# Effects of increasing precipitation on aerosol concentration in the Arctic

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#### **Abstract**

Increased Artic precipitation is expected with global warming. This will affect the aresol concentration, but how the concentration changes is uncertain. In this study, the influence of increased precipitation in a warmer climate on aerosol concentration is investigated, both spatially and sesonally. This study uses a CMIP6 model, NorESM, to compare precipitation and Cloud Condensation Nuclei (CCN) concentration in an abrupt quadrupling of the atmospheric concentration of carbon dioxide (abrupt  $4xCO_2$ ) experiment to the Pre-Industrial Control (piControl). A lack of CCN particles is indicated in areas over the sea where precipitation is enhanced. Over land, the relation between precipitation and CCNs is not as pronounced. Seasonal variations also indicate less increase in CCN concentration in months where precipitation is enhanced. The seasonal variations inn CCN concentration can also be explained by variation in solar insolation.

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#### 1. Introduction

The warming of the Artic is occurring at a much higher rate than in the rest of the world - a phenomenon known as Artic amplification (Previdi et al., 2021). With increasing temperatures, the atmosphere can hold more moisture, and thus an increase in precipitation is expected. In addition, the massive sea ice retreat increases surface evaporation, which makes Artic precipitation much more pronounced than it would be only due to the Arctic warming (Bintanja et al., 2020).

Droplets and ice crystals in clouds together with precipitation can alter the aerosol particle concentration, by acting as

sources and sinks. Wet scavenging is one of the most important sink of aerosol particles in the atmosphere. Particles that are activated to cloud droplets or crystals can grow large enough under the right conditions to fall out of the cloud as precipitation. The particles are then scavenged by in-cloud scavenging, which is a major removal process for the accumulation mode. Aerosol particles can also be scavenged from beneath the cloud (below-cloud scavenging). This occurs when the cloud above is precipitating, and particles get collected and removed by the falling droplets. Below-cloud scavenging is an important sink for particles in the nucleation mode and coarser particles. (Isokääntä, 2022)

When removing the accumulation mode by precipitation, the nucleation mode is more likely to grow (Maso et al., 2002). Hence clouds and precipitation can also act as a source for new particles. The total change in aerosol concentration by precipitation is unclear and needs to be further investigated.

Aerosols have a crucial impact on the earth's energy budget. Aerosols alter the energy budget directly by scattering and absorbing solar and infrared radiation. In addition, aerosols also have an indirect effect where they can work as cloud condensation nuclei (CCN), thus altering the clouds properties such as lifetime and albedo. With an increased amount of CCNs, the particles grow to be smaller which increases the lifetime and albedo of the cloud. Hence inducing a negative effect on the radiative balance.

Further knowledge of how a warmer Arctic climate with increasing precipitation affects the aerosol concentration is thus essential to get a better understanding of their magnitude in the energy budget. This study will analyze the difference in precipitation and CCN concentrations in a warmer climate compared to the control run in a CMIP6 model. The aim is then to address possible effects of precipitation on aerosol concentrations.

#### 2. Methods

#### 2.A. Packages

```
In [1]: # Importing packages
        import os as os
        # for handling the data
        import xarray as xr
        xr.set_options(display_style='html')
        import intake
        import cftime
        import pandas as pd
        import dask
        import numpy as np
        from sklearn.cluster import KMeans
        from sklearn.preprocessing import MinMaxScaler
        # for plotting
        import matplotlib.pyplot as plt
        import cartopy.crs as ccrs
        import cartopy as cy
        import matplotlib.gridspec as gridspec
        %matplotlib inline
        # my functions
        from functions Ingrid import *
        %reload_ext autoreload
        %autoreload 2
        # ignoring warnings
        import warnings
        warnings.filterwarnings('ignore')
```

#### 2.B. Datasets

#### Model, experiments, and variables

I used a coupled Earth System Model from CMIP6; The Norwegian Earth System Model version 2 (NorESM2) which is developed by the NorESM Climate modeling Consortium (NCC) (NorESM, 2020). There are three versions of NorESM2 with different resolutions where NorESM2-MM with 1-degree resolutions is used in this project. To understand how precipitation in a warmer climate affects aerosol concentration I chose the experiments abrupt 4xCO2 and the piControl, to compare the variables without interruptions by future emissions. Hence the changes in aerosol concentration that are caused indirectly due to the increasing temperature can be investigated. The variables I focused on are Precipitation ('pr'), Cloud Condensation Nuclei Concentration at Liquid Cloud Top ('ccn'), and Surface Temperature ('ts').

#### Reading the data

Since aerosols variables were not available in the Pangeo CMIP6 online catalog, I downloaded the data directly from

the Earth System Grid Federation (ESGF) with the software package Wget for the 30 first years (10 years at the time), for both experiments. An example of how that was done is shown below. The time period was selected so that the abrupt 4xCO2 experiment could reach a steady state after the quadrupling.

"\nurls = ['http://noresg.nird.sigma2.no/thredds/fileServer/esg\_dataroot/cmor/CMIP6/CMIP/NCC/NorESM2-MM/abrupt4xC02/r1i1p1f1/Amon/pr/gn/v20191108/pr\_Amon\_NorESM2-MM\_abrupt-4xC02\_r1i1p1f1\_gn\_002101-003012.nc', \n 'http://n
oresg.nird.sigma2.no/thredds/fileServer/esg\_dataroot/cmor/CMIP6/CMIP/NCC/NorESM2-MM/abrupt-4xC02/r1i1p1f1/Amon/
ts/gn/v20191108/ts\_Amon\_NorESM2-MM\_abrupt-4xC02\_r1i1p1f1\_gn\_002101-003012.nc', \n 'http://noresg.nird.sigma2.no
/thredds/fileServer/esg\_dataroot/cmor/CMIP6/CMIP/NCC/NorESM2-MM/abrupt-4xC02/r1i1p1f1/AERmon/ccn/gn/v20191108/c
cn\_AERmon\_NorESM2-MM\_abrupt-4xC02\_r1i1p1f1\_gn\_002101-003012.nc'] \n\n\n# wget all files in the list\nfor url in
urls:\n os.system('wget ' + url)\n"

After downloading the data, the files were read in with the python module, Xarray. Since the data was for 10 years at the time, the datasets for each 10-year period was concatenated together.

Reading files from piControl for the first 30 years:

```
In [3]: # Reading in multiple piControl files for the 10 first years:
         list of files10 piControl = [
               ../../Data/ccn_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc',
               ../../Data/cdnc_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc',
               ../../Data/co2_AERmon_NorESM2-MM_piControl_rli1p1f1_gn_120001-120912.nc'
               '../../Data/emibc_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc',
               ../../Data/emibvoc_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc', ../../Data/emidust_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc',
               '../../Data/emioa AERmon NorESM2-MM piControl rli1p1f1 gn 120001-120912.nc',
               ../../Data/emiso2_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc', ../../Data/emiso4_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc',
               '../../Data/emiss_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc',
               ../../Data/pr_Amon_NorESM2-MM_piControl_rli1p1f1_gn_120001-120912.nc', ../../Data/prc_Amon_NorESM2-MM_piControl_rli1p1f1_gn_120001-120912.nc',
               ../../Data/ts_Amon_NorESM2-MM_piControl_rli1p1f1_gn_120001-120912.nc'
               '../../Data/so2_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc'
              '../../Data/emivoc_AERmon_NorESM2-MM_piControl_rli1p1f1_gn_120001-120912.nc',
              '../../Data/emiisop_AERmon_NorESM2-MM_piControl_r1i1p1f1_gn_120001-120912.nc'
         ds piControl10 = xr.open mfdataset(list of files10 piControl, combine='by coords', compat='override', use cftim
In [4]: # Reading in piControl data for the next 20 years, where the files contains all variables that was read in for
         ds_piControl20 = xr.open_mfdataset('../../Data/NorESM2-MM_piControl_rlilp1f1_gn_121001-121912.nc', use_cftime=T
         ds_piControl30 = xr.open_mfdataset('.../../Data/NorESM2-MM_piControl_rlilp1f1_gn_122001-122912.nc', use_cftime=T
```

Reading files from 4xco2 experiment for the first 30 years:

In [5]: # 10 first years

```
ds\_4xco2\_10 = xr.open\_mfdataset('../../Data/all\_NorESM2-MM\_abrupt-4xC02\_rli1p1f1\_000101-001012.nc', use cftime=0.000101-0.001012.nc' and the context of th
In [6]: # next 10 years
                   list_of_files20 = [
                               ../../Data/ccn_AERmon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn 001101-002012.nc',
                              '../../Data/pr_Amon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn_001101-002012.nc'
                               ../../Data/cdnc AERmon NorESM2-MM abrupt-4xC02 r1i1p1f1 gn 001101-002012.nc',
                              '../../Data/co2_AERmon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn_001101-002012.nc',
                               ../../Data/emibc_AERmon_NorESM2-MM_abrupt-4xCO2_r1i1p1f1_gn_001101-002012.nc'
                               ../../Data/emibvoc_AERmon_NorESM2-MM_abrupt-4xC02_rli1p1f1_gn_001101-002012.nc'
                               ../../Data/emidust_AERmon_NorESM2-MM_abrupt-4xC02_rli1p1f1_gn_001101-002012.nc',
                               ../../Data/emiisop_AERmon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn_001101-002012.nc',
                               ../../Data/emioa AERmon NorESM2-MM abrupt-4xC02 rli1p1f1 gn 001101-002012.nc'
                              '../../Data/emiso2_AERmon_NorESM2-MM_abrupt-4xCO2_r1i1p1f1_gn_001101-002012.nc'
                               ../../Data/emiso4_AERmon_NorESM2-MM_abrupt-4xC02_rlilp1f1_gn_001101-002012.nc',
                               ../../Data/emiss_AERmon_NorESM2-MM_abrupt-4xC02_rli1p1f1_gn_001101-002012.nc'
                              '../../Data/emivoc AERmon NorESM2-MM abrupt-4xCO2 rlilp1f1 gn 001101-002012.nc',
                               ../../Data/prc Amon NorESM2-MM abrupt-4xC02 rlilplf1 gn 001101-002012.nc'
                               ../../Data/so2 AERmon NorESM2-MM abrupt-4xC02 rlilp1f1 qn 001101-002012.nc',
                             '../../Data/ts_Amon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn_001101-002012.nc']
                   ds 4xco2 20 = xr.open mfdataset(list of files20, combine='by coords', compat='override', use cftime=True)
```

```
In [7]: # last 10 years
         list of files30 = [
              ../../Data/ccn AERmon NorESM2-MM abrupt-4xC02 rlilp1f1 gn 002101-003012.nc',
             '../../Data/pr_Amon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn_002101-003012.nc
              '../../Data/cdnc_AERmon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn_002101-003012.nc',
              ../../Data/co2_AERmon_NorESM2-MM_abrupt-4xC02_rli1p1f1_gn_002101-003012.nc',
              ../../Data/emibc_AERmon_NorESM2-MM_abrupt-4xCO2_r1i1p1f1_gn_002101-003012.nc'
              '../../Data/emibvoc_AERmon_NorESM2-MM_abrupt-4xCO2_r1i1p1f1_gn_002101-003012.nc',
              '../../Data/emidust AERmon NorESM2-MM abrupt-4xCO2 rlilplf1 gn 002101-003012.nc'
              '../../Data/emiisop_AERmon_NorESM2-MM_abrupt-4xC02_r1i1p1f1_gn_002101-003012.nc',
              '../../Data/emioa_AERmon_NorESM2-MM_abrupt-4xCO2_r1i1p1f1_gn_002101-003012.nc',
              '../../Data/emiso2_AERmon_NorESM2-MM_abrupt-4xC02_rli1p1f1_gn_002101-003012.nc
             '../../Data/emiso4 AERmon NorESM2-MM abrupt-4xC02 rli1p1f1 gn 002101-003012.nc',
              ../../Data/emiss_AERmon_NorESM2-MM_abrupt-4xCO2_rli1p1f1_gn_002101-003012.nc',
'../../Data/emivoc_AERmon_NorESM2-MM_abrupt-4xCO2_rli1p1f1_gn_002101-003012.nc',
             '../../Data/prc Amon NorESM2-MM abrupt-4xC02 rli1p1f1 gn 002101-003012.nc',
              ../../Data/so2_AERmon_NorESM2-MM_abrupt-4xCO2_r1i1p1f1_gn_002101-003012.nc',
              '../../Data/ts_Amon_NorESM2-MM_abrupt-4xCO2_r1i1p1f1_gn_002101-003012.nc']
         ds 4xco2 30 = xr.open mfdataset(list of files30, combine='by coords', compat='override', use cftime=True)
```

Making the datasets for each time period to have equal coordinates, and longitude range before concatenating:

#### For piControl

```
In [8]: # dropping variables that dosn't exsist in all time periods
   variables = ["time_bnds", "lev_bnds", "p0", "a", "b", "ps", "a_bnds", "b_bnds", "lat_bnds", "lon_bnds"]
   ds_piControl10 = ds_piControl10.drop_vars(variables)
   variables = ["dms", "emidms"]
   ds_piControl20 = ds_piControl20.drop_vars(variables)
   ds_piControl30 = ds_piControl30.drop_vars(variables)
In [9]: # transforming longitude range for the 10 first years
```

ds piControl10 = ds piControl10.assign coords(lon=(((ds piControl10.lon + 180) % 360) - 180)).sortby('lon')

#### For abrubt 4xCO2

```
In [10]: # the time periods for datasets with different dimension
    time20 = ds_4xco2_20.time.values

In [11]: # converterting datatset for second timeperiod to have the same lat, lon and lev points as first period
    ds_20 = convert(ds_4xco2_20, list_of_files20, time20)

        ../../Data/cdnc_AERmon_NorESM2-MM_abrupt-4xC02_rlilplf1_gn_001101-002012.nc
        ../../Data/co2_AERmon_NorESM2-MM_abrupt-4xC02_rlilplf1_gn_001101-002012.nc
        ../../Data/so2_AERmon_NorESM2-MM_abrupt-4xC02_rlilplf1_gn_001101-002012.nc

In [12]: # converterting datatset for third timeperiod to have the same lat, lon and lev points as first period
    ds_30 = convert(ds_4xco2_30, list_of_files30, time30)

        ../../Data/cdnc_AERmon_NorESM2-MM_abrupt-4xC02_rlilplf1_gn_002101-003012.nc
        ../../Data/co2_AERmon_NorESM2-MM_abrupt-4xC02_rlilplf1_gn_002101-003012.nc
        ../../Data/so2_AERmon_NorESM2-MM_abrupt-4xC02_rlilplf1_gn_002101-003012.nc
        ../../Data/so2_AERmon_NorESM2-MM_abrupt-4xC02_rlilplf1_gn_002101-003012.nc
```

Concatenating the datasets for the three time periods for each experiment:

```
In [13]: # the variables the dataset should contain
    var_list = ['pr', 'ccn', 'cdnc', 'co2', 'emibc', 'emibvoc', 'emidust', 'emiisop', 'emioa', 'emiso2', 'emiso4',

In [14]: # concatinating for abrubt 4xCO2
    ds_all_4xco2 = xr.concat([ds_4xco2_10[var_list], ds_20[var_list], ds_30[var_list]], dim="time")

In [15]: # concatinating for piControl
    ds_all_piControl = xr.concat([ds_piControl10[var_list], ds_piControl20[var_list], ds_piControl30[var_list]], di
```

Fixing variable units:

```
In [16]: ds_4xco2_NorESM = fix_units(ds_all_4xco2)
ds_piControl_NorESM = fix_units(ds_all_piControl)
```

#### 2.C. Analysis methods

```
In [17]: # yearly data
ds_4xco2_NorESM_y = annual(ds_4xco2_NorESM)
ds_piControl_NorESM_y = annual(ds_piControl_NorESM)
```

Calculations for time series plots - Global and Arctic mean

arctic\_mean\_piControl = weighted\_mean(ds\_arctic\_piControl)
global\_mean\_piControl = weighted\_mean(ds\_piControl\_NorESM\_y)

```
In [18]: # defining the Arctic area
    max_lat = 90; min_lat = 70; max_lon = 180; min_lon = -180

# finding all lat and lon within the area
    mask_lon = (ds_4xco2_NorESM_y.lon >= min_lon) & (ds_4xco2_NorESM_y.lon <= max_lon)
    mask_lat = (ds_4xco2_NorESM_y.lat >= min_lat) & (ds_4xco2_NorESM_y.lat<= max_lat)

# delimit the datatsets to only where the lat and lon are True
    ds_arctic_4xco2 = ds_4xco2_NorESM_y.where(mask_lon & mask_lat, drop=True)
    ds_arctic_piControl = ds_piControl_NorESM_y.where(mask_lon & mask_lat, drop=True)

In [19]: # Artic and global mean
    arctic_mean_4xco2 = weighted_mean(ds_arctic_4xco2)
    global_mean_4xco2 = weighted_mean(ds_4xco2_NorESM_y)</pre>
```

Calculations for spatial plots - difference between abrupt 4xCO2 and piControl

```
In [20]: # skipping the 5 first years compare thexperiments after the quardrupling of CO2 is stabalized

ds_4xco2_stable = ds_4xco2_NorESM_y.sel(time=slice('0005-12-31','0030-12-31'))
 ds_piControl_stable = ds_piControl_NorESM_y.sel(time=slice('1204-12-31','1229-12-31'))

ds_4xco2_stable = add_attrs(ds_4xco2_stable)
 ds_piControl_stable = add_attrs(ds_piControl_stable)

In [21]: # computing the mean over time
 ds_4xco2_mean = ds_4xco2_stable.mean('time', keep_attrs=True)
 ds_piControl_mean = ds_piControl_stable.mean('time', keep_attrs=True)

In [22]: # global differences
 ds_diff = ds_4xco2_mean-ds_piControl_mean
```

#### Seasonal differences

```
In [23]: # grouping the datasets into seasons
    ds_season_4xco2 = ds_4xco2_NorESM.groupby('time.season').mean(keep_attrs=True)
    ds_season_piControl = ds_piControl_NorESM.groupby('time.season').mean(keep_attrs=True)

In [24]: # gloabal seasonal differences
    season_diff = ds_season_4xco2-ds_season_piControl

In [25]: # name of seasons
    seasons = season_diff.season.values
```

#### Results and discussion

Figure 1 shows that temperature, precipitation, and CCN concentrations will increase more over the Arctic than for the global mean.

The spatial plots in Figures 3, and 4, show that the most pronounced increase in precipitation occurs on the south coast of Greenland, as well as over the Bering Sea. If we look at the CCN concentration in Figure 4 for the same locations, we see that the concentration is only increasing slightly. Bearing in mind from figure 1 that Arctic CCN concentration will have a large increase in total, the slight increase in CCNs over the two locations could induce that wet scavenging is a dominating process.

On the other hand, CCN concentrations are also only slightly increasing over Scandinavia and western parts of Russia, where precipitation is not pronouncedly increased. In addition, the CCNs is conspicuously decreasing over eastern parts of Russia. The precipitation map shows that there is an increase in precipitation, but not as concentrated in the same locations as the CCN drop. The precipitation is also not increasing as pronouncedly as for the coast of Greenland, and the Bering Sea. One difference between these two scenarios is that the first case is located over the ocean, and the second case is located over the continents. Over the oceans, there is more access to moisture from the sea, while this is not necessarily the case over land. Thus other processes can induce the small increase in CCNs over land, while wet scavenging over the two ocean areas can still be a part of the removal of CCNs in these regions.

