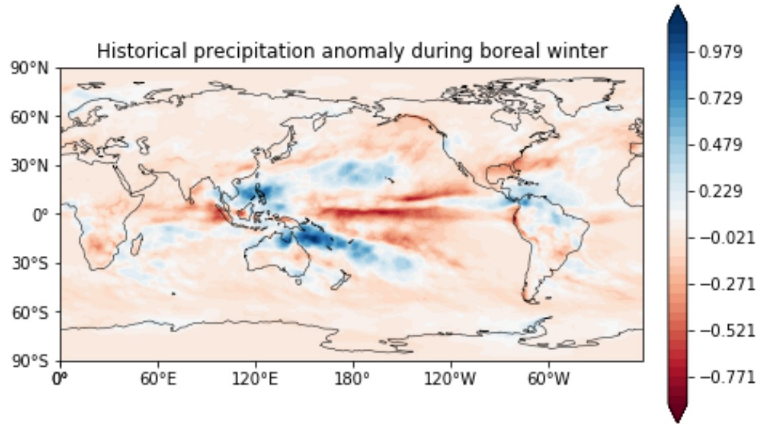
In [52]:
```
pr_anom=get_anom(pr,pr_clim_30y)*24*3600
```

In [267]:
```
def plot_map():
    proj = ccrs.PlateCarree(central_longitude=180)
    fig,ax = plt.subplots(figsize=(8,8),subplot_kw=dict(projection=proj))

    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())

    ax.xaxis.set_major_formatter(LongitudeFormatter())
    ax.yaxis.set_major_formatter(LatitudeFormatter())

    ax.coastlines(zorder=10,lw=0.5)
    return fig,ax
```

Boreal winter months (Nov.-Apr.) precipitation anomalies

In [303]:
```
fig,ax=plot_map()
plt_data=pr_anom.where(pr_anom.time.dt.month.isin([1,2,3,4,11,12])).mean(dim='time')
clevs=np.arange(plt_data.min(),plt_data.max(),0.05)
cf=plt.contourf(plt_data.lon,plt_data.lat,plt_data,clevs,cmap='RdBu',extend='both',transform=ccrs.Plate
Carree())
plt.colorbar(cf,shrink=0.6,pad=0.035)
plt.title('Historical precipitation anomaly during boreal winter')
```

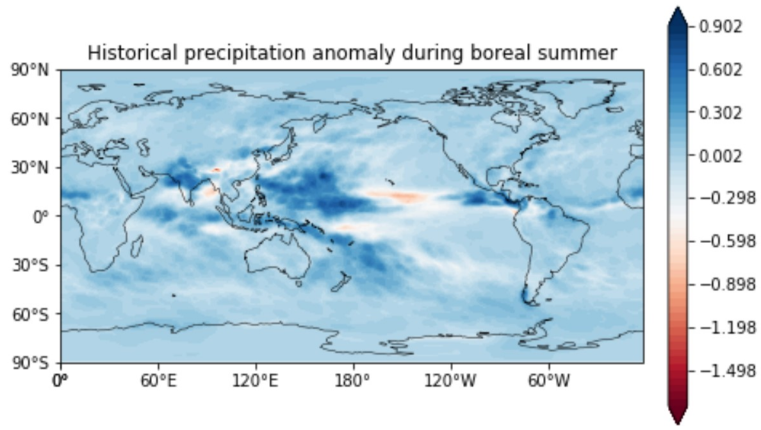
Out[303]: Text(0.5, 1.0, 'Historical precipitation anomaly during boreal winter')



Boreal summer months (May-Oct.) precipitation anomalies

In [304]:
```
fig,ax=plot_map()
plt_data=pr_anom.where(pr_anom.time.dt.month.isin([5,6,7,8,9,10])).mean(dim='time')
clevs=np.arange(plt_data.min(),plt_data.max(),0.05)
cf=plt.contourf(plt_data.lon,plt_data.lat,plt_data,clevs,cmap='RdBu',extend='both',transform=ccrs.Plate
Carree())
plt.colorbar(cf,shrink=0.6,pad=0.035)
plt.title('Historical precipitation anomaly during boreal summer')
```

Out[304]: Text(0.5, 1.0, 'Historical precipitation anomaly during boreal summer')

