

Report of assignment 3

1. Nino

1.1

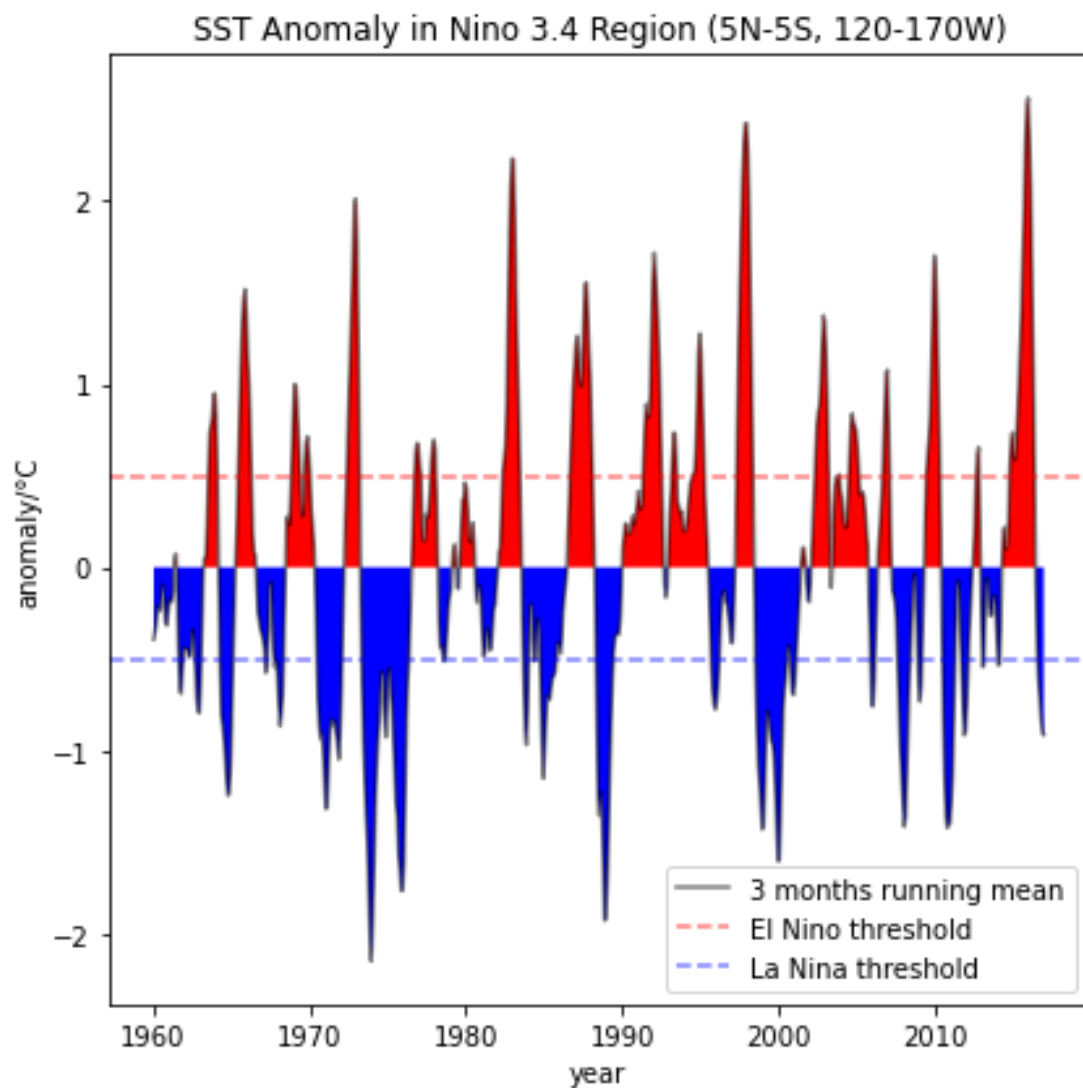
I used os module to edit path, so that it could be smoother to read file. However, in this method, .py file should be read together rather than line by line.

I sliced the Nino 3.4 region by slicing LAT (-5,5) and LON (190,240), then grouped it by month to get monthly mean. Subtract month mean from grouped data to get anomaly data. Then, calculate the 3 month running mean of anomaly data to get a new anomaly data

Regional anomaly data was then weighted by area to represent Nina regional anomaly data

1.2

Reginal weighted anomaly data was utilized to plot SST Anomaly in Nino 3.4 Region (5N-5S, 120-170W) figure. Figure is illustrated below.



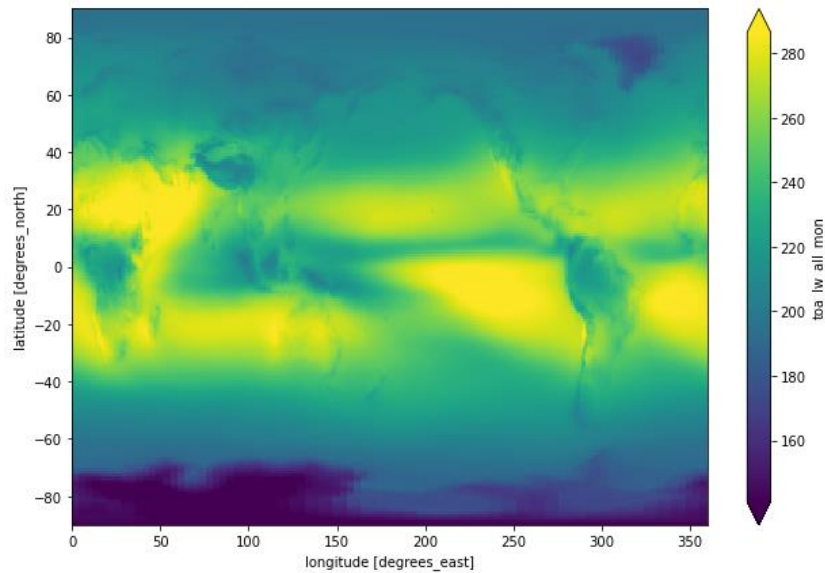
2. Energy budget

Import file as last problem described.