The changes in CCN concentrations strongly vary over the year as Figure 7 shows. The summer months are characterized by high concentrations of CCNs, while winter and spring have the lowest CCN concentrations. Compared

with the seasonal precipitation plots in Figure 6, we see that precipitation is at its lowest in the summer months and highest in winter and spring. Hence when there is less precipitation, there would be less wet scavaging, and we see more CCN concentration. However multiple factors affect the seasonal differences in CCN concentration. In summer there is more solar radiation compared to the winter, especially in the Arctic. Higher solar radiation produces higher chemical activity, and thus also the formation of new aerosol particles. The lack of solar radiation in the spring and winter also reduces the ability for new aerosol particles to form.

```
In [26]: # Plotting time series
         timepoints = []
         for i in range(len(global mean 4xco2['time'])):
             timepoints.append(i)
         fig = plt.figure(figsize=(10, 5))
         gs = gridspec.GridSpec(ncols=2, nrows=3, hspace = 0.7, wspace = 0.3, top = 1,
                                bottom = 0, left = 0, right = 1)
         ax = fig.add_subplot(gs[0, 0])
         ax.plot(timepoints, global_mean_4xco2['ts'], label='4xco2')
         ax.plot(timepoints, global_mean_piControl['ts'], label='piControl')
         ax.set_title('Global mean', fontweight='bold', size=15)
         ax.set_ylabel('Temperature [C$^\circ$]')
         ax.legend()
         fancy(ax, 10)
         ax = fig.add_subplot(gs[1, 0])
         ax.plot(timepoints, global_mean_4xco2['pr'], label='4xco2')
         ax.plot(timepoints, global_mean_piControl['pr'], label='piControl')
         ax.set_ylabel('Precipitation [mm]')
         ax.legend()
         fancy(ax, 10)
         ax = fig.add subplot(gs[2, 0])
         ax.plot(timepoints, global_mean_4xco2['ccn'], label='4xco2')
         ax.plot(timepoints, global_mean_piControl['ccn'], label='piControl')
         ax.set_xlabel('Time [years]')
         ax.set_ylabel('CCN [cm$^{-3}$]')
         ax.legend()
         fancy(ax, 10)
         ax = fig.add_subplot(gs[0, 1])
         ax.plot(timepoints, arctic_mean_4xco2['ts'], label='4xco2')
         ax.plot(timepoints, arctic_mean_piControl['ts'], label='piControl')
         ax.set_title('Arctic mean', fontweight='bold', size=15)
         ax.legend()
         fancy(ax, 10)
         ax = fig.add subplot(gs[1, 1])
         ax.plot(timepoints, arctic_mean_4xco2['pr'], label='4xco2')
         ax.plot(timepoints, arctic_mean piControl['pr'], label='piControl')
         ax.legend()
         fancy(ax, 10)
         ax = fig.add_subplot(gs[2, 1])
         ax.plot(timepoints, arctic_mean_4xco2['ccn'], label='4xco2')
         ax.plot(timepoints, arctic_mean_piControl['ccn'], label='piControl')
         ax.set_xlabel('Time [years]')
         #ax.set yscale('log')
         ax.legend()
         fancy(ax, 10)
```

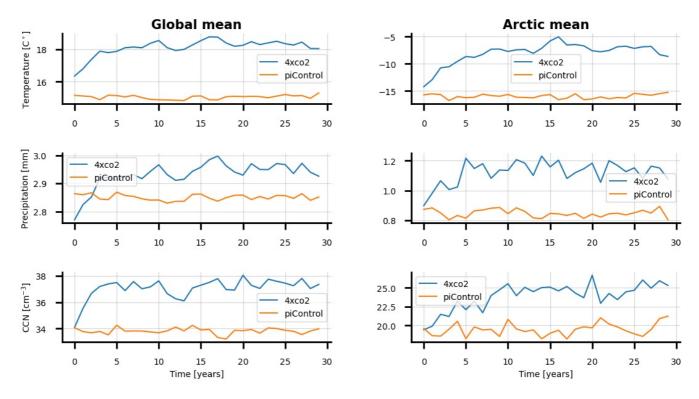


Figure 1: time-series plots of how temperature, precipitation, and CCN concentration varies the 30 first year after the start of runtime, for both experiments.

```
In [27]: # plotting differences in temp, precipitation, and CCN concentration on a map
plot_map(ds_diff['ts'], 'Temperature (4xC02-piControl)', reverse=True, vmin=-12, vmax=12)
```