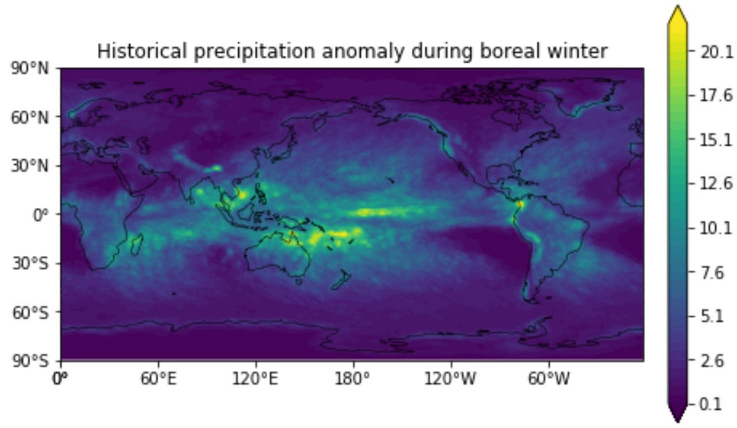


Boreal winter 99th percentile precipitation

In [305]:
```
plt_data=xr.DataArray(
    np.percentile(pr_anom.where((pr_anom.time.dt.month.isin([1,2,3,4,11,12])),drop=True),99,axis=0),
    [('lat',pr_anom.lat),('lon',pr_anom.lon)]
)
```

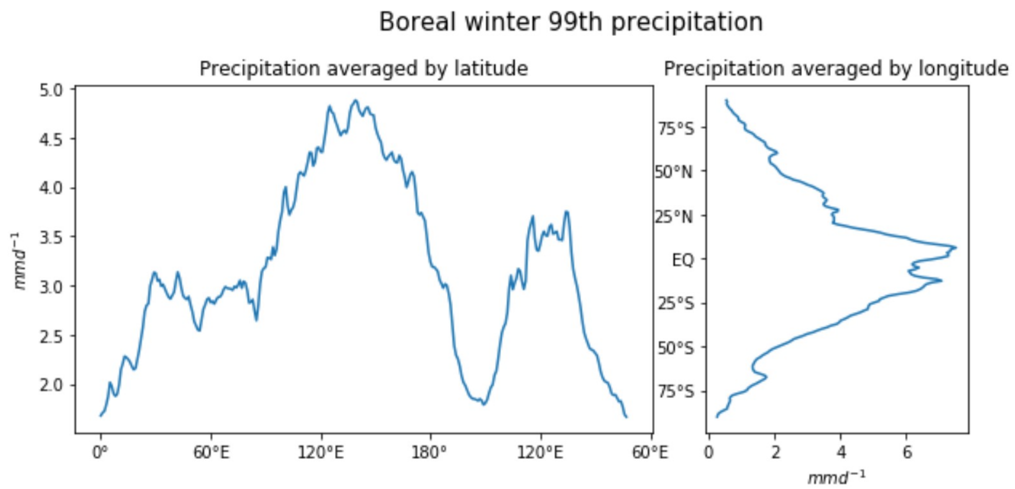
```
In [308]: fig,ax=plot_map()
clevs=np.arange(plt_data.min(),plt_data.max(),.5)
cf=plt.contourf(plt_data.lon,plt_data.lat,plt_data,clevs,extend='both',transform=ccrs.PlateCarree())
plt.colorbar(cf,shrink=0.6,pad=0.035)
plt.title('Historical precipitation anomaly during boreal winter')
```

```
Out[308]: Text(0.5, 1.0, 'Historical precipitation anomaly during boreal winter')
```




```
In [301]: fig = plt.figure(figsize=(10,4))
grid = plt.GridSpec(2, 3)
# Plot each axes

plt.subplot(grid[:,:2])
plt.plot(plt_data.mean(dim=['lat']))
plt.xticks([0,60,120,180,240,300],labels=x_tick_labels)
plt.title('Precipitation averaged by latitude')
plt.ylabel('$mm d^{-1}$')

plt.subplot(grid[:,2])
plt.plot(plt_data.mean(dim=['lon']),plt_data.lat)
plt.yticks([-75,-50,-25,0,25,50,75],labels=y_tick_labels)
plt.title('Precipitation averaged by longitude')
plt.xlabel('$mm d^{-1}$')

plt.text(-10,130,'Boreal winter 99th precipitation',fontsize=15)
```

```
Out[301]: Text(-10, 130, 'Boreal winter 99th precipitation')
```

