The impact of Arctic Amplification and the resulting sea ice extent reduction on the Sea Surface concentration of Dimethylsulfide

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Abstract

This report is prepared as part of participating in a group project nr 4 in the eScience school 2022 in Tjarno - Sweden. In this project, I investigated concentration of Dimethylsulfide (DMS) the Ocean Surface (DMSOS), which its geobiochemical cycle plays a key role in the Earth's climate system, in the Arctic region. Two contrasting areas were chosen, i.e. Greenland Sea (GLS) and Laptev Sea (LPS). Since Arctic ice extent is shrinking in the last few decades due to the arctic amplification, I evaluated how climate models from the Coupled Model Intercomparison Project - phase6 (CMIP6) predicted the DMSOS over the whole historical period as well as in recent decades and how they deviated from Observations for the period from 2003 to 2014. In detail, I compared UKESM-1-0-LL and CNRM-ESM-2-1 from CMIP6, with the observation from the Remote sensing algorithm that estimates the DMSOS based on remotely sensed variables from the Moderate Resolution Imaging Spectroradiometer onboard the Aqua satellite (MODIS-Aqua, 2003–2016). Given that the models are built with different spatial and temporal resolutions and they use different approaches to introduce the DMS, the two models predicted the DMSOS concentrations differently over the whole historical period in both Arctic areas. The long-time trend was also different where UKESM predicted a higher concentration of DMSOS in both areas. Both models were different as well in predicting the seasonal variability, where the peaking month was shifted (not the same) in both areas; being in June by UKESM for both areas and in July and May by CNRM for LPS and GLS areas, respectively. In comparison to observations during the matching period from 2003 to 2014, both models underestimated the concentration of DMS for both Arctic areas. The Observations predicted the peaking month to be in May and June for LPS and GLS areas, respectively. This implies that UKESM was better than CNRM in predicting seasonal variability, especially over the GLS area. Both models did not capture the observed seasonal and annual variability correctly over the LPS area. This can be explained by the larger variability in sea ice extent and salinity (shown in other reports of group members; Jessica and Mateusz) in the LPS area than GLS. However, further and deeper investigation by providing extra observations in other polar areas as well as for other variables, i.e. sea surface temperature as well as radiation, can improve our understanding of these variabilities and can contribute to better predicting the DMSOS by models.

1- Introduction

Dimethylsulfide (DMS) is one of the essential natural volatile compound produced by marine microbial food webs through a series of biogeochemical reactions and transformations at the ocean surfaces (Andreae and Raemdonck 1983; Andreae and

Barnard, 1984; Hulswar et al., 2022; Wang et al., 2020; 2021). In detail, DMS is produced through the microbial decomposition of dimethylsulfoniopropionate (DMSP), which is a compound synthesized in variable amounts by different phytoplankton groups. Once DMS is produced, it can either be oxidized by a photochemical reaction or metabolized by bacteria (Toole et al., 2003). The released DMS portion from oceans is the primary natural source of sulfur as it contributes up to 70% of the sulfur emission into the atmosphere globally (Simo 2001). The oxidation process of DMS produces sulfuric and methanesulfonic acids, which eventually lead to the formation of sulfate aerosols (Andreae and Barnard, 1984; Pazmiño et al., 2005). Thereby, The oxidized products of DMS play a key role in cloud formation once they are emitted into the atmosphere either by contributing to the aerosol formation or by condensing on pre-existing particles contributing to the growth of larger particles sizes that can eventually be cloud condensation nuclei (CCN) (Woodhouse et al., 2010; 2013), thus, altering cloud radiative forcing and precipitation (Charlson et al 1987; Andrea Raemdonck 1983). Thus, the geobiochemical cycle of DMSOS plays a key role in the Earth's climate system (Charlson et al 1987; Andrea and Crutzen 1997; Wang et al., 2021).

In the Arctic regions, the warming is much quicker than in the rest of the globe, causing what is called "Arctic amplification" (AMAP report 2017). This will have an influence on the sea ice extent and can potentially lead to ice-free during summer time in the coming decades. Consequently, this might enhance the productivity cycle of DMS on marine surfaces, which can be resulted in more emission and exchange of gases, e.g. DMS and particles from the marine surfaces into the atmosphere (Woodhouse et al., 2013; Park et al., 2018; Gali et al 2018; 2019). This is because ice retreat would allow more solar radiation to penetrate into the ocean surface, leading to an increase in the production of primary phytoplankton, which is essential in DMS production. For example, between 1998 and 2016, it was found that DMS concentration has increased at a mean rate of 13.3 ± 6.7 Gg S Yr–1 (~33%Yr–1) in summer time in the Arctic (Gali et al., 2019). The increase in the DMS emission from sea surfaces in recent years, especially in the polar regions, suggests that more CCN can be found, which would eventually lead to more cloud cover that might contribute to cooling the Arctic Climate (counterattack process to the Arctic amplification). Since observations were missing in the past, models can provide a proper tool to predict the DMSOS concentrations especially in the pre-industrial time. However, those models are still under test and evaluation to validate their predictions' quality by comparing them to recent observations (in-situ and satallite). Therefore in this study, we carry out a series of data analysis where we compare modeling predictions to observation aiming to answer the following specific research questions: 1- How Dimethylsulfide concentrations are represented in different climate Models in the Arctic regions? 2- How DMS concentration is represented in observations and how these observed concentrations are different from models (matching periods 2003-

2014)? 3- can models capture the seasonal varibility and the peaking season of Dimethylsulfide? 4- How sea ice and ice-melting would impact DMS concentrations and what is the correlation between the predicted Dimethylsulfide and the observed ones?

2- Methodology

2-1 CMIP6 and Observations for DMSOS

In this study, we compare the concentration of DMS at the surface Ocean (DMSOS herein) between models and observations in the Arctic regions. For that purpose, we use two models that predict the DMSOS concentrations, namely: a) CNRM-ESM2-1 (Séférian et al., 2019) and b) UKESM-1-0-LL (Sellar et al., 2019) for the historical period experiment (extend from 1850 to 2014) and for different ensembles (5-ensembles), where the mean over the same list of member_id is calculated for both models, respectively. We compared the predicted DMSOS to the observed ones from Vali et al. (2019). Both models has different spatial resolution for the atmosphere; being ~1° or ~140 km with 91 vertical levels and 1.25°×1.875° with 85 vertical levels for CNRM-ESM2-1 and UKESM-1-0-LL, respectively. The DMS was defined differently in both models, the CNRM-ESM2-1 uses a mechanistic scheme following Masotti et al. (2016) to simulates the distribution of DMS in PISCESv2-gas model, whereas in UKESM-1-0-LL the DMSOS was added as diagnostic submodel (Anderson et al., 2001) to the Ocean biogeochemistry model to support interactive DMS emissions to the atmosphere. The observed DMSOS concentration in Vali et al. (2019) was parameterized based on the observed chlorophyll concentration from Modis-Aqua and SeaWiFS for the periods from 2003 to 2016, and 1998 to 2007, respectively. The spatial and temporal resolution of those observations are 28 km and 8 days, respectively. In this report, we only consider the observed data from Modis-Aqua and compare them with modeling data for the matching period from 2003 to 2014.

2-2 Avialbility of modeling and observational Data

- Modeling data The DMSOS concentrations data extracted from the two models for the historical period of different ensembles are listed in the bucket under the directory 'escience2022/Ada/monthly'.
- Observational data The DMSOS data extracted from observations are listed under the directory 'escience2022/Antoine/Satellite_Arctic_DMS'.

2-3 Domain and locations

In this study, the Arctic region is on focus since we investigate the impact of the retreat of sea ice extent on the production of DMSOS. However, we did not look at the whole Arctic but instead chose to carry out the analysis over two different contrasting areas:

- a) Greenland Sea (GLS herein), with longitude, extending from -10 to 10 and latitude extending from 70 to 85. The Average depth of GLS is ~1444m and the maximum depth is ~3000m. It should be noted that GLS is not surrounded by land, but it's instead an open sea even during maximum sea ice extent and there are NO rivers that feed into it.
- b) Laptev Sea (LPS herein), with longitude extending from 100 to 160 and latitude extending from 70 to 80. The LPS is on a continental shelf with average and maximum depths of ~578m and ~3385m, respectively. It should be noted that around 50% of the LPS region has a depth that is < 50m. The LPS area is also surrounded by land, where most of that surface area is covered by ice during the winter season. In addition, that specific land ice contains rivers that can feed into the LPS and, thus, can potentially impact nutrient availability and salinity. The latter two variables can play a key role in the concentration variability of DMSOS in that region.

3- Results and Discussion

Due to Arctic amplification in recent years, the sea ice extent retreats causing consequences on the production of DMSOS from the marine ecosystems. Here, we map the DMSOS concentrations to check their distribution variability in the LPS andf GLS areas, first by models from CMIP6 and second by observations (see section 2 for the description of CMIP6 and observation used in this study).

3-1 DMSOS in CMIP6 during 1850 to 2014 (historical expirement period)

The prediction of DMSOS from UKESM vs CNRM over the whole historical period is analyzed.

In [1]:
```
# load useful packages
import xarray as xr
xr.set_options(display_style='html')
import intake
import cftime
import matplotlib.pyplot as plt
from matplotlib import cm
import cartopy
import cartopy.crs as ccrs
import Functions_Maher_report
import s3fs
import pandas as pd
from dask.diagnostics import ProgressBar
import cartopy.crs as ccrs
from mpl_toolkits.axes_grid1.inset_locator import inset_axes
import numpy as np
import matplotlib as mpl
from scipy.interpolate import griddata
%matplotlib inline
%load_ext autoreload
%autoreload 2
# access and open the bucket
s3 = s3fs.S3FileSystem(key="K1CQ7M1DMTLUFK182APD",
                       secret="3JuZAQm5I03jtpijCpHOd" \
                       "kAsJDNLNfZxBpM15Pi0",
                       client_kwargs=dict(
                        endpoint_url="https://rgw.met.no"))
```

In [2]:
```
# list the available modeling data in the bucket
dir = 'escience2022/Ada/monthly'
files = [file for file in s3.ls(dir) if 'dmsos' in file ]
```

In [3]:
```
## for UKESM
#list of member-id that we average over
list_member_id = ['1', '2', '3', '4','8','9']
list_ds = []
for imember, member in enumerate(list_member_id):
    remote_files_UK = 's3://escience2022/Ada/monthly/' \
    'dmsos_Omon_UKESM1-0-LL_historical_r'+member+'*.nc'
    remote_files_UK = s3.glob(remote_files_UK)
    fileset = [s3.open(file) for file in remote_files_UK]
    list_ds.append(xr.open_mfdataset(fileset,
                    combine='by_coords'))
## merge all the ensembles files
ds_UKESM = xr.concat(list_ds,"member_id")
with ProgressBar():
    ds_dmsos_UKESM = ds_UKESM.dmsos.mean(
        dim=['member_id']).compute()
```

```
[########################################] | 100% Completed | 194.06 s
```

In [4]:
```
## for CNRM
#same list of member-id as in UKESM
list_member_id2 = ['1', '2', '3', '4','8','9']
list_ds_CN = []
for imember2, member2 in enumerate(list_member_id2):
    remote_files_CN = 's3://escience2022/Ada/monthly/'\
    'dmsos_Omon_CNRM-ESM2-1_historical_r'+member2+'*.nc'
    remote_files_CN = s3.glob(remote_files_CN)
    fileset2 = [s3.open(file) for file in remote_files_CN]
    list_ds_CN.append(xr.open_mfdataset(
        fileset2,combine="nested",compat="override"))
ds_CNRM = xr.concat(list_ds_CN,"member_id")
with ProgressBar():
    ds_dmsos_CNRM = ds_CNRM.dmsos.mean(
        dim=['member_id']).compute()
```

```
[########################################] | 100% Completed | 333.19 s
```

Here, we choose two contrasting areas of interest for both models to investigate whether DMS surface concentration would be different. Those areas are: a) Greenland Sea (herein GLS) and b) Laptev Sea (herein LPS). In the following, the mean of DMSOS over the whole historical period is calculated and the resulting maps are plotted for both models over the GLS and LPS areas.

In [5]:
```
##  Greenland Sea for UKESM model
dmsosset_GLarea_UKESM=ds_dmsos_UKESM.where(
    (ds_dmsos_UKESM.longitude >= -10)
    & (ds_dmsos_UKESM.longitude <= 10)
    & (ds_dmsos_UKESM.latitude <= 85)
    & (ds_dmsos_UKESM.latitude >= 70),
    drop=True).compute()
```

In [6]:
```
dms_MeanAllHistrorical_UKESM_GL= \
dmsosset_GLarea_UKESM.mean(
    dim='time',keep_attrs=True).compute()
```

In [7]:
```
## Laptev sea for UKESM
dmsosset_LapSarea_UKESM = ds_dmsos_UKESM.where(
    (ds_dmsos_UKESM.longitude>=100)
    & (ds_dmsos_UKESM.longitude<=160)
    & (ds_dmsos_UKESM.latitude <= 80)
    & (ds_dmsos_UKESM.latitude >= 70),
    drop=True).compute()
```

In [8]:
```
dms_MeanAllHistrorical_UKESM_LapS = \
dmsosset_LapSarea_UKESM.mean(
    dim='time',keep_attrs=True).compute()
```

In [9]:
```
# Greenland Sea for CNRM model
dmsosset_GLarea_CNRM=ds_dmsos_CNRM.where(
    (ds_dmsos_CNRM.lon >= -10)
    & (ds_dmsos_CNRM.lon <= 10)
    & (ds_dmsos_CNRM.lat <= 85)
    & (ds_dmsos_CNRM.lat >= 70),
    drop=True).compute()
```

In [10]:
```
dms_MeanAllHistrorical_CNRM_GL = \
dmsosset_GLarea_CNRM.mean(
    dim='time',keep_attrs=True).compute()
```

In [11]:
```
# Laptev Sea Sea for CNRM model
dmsosset_LapSarea_CNRM=ds_dmsos_CNRM.where(
    (ds_dmsos_CNRM.lon >= 100)
    & (ds_dmsos_CNRM.lon <= 160)
    & (ds_dmsos_CNRM.lat <= 80)
    & (ds_dmsos_CNRM.lat >= 70),
    drop=True).compute()
```

In [12]:
```
dms_MeanAllHistrorical_CNRM_LapS = \
dmsosset_LapSarea_CNRM.mean(
    dim='time',keep_attrs=True).compute()
```

In [13]:
```
## plotting Figure 1
from Functions_Maher_report import plot_map_2panels
fig1 = plot_map_2panels(
    dms_MeanAllHistrorical_UKESM_GL.longitude,
    dms_MeanAllHistrorical_UKESM_GL.latitude,
    dms_MeanAllHistrorical_UKESM_GL,
    'A) GLS - UKESM',
    dms_MeanAllHistrorical_CNRM_GL.lon,
    dms_MeanAllHistrorical_CNRM_GL.lat,
    dms_MeanAllHistrorical_CNRM_GL,
    'B) GLS - CNRM',
    [-20, 20,65,90])
```

```
/home/jovyan/Tjaernoe2022-group4/notebooks/Maher/Functions_Maher_report.p
y:115: UserWarning: This figure includes Axes that are not compatible wit
h tight_layout, so results might be incorrect.
  fig.tight_layout()
```

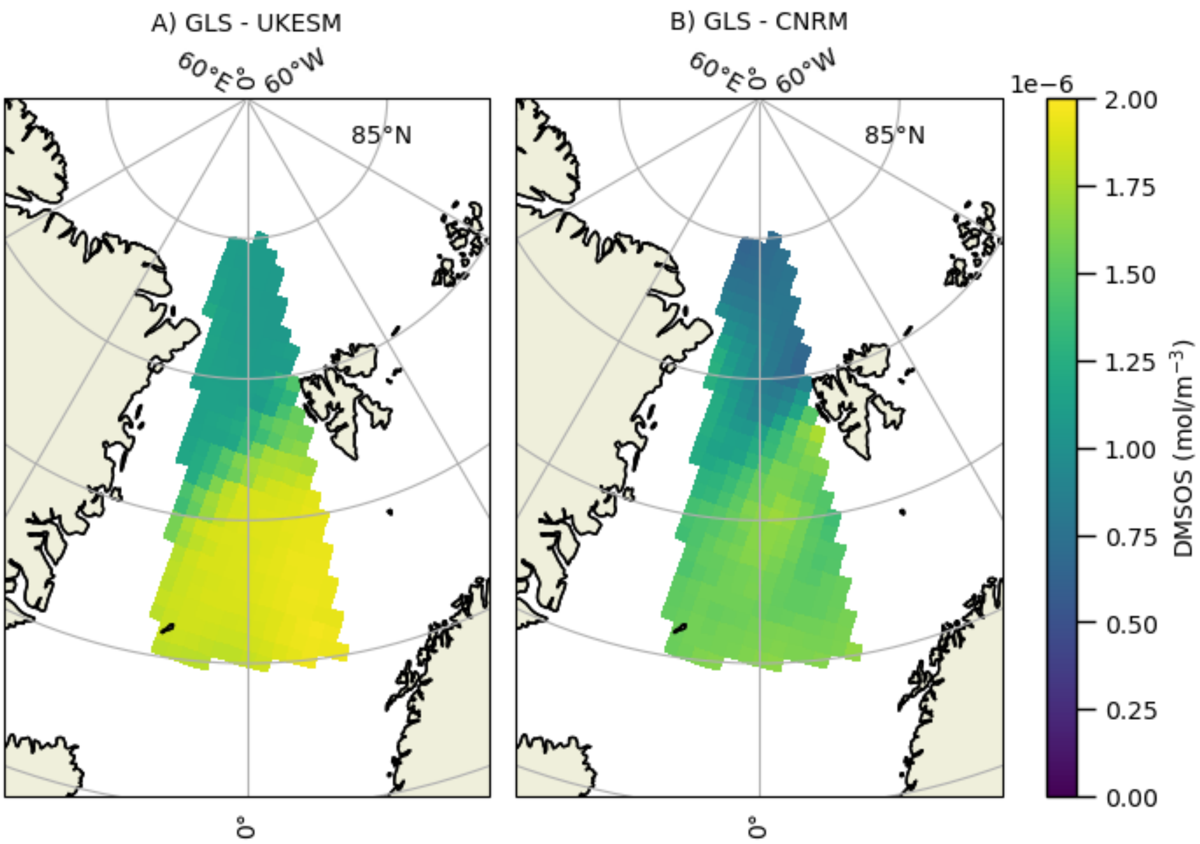

Fig1: Comparing the maps distribution of DMSOS concentration averaged over the whole historical period (1850 to 2014) in the Greenland Sea area predicted by A) UKESM and B) CNRM models

In [14]:
```
## plotting Figure 2
fig2 = plot_map_2panels(
    dms_MeanAllHistrorical_UKESM_LapS.longitude,
    dms_MeanAllHistrorical_UKESM_LapS.latitude,
    dms_MeanAllHistrorical_UKESM_LapS,
    'A) LPS - UKESM',
    dms_MeanAllHistrorical_CNRM_LapS.lon,
    dms_MeanAllHistrorical_CNRM_LapS.lat,
    dms_MeanAllHistrorical_CNRM_LapS,
    'B) LPS - CNRM',
    [90,170,65,85])
```

```
/home/jovyan/Tjaernoe2022-group4/notebooks/Maher/Functions_Maher_report.p
y:115: UserWarning: This figure includes Axes that are not compatible wit
h tight_layout, so results might be incorrect.
  fig.tight_layout()
```

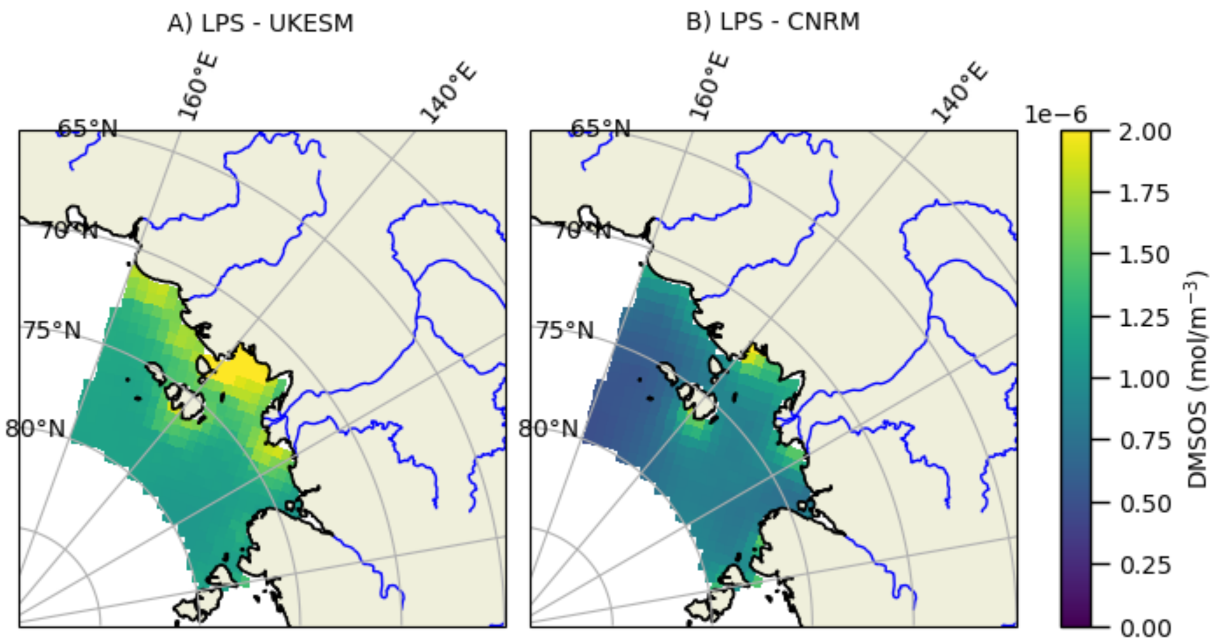

Fig2: Comparing the Maps distribution of the DMSOS concentrations averaged over the whole historical period (1850 to 2014) in the Laptev Sea area predicted by a) UKESM (left) and b) CNRM (right) models

Figures 1, 2 diplays the map distribution of the DMSOS concentration predicted by UKESM-1-0-LL and CNRM-ESM-2-1, and averaged over the whole historical period from 1850 to 2014 for the two arctic regions GLS and LPS, respectively. In both regions, the DMSOS predicted by UKESM was larger than CNRM; being factor of ~ 2 to 3, espicially in the areas where it possess larger DMSOS, e.g. close to the cost in the LPS area and between 70 and 75 in latitude over the GLS area. This differences can be due to the different parametrizations that are used to estimate the DMSOS concentrations as well as to the different spatial resolution in both models. However, both models were capable in capturing similar variation in the distribution of the averaged DMSOS concentration over both areas although the existence of the differences in predicting the actual values. In details, over the GLS area, both models predicted low DMSOS concentration in areas where latitudes ranged from 80 to 85, that increased gradually at lower latitudes between 70 and 75. Over LPS area, both models also could predict area with larger DMSOS concentration being close to the coast and decreased significantly with latitudes.

3-2 DMSOS predicted by CMIP6 vs Observations during recent period 2003 to 2014

To compare with observations, we sliced the modeling data and chose the period from 2003 to 2014 to match the observational data. In a later step, we caluclated the mean over that period for both models in both areas. Similarly to modeling data, we handeled the observational data and calculated the mean over that matching period for both areas LPS and GLS as well.

In [15]:
```
# slicing the modeling data and calculate the mean 2003 to 2014
dms_Mean2003to2014_GLS_UKESM = \
dmsosset_GLarea_UKESM.isel(
    time = slice(1836,None)).mean(
    dim='time',keep_attrs=True).compute()

dms_Mean2003to2014_GLS_CNRM = \
dmsosset_GLarea_CNRM.isel(
    time = slice(1836,None)).mean(
    dim='time',keep_attrs=True).compute()

dms_Mean2003to2014_LapS_UKESM = \
dmsosset_LapSarea_UKESM.isel(
    time = slice(1836,None)).mean(
    dim='time',keep_attrs=True).compute()

dms_Mean2003to2014_LapS_CNRM = \
dmsosset_LapSarea_CNRM.isel(
    time = slice(1836,None)).mean(
    dim='time',keep_attrs=True).compute()
```

In [16]:
```
#list the available observational data in the bucket
s3files = 's3://escience2022/Antoine/Satellite_Arctic_DMS/'\
          'dms_gsm_A*_8D_28km.nc'
remote_files = s3.glob(s3files)
fileset = [s3.open(file) for file in remote_files]
ds_obs = xr.open_mfdataset(fileset, combine='by_coords')
```

Note1: The observational data of DMSOS are incremented differently to the modeling data, where periods of 8 days are considered instead of normal daily or montly periods in models. Therefore, we used the following method to add date and transform the periods of 8 days into month.

In [17]:
```
## add date to the observational data
import datetime
dates = np.array([
    [datetime.datetime(int(y.values), 1, 1) +
     datetime.timedelta(d.values - 1)
     for d in ds_obs.startjulday.sel(year=y)]
        for y in ds_obs.year])

ds_obs=ds_obs.assign_coords({
    "d": (['year','period'], dates ) })
ds_obs=ds_obs.stack(time=['year','period'])
ds_obs=ds_obs.set_index(time='d')
```

In [18]:
```
## Greenland Sea for Observations
DmsObs_GLSarea = ds_obs.where(
    (ds_obs.longitude>=-10)
    & (ds_obs.longitude<=10)
    & (ds_obs.latitude <= 85)
    & (ds_obs.latitude >= 70),
    drop=True).compute()
## we select the period from 2003 to 2014
## and ignore the the last two years
dmsObs_2003to2014_GLS = DmsObs_GLSarea.isel(
    time= slice(552))
# calculate the mean over 2003 to 2014
dmsObs_Mean_2003to2014_GLS = \
dmsObs_2003to2014_GLS.mean(dim='time').compute()
```

In [19]:
```
## Laptev Sea
DmsObs_LapSarea = ds_obs.where(
    (ds_obs.longitude>=100)
    & (ds_obs.longitude<=160)
    & (ds_obs.latitude <= 80)
    & (ds_obs.latitude >= 70),
    drop=True).compute()
## we select the period from 2003 to 2014
## and ignore the the last two years
dmsObs_2003to2014_LapS = DmsObs_LapSarea.isel(
    time= slice(552))
dmsObs_Mean_2003to2014_LapS = \
dmsObs_2003to2014_LapS.mean(dim='time').compute()
```

Note2: The coordinates system of these observations are indexed with pixels instead of (x,y) or (i,j) system. Therefore, we use the following function 'interGali' from the Functions.py to transform the coordinate system and make the DMSOS from observations comparable with CMIP6 modeling data.

In [20]:
```
from Functions_Maher_report import interGali
dmsObs_Mean_2003to2014_GLS = interGali(
    dmsObs_Mean_2003to2014_GLS, 'dms')
dmsObs_Mean_2003to2014_LapS = interGali(
    dmsObs_Mean_2003to2014_LapS, 'dms')
```

In [21]:
```
## plotting Figure 3
from Functions_Maher_report import plot_map_3panels
fig3 = plot_map_3panels(
    dms_MeanAllHistrorical_UKESM_GL.longitude,
    dms_MeanAllHistrorical_UKESM_GL.latitude,
    dms_MeanAllHistrorical_UKESM_GL,
    'A) GLS - UKESM',
    dms_MeanAllHistrorical_CNRM_GL.lon,
    dms_MeanAllHistrorical_CNRM_GL.lat,
    dms_MeanAllHistrorical_CNRM_GL,
    'B) GLS - CNRM',
    dmsObs_Mean_2003to2014_GLS.lon,
    dmsObs_Mean_2003to2014_GLS.lat,
    dmsObs_Mean_2003to2014_GLS*1.0e-6,
    'C) 2003-2014 - Obs MOD-AQ',
    [-20, 20,65,90])
```

```
/home/jovyan/Tjaernoe2022-group4/notebooks/Maher/Functions_Maher_report.p
y:192: UserWarning: This figure includes Axes that are not compatible wit
h tight_layout, so results might be incorrect.
  fig.tight_layout()
```

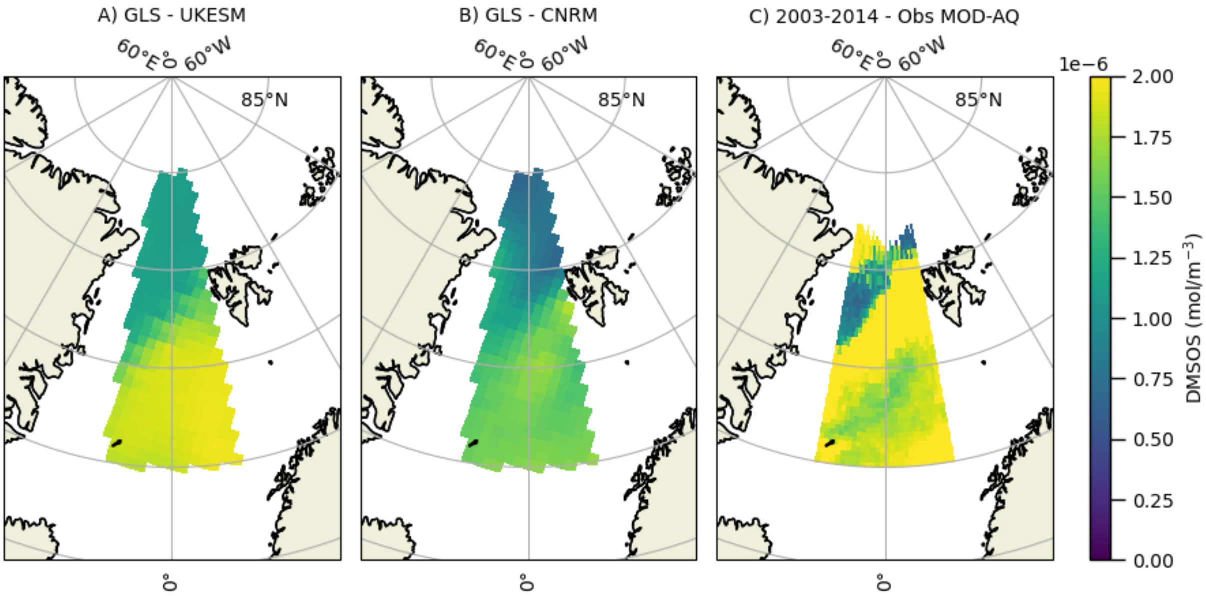

Fig3: Comparing the Maps distribution of DMSOS averaged over the recent period (2003-2014) in the Greenland Sea area predicted by A) UKESM, B) CNRM models, and C) observations from Modis-Aqua (Gali et al. (2019))

In [22]:

```
## plotting Figure 4
fig4 = plot_map_3panels(
    dms_MeanAllHistrorical_UKESM_LapS.longitude,
    dms_MeanAllHistrorical_UKESM_LapS.latitude,
    dms_MeanAllHistrorical_UKESM_LapS,
    'A) LPS - UKESM',
    dms_MeanAllHistrorical_CNRM_LapS.lon,
    dms_MeanAllHistrorical_CNRM_LapS.lat,
    dms_MeanAllHistrorical_CNRM_LapS,
    'B) LPS - CNRM',
    dmsObs_Mean_2003to2014_LapS.lon,
    dmsObs_Mean_2003to2014_LapS.lat,
    dmsObs_Mean_2003to2014_LapS*1.0e-6,
    'C) 2003-2014 - Obs MOD-AQ',
    [90,170,65,85])
```

```
/home/jovyan/Tjaernoe2022-group4/notebooks/Maher/Functions_Maher_report.py:192: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  fig.tight_layout()
```

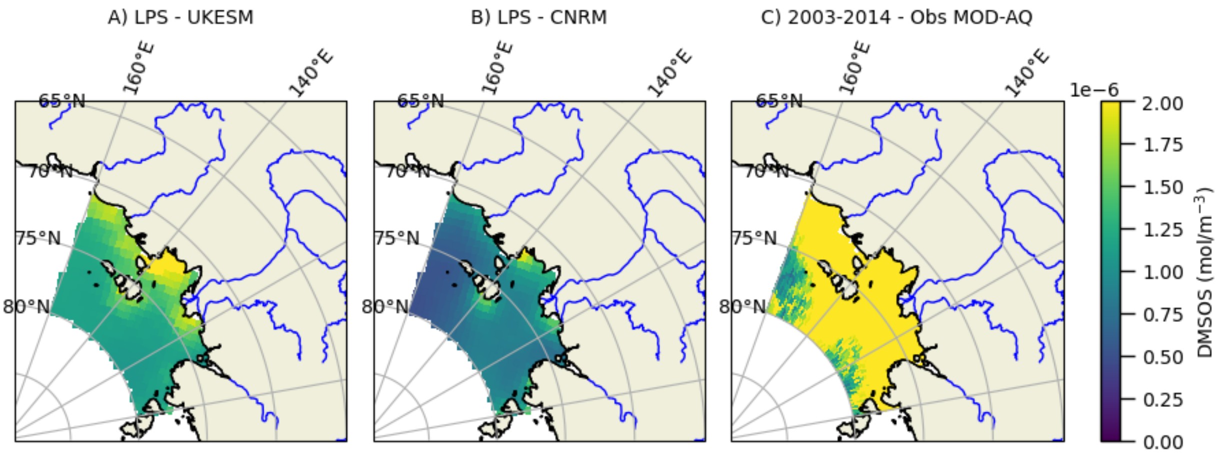

Fig4:Comparing the Maps distribution of DMSOS averaged over the recent period (2003-2014) in the Laptev Sea area predicted by A) UKESM, B) CNRM models, and C) observations from Modis-Aqua (Gali et al. (2019))

During the matching period between 2003 and 2004 and in both the GLS and LPS areas, UKESM still predicts larger DMSOS concentration than CNRM (factor of ~ 2) as illustrated in Figures 3 and 4. In comparison to the historical period, The spots where DMSOS concentrations are predicted to be large are kept for the recent period from 2003 to 2014 for both models. More importantly, both models predict larger DMSOS in the GLS area than in LPS. However, both models predict fewer DMSOS mean concentrations than what has been observed (up to a factor of ~ 4 in many spots) for both GLS and LPS areas and in general over the whole Arctic. In addition, the observed DMSOS mean over the LPS domain is higher than what is observed in the GLS domain. The latter contradicts what models are predicting. This can be explained by the decrease of sea ice content (sea ice melting) during recent years due to Arctic amplification, which has more influence on the LPS domain than GLS, which is more represented by the open Ocean. Moreover, the LPS area is also surrounded by land that has rivers feeding into the ice and the ocean which can impact the nutrient amount that can be thrown into the ocean as well as the salinity. all these factors can play an important role in increasing the productivity of DMSOS in the surface ocean, especially in the melting season. The observed DMSOS mean over the LPS domain is 4.8 umol/m-3 in comparison to 1.0 and 1.82 umol/m-3 for CNRM and UKESM, respectively. On the contrary, the DMSOS mean over the GLS domain during the same matching period is comparable between both models and observations; being 2.4, 1.94, 1.7 umol/m-3 for observation, UKESM, and CNRM, respectively. This difference between observation and models can be explained by the higher spatial and temporal resolution that observations possess; being 28 km. The deviation between what is predicted by models and observations is clear, especially in recent years. This implies that models need to be improved to close the gap with observations.

3-3 DMSOS climatic & seasonality trends; CMIP6 vs Observations

3-3-1 DMSOS long-term trend

Here, the long-range (climatology) trend is calculated and plotted in Fig5, where the annual mean of DMSOS is compared between the two models CNRM and UKESM for the historical period for both LPS and GLS areas (Fig5, A and B, respectively). For that, we first calculated the DMSOS spatial average weighted by the areacello variable, which is a variable that measures the area of the grid box and is extracted for each model and calculated for each of the areas of focus in this study. Then, we calculated the annual mean of DMSOS for both models and areas. In the end, we evaluated the trend to check whether the DMSOS is increasing (the trend is positive) or decreasing (the trend is negative) through the whole historical period. This was achieved by fitting linearly the whole period and calculating the slope (trend).

In [23]:
```
# areacello from CNRM
cat_url = "https://storage.googleapis.com" \
          "/cmip6/pangeo-cmip6.json"
col = intake.open_esm_datastore(cat_url)
cat = col.search(
    source_id=['CNRM-ESM2-1'],
    activity_id = ['CMIP'] ,
    experiment_id=['historical'],
    table_id=['Ofx'],
    variable_id=['areacello'],
    member_id=['r1i1p1f2'])
cat.df
```

Out[23]:

	activity_id	institution_id	source_id	experiment_id	member_id	table_id	variable_id
0	CMIP	CNRM-CERFACS	CNRM-ESM2-1	historical	r1i1p1f2	Ofx	areacello

In [24]:
```
glbArea_dict_CNRM = cat.to_dataset_dict(
    zarr_kwargs={'use_cftime':True})
```

```
--> The keys in the returned dictionary of datasets are constructed as fo
llows:
        'activity_id.institution_id.source_id.experiment_id.table_id.grid
_label'
```

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In [25]:
```
areacello_CNRM = glbArea_dict_CNRM[
    list(glbArea_dict_CNRM.keys())[0]]
areacello_CNRM = areacello_CNRM.squeeze()
```

In [26]:
```
# LPS area
LapSarea = areacello_CNRM.areacello.where(
    (areacello_CNRM.lat>=70)
    & (areacello_CNRM.lat<=80)
    & (areacello_CNRM.lon <= 160)
    & (areacello_CNRM.lon >= 100),
    drop=True)
#GLS area
GLSarea = areacello_CNRM.areacello.where(
    (areacello_CNRM.lat>=70)
    & (areacello_CNRM.lat<=85)
    & (areacello_CNRM.lon <= 10)
    & (areacello_CNRM.lon >= -10),
    drop=True)
```

In [27]:
```
## averaging over LPS
dmsosset_AreaMean_CNRM_LapS = (
    LapSarea*dmsosset_LapSarea_CNRM).sum(
    dim=('x','y'))/LapSarea.sum(
    dim=('x','y'),keep_attrs=True)
## averaging over GLS
dmsosset_AreaMean_CNRM_GLS = (
    GLSarea*dmsosset_GLarea_CNRM).sum(
    dim=('x','y'))/GLSarea.sum(
    dim=('x','y'),keep_attrs=True)
```

In [28]:
```
dmsosset_AreaMean_AnnMean_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.groupby(
    'time.year').mean(dim='time').compute()
dmsosset_AreaMean_AnnSTD_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.groupby(
    'time.year').std(dim='time').compute()

dmsosset_AreaMean_AnnMean_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.groupby(
    'time.year').mean(dim='time').compute()
dmsosset_AreaMean_AnnSTD_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.groupby(
    'time.year').std(dim='time').compute()
```

In [29]:
```
cat_url = "https://storage.googleapis.com"\
          "/cmip6/pangeo-cmip6.json"
col = intake.open_esm_datastore(cat_url)
cat_UK = col.search(
    source_id=['UKESM1-0-LL'],
    activity_id = ['CMIP'],
    variable_id=['areacello'])
cat_UK.df
```

Out[29]:

	activity_id	institution_id	source_id	experiment_id	member_id	table_id	variable_id
0	CMIP	MOHC	UKESM1-0-LL	piControl	r1i1p1f2	Ofx	areacello

In [30]:
```
glbArea_dict_UK = cat_UK.to_dataset_dict(
    zarr_kwargs={'use_cftime':True})
areacello_UK = glbArea_dict_UK[list(
    glbArea_dict_UK.keys())[0]]
areacello_UK = areacello_UK.squeeze()
```

```
--> The keys in the returned dictionary of datasets are constructed as fo
llows:
        'activity_id.institution_id.source_id.experiment_id.table_id.grid
_label'
```

100.00% [1/1 00:00<00:00]

In [31]:
```
LapSarea_UK = areacello_UK.areacello.where(
    (areacello_UK.latitude>=70)
    & (areacello_UK.latitude<=80)
    & (areacello_UK.longitude <= 160)
    & (areacello_UK.longitude >= 100),
    drop=True)
GLSarea_UK = areacello_UK.areacello.where(
    (areacello_UK.latitude>=70)
    & (areacello_UK.latitude<=80)
    & (areacello_UK.longitude <= 10)
    & (areacello_UK.longitude >= -10),
    drop=True)
```

In [32]:
```
## averaging over the whole area of Laptev-Sea
dmsosset_AreaMean_UKESM_LapS = (
    LapSarea_UK*dmsosset_LapSarea_UKESM).sum(
    dim=('i','j'))/LapSarea_UK.sum(
    dim=('i','j'),keep_attrs=True)

## averaging over GLS area
dmsosset_AreaMean_UKESM_GLS = (
    GLSarea_UK*dmsosset_GLarea_UKESM).sum(
    dim=('i','j'))/GLSarea_UK.sum(
    dim=('i','j'),keep_attrs=True)
```

In [33]:
```
dmsosset_AreaMean_AnnMean_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.groupby(
    'time.year').mean(dim='time').compute()

dmsosset_AreaMean_AnnSTD_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.groupby(
    'time.year').std(dim='time').compute()


dmsosset_AreaMean_AnnMean_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.groupby(
    'time.year').mean(dim='time').compute()

dmsosset_AreaMean_AnnSTD_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.groupby(
    'time.year').std(dim='time').compute()
```

The DMSOS observations are provided with the pixel system of 28 km resolution instead of (x,y) or (i,j) system in CMIP6. Therefore, the spatial mean is calculated directly based on the pixel without the need of wieghting the averages with areacello (the area of each grid cell in the model).

In [34]:
```
dmsosObs_AreaMean_2003to2014_LapS = \
dmsObs_2003to2014_LapS.mean(
    dim='pixel', keep_attrs=True).compute()

dmsosObs_AreaMean_2003to2014_GLS = \
dmsObs_2003to2014_GLS.mean(
    dim='pixel', keep_attrs=True).compute()
```

In [35]:
```
dmsosObs_AreaMean_AnnMean_2003to2014_LapS = \
dmsosObs_AreaMean_2003to2014_LapS.groupby(
    'time.year').mean().compute()

dmsosObs_AreaMean_AnnSTD_2003to2014_LapS = \
dmsosObs_AreaMean_2003to2014_LapS.groupby(
    'time.year').std().compute()

dmsosObs_AreaMean_AnnMean_2003to2014_GLS = \
dmsosObs_AreaMean_2003to2014_GLS.groupby(
    'time.year').mean().compute()

dmsosObs_AreaMean_AnnSTD_2003to2014_GLS = \
dmsosObs_AreaMean_2003to2014_GLS.groupby(
    'time.year').std().compute()
```

In [36]:
```
from Functions_Maher_report import linreg
## calculate trends
model_CNRM_LPS_fit1 = linreg(
    dmsosset_AreaMean_AnnMean_CNRM_LapS.year,
    dmsosset_AreaMean_AnnMean_CNRM_LapS)
slope1 = model_CNRM_LPS_fit1[3]

model_UKESM_LPS_fit2 = linreg(
    dmsosset_AreaMean_AnnMean_UKESM_LapS.year,
    dmsosset_AreaMean_AnnMean_UKESM_LapS)
slope2 = model_UKESM_LPS_fit2[3]

model_CNRM_GLS_fit1 = linreg(
    dmsosset_AreaMean_AnnMean_CNRM_GLS.year,
    dmsosset_AreaMean_AnnMean_CNRM_GLS)
slope3 = model_CNRM_GLS_fit1[3]

model_UKESM_GLS_fit2 = linreg(
    dmsosset_AreaMean_AnnMean_UKESM_GLS.year,
    dmsosset_AreaMean_AnnMean_UKESM_GLS)
slope4 = model_UKESM_GLS_fit2[3]

## Plotting the climatology with their calculated trends
## (UKESM vs CNRM) for the whole historical period
## Figure 5
```

```
fig, ax = plt.subplots(2,1,figsize=(8,6))
ax[0].plot(
    dmsosset_AreaMean_AnnMean_CNRM_LapS.year,
    dmsosset_AreaMean_AnnMean_CNRM_LapS,
    label='CNRM',color='red')
ax[0].fill_between(
    dmsosset_AreaMean_AnnMean_CNRM_LapS.year,
    dmsosset_AreaMean_AnnMean_CNRM_LapS
    -0.5*dmsosset_AreaMean_AnnSTD_CNRM_LapS,
    dmsosset_AreaMean_AnnMean_CNRM_LapS
    +0.5*dmsosset_AreaMean_AnnSTD_CNRM_LapS,
    color='lightpink',alpha=0.5)
ax[0].plot(
    model_CNRM_LPS_fit1[0],
    model_CNRM_LPS_fit1[2],'--k', color='red')
ax[0].text(
    1850,0.4e-6,'Trend= {0}'.format(
        slope1),
    color='red')
ax[0].plot(
    dmsosset_AreaMean_AnnMean_UKESM_LapS.year,
    dmsosset_AreaMean_AnnMean_UKESM_LapS,
    label='UKESM',color='blue')
ax[0].fill_between(
    dmsosset_AreaMean_AnnMean_UKESM_LapS.year,
    dmsosset_AreaMean_AnnMean_UKESM_LapS
    -0.5*dmsosset_AreaMean_AnnSTD_UKESM_LapS,
    dmsosset_AreaMean_AnnMean_UKESM_LapS
    +0.5*dmsosset_AreaMean_AnnSTD_UKESM_LapS,
    color='lightblue',alpha=0.5)
ax[0].plot(
    model_UKESM_LPS_fit2[0],
    model_UKESM_LPS_fit2[2],
    '--k', color='blue')
ax[0].text(
    1850,1.7e-6,'Trend= {0}'.format(
        slope2),
    color='blue')
ax[0].set_xticklabels([])


ax[1].plot(
    dmsosset_AreaMean_AnnMean_CNRM_GLS.year,
    dmsosset_AreaMean_AnnMean_CNRM_GLS,
    label='CNRM',color='red')
ax[1].fill_between(
    dmsosset_AreaMean_AnnMean_CNRM_GLS.year,
    dmsosset_AreaMean_AnnMean_CNRM_GLS
    -0.5*dmsosset_AreaMean_AnnSTD_CNRM_GLS,
    dmsosset_AreaMean_AnnMean_CNRM_GLS
    +0.5*dmsosset_AreaMean_AnnSTD_CNRM_GLS,
    color='lightpink',alpha=0.5)
ax[1].plot(
    model_CNRM_GLS_fit1[0],
    model_CNRM_GLS_fit1[2],
    '--k', color='red')
ax[1].text(
```

```
    1850,1.0e-6,'Trend= {0}'.format(
        slope3),
    color='red')

ax[1].plot(
    dmsosset_AreaMean_AnnMean_UKESM_GLS.year,
    dmsosset_AreaMean_AnnMean_UKESM_GLS,
    label='UKESM',color='blue')
ax[1].fill_between(
    dmsosset_AreaMean_AnnMean_UKESM_GLS.year,
    dmsosset_AreaMean_AnnMean_UKESM_GLS
    -0.5*dmsosset_AreaMean_AnnSTD_UKESM_GLS,
    dmsosset_AreaMean_AnnMean_UKESM_GLS
    +0.5*dmsosset_AreaMean_AnnSTD_UKESM_GLS,
    color='lightblue',alpha=0.5)
ax[1].plot(
    model_UKESM_GLS_fit2[0],
    model_UKESM_GLS_fit2[2],
    '--k', color='blue')
ax[1].text(
    1850,2.0e-6,'Trend= {0}'.format(
        slope4),
    color='blue')

ax[1].set_xlabel('Year')
ax[0].set_ylabel('CMIP6 DMSOS (mol m$^{-3}$)')
ax[1].set_ylabel('CMIP6 DMSOS (mol m$^{-3}$)')
major_ticks = np.arange(0.5e-6,3.0e-6, 0.5e-6)
ax[1].set_ylim(0.5e-6,3.0e-6)
ax[1].set_yticks(major_ticks)
ax[0].set_title(
    'A) Climatology - LPS - Historical',
    fontsize=10)
ax[1].set_title(
    'B) Climatology - GLS - Historical',
    fontsize=10)
ax[0].grid()
ax[1].grid()
ax[0].legend(bbox_to_anchor=(
    0.2,1.1,1,0.2),loc="lower left",
             ncol=2)
```

```
/tmp/ipykernel_4496/3508649841.py:38: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[0].plot(
/tmp/ipykernel_4496/3508649841.py:56: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[0].plot(
/tmp/ipykernel_4496/3508649841.py:78: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[1].plot(
/tmp/ipykernel_4496/3508649841.py:98: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[1].plot(
```

Out[36]:

```
<matplotlib.legend.Legend at 0x7fb80d3ebf40>
```

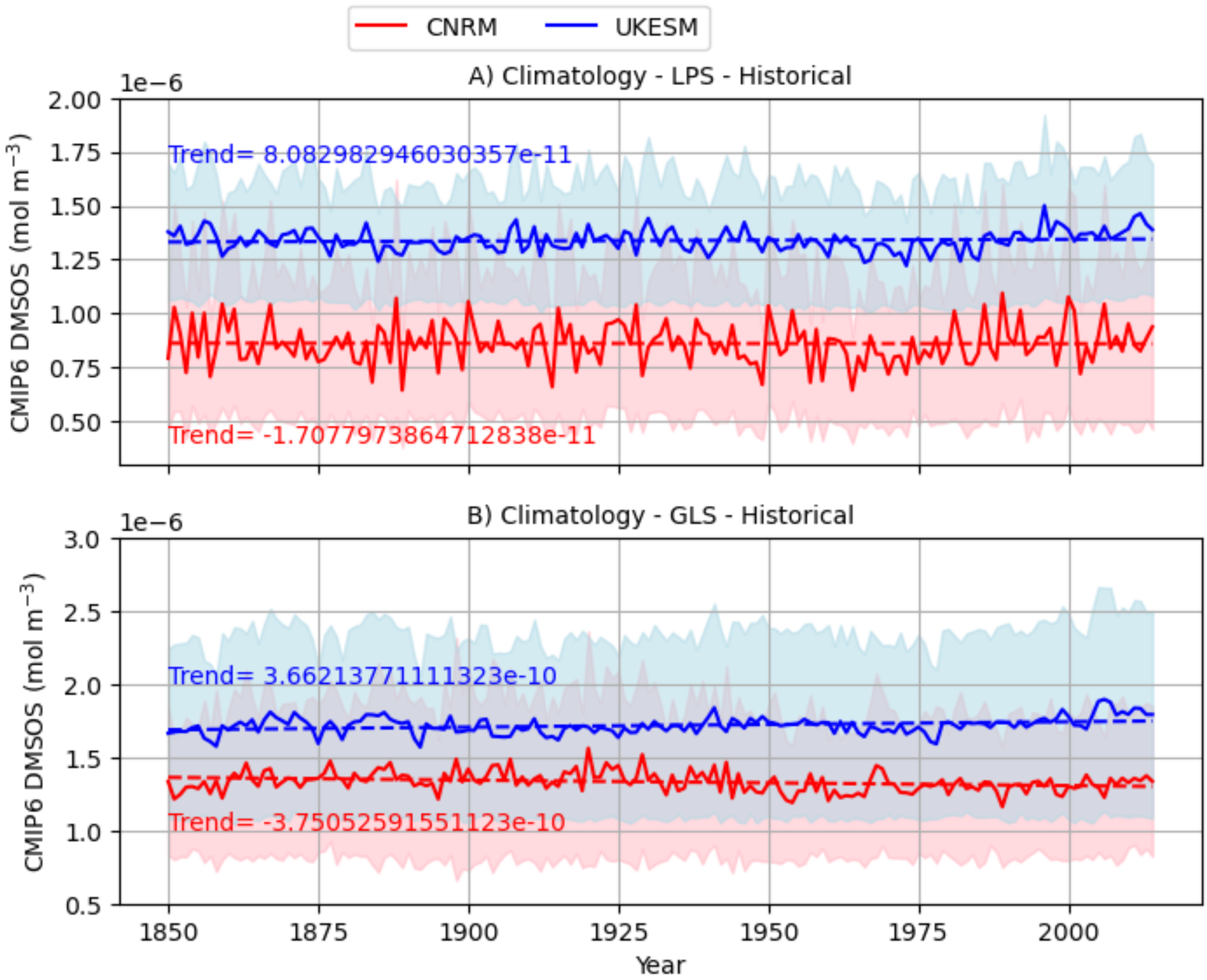

Fig5: The annual spatial average of DMSOS averaged over the historical period from 1850 to 2014 as predicted by UKESM (Blue) and CNRM (Red) models in A) Laptev Sea area and B) Greenland Sea area. The dashed blue and red lines are the linear fit, which represent the long-term trend of each line. The shaded light blue and light red areas represent the standard deviation.

Fig5 displays the long climatological trend of the spatial average of DMSOS concentration annually averaged over the historical period. It's clear that over the whole historical period and for both areas, UKESM predicted larger DMSOS concentration than CNRM did. In addition, the predicted DMSOS by each model in GLS was slightly larger than what has been predicted in LPS. Moreover, for both areas, the calculated trend from UKESM was positive indicating an increase in the DMSOS predictions, whereas, the overall calculated trend from CNRM was negative implying a decrease in predicting the DMSOS for the historical period. This decrease in DMSOS concentration, in general, was not expected at least in the Arctic regions, where the sea ice extent is decreasing with time allowing more biological activities in the surface ocean that eventually lead to higher DMSOS productivity. To further test the latter hypothesis, we recalculated the spatial annual mean of DMSOS for both areas, but for the recent periods from 2003 to 2014 for both models and compared that with observations. We also evaluated their trends similar to what we have done for the historical period.

In [37]:
```
## selecting the years from 2003 to 2014 (matching periods with Obs)
dmsosset_AreaMean_AnnMean_2003to2014_UKESM_LapS = \
dmsosset_AreaMean_AnnMean_UKESM_LapS.isel(
    year = slice(153,None))

dmsosset_AreaMean_AnnMean_2003to2014_CNRM_LapS = \
dmsosset_AreaMean_AnnMean_CNRM_LapS.isel(
    year = slice(153,None))

dmsosset_AreaMean_AnnMean_2003to2014_UKESM_GLS = \
dmsosset_AreaMean_AnnMean_UKESM_GLS.isel(
    year = slice(153,None))

dmsosset_AreaMean_AnnMean_2003to2014_CNRM_GLS = \
dmsosset_AreaMean_AnnMean_CNRM_GLS.isel(
    year = slice(153,None))

## calculating the trends
model_CNRM_LPS_fit1 = linreg(
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_LapS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_LapS)
slope1 = model_CNRM_LPS_fit1[3]

model_UKESM_LPS_fit2 = linreg(
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_LapS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_LapS)
slope2 = model_UKESM_LPS_fit2[3]

model_CNRM_GLS_fit1 = linreg(
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_GLS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_GLS)
slope3 = model_CNRM_GLS_fit1[3]

model_UKESM_GLS_fit2 = linreg(
```

```
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_GLS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_GLS)
slope4 = model_UKESM_GLS_fit2[3]

model_obs_GLS_fit=linreg(
    dmsosObs_AreaMean_AnnMean_2003to2014_GLS.year,
    dmsosObs_AreaMean_AnnMean_2003to2014_GLS[
        'dms']*1.0e-6)
slope5=model_obs_GLS_fit[3]

model_obs_LPS_fit=linreg(
    dmsosObs_AreaMean_AnnMean_2003to2014_LapS.year,
    dmsosObs_AreaMean_AnnMean_2003to2014_LapS[
        'dms']*1.0e-6)
slope6=model_obs_LPS_fit[3]

## plotting the climatology with their trends
## (UKESM vs CNRM vs Obs)for the period 2003 - 2014
## Figure 6
mpl.rcParams.update({'font.size':10})
fig, ax = plt.subplots(2,1,figsize=(8,6))
lns1=ax[0].plot(
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_LapS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_LapS,
    label='CNRM',color='red')
ax[0].plot(
    model_CNRM_LPS_fit1[0],
    model_CNRM_LPS_fit1[2],
    '--k', color='red')
ax[0].text(
    2003,0.75e-6,'Trend= {0}'.format(
        slope1),
    color='red')
lns2=ax[0].plot(
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_LapS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_LapS,
    label='UKESM',color='darkblue')
ax[0].plot(
    model_UKESM_LPS_fit2[0],
    model_UKESM_LPS_fit2[2],
    '--k', color='blue')
ax[0].text(
    2003,1.4e-6,'Trend= {0}'.format(
        slope2),
    color='darkblue')
ax[0].set_xticklabels([])
ax0 = ax[0].twinx()
lns3=ax0.plot(
    dmsosObs_AreaMean_AnnMean_2003to2014_LapS.year,
    dmsosObs_AreaMean_AnnMean_2003to2014_LapS[
        'dms']*1.0e-6,
    label='Obs',color='green')
ax0.plot(
    model_obs_LPS_fit[0],model_obs_LPS_fit[2],
    '--k', color='green')
ax0.text(
    2003,6.5e-6,'Trend= {0}'.format(
```

```
        slope6),
    color='green')
ax0.set_ylabel("Observed DMSOS (mol m$^{-3}$)",
               color="green",fontsize=10)
# added these three legends in one legend
lns = lns1+lns2+lns3
labs = [l.get_label() for l in lns]
ax[0].legend(lns, labs, bbox_to_anchor=(
    0.2,1.1,1,0.2),
             loc="lower left",ncol=3)

ax[1].plot(
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_GLS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_CNRM_GLS,
    label='CNRM',color='red')
ax[1].plot(
    model_CNRM_GLS_fit1[0],model_CNRM_GLS_fit1[2],
    '--k', color='red')
ax[1].text(
    2006,1.25e-6,'Trend= {0}'.format(slope3),
    color='red')
ax[1].plot(
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_GLS.year,
    dmsosset_AreaMean_AnnMean_2003to2014_UKESM_GLS,
    label='UKESM',color='darkblue')
ax[1].plot(
    model_UKESM_GLS_fit2[0],model_UKESM_GLS_fit2[2],
    '--k', color='blue')
ax[1].text(
    2003,1.7e-6,'Trend= {0}'.format(slope4),
    color='darkblue')
ax1 = ax[1].twinx()
ax1.plot(
    dmsosObs_AreaMean_AnnMean_2003to2014_GLS.year,
    dmsosObs_AreaMean_AnnMean_2003to2014_GLS[
        'dms']*1.0e-6,
    label='Obs',color='green')
ax1.plot(
    model_obs_GLS_fit[0],model_obs_GLS_fit[2],
    '--k', color='green')
ax1.text(
    2006,1.8e-6,'Trend= {0}'.format(slope5),
    color='green')
ax1.set_ylabel("Observed DMSOS (mol m$^{-3}$)",
               color="green",fontsize=10)

#ax.legend()
ax[1].set_xlabel('Year')
ax[0].set_ylabel('CMIP6 DMSOS (mol m$^{-3}$)')
ax[1].set_ylabel('CMIP6 DMSOS (mol m$^{-3}$)')
ax[0].set_title('A) Climatology - LPS - 2003 to 2014',
                fontsize=10)
ax[1].set_title('B) Climatology - GLS - 2003 to 2014',
                fontsize=10)
ax[0].grid()
ax[1].grid()
```

```
/tmp/ipykernel_4496/2163309358.py:60: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[0].plot(
/tmp/ipykernel_4496/2163309358.py:72: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[0].plot(
/tmp/ipykernel_4496/2163309358.py:87: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax0.plot(
/tmp/ipykernel_4496/2163309358.py:107: UserWarning: color is redundantly
defined by the 'color' keyword argument and the fmt string "--k" (-> colo
r='k'). The keyword argument will take precedence.
  ax[1].plot(
/tmp/ipykernel_4496/2163309358.py:117: UserWarning: color is redundantly
defined by the 'color' keyword argument and the fmt string "--k" (-> colo
r='k'). The keyword argument will take precedence.
  ax[1].plot(
/tmp/ipykernel_4496/2163309358.py:129: UserWarning: color is redundantly
defined by the 'color' keyword argument and the fmt string "--k" (-> colo
r='k'). The keyword argument will take precedence.
  ax1.plot(
```

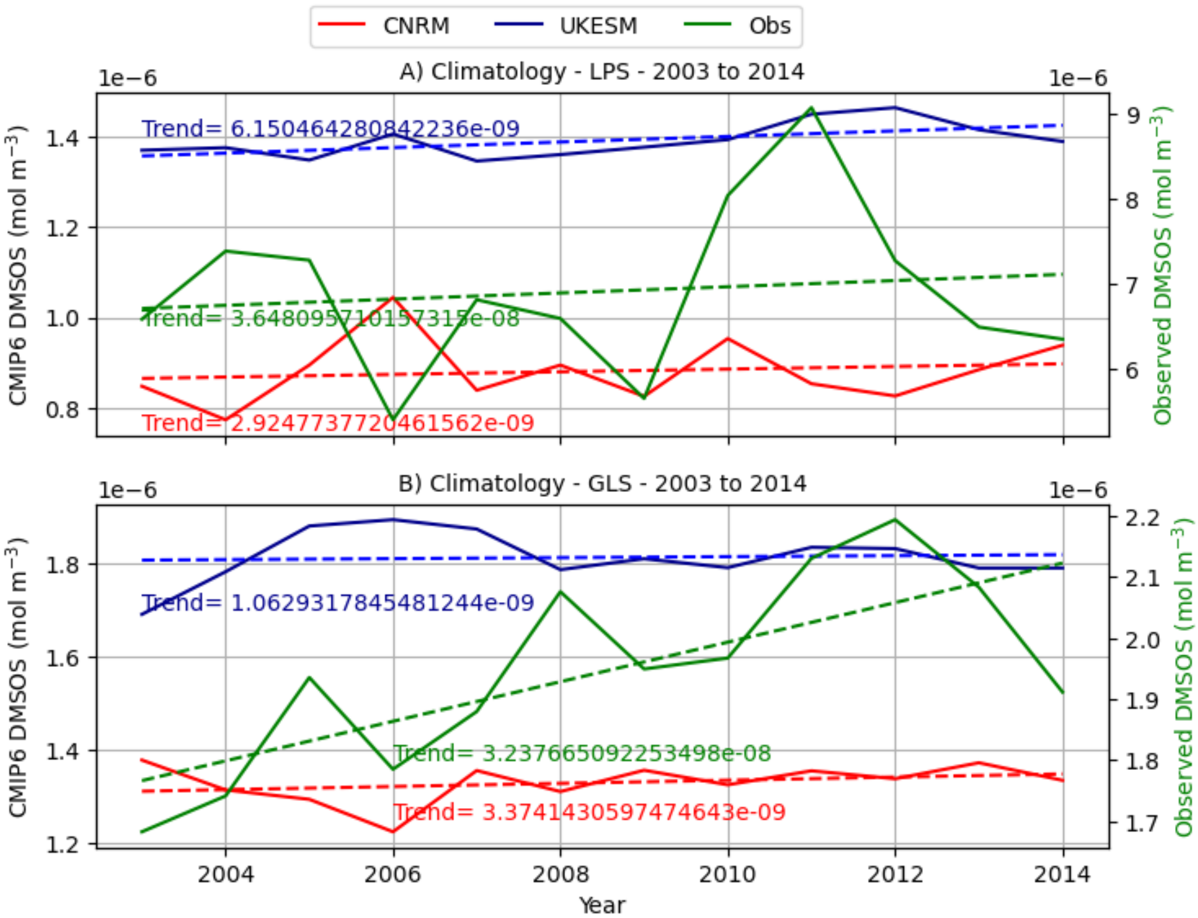

Fig 6 shows the same climatological trend as in Fig5, but for the recent period from 2003 to 2014 and compared to observations in both areas LPS (A) and GLS (B).

Fig6 illustrates the annual spatial mean of DMSOS concentrations for both models compared to observations for the period 2003 to 2014. In this period, both models kept the same behavior as in the historical period, where UKESM predicted larger DMSOS than CNRM did for both areas. In addition, each model predicted larger DMSOS in the GLS area than each of them did in the LPS area. More importantly, the observed DMSOS concentration was larger than what has been predicted by both models and for both areas. However, this difference was more pronounced in the LPS area than in GLS; being ~ an order of magnitude higher in LPS. Nevertheless, all trends either those estimated from models or observations were positive suggesting an increase in the DMSOS concentrations in recent years and for both areas, which is in agreement with what has been hypothesized for the Arctic regions.

3-3-2 DMSOS seasonal variation

Here, we check out the seasonal variability of DMSOS concentrations, where we also compared the seasonal variability of DMSOS predicted by models with observations. First, we started with the historical period, where we calculated the spatial mean of DMSOS averaged monthly over the whole historical period for both ULESM and CNRM (Fig7).

In [38]:
```
## calculating the monthly mean for 4 periods
# A ) Laptev Sea area LPS
# historical
dmsosset_AreaMean_MonMean_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.groupby(
    'time.month').mean().compute()

dmsosset_AreaMean_MonSTD_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.groupby(
    'time.month').std().compute()

dmsosset_AreaMean_MonMean_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.groupby(
    'time.month').mean().compute()

dmsosset_AreaMean_MonSTD_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.groupby(
    'time.month').std().compute()
# 2003 -2014
dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.isel(
    time=slice(1836,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_2003to2014_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.isel(
    time=slice(1836,None)).groupby(
    'time.month').std().compute()

dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS = \
```

```
dmsosset_AreaMean_CNRM_LapS.isel(
    time=slice(1836,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_2003to2014_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.isel(
    time=slice(1836,None)).groupby(
    'time.month').std().compute()

dmsosObs_AreaMean_MonMean_LapS = \
dmsosObs_AreaMean_2003to2014_LapS.groupby(
    'time.month').mean().compute()
dmsosObs_AreaMean_MonSTD_LapS = \
dmsosObs_AreaMean_2003to2014_LapS.groupby(
    'time.month').std().compute()

# first 30 years
dmsosset_AreaMean_MonMean_1850to1880_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.isel(
    time=slice(372)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1850to1880_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.isel(
    time=slice(372)).groupby(
    'time.month').std().compute()

dmsosset_AreaMean_MonMean_1850to1880_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.isel(
    time=slice(372)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1850to1880_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.isel(
    time=slice(372)).groupby(
    'time.month').std().compute()

# last 30 years
dmsosset_AreaMean_MonMean_1984to2014_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.isel(
    time=slice(1608,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1984to2014_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.isel(
    time=slice(1608,None)).groupby(
    'time.month').std().compute()

dmsosset_AreaMean_MonMean_1984to2014_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.isel(
    time=slice(1608,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1984to2014_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.isel(
    time=slice(1608,None)).groupby(
    'time.month').std().compute()


# B) Greenland Sea area GLS
# historical
dmsosset_AreaMean_MonMean_UKESM_GLS = \
```

```
dmsosset_AreaMean_UKESM_GLS.groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.groupby(
    'time.month').std().compute()
dmsosset_AreaMean_MonMean_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.groupby(
    'time.month').std().compute()

# 2003 -2014
dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.isel(
    time=slice(1836,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_2003to2014_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.isel(
    time=slice(1836,None)).groupby(
    'time.month').std().compute()

dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.isel(
    time=slice(1836,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_2003to2014_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.isel(
    time=slice(1836,None)).groupby(
    'time.month').std().compute()

dmsosObs_AreaMean_MonMean_GLS = \
dmsosObs_AreaMean_2003to2014_GLS.groupby(
    'time.month').mean().compute()
dmsosObs_AreaMean_MonSTD_GLS = \
dmsosObs_AreaMean_2003to2014_GLS.groupby(
    'time.month').std().compute()

# first 30 years
dmsosset_AreaMean_MonMean_1850to1880_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.isel(
    time=slice(372)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1850to1880_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.isel(
    time=slice(372)).groupby(
    'time.month').std().compute()

dmsosset_AreaMean_MonMean_1850to1880_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.isel(
    time=slice(372)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1850to1880_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.isel(
    time=slice(372)).groupby(
    'time.month').std().compute()
# last 30 years
```

```
dmsosset_AreaMean_MonMean_1984to2014_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.isel(
    time=slice(1608,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1984to2014_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.isel(
    time=slice(1608,None)).groupby(
    'time.month').std().compute()

dmsosset_AreaMean_MonMean_1984to2014_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.isel(
    time=slice(1608,None)).groupby(
    'time.month').mean().compute()
dmsosset_AreaMean_MonSTD_1984to2014_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.isel(
    time=slice(1608,None)).groupby(
    'time.month').std().compute()
```

```
/srv/conda/envs/notebook/lib/python3.9/site-packages/flox/aggregate_flox.
py:105: RuntimeWarning: invalid value encountered in divide
  out /= nanlen(group_idx, array, size=size, axis=axis, fill_value=0)
/srv/conda/envs/notebook/lib/python3.9/site-packages/flox/aggregate_flox.
py:105: RuntimeWarning: invalid value encountered in divide
  out /= nanlen(group_idx, array, size=size, axis=axis, fill_value=0)
```

In [39]:
```
## Plotting seasonality for the historical period
## 1850 - 2014
## Figure 7
mpl.rcParams.update({'font.size':10})
fig, ax = plt.subplots(1,2, figsize=(12,4))
ax[0].plot(
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS,
    label='CNRM',color='red')
ax[0].plot(
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS,
    label='UKESM', color='blue')
ax[0].legend()
ax[0].set_xlabel('Month of the Year')
ax[0].set_ylabel('DMSOS (mol m$^{-3}$)')
ax[0].set_title('A) Seasonality - Historical - LPS',
                fontsize=10)
ax[0].grid()

ax[1].plot(
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS,
    label='CNRM',color='red')
ax[1].plot(
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS,
    label='UKESM', color='blue')
ax[1].legend()
ax[1].set_xlabel('Month of the Year')
ax[1].set_ylabel('DMSOS (mol m$^{-3}$)')
ax[1].set_title('B) Seasonality - Historical - GLS',
                fontsize=10)
ax[1].grid()
```

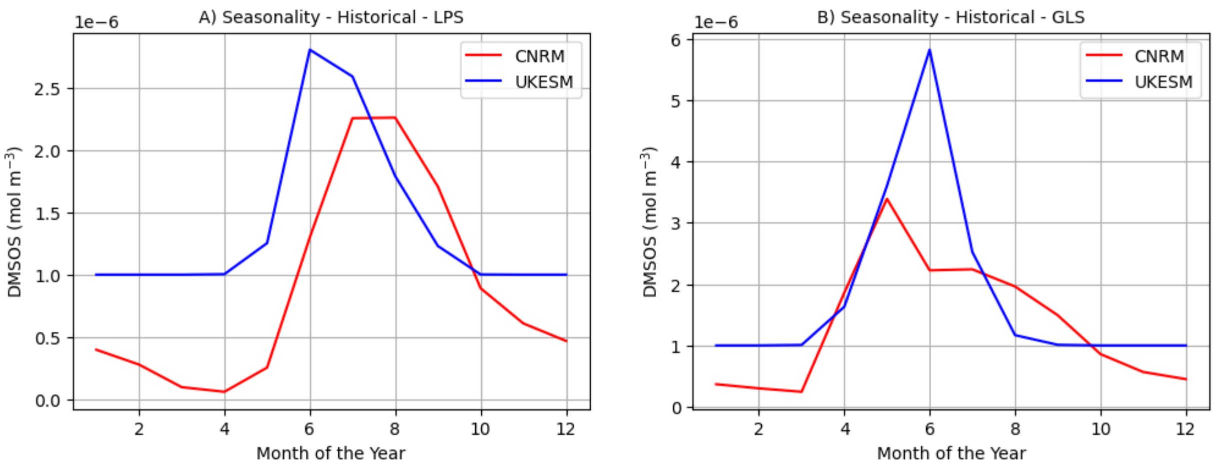

Fig7 The seasonal variability of DMSOS concentration predicted by UKESM (Blue) and CNRM (Red) monthly averaged over the whole historical period from 1850 to 2014 for A) LPS and B) GLS.

In the LPS area, both models predicted the peaking season to be in summer time. However, the peaking month was predicted differently between models, the UKESM predicted the peak to be on June, whereas, it was predicted to be on July-August by CNRM. In comparison to GLS, UKESM kept its prediction for the peaking month to be on June, whereas CNRM shifted the peak to be in spring time on May. To validate whether models captured the seasonal variability with the peaking month correctly and whether the peaking month would be predicted differently for different period of times, we compared the seasonal varibility predicted by each model for different periods and then we compared their seasonal varibility predictions to observations for the period from 2003 to 2014 only. Thus, we did the same calculations for the monthly mean for both areas, but for different periods including: a- the historical period, b- the first three decades in the historical period from 1850 to 1880, c- the last three decades of the historical period from 1984 to 2014, and d- from 2003 to 2014 the period from 2003 to 2014.

In [40]:

```
## plotting seasonality for different periods
## CNRM vs OBS
## Figure 8
mpl.rcParams.update({'font.size':12})
fig, ax = plt.subplots(1,2,figsize=(12,4))
# plotting LPS area
lns1=ax[0].plot(
    dmsosset_AreaMean_MonMean_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_CNRM_LapS,
    label='CNRM 1850-2014',color='red')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_CNRM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_CNRM_LapS,
    dmsosset_AreaMean_MonMean_CNRM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_CNRM_LapS,
    color='lightpink',alpha=0.5)
lns2=ax[0].plot(
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_LapS,
    label='CNRM 1850-1880',color='darkred')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_1850to1880_CNRM_LapS,
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_1850to1880_CNRM_LapS,
    color='mistyrose',alpha=0.5)
lns3=ax[0].plot(
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_LapS,
    label='CNRM 1984-2014',color='maroon')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_1984to2014_CNRM_LapS,
```

```
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_1984to2014_CNRM_LapS,
    color='seashell',alpha=0.5)
lns4=ax[0].plot(
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS,
    label='CNRM 2003-2014',color='peru')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS.month,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_2003to2014_CNRM_LapS,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_2003to2014_CNRM_LapS,
    color='linen',alpha=0.5)

ax0 = ax[0].twinx()
lns5=ax0.plot(
    dmsosObs_AreaMean_MonMean_LapS.month,
    dmsosObs_AreaMean_MonMean_LapS['dms']*1.0e-6,
    label='Obs 2003 - 2014',
         color='green')
ax0.fill_between(
    dmsosObs_AreaMean_MonMean_LapS.month,
    (dmsosObs_AreaMean_MonMean_LapS['dms']*1.0e-6)-0.5*
    (dmsosObs_AreaMean_MonSTD_LapS['dms']*1.0e-6),
    (dmsosObs_AreaMean_MonMean_LapS['dms']*1.0e-6)+0.5*
    (dmsosObs_AreaMean_MonSTD_LapS['dms']*1.0e-6),
    color='lightgreen',alpha=0.5)
# adding these three legends in one legend
lns = lns1+lns2+lns3+lns4+lns5
labs = [l.get_label() for l in lns]
ax[0].legend(lns, labs, bbox_to_anchor=(0,1.1,1,0.),
             loc="lower left",ncol=5,fontsize=10)
ax[0].set_xlabel('Month of the Year')
ax[0].set_ylabel('CMIP6 DMSOS (mol m$^{-3}$)')
ax[0].set_title('A) Seasonality - LPS - CNRM vs bs',
                fontsize=10)
ax[0].grid()
lns = lns1+lns2+lns3+lns4+lns5
labs = [l.get_label() for l in lns]
ax[0].legend(lns, labs, bbox_to_anchor=(0,1.1,1,0.),
             loc="lower left",ncol=5,fontsize=10)
# GLS area
ax[1].plot(
    dmsosset_AreaMean_MonMean_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_CNRM_GLS,
    label='1850-2014',color='red')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_CNRM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_CNRM_GLS,
    dmsosset_AreaMean_MonMean_CNRM_GLS
    +0.5*dmsosset_AreaMean_MonSTD_CNRM_GLS,
    color='lightpink',alpha=0.5)
ax[1].plot(
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_GLS,
```

```
    label='1850-1880',color='darkred')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_1850to1880_CNRM_GLS,
    dmsosset_AreaMean_MonMean_1850to1880_CNRM_GLS
    +0.5*dmsosset_AreaMean_MonSTD_1850to1880_CNRM_GLS,
    color='mistyrose',alpha=0.5)
ax[1].plot(
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_GLS,
    label='1984-2014',color='maroon')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_1984to2014_CNRM_GLS,
    dmsosset_AreaMean_MonMean_1984to2014_CNRM_GLS
    +0.5*dmsosset_AreaMean_MonSTD_1984to2014_CNRM_GLS,
    color='seashell',alpha=0.5)
ax[1].plot(
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS,
    label='2003-2014',color='peru')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS.month,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_2003to2014_CNRM_GLS,
    dmsosset_AreaMean_MonMean_2003to2014_CNRM_GLS
    +0.5*dmsosset_AreaMean_MonSTD_2003to2014_CNRM_GLS,
    color='linen',alpha=0.5)

ax1 = ax[1].twinx()
ax1.plot(
    dmsosObs_AreaMean_MonMean_GLS.month,
    dmsosObs_AreaMean_MonMean_GLS['dms']*1.0e-6,
    label='Obs 2003 - 2014',
    color='green')
ax1.fill_between(
    dmsosObs_AreaMean_MonMean_GLS.month,
    (dmsosObs_AreaMean_MonMean_GLS['dms']*1.0e-6)-0.5*
    (dmsosObs_AreaMean_MonSTD_GLS['dms']*1.0e-6),
    (dmsosObs_AreaMean_MonMean_GLS['dms']*1.0e-6)+0.5*
    (dmsosObs_AreaMean_MonSTD_GLS['dms']*1.0e-6),
    color='lightgreen',alpha=0.5)
ax1.set_ylabel("Observed DMSOS (mol m$^{-3}$)",
               color="green",fontsize=12)
ax[1].set_xlabel('Month of the Year')
#ax[1].set_ylabel('CMIP6 DMSOS (mol m$^{-3}$)')
ax[1].set_title('B) Seasonality - GLS - CNRM vs Obs',
                fontsize=10)
ax[1].grid()
```

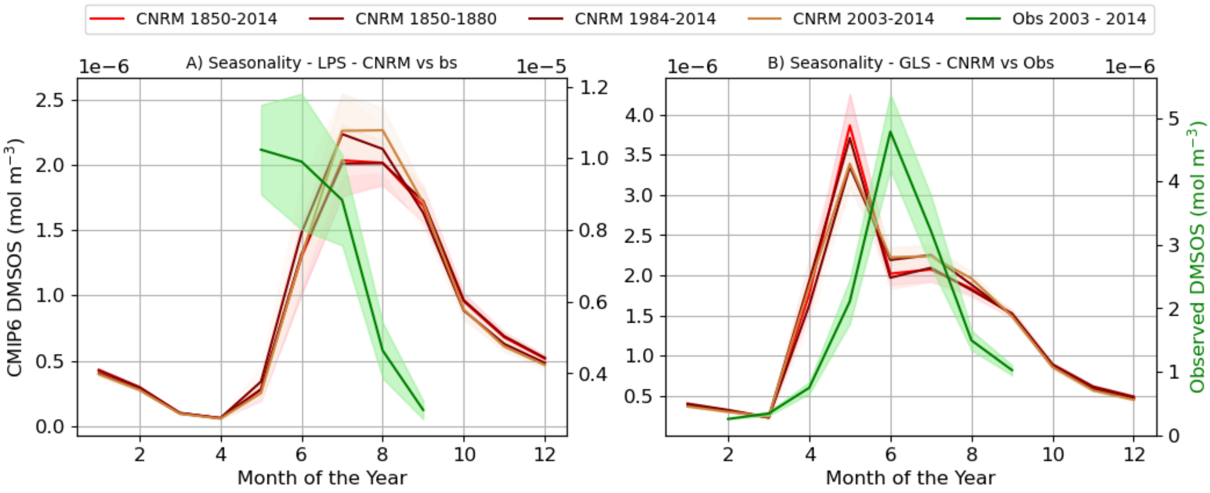

Fig8 The seasonal variability of DMSOS concentration predicted by CNRM, where it's monthly averaged over different periods of time including historical (red), 1850-1880 (darkred), 1984-2014 (maroon), and 2003-2014 (orange) compared to observations (green) for A) LPS and B) GLS. The sahded areas represent the standards deviation. Note that observations has its own y scale axes in the right handside for A and B.

As shown in Fig8, the observed peaking month of DMSOS was in May for LPS and in June for GLS, indicating that CNRM could not capture the observed seasonal peaking correctly and the deviation was more pronounced in the LPS area (2-month shift). In the LPS, the observed DMSOS concentration was almost an order of magnitude larger than has been predicted for the same period. In comparison to GLS, the observed concentration of DMSOS was comparable with CNRM predictions. The DMSOS predicted by CNRM was increasing in recent decades/years in the LPS area. On the other hand, a contradicting behavior can be seen in the GLS area, where CNRM tends to predict less DMSOS concentrations in the peaking season in recent years (Fig8, B). This might be related to the variation in the sea ice melting behavior in both areas, however, this needs further investigations in future studies.
To make it more clear, we did the same analysis but using UKESM and the results are shown in Fig9.

In [41]:
```
## same as figure 8 but for UKESM vs OBS
## Figure 9
mpl.rcParams.update({'font.size':12})
fig, ax = plt.subplots(1,2, figsize=(12,4))
## LPS area
lns1=ax[0].plot(
    dmsosset_AreaMean_MonMean_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_UKESM_LapS,
    label='UKESM 1850-2014',color='blue')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_UKESM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_UKESM_LapS,
    dmsosset_AreaMean_MonMean_UKESM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_UKESM_LapS,
    color='lightblue',alpha=0.5)
lns2=ax[0].plot(
```

```
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_LapS,
    label='UKESM 1850-1880',color='skyblue')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_1850to1880_UKESM_LapS,
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_1850to1880_UKESM_LapS,
    color='lightskyblue',alpha=0.5)
lns3=ax[0].plot(
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_LapS,
    label='UKESM 1984-2014',color='purple')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_1984to2014_UKESM_LapS,
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_1984to2014_UKESM_LapS,
    color='thistle',alpha=0.5)
lns4=ax[0].plot(
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS,
    label='UKESM 2003-2014',color='cyan')
ax[0].fill_between(
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS.month,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS
    -0.5*dmsosset_AreaMean_MonSTD_2003to2014_UKESM_LapS,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_LapS
    +0.5*dmsosset_AreaMean_MonSTD_2003to2014_UKESM_LapS,
    color='lightcyan',alpha=0.5)
ax0=ax[0].twinx()
lns5=ax0.plot(
    dmsosObs_AreaMean_MonMean_LapS.month,
    dmsosObs_AreaMean_MonMean_LapS['dms']*1.0e-6,
    label='Obs 2003 - 2014',
    color='green')
ax[0].set_xlabel('Month of the Year')
ax[0].set_ylabel('DMSOS (mol m$^{-3}$)')
ax[0].set_title('Seasonality - LPS - UKESM vs Obs',
                fontsize=10)
ax[0].grid()
lns = lns1+lns2+lns3+lns4+lns5
labs = [l.get_label() for l in lns]
ax[0].legend(lns, labs, bbox_to_anchor=(0,1.1,1,0.),
             loc="lower left",ncol=5,fontsize=10)
# GLS area
ax[1].plot(
    dmsosset_AreaMean_MonMean_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_UKESM_GLS,label='UKESM; 1850-2014',
    color='blue')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_UKESM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_UKESM_GLS,
    dmsosset_AreaMean_MonMean_UKESM_GLS
```

```
    +0.5*dmsosset_AreaMean_MonSTD_UKESM_GLS,
    color='lightblue',alpha=0.5)
ax[1].plot(
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_GLS,
    label='UKESM; 1850-1880',color='skyblue')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_1850to1880_UKESM_GLS,
    dmsosset_AreaMean_MonMean_1850to1880_UKESM_GLS
    +0.5*dmsosset_AreaMean_MonSTD_1850to1880_UKESM_GLS,
    color='lightskyblue',alpha=0.5)
ax[1].plot(
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_GLS,
    label='UKESM; 1984-2014',color='purple')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_1984to2014_UKESM_GLS,
    dmsosset_AreaMean_MonMean_1984to2014_UKESM_GLS
    +0.5*dmsosset_AreaMean_MonSTD_1984to2014_UKESM_GLS,
    color='thistle',alpha=0.5)
ax[1].plot(
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS,
    label='UKESM; 2003-2014',color='cyan')
ax[1].fill_between(
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS.month,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS
    -0.5*dmsosset_AreaMean_MonSTD_2003to2014_UKESM_GLS,
    dmsosset_AreaMean_MonMean_2003to2014_UKESM_GLS
    +0.5*dmsosset_AreaMean_MonSTD_2003to2014_UKESM_GLS,
    color='lightcyan',alpha=0.5)
ax1=ax[1].twinx()
ax1.plot(
    dmsosObs_AreaMean_MonMean_GLS.month,
    dmsosObs_AreaMean_MonMean_GLS['dms']*1.0e-6,
    label='Obs; 2003 - 2014',color='green')
ax1.set_ylabel("Observed DMSOS (mol m$^{-3}$)",
               color="green",fontsize=12)
ax[1].set_xlabel('Month of the Year')
#ax[1].set_ylabel('DMSOS (mol m$^{-3}$)')
ax[1].set_title('A) Seasonality - GLS - UKESM vs Obs',
                fontsize=10)
ax[1].grid()
```

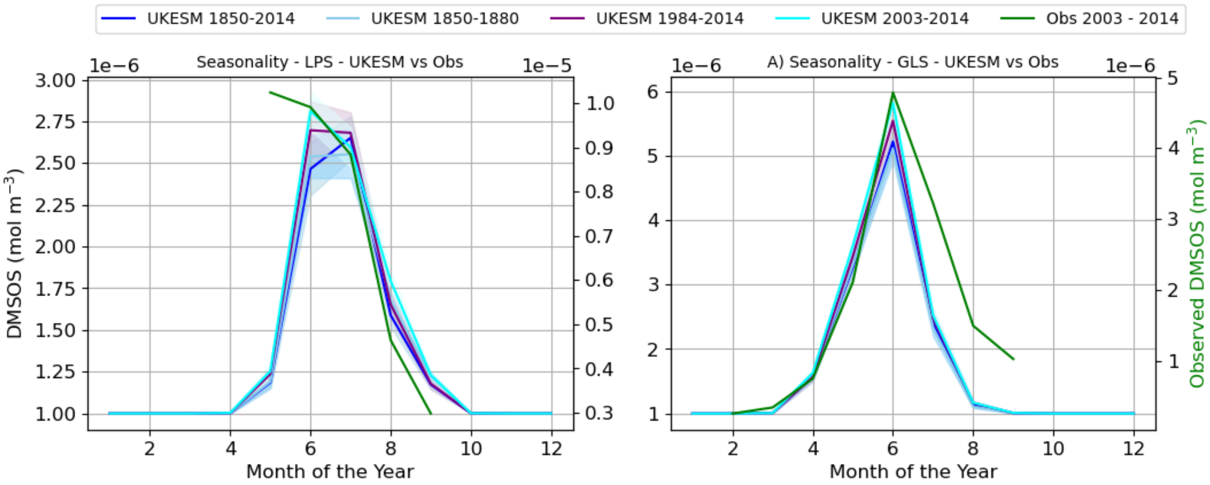

Fig9 The seasonal variability of DMSOS concentration predicted by UKESM, where it's monthly averaged over different periods of time including historical (blue), 1850-1880 (lightblue), 1984-2014 (violet), and 2003-2014 (cyan) compared to observations (green) for A) LPS and B) GLS. The sahded areas represent the standards deviation. Note that observations has its own y scale axes in the right handside for A and B.

In the LPS area, the observed DMSOS concentration was an order of magnitude larger than what is predicted by UKESM, but it was comparable in the GLS area. In both areas, the DMSOS concentration predicted by UKESM increased through the years similarly to what CNRM has predicted for LPS, but in contradiction for GLS area. This indicates that CNRM might have tendency to wrongly estimate the seasonal varibility of DMSOS, and improvements needs to be established for CNRM. Interestingly, UKESM could capture the observed peaking month in the GLS area, but it was one month shifted to summer time in the LPS area. This suggests that UKESM can better capture the climatological and the seasonal variability of DMSOS concentrations than CNRM.

3-4 Correlation between CMIP6 and Observations

To further Check out the correlation between CMIP6 and observations, we plotted the spatial mean of DMSOS that were monthly averaged for the period 2003 to 2014 for each studied domain (LPS and GLS) predicted by each model versus observations. In a later step, we estimated the correlation/relationship between CMIP6 predictions and observation by fitting the data (CMIP6 vs Observations) linearly as shown in Fig10.

In [42]:
```
# CMIP6 over LapSea
dmsosset_AreaMean_2003to2014_UKESM_LapS = \
dmsosset_AreaMean_UKESM_LapS.isel(
    time=slice(1836,None))

dmsosset_AreaMean_2003to2014_CNRM_LapS = \
dmsosset_AreaMean_CNRM_LapS.isel(
    time=slice(1836,None))
# CMIP6 over GLS
dmsosset_AreaMean_2003to2014_UKESM_GLS = \
dmsosset_AreaMean_UKESM_GLS.isel(
    time=slice(1836,None))

dmsosset_AreaMean_2003to2014_CNRM_GLS = \
dmsosset_AreaMean_CNRM_GLS.isel(
    time=slice(1836,None))
```

In [43]:
```
dmsObs_mthlymean_LapS = \
dmsosObs_AreaMean_2003to2014_LapS.resample(
    time='d').nearest().resample(time='m').mean()

dmsObs_mthlymean_GLS = \
dmsosObs_AreaMean_2003to2014_GLS.resample(
    time='d').nearest().resample(time='m').mean()
```

```
/srv/conda/envs/notebook/lib/python3.9/site-packages/flox/aggregate_flox.
py:105: RuntimeWarning: invalid value encountered in divide
  out /= nanlen(group_idx, array, size=size, axis=axis, fill_value=0)
/srv/conda/envs/notebook/lib/python3.9/site-packages/flox/aggregate_flox.
py:105: RuntimeWarning: invalid value encountered in divide
  out /= nanlen(group_idx, array, size=size, axis=axis, fill_value=0)
```

In [44]:
```
## calculating linear regression
model_CNRM_LPS_fit=linreg(
    dmsosset_AreaMean_2003to2014_CNRM_LapS,
    dmsObs_mthlymean_LapS['dms']*1e-6)

model_UKESM_LPS_fit=linreg(
    dmsosset_AreaMean_2003to2014_UKESM_LapS,
    dmsObs_mthlymean_LapS['dms']*1e-6)

model_CNRM_GLS_fit=linreg(
    dmsosset_AreaMean_2003to2014_CNRM_GLS,
    dmsObs_mthlymean_GLS['dms']*1e-6)

model_UKESM_GLS_fit=linreg(
    dmsosset_AreaMean_2003to2014_UKESM_GLS,
    dmsObs_mthlymean_GLS['dms']*1e-6)
## plotting correlation of models vs obs
## Figure 10
mpl.rcParams.update({'font.size':11})
fig, ax = plt.subplots(1,2,figsize=(12,4))

ax[0].scatter(
    dmsosset_AreaMean_2003to2014_CNRM_LapS,
    dmsObs_mthlymean_LapS['dms']*1e-6,
```

```
    color='red', label='CNRM')
ax[0].scatter(
    dmsosset_AreaMean_2003to2014_UKESM_LapS,
    dmsObs_mthlymean_LapS['dms']*1e-6,
    color='blue', label='UKESM')
ax[0].plot(
    model_CNRM_LPS_fit[0],model_CNRM_LPS_fit[2],
    '--k', color='red')
ax[0].plot(
    model_UKESM_LPS_fit[0],model_UKESM_LPS_fit[2],
    '--k', color='blue')

ax[1].scatter(
    dmsosset_AreaMean_2003to2014_CNRM_GLS,
    dmsObs_mthlymean_GLS['dms']*1e-6,
    color='red', label='CNRM')
ax[1].scatter(
    dmsosset_AreaMean_2003to2014_UKESM_GLS,
    dmsObs_mthlymean_GLS['dms']*1e-6,
    color='blue', label='UKESM')
ax[1].plot(
    model_CNRM_GLS_fit[0],model_CNRM_GLS_fit[2],
    '--k', color='red')
ax[1].plot(
    model_UKESM_GLS_fit[0],model_UKESM_GLS_fit[2],
    '--k', color='blue')
ax[0].set_xlabel('DMSOS (mol m$^{-3}$) - Model')
ax[1].set_xlabel('DMSOS (mol m$^{-3}$) - Model')
ax[0].set_ylabel('DMSOS (mol m$^{-3}$) - Obs (MOD-Aqu)')
ax[1].set_ylabel('DMSOS (mol m$^{-3}$) - Obs (MOD-Aqu)')
ax[0].set_title('A) LPS - UKESM & CNRM vs Obs Corr')
ax[1].set_title('B) GLS - UKESM & CNRM vs Obs Corr')
ax[0].legend()
ax[1].legend()
ax[0].grid(), ax[1].grid()
```

```
/tmp/ipykernel_4496/1773575409.py:30: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[0].plot(
/tmp/ipykernel_4496/1773575409.py:33: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[0].plot(
/tmp/ipykernel_4496/1773575409.py:45: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[1].plot(
/tmp/ipykernel_4496/1773575409.py:48: UserWarning: color is redundantly d
efined by the 'color' keyword argument and the fmt string "--k" (-> color
='k'). The keyword argument will take precedence.
  ax[1].plot(
```

Out[44]:

```
(None, None)
```

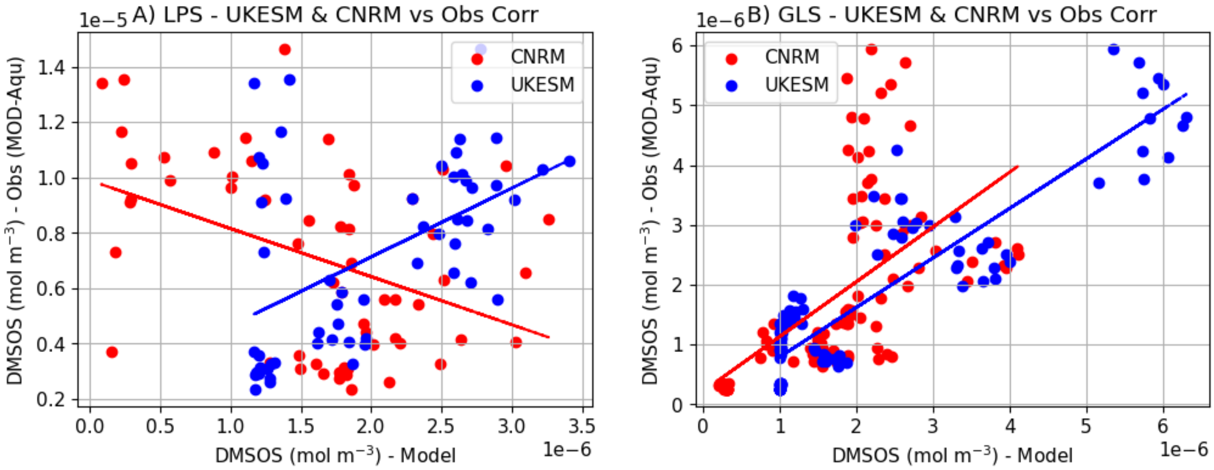

Fig10 The correlation of spatial monthly averaged DMSOS concentration predicted by CMIP6 models, i.e. UKESM (blue circles) and CNRM (red circles) and observations. The lines represent the fitting (correlations) between UKESM and observations (blue line) and between CNRM and observations (red line) for both areas A) LPS and B) GLS.

