Reduced sea ice extent and implications for nutrient availibity in the Arctic: A case study of the Laptev Sea

Jessica Burger [brgjes006@myuct.ac.za]

Group 4: Assisted by Antoine Haddon

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1.0 Abstract

This report investigates whether reduced sea ice extent in the Laptev Sea on the Arctic Siberian Shelf, has influenced nutrient availability. The Laptev Sea recieves large amounts of nutrients from the Lena River and acts as an important source region for the Transpolar Drift, which ultimately distributes these nutrients to the central Arctic basin. Thus, Laptev Sea nutrients are important for supporting primary productivity locally and elsewhere in the Arctic. First, the reduction in summertime sea ice extent over Laptev Sea region is analysed using high resolution daily satellite observations from 2002 to 2019. These observations are compared to two CMIP6 models, namely CNRM and UKESM to asses the ability of these models in reproducing the seasonality and extent of sea over the recent past. CNRM is further utilised to assess differences in sea ice extent and nutrient availabilty (here defined as sea surface nitrate concentration) between the histrorical period of 1850 to 2001 and the recent period of 2002 to 2014.

2.0 Introduction

Retreating summertime sea ice cover in the Arctic has occured concurrrently with increased primary productivity over the recent past (Arrigo and van Dijken, 2015). This has been attributed to a number of factors, some of which include increased light penetration and lengthening of the phytoplankton growing season (Arrigo and van Dijken, 2015).
In sunlit surface waters, primary productivity can be limited by nutrient availability (Laukert et al., 2022). In Arctic shelf regions, terrigenous nutrient inputs from land exert a strong control on nutrient availability in addition to vertical mixing, supporting approximately one third of current Arctic ocean net primary production (Terhaar et al., 2021).
Despite the generally observed trends and reduction in sea ice extent, some coastal areas of the Arctic have experienced a decline in primary productivity (Ardyna and Arrigo et al., 2020). It remains unclear how this inconsistent phytoplankton repsonse is linked to stratification and nutrient cycling (Laukert et al., 2022). However, it suggests that a better understanding of the controlling mechanisms in shelf regions is required, to assess ecosystem functioning and how it might change under future climate scenarios.
The Laptev Sea recieves large amounts of fresh water and nutrients from the Lena River and is the main source region for the Transpolar Drift (TPD), exporting nutrients to the central Arctic basin (Paffrath et al., 2021). As such, the Laptev sea is a key region for investigating

nutrient dynamics on the Siberian Shelf.
This report investigates seasonal and long term trends in sea ice extent as observed from satellites and compares observations with two CMIP6 models. Further more, CMIP6 model output is used to investigate the relationship between sea ice extent and nutrient availabilty (here: surface nitrate (NO$_{3}^{-}$) concentrations).

3.0 Methods

This report makes use of both observations and model data. High resolution (6.35 km) daily satellite derived sea ice concentration data was obtained from the AMSR2 and AMSR-E satellite products (Melsheimer & Spreen (2019a & b)), with data available for the years 2002 to 2019. A function was defined to import the data, create a time variable and produce monthly netcdf files from the daily data (see Supplementary Material).
The CMIP6 models investigated were CNRM and UKESM. In both cases the historical runs were imported with data available for years 1850 to 2014. The variables of interest were sea ice concentration and nitrate concentration.

3.1 Packages

First, all useful packages were imported.

In [1]:
```
import xarray as xr
import matplotlib.pyplot as plt
import pandas as pd
import cartopy.crs as ccrs
import cartopy
from datetime import datetime, timedelta
import numpy as np
import pyproj
from dask.diagnostics import ProgressBar
import matplotlib.dates as mdate
import intake
import cftime
```

3.2 Satellite sea ice data

Initially, all the available sea ice concentration data was imported and combined to form a single dataset.
First all the satellite observational data was imported, and the co-ordinates converted from x and y to latitude and longitude.
This needed to be done before any areas of interest can be selected.

In [29]:
```
sat = xr.open_mfdataset("SICdata/AMSR*.nc", combine='by_coords')
# We want the output coordinates in WGS 84 Longitude and Latitude
projOut = pyproj.Proj(init='epsg:4326')
# The input coordinates are in meters on a North Polar Stereographic grid
projIn = pyproj.Proj(init='epsg:3411', preserve_units=True)
xx, yy = np.meshgrid( sat.x.values, sat.y.values)
lon,lat= pyproj.transform(projIn, projOut, xx, yy )
sat['lon'] = (('y','x'),lon)
sat['lat'] = (('y','x'),lat)
```

```
/srv/conda/envs/notebook/lib/python3.9/site-packages/pyproj/crs/crs.py:130: Future
Warning: '+init=<authority>:<code>' syntax is deprecated. '<authority>:<code>' is
the preferred initialization method. When making the change, be mindful of axis or
der changes: https://pyproj4.github.io/pyproj/stable/gotchas.html#axis-order-chang
es-in-proj-6
  in_crs_string = _prepare_from_proj_string(in_crs_string)
/srv/conda/envs/notebook/lib/python3.9/site-packages/pyproj/crs/crs.py:130: Future
Warning: '+init=<authority>:<code>' syntax is deprecated. '<authority>:<code>' is
the preferred initialization method. When making the change, be mindful of axis or
der changes: https://pyproj4.github.io/pyproj/stable/gotchas.html#axis-order-chang
es-in-proj-6
  in_crs_string = _prepare_from_proj_string(in_crs_string)
/tmp/ipykernel_399/1579399248.py:7: DeprecationWarning: This function is deprecate
d. See: https://pyproj4.github.io/pyproj/stable/gotchas.html#upgrading-to-pyproj-2
-from-pyproj-1
  lon,lat= pyproj.transform(projIn, projOut, xx, yy )
```

Next, an area of interest is selected: The Laptev Sea on the Siberian Shelf.