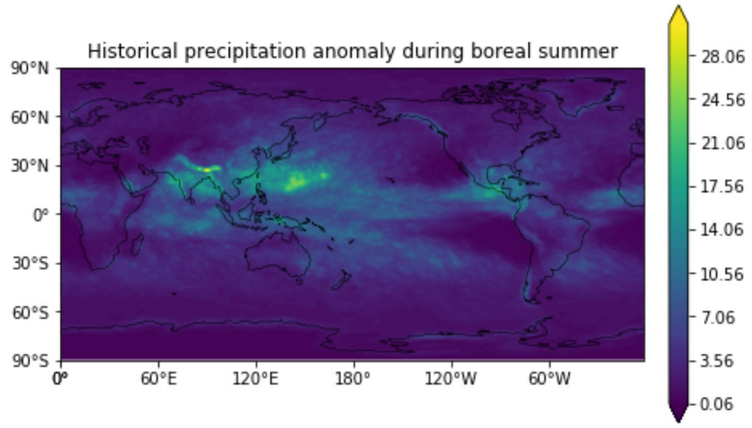


Boreal summer 99th percentile precipitation

```
In [309]: plt_data=xr.DataArray(
    np.percentile(pr_anom.where((pr_anom.time.dt.month.isin([5,6,7,8,9,10])),drop=True),99,axis=0),
    [('lat',pr_anom.lat),('lon',pr_anom.lon)]
)
```

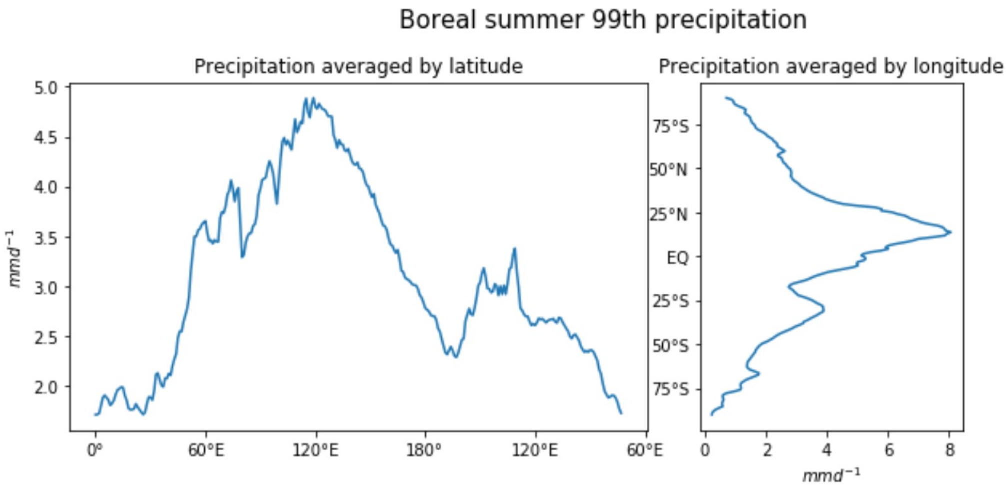
In [310]:
```
fig,ax=plot_map()
clevs=np.arange(plt_data.min(),plt_data.max(),.5)
cf=plt.contourf(plt_data.lon,plt_data.lat,plt_data,clevs,extend='both',transform=ccrs.PlateCarree())
plt.colorbar(cf,shrink=0.6,pad=0.035)
plt.title('Historical precipitation anomaly during boreal summer')
```

Out[310]:
```
Text(0.5, 1.0, 'Historical precipitation anomaly during boreal summer')
```



In [312]:
```
fig = plt.figure(figsize=(10,4))
grid = plt.GridSpec(2, 3)
# Plot each axes

plt.subplot(grid[:,:2])
plt.plot(plt_data.mean(dim=['lat']))
plt.xticks([0,60,120,180,240,300],labels=x_tick_labels)
plt.title('Precipitation averaged by latitude')
plt.ylabel('$mm d^{-1}$')

plt.subplot(grid[:,2])
plt.plot(plt_data.mean(dim=['lon']),plt_data.lat)
plt.yticks([-75,-50,-25,0,25,50,75],labels=y_tick_labels)
plt.title('Precipitation averaged by longitude')
plt.xlabel('$mm d^{-1}$')

plt.text(-10,130,'Boreal summer 99th precipitation',fontsize=15)
```

Out[312]:
```
Text(-10, 130, 'Boreal summer 99th precipitation')
```



In [ ]: