BoB_eutrophication

August 5, 2022

1 Evolution of the eutrophication in the Bay of Bengal

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General Note 1: Execute each cell through the button from the top MENU (or keyboard shortcut `Shift` + `Enter`). **General Note 2**: If, for any reason, the kernel is not working anymore, in the top MENU, click on the button. Then, in the top MENU, click on "Cell" and select "Run All Above Selected Cell". ***

1.1 Required Python modules

Go back to the Table of contents

First, the notebook must be set up with all the necessary tools available from the Jupyter Notebook Ecosystem.

Module name	Description
numpy	NumPy is the fundamental package for scientific computing with Python and for managing ND-arrays.
xarray	Xarray is a very user friendly librairy to manipulate NetCDF files within Python. It introduces labels in the form of dimensions, coordinates and attributes on top of raw NumPy-like arrays, which allows for a more intuitive, more concise, and less error-prone developer experience.
matplotlib	Matplotlib is a Python 2D plotting library which produces high quality figures.
cartopy	Cartopy is a library for plotting maps and geospatial data analyses in Python.

Import libraries

```
[ ]: # Import libraries
     import numpy as np
     import xarray as xr
     import matplotlib.pyplot as plt
     import matplotlib.colors as colors
     import matplotlib.patches as mpatches
     import cartopy.crs as ccrs
     import cartopy.feature as cfeature

     # To avoid warning messages
     import warnings
     warnings.filterwarnings('ignore')
```

1.2 Set up OPeNDAP

In the first notebook, we have seen that the Copernicus Marine Service Products could be used directly, without having to download any file, thanks to the OPeNDAP service. A specific Python script has been developped for this workshop and will give you access to the Copernicus Marine Service products. To use it, run the following cell and enter your credentials.

In the following sections, you will be able to use the products either from the files which have already been downloaded, or thanks to OPeNDAP service, depending on what you prefer !

```
[ ]: %run opendap_config.py
```

```
Enter your Copernicus Marine Service username: mgolder
Enter your password: ········
```

1.3 Presentation of the product used

In this notebook, we are going to use the Global Biogeochemistry Reanalysis model, with the **monthly means** of the biogeochemical parameters from **1993 to 2020**. Reanalysis models combine the advantages of a model simulation constrained by existing measurements. Here is a brief overview of the product's characteristics:

Parameter	Value
Variables used	o2 *(oxygen concentration)*, chl *(concentration of chlorophyll)*, no4 *(concentration of Nitrate)*
Product identifier	cmems_mod_glo_bgc_my_0.25_P1M-m_1653111433679
Spatial resolution	4km x 4km
Temporal resolution	monthly mean
Temporal coverage	from 1993-01-01 to 2020-12-31
Vertical coverage	from -700m to 0m

2 Analyse the evolution of the Bay of Bengal parameters

We are now all set to begin our study of the eutrophication of the Bay of Bengal. In this first section, we are going to analyse the evolution of the eutrophication through the evolution of the nutrient input (Nitrate concentration), the algae blooms (Chlorophyll concentration), and sea hypoxia (Oxygen concentration) in the Bay of Bengal.

2.1 Load the product

As we have seen before, you have two options to load the product : you can either use the files that have been downloaded and stored in the `data/` folder, or use the OPeNDAP service.

We are going to load two files : the first one, under the Python variable `chl_N_O` contains the surface parameters (nitrate, chlorophyll and oxygen) from 1993 to 2020, whereas the second one `o2` contains the oxygen concentration of all the depths and from 1993 to 2020.

In the following cell, you can comment/uncomment the lines and select the option you prefer. You can then check the dataset coordinates and variables and make sure that both methods output the same information.

```
[ ]: # Open the datasets with OPeNDAP
     #chl_N_O = xr.open_dataset('https://my.cmems-du.eu/thredds/dodsC/
      ↪dataset-reanalysis-scobi-monthlymeans').
      ↪sel(depth=0,method='nearest')[['chl','no3','o2']]
     #o2 = xr.open_dataset('https://my.cmems-du.eu/thredds/dodsC/
      ↪dataset-reanalysis-scobi-monthlymeans')[['o2']]

     # Open the datasets
     chl_N_O = xr.open_dataset('data/chl_N_O.nc')
     o2 = xr.open_dataset('data/o2_all_depths.nc')
```

```
[ ]: # check what the dataset contains
     chl_N_O
```

```
[ ]: <xarray.Dataset>
     Dimensions:    (time: 336, depth: 1, latitude: 81, longitude: 81)
     Coordinates:
       * depth      (depth) float32 0.5058
       * latitude   (latitude) float32 5.0 5.25 5.5 5.75 … 24.25 24.5 24.75 25.0
       * time       (time) datetime64[ns] 1993-01-16T12:00:00 … 2020-12-16T12:00:00
       * longitude  (longitude) float32 80.0 80.25 80.5 80.75 … 99.5 99.75 100.0
     Data variables:
         no3        (time, depth, latitude, longitude) float32 …
         o2         (time, depth, latitude, longitude) float32 …
         chl        (time, depth, latitude, longitude) float32 …
     Attributes: (12/17)
         product:                         GLOBAL_REANALYSIS_BIO_001_029
         producer:                        CMEMS - Global Monitoring and Forecasting …
         title:                           Monthly mean fields for product GLOBAL_REA…
```

```
    area:                           GLOBAL
    quality_information_document:   http://marine.copernicus.eu/documents/QUID…
    Conventions:                    CF-1.6
    …                              …
    dataset:                        global-reanalysis-bio-001-029-monthly
    institution:                    Mercator Ocean
    product_user_manual:            http://marine.copernicus.eu/documents/PUM/…
    _CoordSysBuilder:               ucar.nc2.dataset.conv.CF1Convention
    comment:
    history:                        Data extracted from dataset http://localho…
```

2.2 Calculate the regional average of the parameters

We will calculate the average value of each of the surface Nitrate, Chlorophyll and Oxygen concentrations over the whole Bay of Bengal region (average on the longitude and latitude coordinates).
.

[ ]:
```
# Calculate the average parameters
chl_N_O_average = chl_N_O.mean('latitude').mean('longitude')

# Check the results
chl_N_O_average
```

[ ]:
```
<xarray.Dataset>
Dimensions:  (time: 336, depth: 1)
Coordinates:
  * depth    (depth) float32 0.5058
  * time     (time) datetime64[ns] 1993-01-16T12:00:00 … 2020-12-16T12:00:00
Data variables:
    no3      (time, depth) float32 0.9356 0.643 0.5778 … 2.163 2.111 1.315
    o2       (time, depth) float32 208.7 208.9 207.2 204.5 … 202.6 203.9 205.1
    chl      (time, depth) float32 0.2082 0.175 0.1492 … 0.2453 0.1998 0.199
```

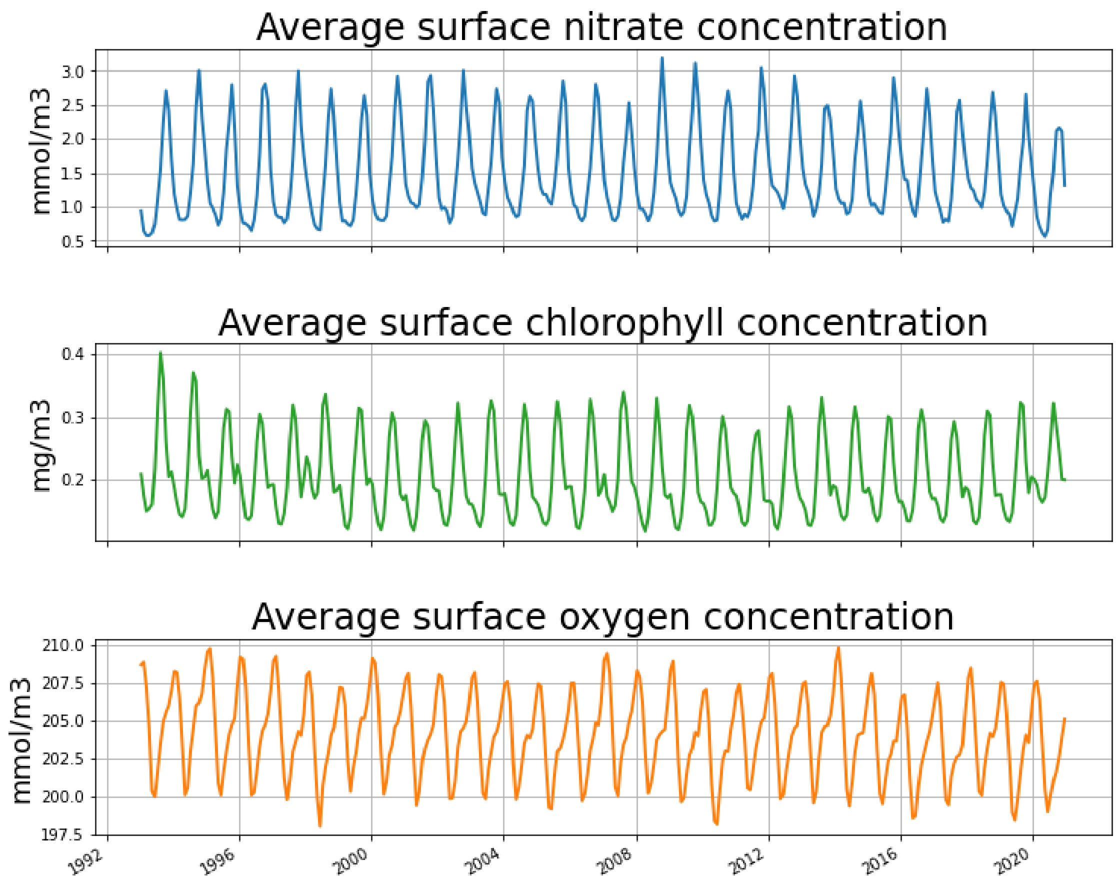
2.3 Plot the evolution of the parameters

Let's plot the evolution of the parameters over time, with the 28 years available in the product.

[ ]:
```
# Define the characteristics of the plot
f = plt.figure(figsize=(12,12))
ax1 = f.add_subplot(311)
ax2 = f.add_subplot(312)
ax3 = f.add_subplot(313)
f.subplots_adjust(top=0.8,bottom=0.05,hspace = 0.5)

# First plot : Nitrate
ax1.set_title("Average surface nitrate concentration",fontsize=24)
ax1.grid()
ax1.set_ylabel("mmol/m3",fontsize=18)
```

```
ax1.plot(chl_N_O_average.time,chl_N_O_average.no3,c='tab:blue',linewidth=2)
f.autofmt_xdate()

# Second plot : Chlorophyll
ax2.set_title("Average surface chlorophyll concentration",fontsize=24)
ax2.grid()
ax2.set_ylabel("mg/m3",fontsize=18)
ax2.plot(chl_N_O_average.time,chl_N_O_average.chl,c='tab:green',linewidth=2)

# Third plot : Oxygen
ax3.set_title("Average surface oxygen concentration",fontsize=24)
ax3.grid()
ax3.set_ylabel("mmol/m3",fontsize=18)
ax3.plot(chl_N_O_average.time,chl_N_O_average.o2,c='tab:orange',linewidth=2)
```

```
[ ]: [<matplotlib.lines.Line2D at 0x7fe59e95e5c0>]
```



The above figure shows the variations of the Global biogeochemical parameters from 1993 to 2020. We can already see some trends : the nitrate and chlorophyll surface concentrations seem to be decreasing over the years, whereas the oxygen surface concentration seems to be stable.

2.4 Calculate the yearly average

The previous plots have used the spatially averaged monthly values of the parameters and we displayed their seasonal variations as well as the interannual ones. In the next cell, we are going to calculate the annual values with the `xarray.groupby` method. We will therefore be able to focus the analysis on the interannual variations of the sea parameters.

```
[ ]: # Group the data by year and calculate the average for each year
chl_N_O_average_annual = chl_N_O_average.groupby('time.year').mean('time')

# Check the results
chl_N_O_average_annual
```

```
[ ]: <xarray.Dataset>
Dimensions:  (year: 28, depth: 1)
Coordinates:
  * depth    (depth) float32 0.5058
  * year     (year) int64 1993 1994 1995 1996 1997 … 2016 2017 2018 2019 2020
Data variables:
    no3      (year, depth) float32 1.32 1.495 1.451 1.435 … 1.578 1.388 1.256
    o2       (year, depth) float32 204.8 205.1 204.9 204.6 … 204.1 203.2 203.2
    chl      (year, depth) float32 0.2347 0.2228 0.2166 … 0.1999 0.2044 0.218
```

You can see from the previous cell output that the dataset does not have the `time` coordinate anymore, as it has been replaced with the `year` coordinate. The `o2` variable now contains the spatially and temporally averaged annual values of the parameters.

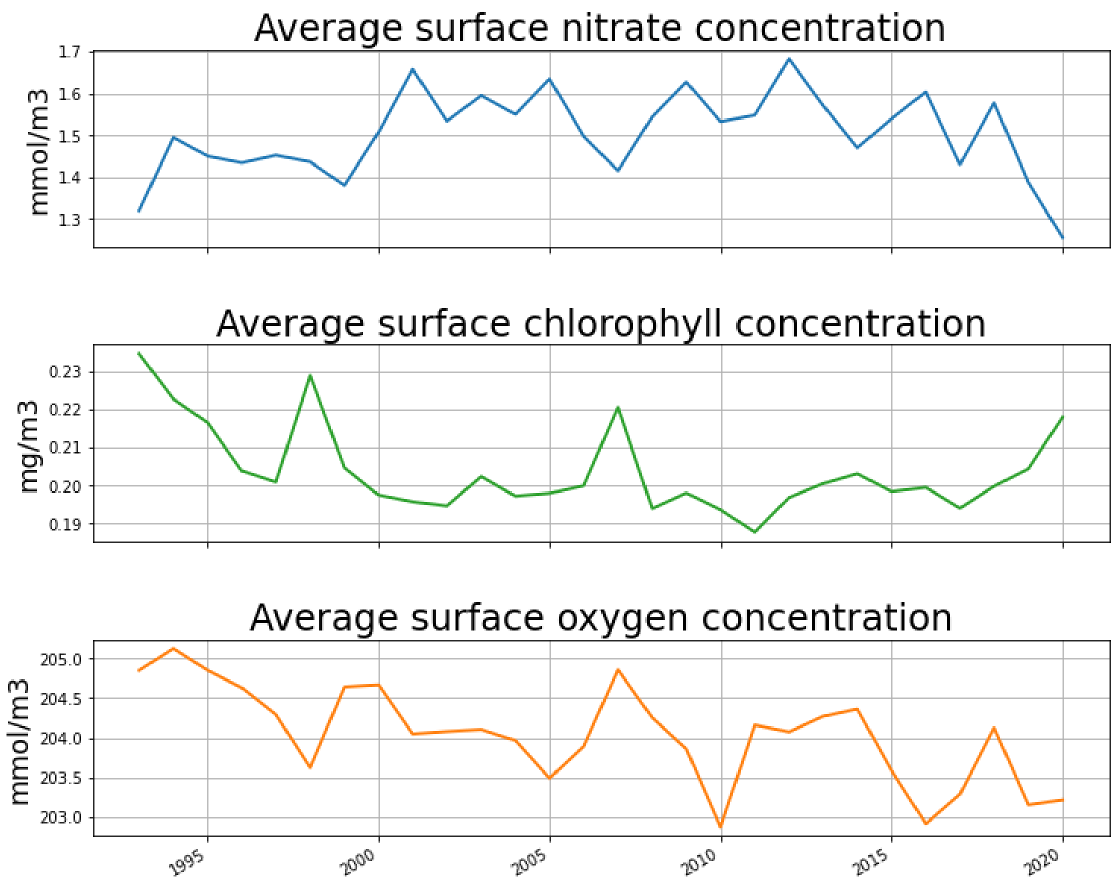
2.5 Plot the interannual variations of the parameters

Let's plot their evolution !

```
[ ]: # Define the characteristics of the plot
f = plt.figure(figsize=(12,12))
ax1 = f.add_subplot(311)
ax2 = f.add_subplot(312)
ax3 = f.add_subplot(313)
f.subplots_adjust(top=0.8,bottom=0.05,hspace = 0.5)

# First plot : Nitrate
ax1.set_title("Average surface nitrate concentration",fontsize=24)
ax1.grid()
ax1.set_ylabel("mmol/m3",fontsize=18)
ax1.plot(chl_N_O_average_annual.year,chl_N_O_average_annual.no3,c='tab:
 ↪blue',linewidth=2)
f.autofmt_xdate()

# Second plot : Chlorophyll
ax2.set_title("Average surface chlorophyll concentration",fontsize=24)
ax2.grid()
```

```
ax2.set_ylabel("mg/m3",fontsize=18)
ax2.plot(chl_N_O_average_annual.year,chl_N_O_average_annual.chl,c='tab:
  ↪green',linewidth=2)

# Third plot : Oxygen
ax3.set_title("Average surface oxygen concentration",fontsize=24)
ax3.grid()
ax3.set_ylabel("mmol/m3",fontsize=18)
ax3.plot(chl_N_O_average_annual.year,chl_N_O_average_annual.o2,c='tab:
  ↪orange',linewidth=2)
```

```
[ ]: [<matplotlib.lines.Line2D at 0x7fe59cfc9690>]
```



2.6 Analyse the results

3 Monitor the hypoxia of the Bay of Bengal

In this section, we are going to study the oxygen concentration in the Bay of Bengal and provide an assessment of the hypoxia. As previously mentioned, the algae blooms prevent the light absorption in the deeper sea levels, which is one of the reasons for oxygen depletion mostly occuring near the sea floor. A conventional criterion for water to be considered hypoxic is a dissolved oxygen concentration lower than **2 mg of O2 / L** at the bottom of the sea floor (see oceanservice.noaa.gov). In the following sections, we are going to locate the regions which have suffered and still suffer from hypoxia depending on this criterion.

3.1 Convert the units

We are going to use the o2 variable set before. This variable contains the oxygen concentrations for all the depths and dates included in the model.

```
[ ]: # Check the products variables
     o2
```

```
[ ]: <xarray.Dataset>
     Dimensions:    (time: 336, depth: 26, latitude: 81, longitude: 81)
     Coordinates:
       * depth      (depth) float32 0.5058 1.556 2.668 3.856 … 97.04 108.0 120.0
       * latitude   (latitude) float32 5.0 5.25 5.5 5.75 … 24.25 24.5 24.75 25.0
       * time       (time) datetime64[ns] 1993-01-16T12:00:00 … 2020-12-16T12:00:00
       * longitude  (longitude) float32 80.0 80.25 80.5 80.75 … 99.5 99.75 100.0
     Data variables:
         o2         (time, depth, latitude, longitude) float32 …
     Attributes: (12/17)
         product:                       GLOBAL_REANALYSIS_BIO_001_029
         producer:                      CMEMS - Global Monitoring and Forecasting …
         title:                         Monthly mean fields for product GLOBAL_REA…
         area:                          GLOBAL
         quality_information_document:  http://marine.copernicus.eu/documents/QUID…
         Conventions:                   CF-1.6
         …                             …
         dataset:                       global-reanalysis-bio-001-029-monthly
         institution:                   Mercator Ocean
         product_user_manual:           http://marine.copernicus.eu/documents/PUM/…
         _CoordSysBuilder:              ucar.nc2.dataset.conv.CF1Convention
         comment:
         history:                       Data extracted from dataset http://localho…
```

You can see from the previous cell output that the unit of the oxygen concentration is **mmol/m3**. The threshold we are using to diagnose hypoxia is 2 **mg/L** at the bottom of the sea floor. In order to compare our dataset to this threshold, we are going to convert this the *mmol/m3* into *mg/L*. (Tips : the O2 molar mass is 32 g/mol)

```
[ ]: # Convert the units
     o2 = o2 * 32 / 1000
```

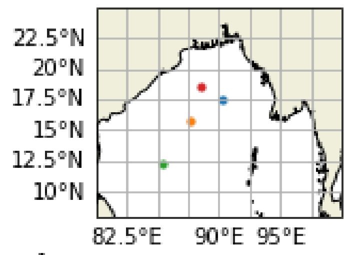
3.2 Study the vertical distribution of oxygen

First, let's have a look at the vertical distribution of the oxygen concentration. In the next cells we are setting the location of 4 points and one date, then selecting the model values at these locations and dates and finally plotting the vertical profiles.

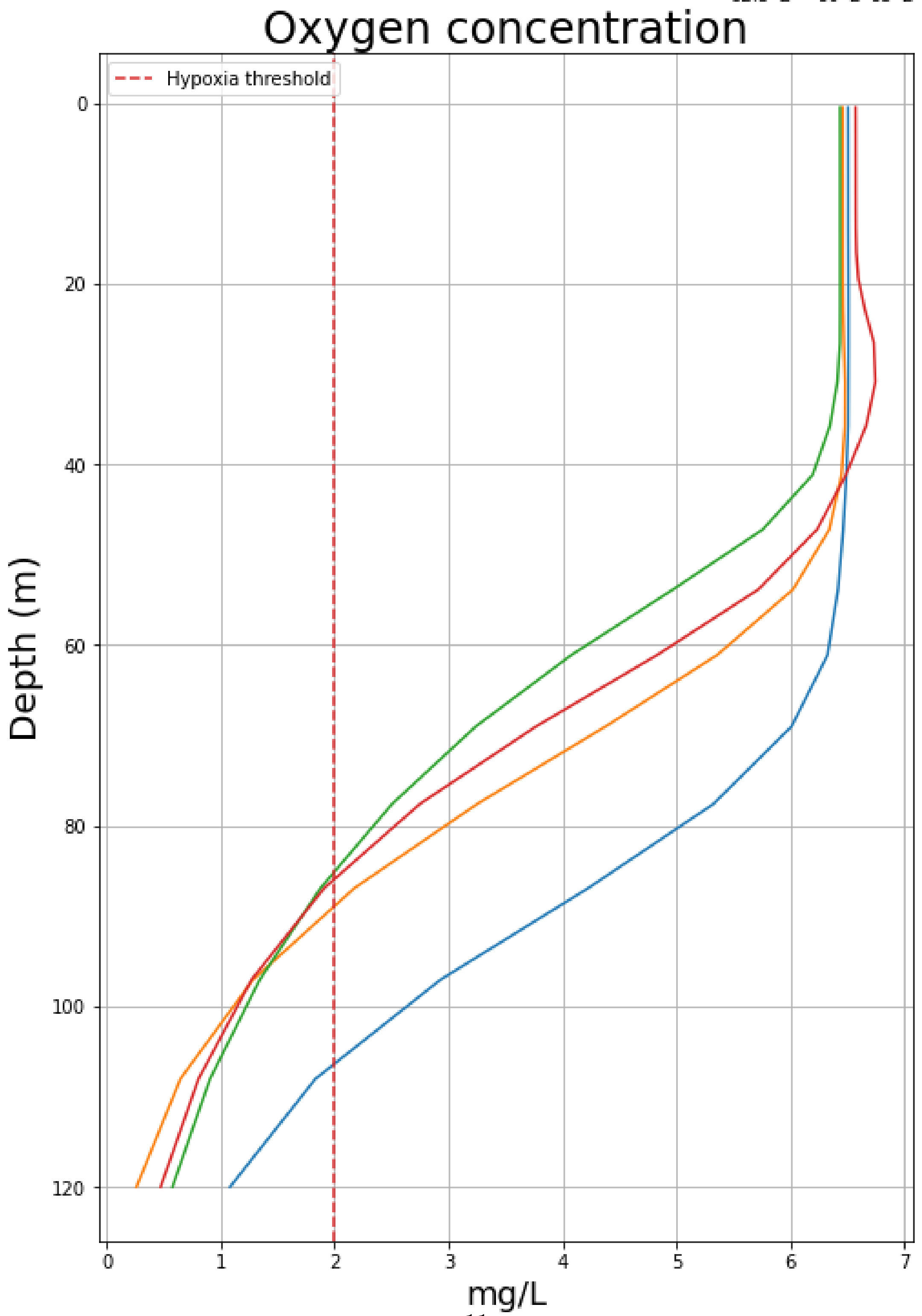
```
[ ]: # Define the coordinates of the points to study
     lon1, lat1 = 90.31 , 17.51
     lon2, lat2 = 87.69 , 15.72
     lon3, lat3 = 85.49, 12.31
     lon4, lat4 = 88.50, 18.56

     # Define the date to study
     date = '2018-11-01T00'

     # Select the product at this location and date and select the variable o2
     o2_1 = o2.sel(longitude = lon1, latitude = lat1, time = date, method =␣
      ↪'nearest').o2
     o2_2 = o2.sel(longitude = lon2, latitude = lat2, time = date, method =␣
      ↪'nearest').o2
     o2_3 = o2.sel(longitude = lon3, latitude = lat3, time = date, method =␣
      ↪'nearest').o2
     o2_4 = o2.sel(longitude = lon4, latitude = lat4, time = date, method =␣
      ↪'nearest').o2
```

```
[ ]: # Define the characteristics of the plot
     f = plt.figure(figsize=(8,12)) # create a figure and define its size
     ax = f.add_subplot(111) # create the axes of the plot
     ax.grid() # add the grid lines
     ax.set_title("Oxygen concentration",fontsize=24) # add the figure title
     ax.invert_yaxis() # reverse the y axis
     ax.set_xlabel("mg/L",fontsize=18) # set x axis label
     ax.set_ylabel("Depth (m)",fontsize=20) # set y axis label

     # Plot the vertical profiles
     ax.plot(o2_1,o2_1['depth'],'tab:blue')
     ax.plot(o2_2,o2_2['depth'],'tab:orange')
     ax.plot(o2_3,o2_3['depth'],'tab:green')
     ax.plot(o2_4,o2_4['depth'],'tab:red')

     # Add the threshold value
     ax.axvline(x = 2, ls='--',color = 'tab:red',label='Hypoxia threshold')

     # Display the locations of the glider on a mini map
     ax_mini_map = f.add_axes([0.73, 0.91, 0.2, 0.15], projection=ccrs.
      ↪PlateCarree()) # create the minimap and define its projection
     gl = ax_mini_map.gridlines(draw_labels=True) # add the coastlines
     gl.right_labels = False # remove latitude labels on the right
     gl.top_labels = False # remove longitude labels on the top
     ax_mini_map.add_feature(cfeature.LAND, zorder=0, edgecolor='k') # add land mask
     ax_mini_map.set_extent([80, 100, 8, 25], crs=ccrs.PlateCarree()) # define the␣
     ↪extent of the map [lon_min,lon_max,lat_min,lat_max]
     ax_mini_map.scatter(lon1, lat1, 10,'tab:blue',transform=ccrs.PlateCarree()) #␣
     ↪plot location of point 1
     ax_mini_map.scatter(lon2, lat2, 10,'tab:orange',transform=ccrs.PlateCarree()) #␣
     ↪plot location of point 2
     ax_mini_map.scatter(lon3, lat3, 10,'tab:green',transform=ccrs.PlateCarree()) #␣
     ↪plot location of point 3
     ax_mini_map.scatter(lon4, lat4, 10,'tab:red',transform=ccrs.PlateCarree()) #␣
     ↪plot location of point 4
     ax.legend(loc="upper left") # add the legend                                 ␣
     ↪       # add the legend

     #Save figure
     #plt.savefig('out/temp_vertical_profile.png')
```

```
[ ]: <matplotlib.legend.Legend at 0x7fe59c814700>
```



22.5°N
20°N
17.5°N
15°N
12.5°N
10°N
82.5°E
90°E
95°E



Oxygen concentration
Hypoxia threshold
Depth (m)
0
20
40
60
80
100
120
mg/L
0
1
2
3
4
5
6
7

The previous cell's output shows that the highest oxygen concentrations are located in the surface layer. There are several reasons for this distribution : - the oxygen dissolves into the ocean from the atmosphere at the surface ; - the surface water is where oxygen is produced by phytoplankton through photosynthesis; - the deeper water is too far from the surface for any atmospheric exchange, and there is not enough light to support photosynthesis; - the oxygen is removed from the deeper water through the respiration of deep water organisms and the decomposition of organic material.

You can learn more about the sea oxygen concentration on this article!

3.3 Locate the hypoxic regions

We are now going to locate the regions which suffer from hypoxia, our criteria still being the oxygen concentration on the sea floor. The previous vertical profiles have shown that the oxygen concentration was the lowest at the bottom of the sea. We are therefore going to select the minimum oxygen value in the water column, for each point of the region and for all date times. We will then select a date time and see the regions where the Bay of Bengal was hypoxic.

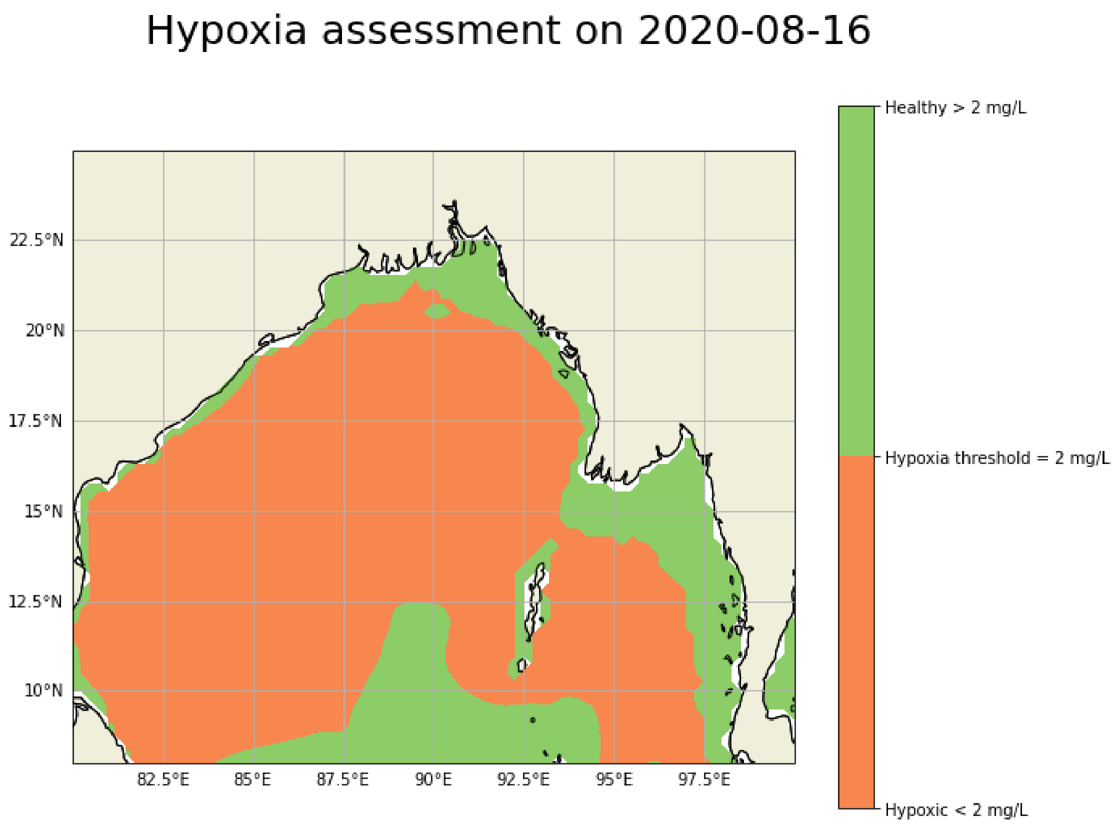
```
[ ]: # Select the minimum oxygen value
     o2_min = o2.min('depth')

     # See the result
     o2_min
```

```
[ ]: <xarray.Dataset>
     Dimensions:    (latitude: 81, time: 336, longitude: 81)
     Coordinates:
       * latitude   (latitude) float32 5.0 5.25 5.5 5.75 … 24.25 24.5 24.75 25.0
       * time       (time) datetime64[ns] 1993-01-16T12:00:00 … 2020-12-16T12:00:00
       * longitude  (longitude) float32 80.0 80.25 80.5 80.75 … 99.5 99.75 100.0
     Data variables:
         o2         (time, latitude, longitude) float32 1.219 1.21 1.195 … nan nan
```

```
[ ]: # Define the date to display
     date = '2020-08-16'

     # Select the model oxygen variable at this date
     o2_min_date = o2_min.sel(time=date).squeeze().o2

     # Define the characteristics of the plot
     f = plt.figure(figsize=(10, 8))                                          ␣
      ↪   # create a figure and define its size
     ax = plt.axes(projection=ccrs.PlateCarree())                             ␣
      ↪   # create an ax and select the projection of the map
     ax.coastlines()                                                          ␣
      ↪   # add the coastlines
```

```
gl = ax.gridlines(crs=ccrs.PlateCarree(), draw_labels=True)                    ␣
 ↪   # add the longitude / latitude lines
gl.right_labels = False                                                        ␣
 ↪   # remove latitude labels on the right
gl.top_labels = False                                                          ␣
 ↪   # remove longitude labels on the top
ax.add_feature(cfeature.LAND, zorder=1, edgecolor='k')                         ␣
 ↪   # add land mask
ax.set_extent([80, 100, 8, 25],crs=ccrs.PlateCarree())                         ␣
 ↪   # define the extent of the map [lon_min,lon_max,lat_min,lat_max]

# Plot the sea surface temperature, set the min/max values of the colorbar and␣
 ↪the colormap to use
# im = ax.pcolor(o2_2005_2014['longitude'].data, o2_2005_2014['latitude'].
 ↪data,o2_2005_2014,shading='nearest',cmap='plasma')
#im = ax.pcolor(o2_min['longitude'].data, o2_min['latitude'].
 ↪data,o2_min,shading='nearest',cmap='plasma')
im = ax.contourf(o2_min_date['longitude'].data, o2_min_date['latitude'].
 ↪data,o2_min_date,[-10,2,15],cmap='RdYlGn')

# Add the titles and legend
f.suptitle('Hypoxia assessment on ' + date ,fontsize=25)                       ␣
 ↪   # add a title to the figure
cbar = f.colorbar(im,ax=ax)                                                    ␣
 ↪   # add the colorbar
cbar.ax.set_yticklabels(['Hypoxic < 2 mg/L', 'Hypoxia threshold = 2 mg/L',␣
 ↪'Healthy > 2 mg/L'])                          # add the labels of the colorbar
```

```
[ ]: [Text(1, -10.0, 'Hypoxic < 2 mg/L'),
      Text(1, 2.0, 'Hypoxia threshold = 2 mg/L'),
      Text(1, 15.0, 'Healthy > 2 mg/L')]
```



3.4 Analyse hypoxia evolution

The last steps of our study will be to calculate the area of our sub-region that is affected by hypoxia. For each year, we will state that a pixel of the model is hypoxic if the average of the bottom oxygen concentration, over the year, is below the threshold of 2mg/L. Note that this criterion is just a suggestion and some other ones, such as the median oxygen value over the year, may also be relevant.