In [30]:
```
sat_SS = sat.where((sat.lon>= 100) & (sat.lon<= 160)
        & (sat.lat<= 80) & (sat.lat>= 70), drop = True)
```

Finally, the sea ice extent was calculated, bearing in mind that all grid cells are the same size (6.25 km x 6.25 km).
Only grid cells with sea ice concentrations greater than 15% were considered.

In [31]:
```
area = 6.25**2
with ProgressBar():
    iceExt = ((xr.where(sat_SS.z>15, 1.,0).sum(dim=['x','y']))*area).compute()
iceExt=xr.where(iceExt>0,iceExt,np.NaN)
```

```
[########################################] | 100% Completed | 170.73 s
```

Lastly, 2-dimensional arrays of 'time' and 'sea ice extent' were created.

In [32]:
```
ys = np.unique(sat_SS.time.dt.year) #x axis = years
doy= np.arange(150,330) #y axis = day of years
t2d = np.array([
    [np.datetime64(str(y)) + np.timedelta64(d, 'D') for d in doy ]
        for y in ys])
ice2d = np.array([
        [ iceExt.sel(time=d) if d in iceExt.time else np.NaN for d in y ]
            for y in t2d ])
```

3.3 CMIP6 model data

Next, all relevant CMIP6 model data were imported. Datasets were created for UKESM and CNRM areacello, no3 and siconc.
The processing methods are subdivided by variable in sections 3.4 to 3.6 below.

To include model data for comparison, the CMIP6 online catalogue was opened and utilised.
I was interedted in historical data from CNRM and UKESM with variables including siconc, no3, and areacello.
As a result, these are included in the dataset search.

In [2]:
```
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','UKESM1-0-LL'],
                 experiment_id=['historical','piControl'],
                 table_id=['SImon','Omon','Ofx'],
                 variable_id=['siconc','no3','areacello'])
                 #member_id=['r1i1p1f1'])
```

A dictionary was then created from the list of datasets found.

In [5]:
```
dset_dict = cat.to_dataset_dict(zarr_kwargs={'use_cftime':True})
```

```
--> The keys in the returned dictionary of datasets are constructed as follows:
        'activity_id.institution_id.source_id.experiment_id.table_id.grid_label'
```

100.00% [12/12 00:03<00:00]

In [7]:
```
#Explore what data is inside the dictionary
dset_dict.keys()
```

Out[7]:
```
dict_keys(['CMIP.CNRM-CERFACS.CNRM-ESM2-1.piControl.Ofx.gn', 'CMIP.CNRM-CERFACS.CN
RM-ESM2-1.historical.Ofx.gn', 'CMIP.MOHC.UKESM1-0-LL.piControl.Ofx.gn', 'CMIP.CNRM
-CERFACS.CNRM-ESM2-1.historical.SImon.gn', 'CMIP.CNRM-CERFACS.CNRM-ESM2-1.piContro
l.SImon.gn', 'CMIP.NIMS-KMA.UKESM1-0-LL.historical.SImon.gn', 'CMIP.CNRM-CERFACS.C
NRM-ESM2-1.piControl.Omon.gn', 'CMIP.CNRM-CERFACS.CNRM-ESM2-1.historical.Omon.gn',
'CMIP.NIMS-KMA.UKESM1-0-LL.historical.Omon.gn', 'CMIP.MOHC.UKESM1-0-LL.historical.
SImon.gn', 'CMIP.MOHC.UKESM1-0-LL.piControl.SImon.gn', 'CMIP.MOHC.UKESM1-0-LL.hist
orical.Omon.gn'])
```

Finally, datasets were created for each model and each variable of interest.

In [9]:
```
cnrm_area = dset_dict[list(dset_dict.keys())[1]]
cnrm_si = dset_dict[list(dset_dict.keys())[3]]
cnrm_no3 = dset_dict[list(dset_dict.keys())[7]]
uk_area = dset_dict[list(dset_dict.keys())[2]]
uk_si = dset_dict[list(dset_dict.keys())[9]]
uk_no3 = dset_dict[list(dset_dict.keys())[11]]
```

In [39]:
```
uk_si
```

Out[39]: xarray.Dataset

► Dimensions: (**i**: 360, **j**: 330, **member_id**: 16, **time**: 1980, bnds: 2, vertices: 4)

▼ Coordinates:

i	(i)	int32	0 1 2 3 4 5 ... 355 356 357 3...
j	(j)	int32	0 1 2 3 4 5 ... 325 326 327 3...
latitude	(j, i)	float32	dask.array<chunksize=(330...
longitude	(j, i)	float32	dask.array<chunksize=(330...
time	(time)	object	1850-01-16 00:00:00 ... 201...
time_bnds	(time, bnds)	object	dask.array<chunksize=(198...
type	()	|S7	...
member_id	(member_id)	<U9	'r2i1p1f2' ... 'r19i1p1f2'

▼ Data variables:

siconc	(member_id, time, j, i)	float32	dask.array<chunksize=(1, 6...
vertices_latitude	(j, i, vertices)	float32	dask.array<chunksize=(330...
vertices_longitude	(j, i, vertices)	float32	dask.array<chunksize=(330...

► Attributes: (45)

3.4 CMIP6 Areacello

An area of interest was selected from the Areacello variable for both CNRM and UKESM.