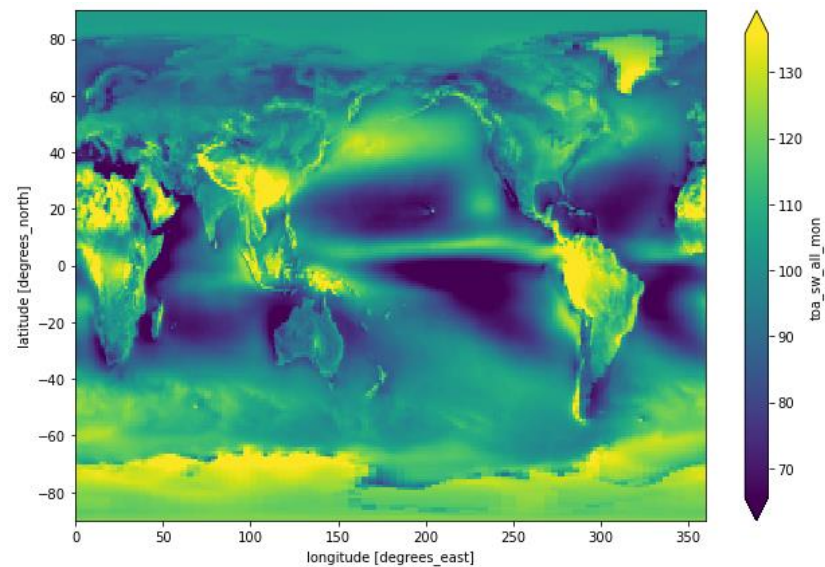
2.1

toa_lw_all_mon, toa_sw_all_mon, toa_net_all_mon, solar_mon represent TOA longwave, shortwave, and solar radiation for all-sky conditions and TOA net flux respectively.

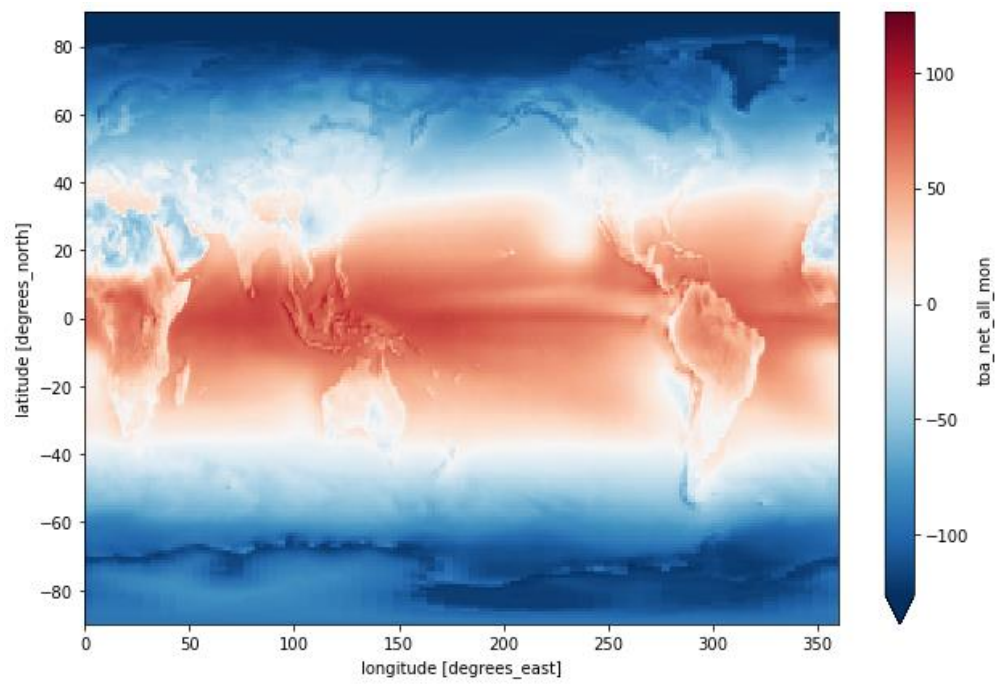
Time-mean figures are shown below as the same order of their listed in last paragraph:



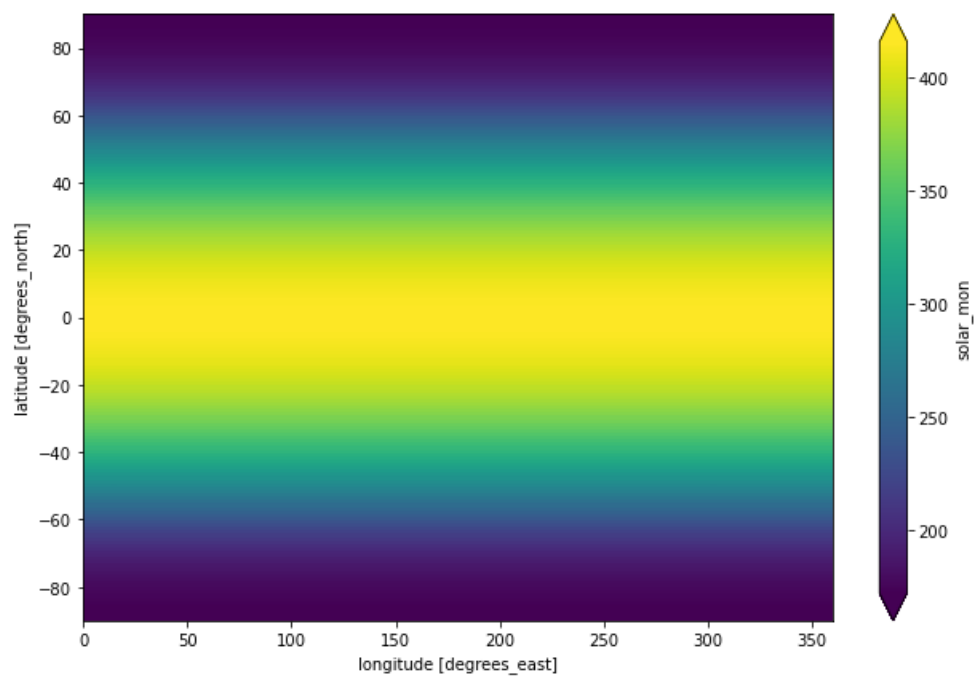
F1. Long wave radiation



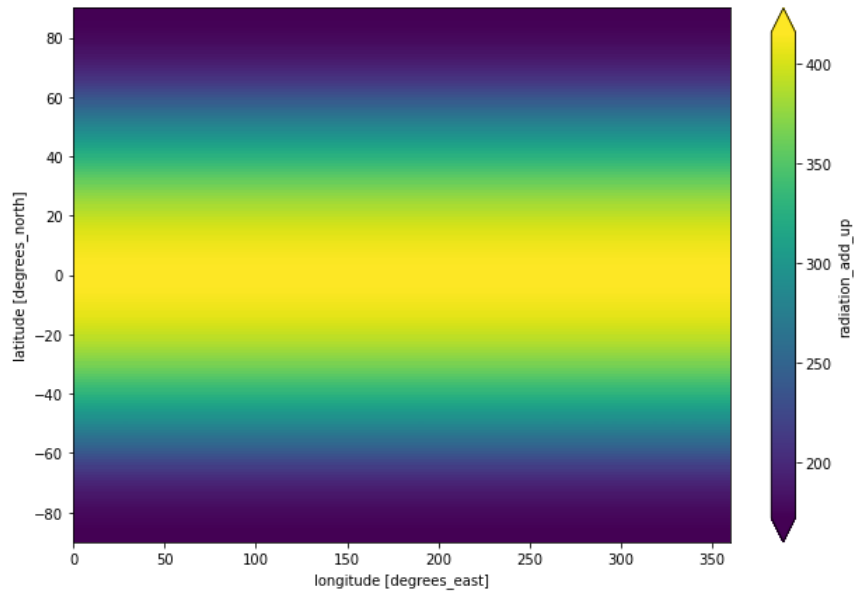
F2. Short wave radiation



F3. Toa net radiation



F4. Total flux in solar radiation



F5. Radiation add-up (sw+lw+net)

F5 looks same as F4

2.2

TOA incoming solar, outgoing longwave, and outgoing shortwave were calculated by area weighting. Results are shown below and is quite matched with data in cartoon:

outgoing longwave

```
ds2.toa_lw_all_mon.mean(dim = 'time').weighted(weights).mean(dim = ('lon','lat'))
#240.26666558
```

outgoing shortwave

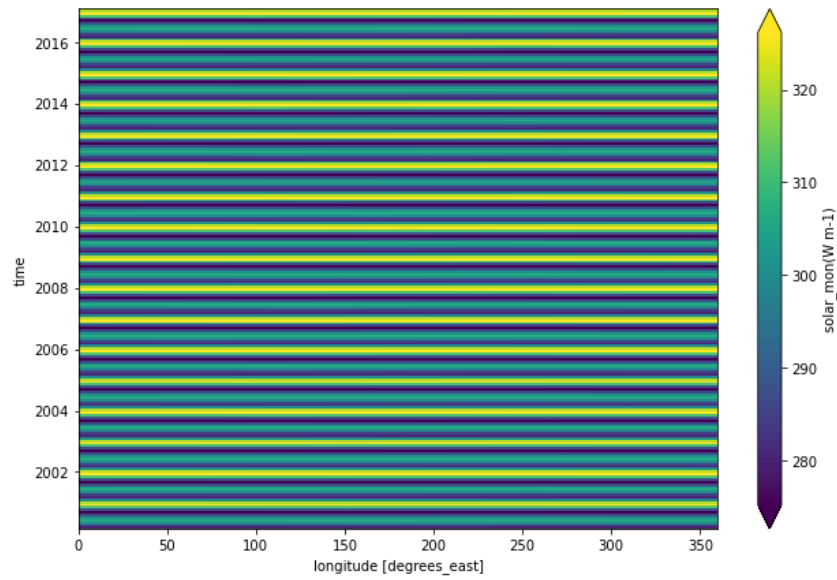
```
ds2.toa_sw_all_mon.mean(dim = 'time').weighted(weights).mean(dim = ('lon','lat'))
#99.13858336
```