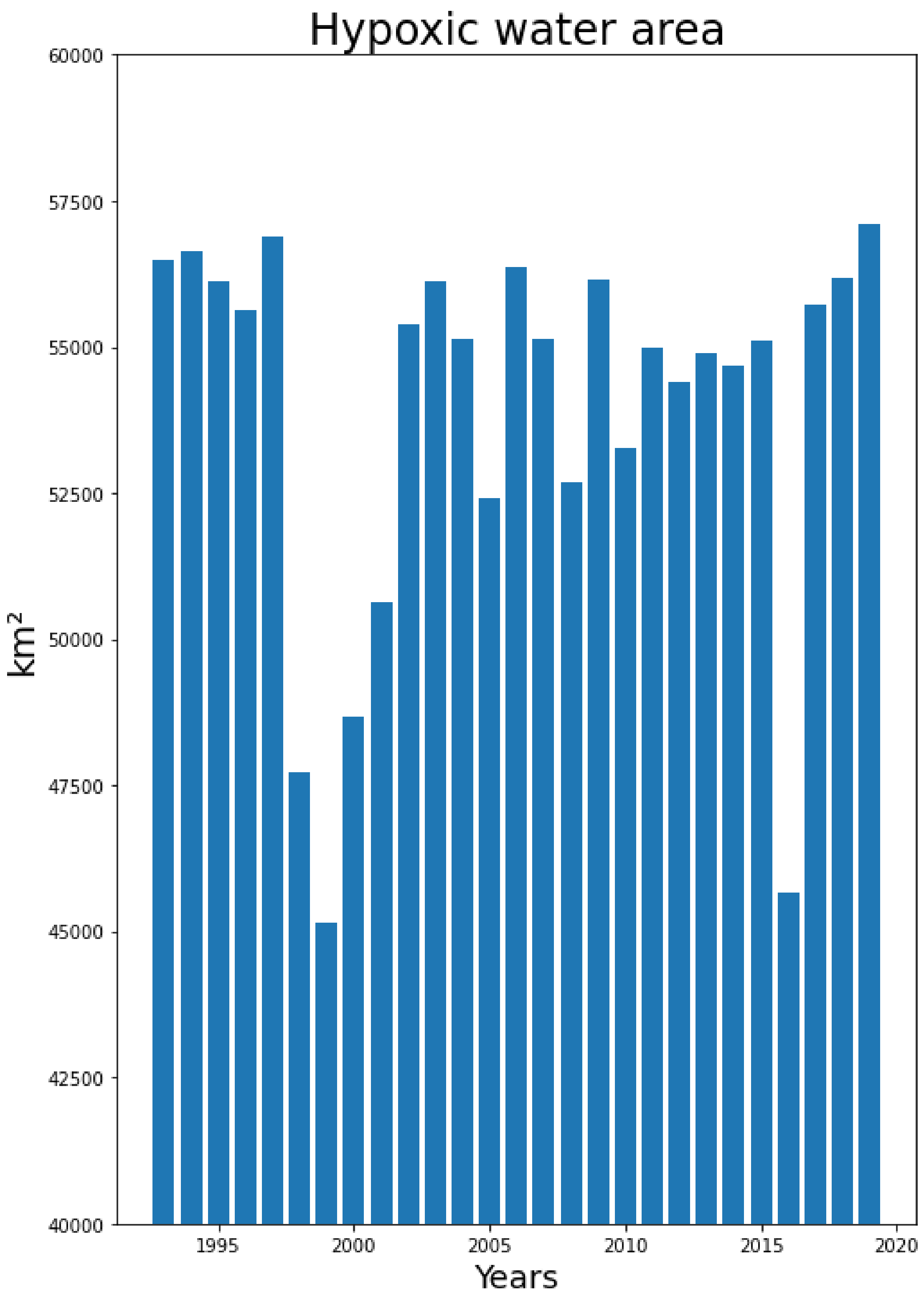
To do this study, we will be using the functions `xarray.where` to apply a filter on the regions where the bottom oxygen is below the threshold, and `xarray.count` to calculate the number of pixels which pass the filter. Knowing that the spatial resolution of the model is 4 km x 4 km, each pixel has an area of 16 km^2 !

In the following cell, we are going group the `o2_min` Python variable by year, like we did in before, We will then make a loop on each year and see the how hypoxia has evolved in the Bay of Bengal over the 28 last years.

[ ]:
```
# Calculate the yearly average
o2_min_year = o2_min.groupby('time.year').mean('time')

# Initialize the lists to be ploted
years = []
```

```
areas = []

# Loop on the years
for year in range(1993,2020):
    o2_min_year_date = o2_min_year.sel(year=year)             # Select the year
    area = o2_min_year_date.o2.where(o2_min_year_date<2).count().o2 * 16      #␣
 ↪Calculate the area
    areas.append(float(area))
    years.append(year)

# Define the characteristics of the plot
f = plt.figure(figsize=(8,12))                                # create a figure␣
 ↪and define its size
ax = f.add_subplot(111)                                       # create the axes␣
 ↪of the plot
ax.set_title("Hypoxic water area",fontsize=24)                     # add the␣
 ↪figure title
ax.set_xlabel("Years",fontsize=18)                        # set x axis label
ax.set_ylabel("km²",fontsize=20)                              # set y axis␣
 ↪label
ax.set_ylim(ymin=40000, ymax=60000)

# Plot the bar charts
ax.bar(years,areas)
```

```
[ ]: <BarContainer object of 27 artists>
```



```
<b>Congratulations !!</b><br>
```

And thank you for your attention! :)