In [17]:
```
cnrm_SS = cnrm_area.areacello.where((cnrm_area.lat>=70) & (cnrm_area.lat<=80)
                                    & (cnrm_area.lon <= 160)
                                    & (cnrm_area.lon >= 100), drop = True)
cnrm_SS = cnrm_SS.isel(member_id = 0) #for cnrm select one member ID
uk_SS = uk_area.areacello.where((uk_area.latitude>=70)
                                    & (uk_area.latitude<=80)
                                    & (uk_area.longitude <= 160)
                                    & (uk_area.longitude >= 100), drop = True)
uk_SS = uk_SS.isel(member_id = 0) #for ukesm select one member ID
```

3.5 CMIP6 Nitrate

Using CNRM and UKESM the surface nitrate concentration was selected for the Laptev Sea. Following this an ensemble mean created.

In [18]:
```
#CNRM
cnrm_no3_SS = cnrm_no3.isel(lev = 0).where((cnrm_no3.lat>=70)
            & (cnrm_no3.lat<=80) & (cnrm_no3.lon >=100)
            & (cnrm_no3.lon <= 160),
            drop = True).mean(dim = ['member_id'], keep_attrs=True)
#UKESM
uk_no3_SS = uk_no3.isel(lev = 0).where((uk_no3.latitude>=70)
            & (uk_no3.latitude<=80) & (uk_no3.longitude >=100)
            & (uk_no3.longitude <= 160),
            drop = True).mean(dim = ['member_id'], keep_attrs=True)
```

The nitrate concentration was then weighted by the area of the cells in the model.

In [19]:
```
cnrm_no3_w = (cnrm_SS*cnrm_no3_SS).sum(dim=('y','x'))/cnrm_SS.sum(dim=('y','x'))
uk_no3_w = (uk_SS*uk_no3_SS).sum(dim=('j','i'))/uk_SS.sum(dim=('j','i'))
```

Below, the mean and standard deviation of the monthly nitrate concentration from CNRM for the time period overlapping with observations (2002 to 2014), was calculated.

In [20]:
```
cnrm_no3_obs = cnrm_no3_w.sel(time = slice('2002','2014')).groupby('time.month').m
cnrm_no3_obs_sd = cnrm_no3_w.sel(time = slice('2002','2014')).groupby('time.month'
```

Next, the meand and standard deviation of the monthly nitrate concentration from CNRM for the historical time period (1850 to 2001), was calculated.

In [21]:
```
# Calculate the mean and standard deviation of the monthly nitrate concentration fr
# historical time period: 1850 to 2001
cnrm_no3_hist = cnrm_no3_w.sel(time = slice('1850','2001')).groupby('time.month').
cnrm_no3_hist_sd = cnrm_no3_w.sel(time = slice('1850','2001')).groupby('time.month
```

3.6 CMIP6 Sea ice

The sea ice concentration from CNRM and UKESM for the Laptev Sea area was selected, and an esemble mean was created.

In [22]:
```
#CNRM
cnrm_si_SS = cnrm_si.where((cnrm_si.lat>=70) & (cnrm_si.lat<=80)
            & (cnrm_si.lon >=100)
            & (cnrm_si.lon <= 160),
            drop = True).mean(dim = ['member_id'], keep_attrs=True)
#CNRM
uk_si_SS = uk_si.where((uk_si.latitude>=70) & (uk_si.latitude<=80)
            & (uk_si.longitude >=100)
            & (uk_si.longitude <= 160),
            drop = True).mean(dim = ['member_id'], keep_attrs=True)
```

Below, the sea ice extent was calculated for each CMIP6 model and for the satellite data.

In [35]:
```
# Model extent
cnrm_iceExt = ((xr.where(cnrm_si_SS['siconc']>15, 1.,0))*cnrm_SS).sum(dim=['y','x'
uk_iceExt = ((xr.where(uk_si_SS['siconc']>15, 1.,0))*uk_SS).sum(dim=['j','i'])
# Satellite extent
sat_iceExt = ((xr.where(sat_SS.z>15, 1.,0).sum(dim=['x','y']))*area).compute()
```

In order to compare satellite data with model data for the overlapping time period (2002-2014),
the mean and standard deviation of the monthly sea ice extent from CNRM and UKESM for this time period was calculated.

In [36]:
```
#Find means:
cnrm_iceExt_obs = cnrm_iceExt.sel(time = slice('2002','2014')).groupby('time.month
uk_iceExt_obs = uk_iceExt.sel(time = slice('2002','2014')).groupby('time.month').m
sat_iceExt_obs = sat_iceExt.sel(time = slice('2002','2014')).groupby('time.month')
# Find standard deviations:
cnrm_iceExt_obs_sd = cnrm_iceExt.sel(time = slice('2002','2014')).groupby('time.mo
uk_iceExt_obs_sd = uk_iceExt.sel(time = slice('2002','2014')).groupby('time.month'
sat_iceExt_obs_sd = sat_iceExt.sel(time = slice('2002','2014')).groupby('time.mont
```

Lastly, the mean and standard deviation of the monthly sea ice extent from CNRM, was calculated for the historical time period (1850 to 2001).

In [37]:
```
cnrm_iceExt_hist = cnrm_iceExt.sel(time = slice('1850','2001')).groupby('time.montl
cnrm_iceExt_hist_sd = cnrm_iceExt.sel(time = slice('1850','2001')).groupby('time.mo
```

4.0 Results

According to observations, the Laptev Sea has experienced a lengthening of the open water period over the last two decades (2002 to 2019) (Fig. 1 blue shaded area).
Figure 1 utilises daily satellite derived sea ice extent plotted as a function of year and month. Figure 1 shows that over time, the sea ice has started to melt sooner in July and reform later in October,
as evidenced by a sea ice extent of less than 200 000 km^{2} visible during these time periods.