TOA incoming solar

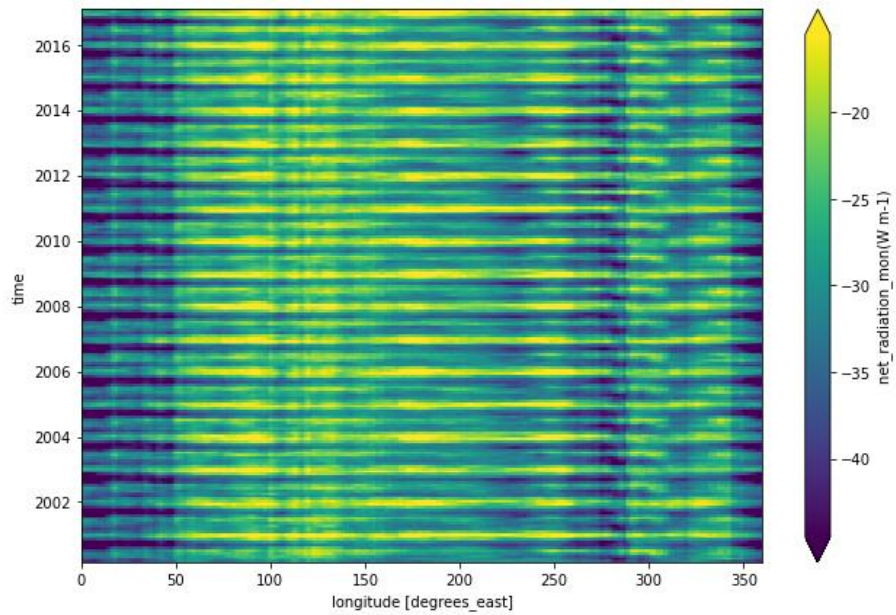
```
ds2.solar_mon.mean(dim = 'time').weighted(weights).mean(dim = ('lon','lat'))
#340.28355233
```

2.3

Total amount of net radiation of solar in each 1-degree latitude band based on solar_mon:

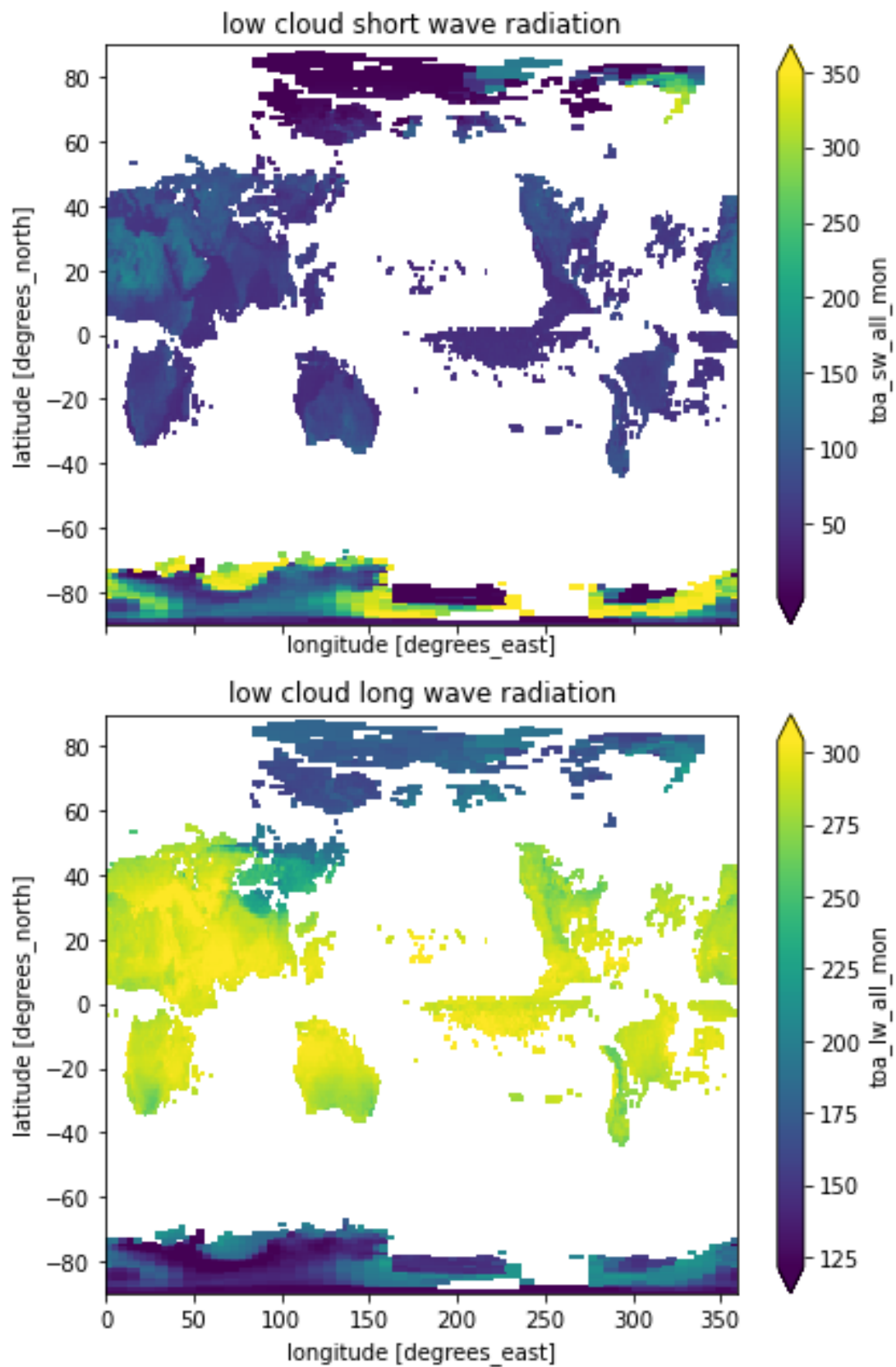


Total amount of net radiation in each 1-degree latitude band based on toa_net_all_mon:

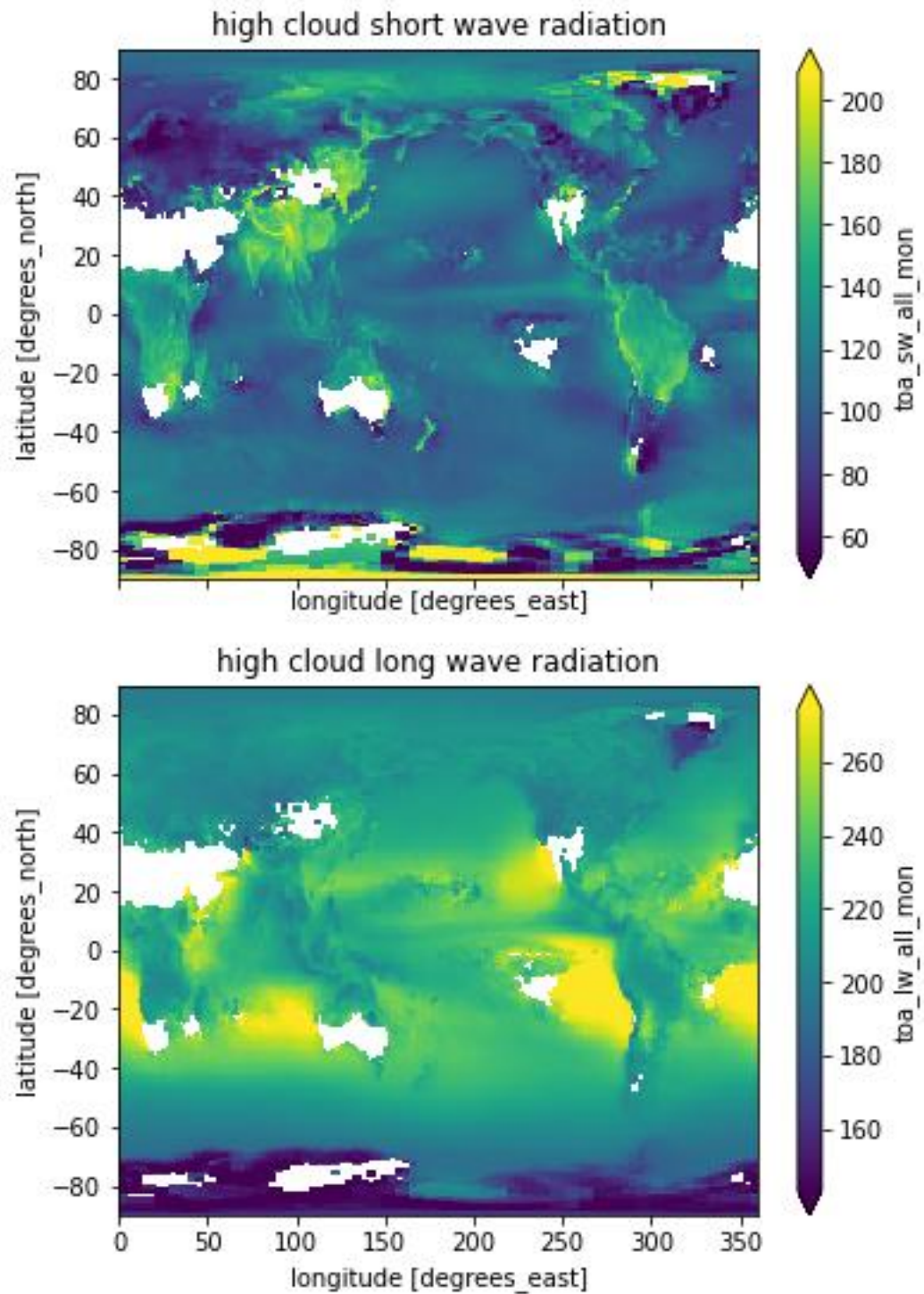


2.4

Low cloud ($\leq 25\%$) short and long wave radiation figure is shown below:



High cloud ($\geq 75\%$) short and long wave radiation figure is shown below:



2.5

the global mean values of shortwave and longwave radiation, composited in high and low cloud regions, were calculated. Results are shown below:

low cloud:

```
ds2.toa_lw_all_mon.where(ds2.cldarea_total_daynight_mon <= 25).mean(dim = 'time').weighted(weights).mean(dim = ('lon','lat'))
```

#270.8530266 v.s. #240.26666558

```
ds2.toa_sw_all_mon.where(ds2.cldarea_total_daynight_mon <= 25).mean(dim = 'time').weighted(weights).mean(dim = ('lon','lat'))
```

#75.49432387 v.s. #99.13858336

High cloud:

```
ds2.toa_lw_all_mon.where(ds2.cldarea_total_daynight_mon >= 75).mean(dim = 'time').weighted(weights).mean(dim = ('lon','lat'))
```

#225.7084414 v.s. #240.26666558

```
ds2.toa_sw_all_mon.where(ds2.cldarea_total_daynight_mon >= 75).mean(dim = 'time').weighted(weights).mean(dim = ('lon','lat'))
```

#113.15712212 v.s. #99.13858336

Analysis:

In low cloud area, long wave radiation is higher than global mean (calculated in 2.2), and global mean is higher than that in high cloud, while short wave radiation has a reversed phenomenon.

Cloud reflects more long wave radiation out to space while impede the flux-out of short wave radiation to space.

3.

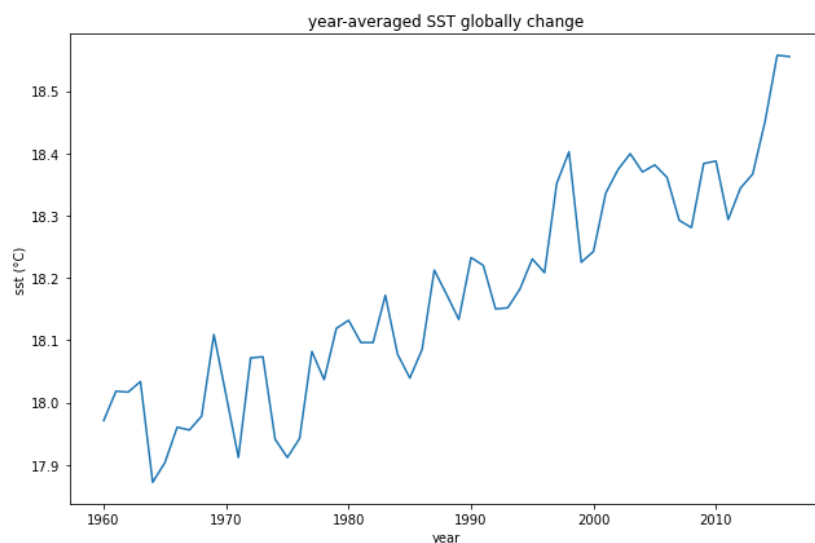
Dataset: **1. FLDAS_NOAH01_CP_GL_M.A201912.001.nc (snow cover, water cycle)**

Dataset guide: [README_FLDAS.pdf \(nasa.gov\)](#)

2. NOAA_NCDC_ERSST_v3b_SST.nc

3.1

Dataset 1 only have two-year data, therefore, I used NOAA sst dataset to plot sst time series with monthly seasonal cycle removed. See figure below:



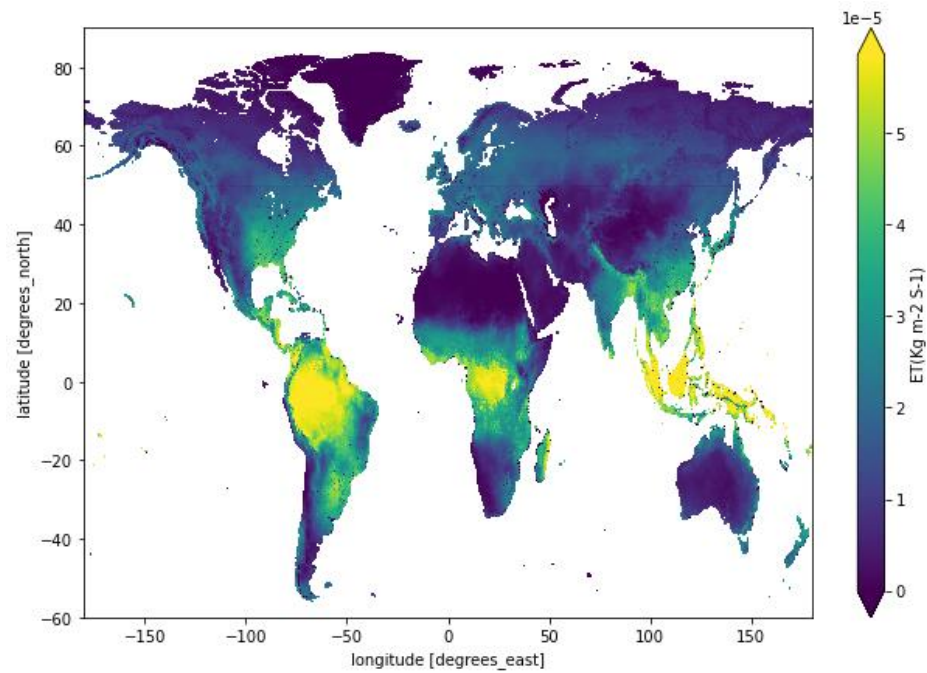
Sea surface temperature has an tendency of increasing year by year.