## Temperature (4xCO2-piControl)

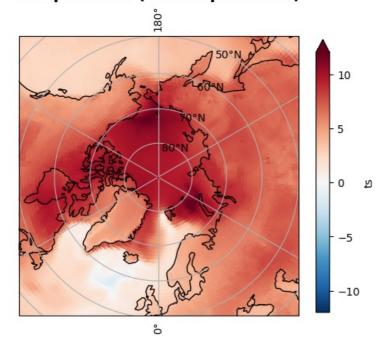


Figure 2: Spatial plot for tempereature changes for the abrupt 4xCO2-piControl experiment over the Artic area. Units are given in C°.

In [28]: plot\_map(ds\_diff['pr'], 'Precipitation (4xCO2-piControl)', vmin=-0.8, vmax=0.8)

# Precipitation (4xCO2-piControl)

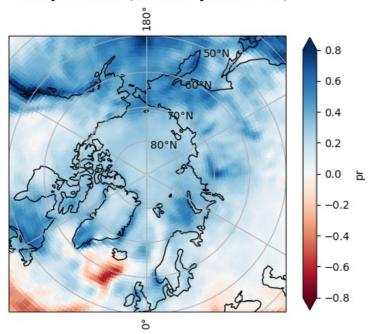


Figure 3: Sptial plot for precipitation changes for the abrupt 4xCO2-piControl experiment over the Artic area. Units are given in mm/day.

In [29]: plot\_map(ds\_diff['ccn'], 'CCN (4xC02-piControl)', cmap='PiYG', vmin=-20, vmax=20)

## CCN (4xCO2-piControl)

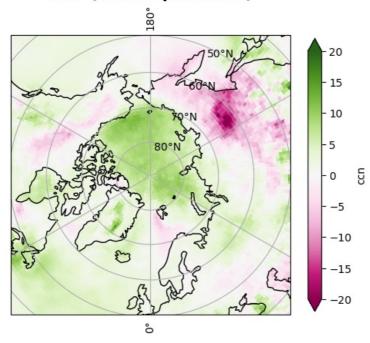


Figure 4: Spatial plot for changes in ccn concentration for the abrupt 4xCO2-piControl experiment over the Artic area. Units are given in  $cm^{-3}$ .

In [30]: plot\_seasons\_map(season\_diff, 'ts', seasons, 'Temperature [C\$^\circ\$]', np.linspace(-25,25,100), cmap='RdBu\_r')

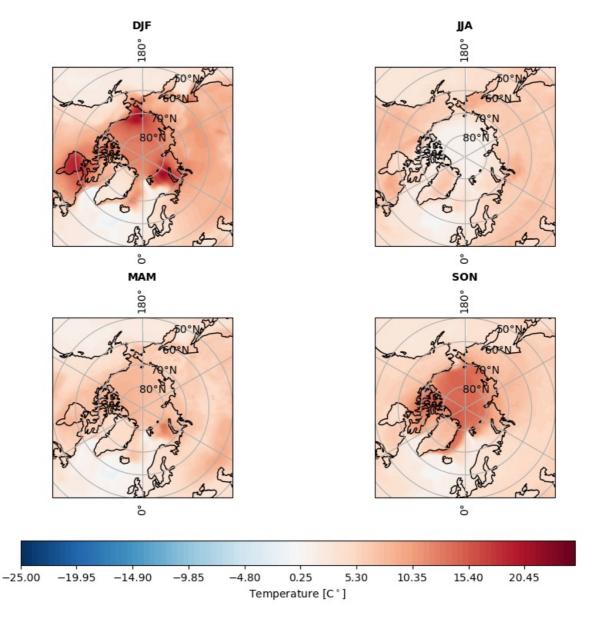


Figure 5: Seasonal plot for changes in temperature.