In [11]:
```
#Create figure 1
fig, ax = plt.subplots(figsize = (8,5))
pl=ax.pcolormesh(ys,
            [np.datetime64('2000') + np.timedelta64(d, 'D') for d in doy],
               ice2d.T,
                cmap=plt.colormaps['cool'])
cbar = fig.colorbar(pl)
cbar.set_label(r'Sea ice extent (km$^{2}$)', size = 14)
fmt = mdate.DateFormatter('%b')
ax.yaxis.set_major_formatter(fmt)
ax.yaxis.set_major_locator(mdate.MonthLocator())
ax.set_ylabel('Month', size = 12)
ax.set_xlabel('Year', size = 12)
fig.tight_layout()
plt.savefig('Heatmap SS.png')
```

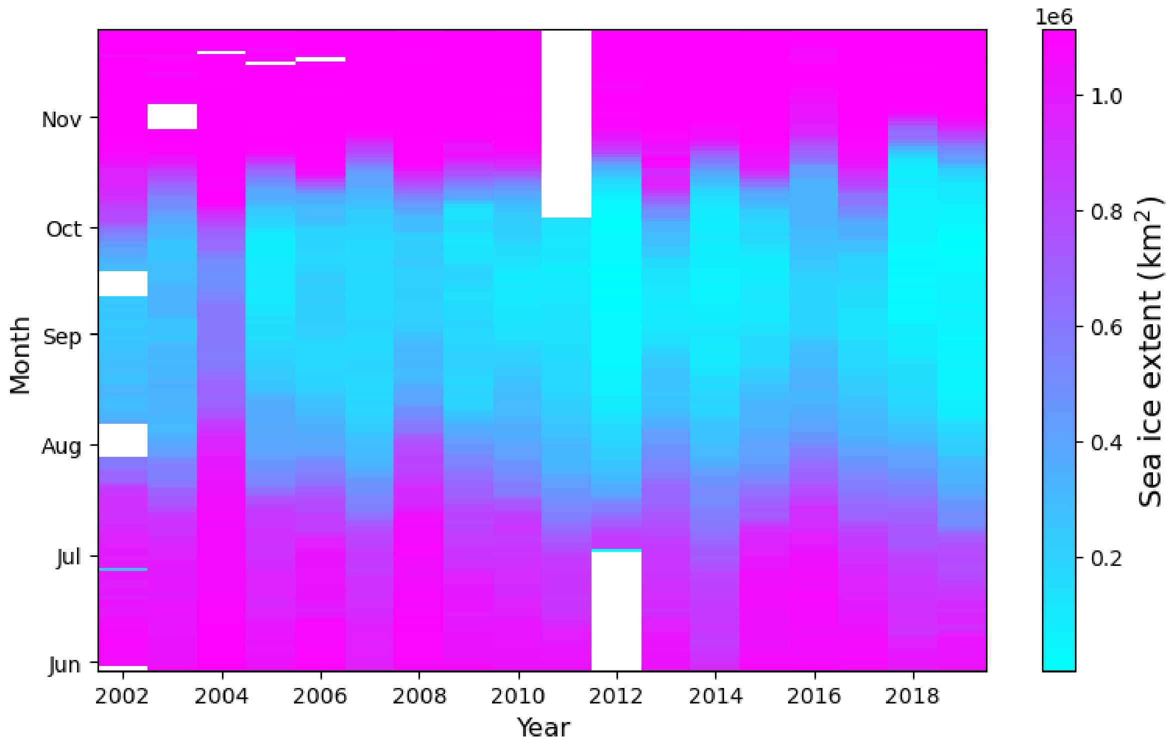

Figure 1: Heat map indicating the timing of sea ice melt and reformation over 18 years from 2002 to 2019.

The color bar (blue to purple) shows sea ice extent (km^{2}).

When comparing sea ice extent from CNRM and UKESM to satellite observations, we see that the seasonal variability is captured moderately well by both models (Fig. 2). Like observations both models show a September minimum sea ice extent, however the observations suggest that sea ice extent begins to decline around May, while initial sea ice melt is observed later in both models (June and July for UKESM and CNRM, respectively). On the other hand, maximum sea ice extent is similarly achieved again by November in the observations and both models. In both models, the summertime sea ice extent is largely overestimated in comparison to the observations.

In [38]:

```
# Creat figure 2
fig, ax = plt.subplots(figsize = (6,4))
#ax.errorbar([datetime.strptime(str(m).zfill(2), '%m') for m in sat_iceExt_obs.mont
#             sat_iceExt_obs, yerr = sat_iceExt_obs_sd, capsize = 3,
#             elinewidth = 1, color='skyblue',
#             lw = 2, label = 'Satellite', linestyle = '-')
ax.errorbar([datetime.strptime(str(m).zfill(2), '%m') for m in sat_iceExt_obs.montl
            cnrm_iceExt_obs/1e6, yerr = cnrm_iceExt_obs_sd/1e6, capsize = 3,
            elinewidth = 1, color='Grey',
            lw = 2, label = 'CNRM', linestyle = '--')
ax.errorbar([datetime.strptime(str(m).zfill(2), '%m') for m in sat_iceExt_obs.montl
            uk_iceExt_obs/1e6, yerr = uk_iceExt_obs_sd/1e6, capsize = 3,
            elinewidth = 1, color='k',
            lw = 2, label = 'UKESM', linestyle = '--')
ax.set_xlabel('Month', fontsize=14)
ax.set_ylabel(r'Sea ice extent (km${^2})$', fontsize=14)
ax.tick_params(axis="x", labelsize=12)
ax.tick_params(axis="y", labelsize=12)
ax.legend(loc = 'best')
fmt = mdate.DateFormatter('%b')
ax.xaxis.set_major_formatter(fmt)
ax.xaxis.set_major_locator(mdate.MonthLocator())
plt.tight_layout()
#plt.savefig('Fig 2.png')
```