3.2

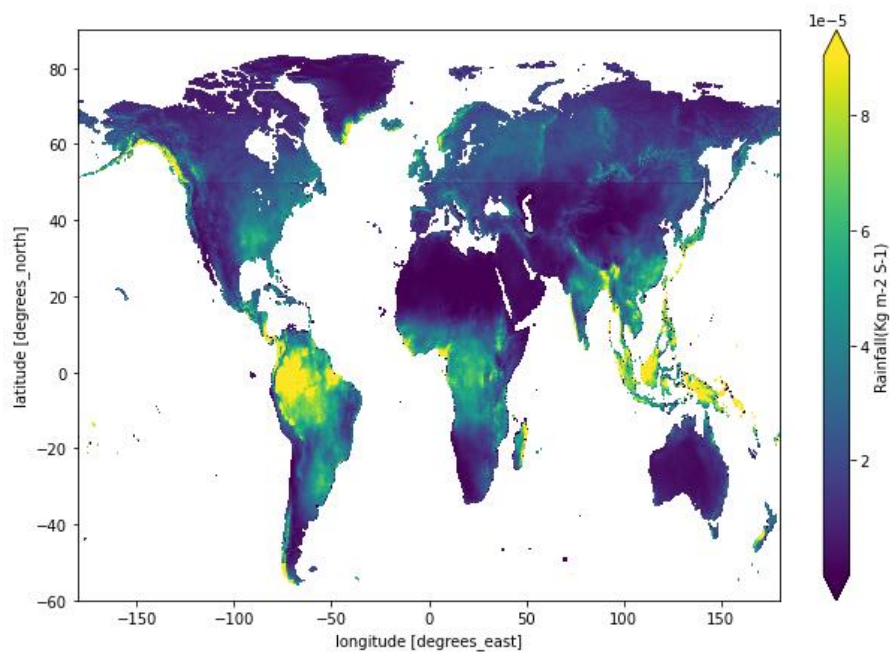
Snow cover and water cycle dataset (rainfall, Evapotranspiration, soli water content, snow cover factor, snow depth)

FIGURES:

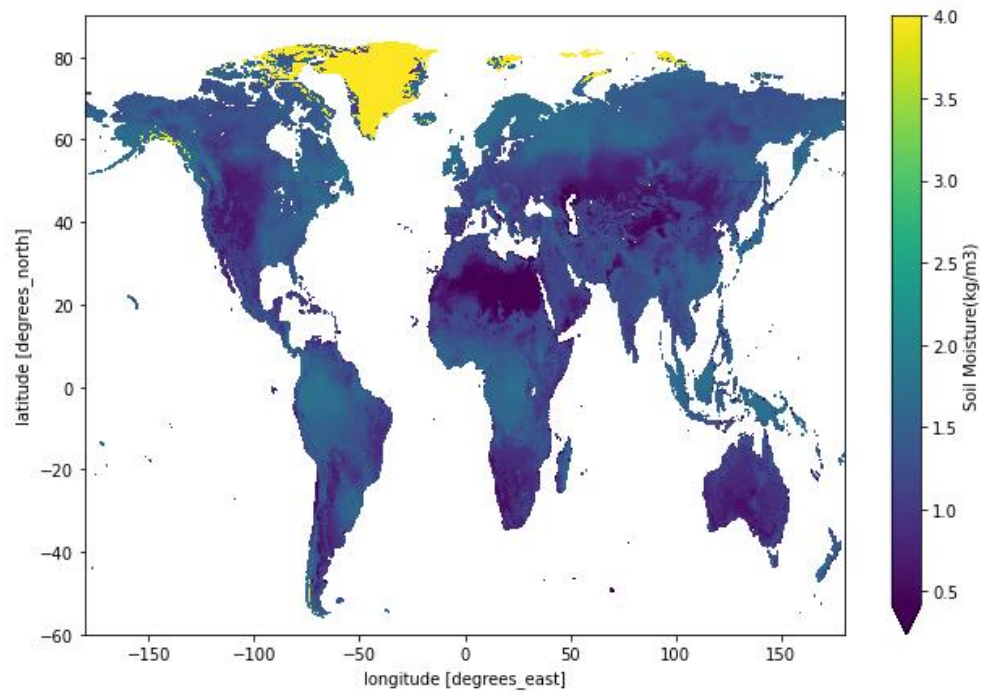
2019 average global land ET:



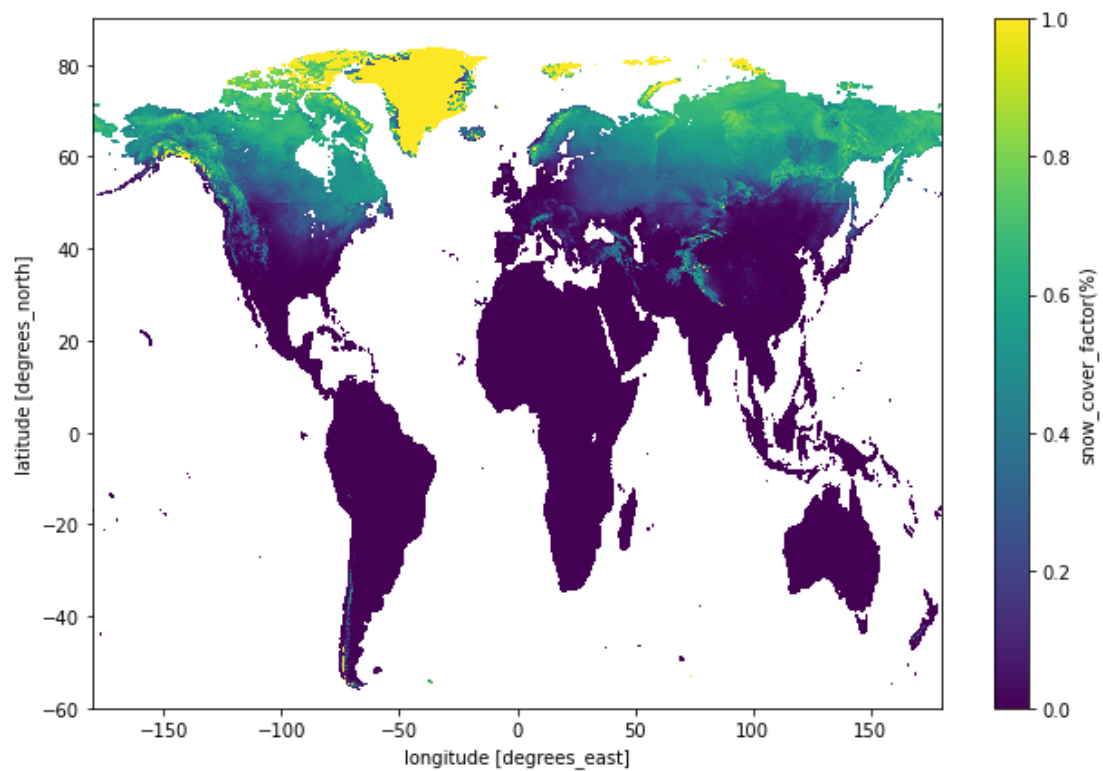
2019 average global land rainfall:



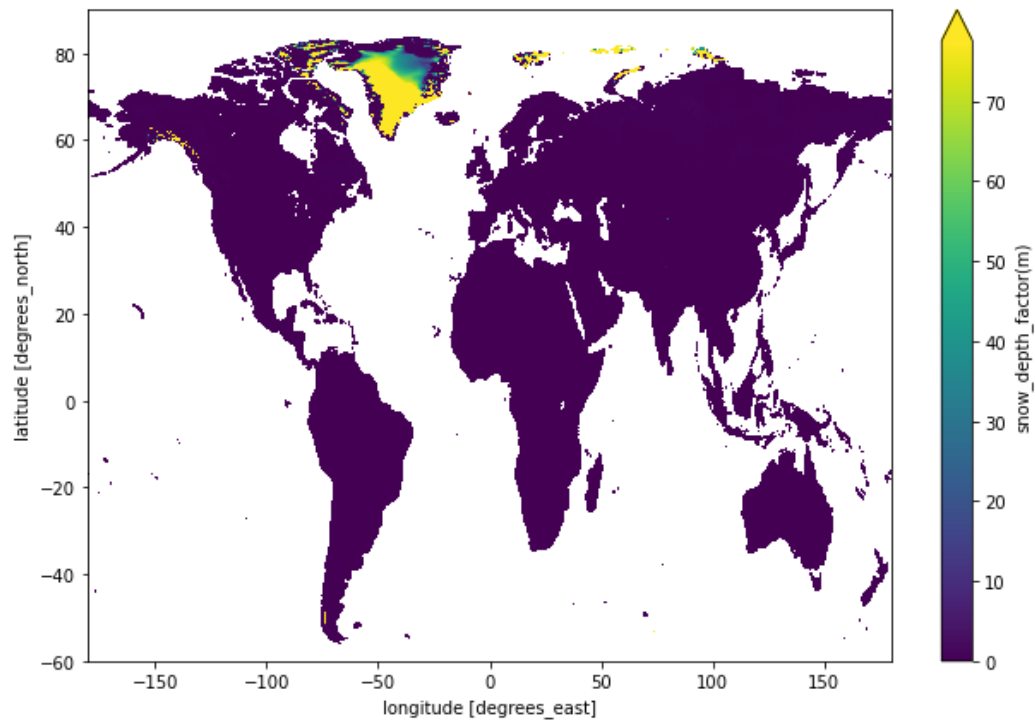
2019 average global land soil water content:



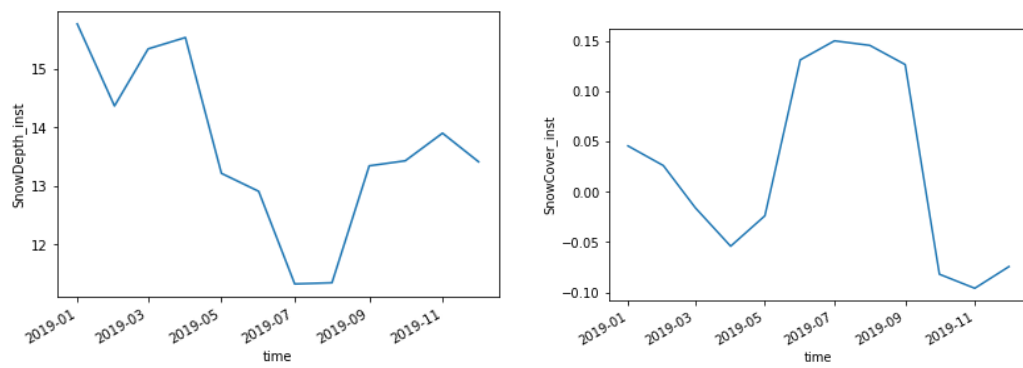
2019 average global land snow cover factor (representing snow area):



2019 average global land snow depth:



Snow cover and snow depth change in year:



Snow cover area has a reverse changing tendency of snow depth.