In both LPS and GLS areas, the DMSOS concentartion predicted by UKESM correlates well and positively with observations (blue lines in Fig 10). This goes well with the hypothesis of the impact of sea ice melting in increasing the productivity and the surface concentration of DMSOS in the Arctic region. However, the DMSOS concentartion predicted by CNRM correlates well and positively with observations in the GLS area (red line in Fig 10 B), but the correlation was negative in the LPS area (red line in Fig 10 A). There is no clear explanation to the latter point. Once again, CNRM failed in illustrating the expected correlation with observations in the LPS area indicating that CNRM should be improved to better capture the seasonal variability and the increase of DMSOS concentrations in the recent years.

4- Conclusions

In this study, we aim to discuss the impact of Arctic amplification on the productivity and variability in estimating and predicting the sea surface concentrations of Dimethylsulfide gas in the Arctic regions. For that purpose, we chose two contrasting domains in the Arctic, namely the Laptev Sea and the Greenland Sea. We used CMIP6 model diagnostic called "DMSOS" which represents the sea surface concentration of Dimethylsulfide. Two models from CMIP6, i.e. UKESM-1-0-LL and CNRM-ESM-2-1, were compared to each other (map distribution, climatology, and seasonal variability) for the different periods (historical, 1850 to 1880, 1984 to 2014, and 2003 to 2014). In a later step, both models were compared to observations for the period 2003 to 2014 and a correlation between models and observations was evaluated and analyzed. The observation was a remote sensing algorithm that estimates the Dimethylsulfide Concentration based on remotely sensed variables in the Moderate Resolution Imaging Spectroradiometer onboard the Aqua satellite (MODIS-Aqua, 2003–2016) (Gali et al. (2019)). Given that in the Arctic and during the melting season (summer and spring), the conditions at the Arctic sea ice favor the growth of phytoplankton and ice algae, that are responsible for Dimethylsulfide production, therefore, we hypothesized that the Dimethylsulfide surface concentration increases in recent years due to sea ice melting. Thus, this study aims to answer the following research questions:

1- How Dimethylsulfide concentrations are represented in different climate Models in the Arctic regions? Models predicted the overall annual mean of sea surface concentration of Dimethylsulfide differently over both chosen domains, whereas UKESM predicted a larger concentration than CNRM did. This is something expected and can be due to the different spatial and temporal resolutions that both models have as well as the different mechanisms that are used to introduce the Dimethylsulfide in each of those models. The long-term (climatology) trend of the DMSOS for the whole historical period predicted by UKESM and CNRM was generally positive (increase) for both areas, except for CNRM predictions in the Laptev Sea area. However, in recent years all models predicted a positive trend similar to observations.

2- How DMS concentration is represented in observations and how these observed concentrations are different from models (matching periods 2003-2014)? The observed sea surface concentration of Dimethylsulfide was larger than what has been predicted by both models for both areas; being an order of magnitude higher in the Laptev sea area and up to a factor of ~2 in the Greenland Sea. This suggests that both models underestimated the Dimethylsulfide sea surface concentration relative to observations. More importantly, the observed mean of DMSOS over the LPS domain is higher than what is observed in the GLS domain. The latter contradicts what models are predicting. This can be explained by the more pronounced decrease of sea ice content (sea ice melting) during recent years due to Arctic amplification, which has more influence on the LPS domain than GLS, which is more represented by the open sea. In addition, the LPS area is also surrounded by land that has rivers feeding into the ice and the ocean that can impact the nutrient amount that can be thrown to the ocean as well as the salinity. all these factors can play an important role in increasing the productivity of DMSOS in the surface ocean especially in the melting season.

3- can models capture the seasonal variability and the peaking season of Dimethylsulfide? Both models differentiate from each other in estimating the seasonal variability as well as in predicting the peaking month for both areas and for different time periods. The peaking month predicted by UKESM was on June for both regions, whereas the peak shifted from July (summer) to May (spring) for the Laptev Sea and Greenland Sea, respectively, as predicted by CNRM. Validating the seasonal variability in recent years to observations, it was found that UKESM could capture the peaking month similarly to observations in the Greenland Sea area, but it was one month shifted in the Laptev Sea (observation peak was in May). On the other hand, CNRM deviated by two months shifted to summertime in the Laptev Sea and one month in the Greenland Sea (CNRM peak was in May). This suggests that UKESM can do better predictions of Dimethylsulfide than CNRM.

4- How sea ice and ice-melting would impact DMS concentrations and what is the correlation between the predicted Dimethylsulfide and the observed ones? The impact of the sea ice retreat on changing the productivity and concentration of Dimethylsulfide was obvious specifically when comparing UKESM predictions to observations in both areas especially in the Laptev sea (comparing the first 4 figures in this report to fig 4 in Jessica's report). In Gali et al. (2019), where the observations are taken, the authors showed that Dimethylsulfide concentrations have increased significantly in the Arctic regions due to ice melting and sea ice retreat in recent years. In this report, we further evaluated the correlation between CMIP6 data and observations to test the latter hypothesis. It's clear that Dimethylsulfide predicted by UKESM correlates well with observations and that the increase in their concentration was proven.
In summary, the Dimethylsulfide was predicted differently by different models, and models predictions still deviates from observations. However, some models can do a better job than others. Nevertheless, this suggests that there is a need to improve our models to better predicts the Dimethylsulfide surface concentration and emissions to better assess their relative atmospheric processes and climatic impacts and decrease their uncertainties.

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Appendix A:

Useful functions that are used here in this code including 4 functions:

- interGali
- plot_map_2panels
- plot_map_3panels
- linreg Thise functions were all in a python file called Functions_Maher_report.py

In [45]:
```
## Libraries
# load useful packages
import xarray as xr
xr.set_options(display_style='html')
import intake
import cftime
import matplotlib.pyplot as plt
from matplotlib import cm
import cartopy
import cartopy.crs as ccrs
import s3fs
import pandas as pd
from dask.diagnostics import ProgressBar
import cartopy.crs as ccrs
from mpl_toolkits.axes_grid1.inset_locator import inset_axes
import numpy as np
import matplotlib as mpl
from scipy.interpolate import griddata


## Function for Interploting data on a regular lat,lon grid
from scipy.interpolate import griddata
def interGali(ds,var):
    '''

        grid is built from latitudes and the longitudes
        on the lowest latitude
        Input :
            ds : xarray dataset with latitude,
            longitude and variable "var" to be interpolated.
            var, lat,long must be 1d (ie. not depend on time)
            var : string name of variable
        Returns a xarray dataArray with the gridded
        variable and lat lon as coords
    '''
    # sorting according to latitudes
    lalo = pd.MultiIndex.from_arrays([ds.latitude.values,
                                      ds.longitude.values]
                                    ).sortlevel(level=0)[0]
    # get longitudes of lowest latitude
    lowlat = lalo.values[0][0]
    lon1d = np.array([x[1]
                      for x in lalo.values if x[0]==lowlat])
    # get latitudes
    lat1d = np.unique(ds.latitude.values)
    # Building regular grid of lat and lon
    lon, lat = np.meshgrid(lon1d,lat1d)

    # interpolation
    var_gridded =griddata(
            (ds.longitude.values, ds.latitude.values), #points
            ds[var].values, #data
            (lon, lat), #grid on which to interpolate
            method='nearest')

    return  xr.DataArray(
```

```
        var_gridded,
        dims=("lat","lon"),
        coords={
            "lat": lat1d,
            "lon": lon1d
        }
    )

## Function to plot 2 panels maps
def plot_map_2panels(lon1,lat1,data1,title1,
                     lon2,lat2,data2,title2,extent):
    mpl.rcParams.update({'font.size':10})

    fig, ax = plt.subplots(1,2,figsize=(6,5),
                           subplot_kw={
                               'projection'\
                               :ccrs.NorthPolarStereo()})
    MapL=ax[0].pcolormesh(lon1,lat1,data1,
        vmin=0,vmax=2.0e-6,
        transform=ccrs.PlateCarree(),
            )
    ax[0].add_feature(
        cartopy.feature.LAND, zorder=1,
        edgecolor='black')
    ax[0].set_title(title1, fontsize = 10)
    ax[0].gridlines(draw_labels=True)
    ax[0].coastlines()
    ax[0].set_extent(extent, ccrs.PlateCarree())
    ax[0].add_feature(
        cartopy.feature.RIVERS, zorder=1,
        edgecolor='blue')

    MapR=ax[1].pcolormesh(lon2,lat2,data2,
                          vmin=0,vmax=2.0e-6,
                          transform=ccrs.PlateCarree(),
            )
    ax[1].add_feature(
        cartopy.feature.LAND, zorder=1,
        edgecolor='black')
    ax[1].gridlines(draw_labels=True)
    ax[1].coastlines()
    ax[1].set_extent(extent, ccrs.PlateCarree())
    ax[1].set_title(title2, fontsize = 10)
    ax[1].add_feature(cartopy.feature.RIVERS,
                      zorder=1, edgecolor='blue')

#fig.colorbar(pl_CMIP6,shrink=0.4)
############# COLORBAR properties ##############
# create the ax based on an ax dimensions
    axins = inset_axes(ax[1],
            width="6%",
            height="100%",
            loc='right',
            borderpad=-3
                )

# add colorbar from ax
```

```
    cbar = fig.colorbar(
        MapL, cax=axins, orientation='vertical')
    cbar = fig.colorbar(
        MapR, cax=axins, orientation='vertical')
# style(axins)
    cbar.set_label(
        'DMSOS (mol/m$^{-3}$)', fontsize=10)

# thickness of spines around the colorbar
    cbar.outline.set_linewidth(1)
    fig.tight_layout()
    def style_cbar(ax):
        ax.tick_params(
            axis='both', which='major',
            labelsize=10)
        ax.tick_params(
            axis='both', which='both',
            length=8, width=1, direction='out')
    style_cbar(axins)
    return (MapL,MapR)

## Function to plot 3 panels maps
def plot_map_3panels(
    lon1,lat1,data1,title1,
    lon2,lat2,data2,title2,
    lon3,lat3,data3,title3,
    extent):
    mpl.rcParams.update({'font.size':10})

    fig, ax = plt.subplots(
        1,3,figsize=(8,7),
        subplot_kw={
            'projection':ccrs.NorthPolarStereo()})
    MapL=ax[0].pcolormesh(lon1,lat1,data1,
        vmin=0,vmax=2.0e-6,
        transform=ccrs.PlateCarree(),
            )
    ax[0].add_feature(
        cartopy.feature.LAND,
        zorder=1, edgecolor='black')
    ax[0].set_title(title1, fontsize = 10)
    ax[0].gridlines(draw_labels=True)
    ax[0].coastlines()
    ax[0].set_extent(extent, ccrs.PlateCarree())
    ax[0].add_feature(
        cartopy.feature.RIVERS,
        zorder=1, edgecolor='blue')

    MapM=ax[1].pcolormesh(lon2,lat2,data2,
        vmin=0,vmax=2.0e-6,
        transform=ccrs.PlateCarree(),
            )
    ax[1].add_feature(
        cartopy.feature.LAND,
        zorder=1, edgecolor='black')
    ax[1].gridlines(draw_labels=True)
    ax[1].coastlines()
```

```
    ax[1].set_extent(extent, ccrs.PlateCarree())
    ax[1].set_title(title2, fontsize = 10)
    ax[1].add_feature(cartopy.feature.RIVERS,
                      zorder=1, edgecolor='blue')

    MapR=ax[2].pcolormesh(lon3,lat3,data3,
        vmin=0,vmax=2.0e-6,
        transform=ccrs.PlateCarree(),
            )
    ax[2].add_feature(
        cartopy.feature.LAND,
        zorder=1, edgecolor='black')
    ax[2].gridlines(draw_labels=True)
    ax[2].coastlines()
    ax[2].set_extent(extent, ccrs.PlateCarree())
    ax[2].set_title(title3, fontsize = 10)
    ax[2].add_feature(
        cartopy.feature.RIVERS,
        zorder=1, edgecolor='blue')


#fig.colorbar(pl_CMIP6,shrink=0.4)
############# COLORBAR properties #############
# create the ax based on an ax dimensions
    axins = inset_axes(ax[2],
            width="6%",
            height="100%",
            loc='right',
            borderpad=-3
                )

# add colorbar from ax
    cbar = fig.colorbar(
        MapL, cax=axins, orientation='vertical')
    cbar = fig.colorbar(
        MapM, cax=axins, orientation='vertical')
    cbar = fig.colorbar(
        MapR, cax=axins, orientation='vertical')
# style(axins)
    cbar.set_label('DMSOS (mol/m$^{-3}$)', fontsize=10)

# thickness of spines around the colorbar
    cbar.outline.set_linewidth(1)
    fig.tight_layout()
    def style_cbar(ax):
        ax.tick_params(axis='both',
                       which='major',
                       labelsize=10)
        ax.tick_params(axis='both',
                       which='both',
                       length=8, width=1,
                       direction='out')
    style_cbar(axins)
    return (MapL,MapM,MapR)
```

```
## Function to calculate the linear regression
## for the climatic and seasonal trends
from scipy import stats
def linreg(x,y):
    dict_ = {'x':x.values,'y':y.values}
    df_ = pd.DataFrame.from_dict(dict_)
    df_ = df_.dropna()
    slope, intercept, r_value, p_value, std_err = \
    stats.linregress(df_['x'],df_['y'])
    fitted_model = slope*df_['x'] + intercept
    return (
        df_['x'],df_['y'],fitted_model,
        slope,intercept)
```