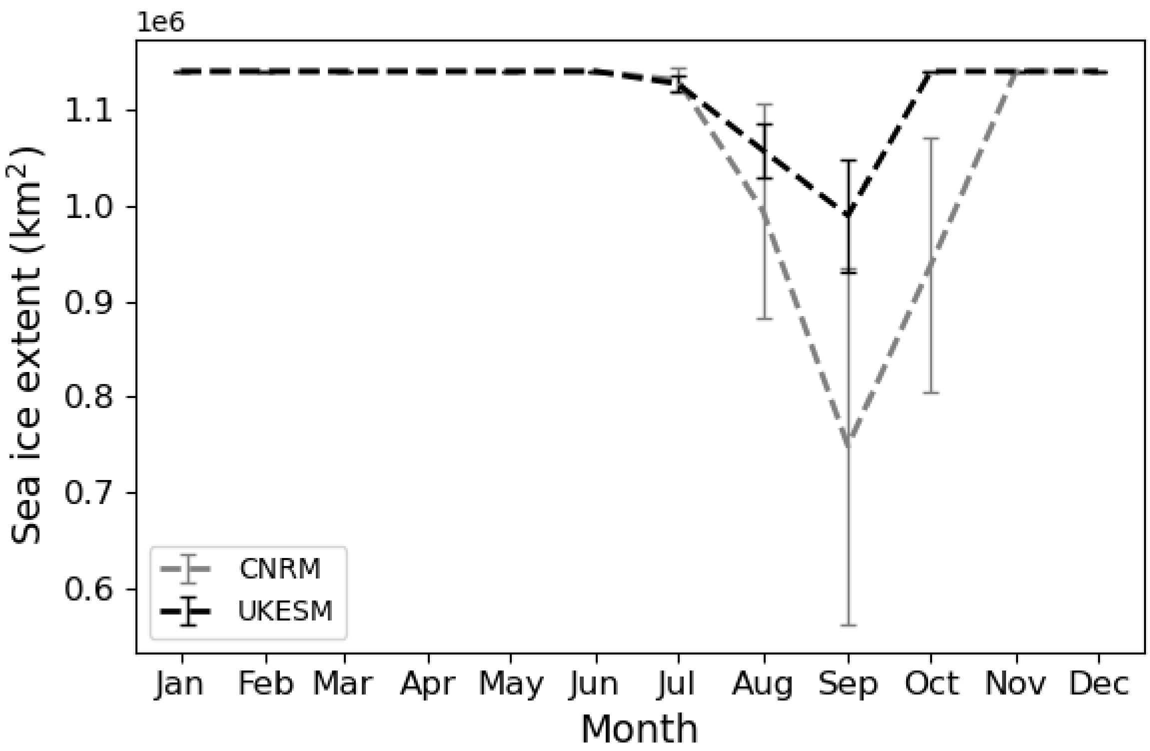

Figure 2: Monthly averaged sea ice extent from 2002 to 2014 in CNRM (broken grey line) and UKESM (broken black line)
in comparison to satellite data (solid blue line).

Given that the sea ice extent from both models are so similar to each other, I chose to work only with one of the models (CNRM) in the analyses below.
Figure 3 compares the monthly averaged sea ice extent (grey) and surface nitrate concentration (pink) from CNRM for the Laptev Sea. The historical time period from 1850 to 2001 is shown by broken lines and the more recent time period, which overlaps with the observational data (2002 to 2014), is shown by the solid lines. From the CNRM sea ice extent, one clearly observes a reduction in summertime sea ice extent for the recent period in comparison to the historical period. From the CNRM surface nitrate concentrations, one observes a reduction in the quantity of nitrate available during the summer period. In both cases (sea ice extent and nitrate availabilty), there is no significant change in seasonality between the historical and recent time periods. Based on CNRM, the surface nitrate concentration in the Laptev Sea starts to decline when sea ice starts to melt. Both sea ice and nitrate are at a minimum in September.