In [31]: plot\_seasons\_map(season\_diff, 'pr', seasons, 'precipitation [mm/day]', np.linspace(-2,2,100))

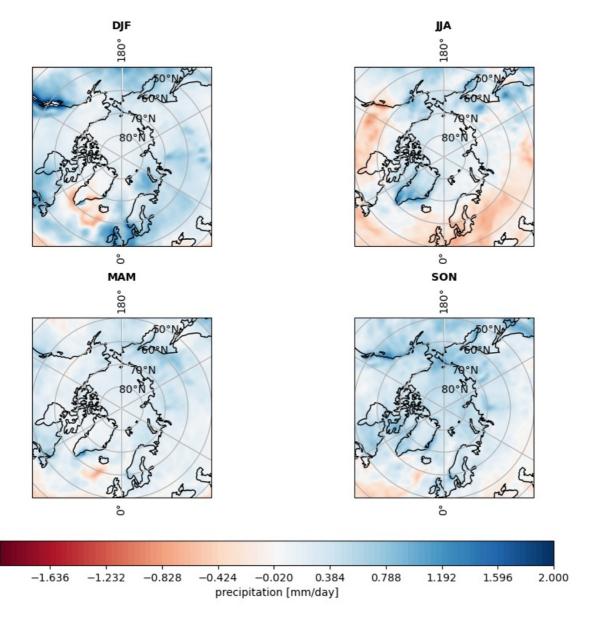


Figure 6: Seasonal plot for changes in precipitation.

In [32]: plot\_seasons\_map(season\_diff, 'ccn', seasons, 'CCN [cm\$^{-3}\$]', np.linspace(-20,20,100), cmap='PiYG')

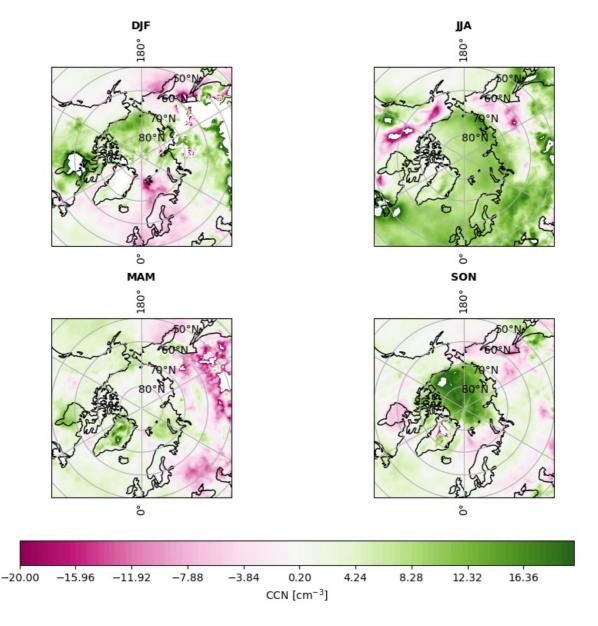


Figure 7: Seasonal plot for changes in CCN concentrations.

#### 4. Conclusion

The increasing precipitation in a warmer climate is shown to have a possible influence on aerosol concentration. The south coast of Greenland and The Bering sea shows a less increase in CCN concentration when precipitation is enhanced, indicating a dominating wet scavenging process. Scandinavia and the west of Russia do not show the same correlation. Hence, there is not a significant pattern of how increasing precipitation affects aerosol concentration. The seasonal differences show that seasons with a low concentration of CCN have pronounced precipitation, and the other way around. This can amplify that wet scavenging is a domination process. However, multiple factors play an important role in the variations in aerosol concentration. Large seasonal variations in solar insolation are known to affect seasonal variations in CCN concentration. This is also well represented in the seasonal plot for CCN concentration. Multiple factors, such as solar radiation, are needed to be accounted for to completely understand the influence of precipitation on aerosol concentration.

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Processing math: 100%