In [42]:
```
# Create figure 3
fig, ax = plt.subplots(figsize = (8,6))
#with ProgressBar():
ax.errorbar([datetime.strptime(str(m).zfill(2), '%m') for m in cnrm_iceExt_obs.mon
            cnrm_iceExt_obs/1e6, yerr = cnrm_iceExt_obs_sd/1e6, capsize = 3,
            elinewidth = 1, color='grey',
            lw = 2, label = 'CNRM sea ice extent 2002-2014',
            linestyle = '-')
ax.errorbar([datetime.strptime(str(m).zfill(2), '%m') for m in cnrm_iceExt_obs.mon
            cnrm_iceExt_hist/1e6, yerr = cnrm_iceExt_hist_sd/1e6, capsize = 3,
            elinewidth = 1, color='grey',
            lw = 2, label = 'CNRM sea ice extent 1850-2001',
            linestyle = '--')
ax2 = ax.twinx()
ax2.errorbar(x = [datetime.strptime(str(m).zfill(2), '%m') for m in cnrm_iceExt_ob
            y = cnrm_no3_obs['no3']*1e3, yerr = cnrm_no3_obs_sd['no3']*1e3,
            capsize = 3, elinewidth = 1, color='hotpink',
            lw = 2, label = r'CNRM [NO${_3}^{-}$] 2002-2014',
            linestyle = '-')
ax2.errorbar(x = [datetime.strptime(str(m).zfill(2), '%m') for m in cnrm_iceExt_ob
            y = cnrm_no3_hist['no3']*1e3, yerr = cnrm_no3_hist_sd['no3']*1e3,
            capsize = 3, elinewidth = 1, color='hotpink',
            lw = 2, label = r'CNRM [NO${_3}^{-}$] 1850-2001',
            linestyle = '--')
ax.set_xlabel('Month', fontsize=14)
ax.set_ylabel(r'Sea ice extent (km${^2})$', fontsize=12)
ax2.set_ylabel(r'[NO${_3}^{-}$] (μmol L$^{-1})$', fontsize=12)
ax.tick_params(axis="x", labelsize=10)
ax.tick_params(axis="y", labelsize=10)
ax.legend(loc = 'best')
ax2.legend(loc = 'lower right')
fmt = mdate.DateFormatter('%b')
ax.xaxis.set_major_formatter(fmt)
ax.xaxis.set_major_locator(mdate.MonthLocator())
plt.tight_layout()
plt.savefig('Fig 3.png')
```

```
/srv/conda/envs/notebook/lib/python3.9/site-packages/flox/aggregations.py:273: Run
timeWarning: invalid value encountered in sqrt
  return np.sqrt(_var_finalize(sumsq, sum_, count, ddof))
```

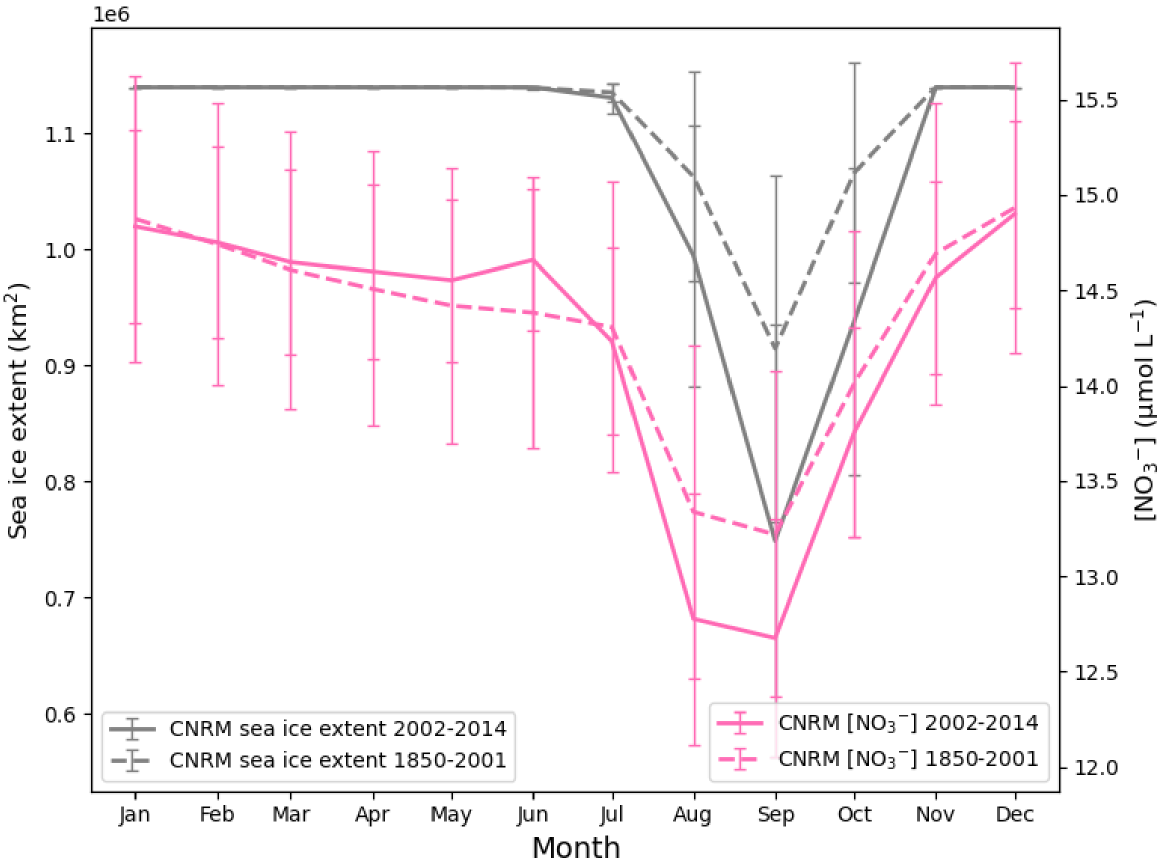

Figure 3. Monthly averaged sea ice extent (grey) and surface nitrate concentrations (pink) for historical (broken line) and recent (solid line) time periods from CNRM, for the Laptev Sea area.

To explore any variation in the spatial distribution of sea ice and surface nitrate between the historical and recent time periods, the data are plotted on maps of the Laptev Sea in Figure 4 below. For the purpose of this comparison, the month of September was plotted in all cases, as this is when the least ice and nitrate is present. It is also the time of year when the biggest differences between the historical and recent time periods are observed.

In [40]:
```
# Here I make new data sets grouped by month and select for September,
#when we see a minimum in both sea ice and nitrate.
cnrm_si_SS_m = cnrm_si_SS.groupby('time.month')
cnrm_no3_SS_m = cnrm_no3_SS.groupby('time.month')
# Here I separate the datasets into historical and recent time periods,
#the recent time period defined by the period of overlap with observations.
si_past = cnrm_si_SS_m[9]['siconc'][:-13]
si_pres = cnrm_si_SS_m[9]['siconc'][-13:]
no3_past = cnrm_no3_SS_m[9]['no3'][:-13]
no3_pres = cnrm_no3_SS_m[9]['no3'][-13:]
```

In [41]:
```
import Functions as f
# Defined a function to include some commonly utilised map features,
#which is loaded here.
%load_ext autoreload
%autoreload 2
```

In [42]:
```
# Create figure 4
extent = [100,160, 80, 70]
fig = plt.figure(1, figsize=[10,10])
ax = plt.subplot(2, 2, 1, projection=ccrs.NorthPolarStereo())
f.mapfeatures(ax,extent)
ax = si_past.mean(dim = ['time']).plot.pcolormesh(x='lon', y='lat',
    cmap='PiYG_r', vmax = 100, vmin = 0,
    transform = ccrs.PlateCarree(),
    cbar_kwargs={ 'orientation':'vertical', 'shrink':.8})
plt.title('A: September 1850-2001')

ax = plt.subplot(2, 2, 2, projection=ccrs.NorthPolarStereo() )
f.mapfeatures(ax,extent)
ax = si_pres.mean(dim = ['time']).plot.pcolormesh(x='lon', y='lat',
    cmap='PiYG_r', vmax = 100, vmin = 0,
    transform = ccrs.PlateCarree(),
    cbar_kwargs={ 'orientation':'vertical', 'shrink':.8})
plt.title('B: September 2002-2014')

ax = plt.subplot(2, 2, 3, projection=ccrs.NorthPolarStereo() )
f.mapfeatures(ax,extent)
ax = (no3_past*1e3).mean(dim = ['time']).plot.pcolormesh(x='lon', y='lat',
    cmap='coolwarm', vmax =40 , vmin = 0,
    transform = ccrs.PlateCarree(),
    cbar_kwargs={ 'orientation':'vertical', 'shrink':.8})
#ax.add_feature(cartopy.feature.RIVERS, zorder=1, edgecolor='black')
plt.title('C: September 1850-2001')

ax = plt.subplot(2, 2, 4, projection=ccrs.NorthPolarStereo() )
f.mapfeatures(ax,extent)
ax = (no3_pres*1e3).mean(dim = ['time']).plot.pcolormesh(x='lon', y='lat',
    cmap='coolwarm', vmax =40 , vmin = 0,
    transform = ccrs.PlateCarree(),
    cbar_kwargs={ 'orientation':'vertical', 'shrink':.8})
#ax.add_feature(cartopy.feature.RIVERS, zorder=1, edgecolor='black')
plt.title('D: September 2002-2014')
plt.savefig('Fig 4.png')
```

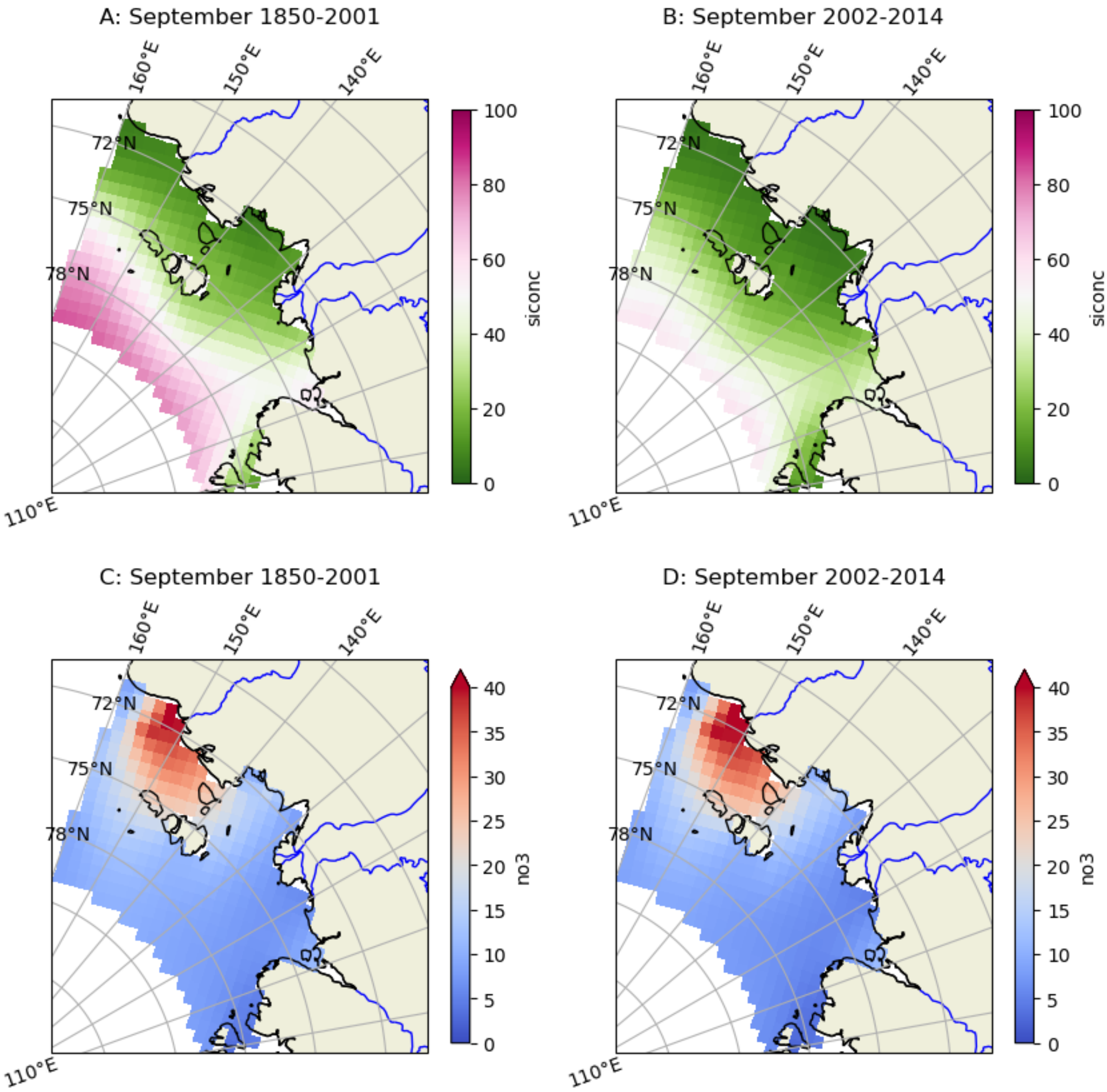

Figure 4: A comparison of sea ice concentration (top row) and nitrate concentration (bottom row) from CMIP6, for the present period of overlap
with observations (2002-2014) (right column) and past period (1850-2001) (left column) for September,
the month of minimum sea ice and nutrient availabilty.

During the historical time period, the Laptev Sea was still partially covered by sea ice in September (Fig. 4A). September sea ice extent has been dramatically reduced in the recent past with sea ice concentrations greater than 50% only seen north of 78 N(Fig. 4B). Despite this, very little difference between historical and recent surface nitrate concentrations are visible for the Laptev Sea in September (Fig. 4C & D).

5.0 Discussion and conclusions

It is clear from both observations and models that the Laptev Sea area on the Siberian Shelf has experienced a significant decline in summertime sea ice extent over the recent past. Both UKESM and CNRM are able to capture the seasonality in observed sea ice extent over the region, but overestimate the September sea ice minimum by similar amounts. For the Laptev Sea region, surface nitrate concentrations from CNRM decline as the sea starts to melt in summer. This can be attributed to consumption by phytoplankton. Demidove et al.

(2021) shows that maximum rates of primary productivity in the Laptev Sea are observed from May to July.
It is interesting to note that seasonally, summer time surface nitrate concentrations have decreased slightly over recent years in comparison to the historical time period. This could be indicative of increased phytoplankton consumption in the region during summer, which suggests that primary production may be increasing as sea ice melts for this coastal Arctic region, at least in the CNRM model.
In contrast, wintertime surface nitrate concentrations have remained relatively unchanged, perhaps due to a consistent riverine input and lack of consumption by phytoplankton.
The Laptev Sea recieves high amounts of nitrate from the Lena River as highlighted by the plume of high concentrations in the south east region (Figure 4C & D). No significant changes are observed in nitrate availability between historical and recent times for the month of September, when nitrate has the potential to be the most limiting. This suggests that despite a reduction in Sea ice extent, and potential increase in primary productivity, enough nutrients are still available to support phytoplankton growth.
Numerous previous studies have been undertaken to assess the mecheanisms controlling both the distribution and availability of nutrients in the Laptev Sea. Most of these studies were based on in situ nutrient concentration measurements in combination with hydrographic parameters like salinity (Laukert et al., 2022). The ability of CNRM to reproduce important features like the Lena River outflow region, suggests that CMIP6 models may serve as a useful addtional tool for further investiagtion of the nutrient dynamics in this important region.

6.0 Outlook

Due to time constraints and for the purpose of this report, the analyses performed are limited to 2 CMIP6 models. This work could be improved upon in the future by examining more models available in CMIP6. One could also assess not just surface level nitrate concentrations but total euphotic zone integrated nitrate concentrations. It would also be useful to look at some observational nitrate concentration data perhaps from field campaigns to the region, and do a model/observation intercomparison as done for sea ice. Lastly, it would be interesting to assess not only nitrate, but other species that could potentially limit phytoplankton growth like Silica (Si).

7.0 Acknowledgements

I would like to thank our assistant, Antoine Haddon, for his guidance and support in producing the work reported here. I would also like to thank Paul Zieger and Micheal Schulz, for allowing me to attend the eScience course (2022) and CRiceS for funding my attendance.

8.0 References

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9.0 Supplementary Material

The satellite data was processed prior to analysing the data as follows:

In [ ]:
```
s3 = s3fs.S3FileSystem(key="K1CQ7M1DMTLUFK182APD",
                       secret="3JuZAQm5I03jtpijCpHOdkAsJDNLNfZxBpM15Pi0",
                       client_kwargs=dict(endpoint_url="https://rgw.met.no"))
```

In [ ]:
```
# Define function to create time variable from AMSR2/AMSR-E netcdf file name
def paths_to_datetimeindex(paths):
    return  [datetime.strptime(date.split('/')[-1].split('-')[3], '%Y%m%d') for da
```

In [ ]:
```
# Define function to create monthly files from daily sea ice concentration data
def read_daily_files(year):
    for month in range (1,13):
        remote_files = 's3://escience2022/Antoine/AMSR2_ASI_sea_ice_concentration/
        remote_files = s3.glob(remote_files)
        fileset = [s3.open(file) for file in remote_files]
        time_var = xr.Variable('time', paths_to_datetimeindex(remote_files))
        dset =xr.open_mfdataset(fileset, concat_dim="time", combine = "nested")
        dset = dset.assign_coords(time=time_var)
        dset.to_netcdf('AMSR2_ASI_sea_ice_concentration_%i%s.nc'%(year,str(month).
        del remote_files, dset, time_var
```

In [ ]:
```
[read_daily_files(year) for year in range(2002,2011)]
```