## Lab4 submission

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### 0.1 Lab 4: Gridded data in Python

**Objectives:** \* We will learn how to read, inspect, and write gridded data using rasterio and xarray. \* Learn how to index, slice and manipulate our gridded data. \* Export our data as GeoTIFF or NetCDF format.

We will start by reading/writing some remote sensing data where each band is saved as separate GeoTIFFs. After that, we will read some climate reanalysis data saved as NetCDF format.

The questions are the end of the notebook.

```
[1]: # Import packages
import os
import glob

import matplotlib.pyplot as plt
from mpl_toolkits.axes_grid1 import make_axes_locatable

import numpy as np
import rasterio
import xarray
```

#### 0.2 Read and inspect a Landsat 8 raster layer

[2]: # Define filepath

```
filepath = 'E:/GitHub/GeospatialDataAnalysis/geospatial-data-science/labs/lab4/'

# Define list of Landsat bands
files = sorted(glob.glob(filepath + 'landsat/*.tif'))
print(files)

['E:/GitHub/GeospatialDataAnalysis/geospatial-data-
science/labs/lab4/landsat\\LCO8_L2SP_047029_20200814_20210330_02_T1_SR_B1.tif',
'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
science/labs/lab4/landsat\\LCO8_L2SP_047029_20200814_20210330_02_T1_SR_B2.tif',
'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
science/labs/lab4/landsat\\LCO8_L2SP_047029_20200814_20210330_02_T1_SR_B3.tif',
'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
science/labs/lab4/landsat\\LCO8_L2SP_047029_20200814_20210330_02_T1_SR_B4.tif',
'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
science/labs/lab4/landsat\\LCO8_L2SP_047029_20200814_20210330_02_T1_SR_B4.tif',
'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
```

```
science/labs/lab4/landsat\\LC08_L2SP_047029_20200814_20210330_02_T1_SR_B5.tif',
    'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
    science/labs/lab4/landsat\\LC08_L2SP_047029_20200814_20210330_02_T1_SR_B6.tif',
    'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
    science/labs/lab4/landsat\\LC08_L2SP_047029_20200814_20210330_02_T1_SR_B7.tif',
    'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
    science/labs/lab4/landsat\\inf.tif',
    'E:/GitHub/GeospatialDataAnalysis/geospatial-data-
    science/labs/lab4/landsat\\rgb.tif']
    Next, open a single band from your Landsat scene.
[3]: # Open a single band
     src = rasterio.open(files[0])
     band_1 = src.read(1)
    The dataset's profile contains number of parameters, several of which are required for georefer-
    encing and writing a new dataset
[4]: # Find metadata (e.g. driver, data type, coordinate reference system, transform
      ⇔etc.)
     print(src.profile)
    {'driver': 'GTiff', 'dtype': 'uint16', 'nodata': 0.0, 'width': 1208, 'height':
    1422, 'count': 1, 'crs': CRS.from_epsg(32610), 'transform': Affine(30.0, 0.0,
    391695.0,
           0.0, -30.0, 4880565.0), 'tiled': False, 'interleave': 'band'}
    We can also get some of these parameters separately.
```

```
[5]: # Find coordinate reference system
     src.crs # https://epsq.io/32610
```

[5]: CRS.from\_epsg(32610)

```
[6]: # Find format
     src.driver
```

[6]: 'GTiff'

```
[7]: # Find pixel size
     src.transform[0]
```

[7]: 30.0

```
[8]: # Find bounds of dataset
     src.bounds
```

[8]: BoundingBox(left=391695.0, bottom=4837905.0, right=427935.0, top=4880565.0)

```
[9]: # Get corners of dataset
      full_extent = [src.bounds.left, src.bounds.right, src.bounds.bottom, src.bounds.
       →top]
      print(full_extent)
     [391695.0, 427935.0, 4837905.0, 4880565.0]
[10]: # Find number of columns and rows in array
      band_1.shape
[10]: (1422, 1208)
[11]: # Find total number of pixels in array
      band_1.size
[11]: 1717776
[12]: # Find maximum value in array
      band_1.max()
[12]: 25983
[13]: # Find datatype
      band_1.dtype
[13]: dtype('uint16')
[14]: # Find maximum possible value in array
      2**16
[14]: 65536
[15]: # Find file size (in MB)
      band_1.nbytes / 1000000
[15]: 3.435552
```

### 0.3 Question 1 (10 points):

Now that we have gone through some examples in the lecture and lab we are ready to apply some of these methods ourselves. Start by making a **new jupyter notebook** called lab4\_submission.ipynb and complete the following tasks.

Find the following numbers in the climate reanalysis dataset:

• a) the air temperature (in F) and cloud cover (in %) in Florence, OR (in 2020) on January 31, 2020?

• b) the air temperature (in F) and cloud cover (in %) in Eugene, OR (in 2020) on February 15, 2020?

You can use the following table to convert from a **date** to a **day-of-year**: https://landweb.modaps.eosdis.nasa.gov/browse/calendar.html

#### 0.4 Read climate reanalysis data

We usually use the netCDF4 or xarray packages for this task.

```
[16]: # Read data
      xds = xarray.open_dataset(filepath + 'era/usa_t2m_tcc_2020.nc',_
       ⇔decode_coords='all')
      xds
[16]: <xarray.Dataset>
      Dimensions:
                      (longitude: 233, latitude: 99, time: 1464)
      Coordinates:
        * longitude (longitude) float32 -125.0 -124.8 -124.5 ... -67.5 -67.25 -67.0
        * latitude
                     (latitude) float32 49.24 48.99 48.74 48.49 ... 25.24 24.99 24.74
                     (time) datetime64[ns] 2020-01-01 ... 2020-12-31T18:00:00
        * time
      Data variables:
          t2m
                     (time, latitude, longitude) float32 ...
                     (time, latitude, longitude) float32 ...
          tcc
      Attributes:
                        CF-1.6
          Conventions:
                        2022-01-05 17:55:44 GMT by grib_to_netcdf-2.23.0: /opt/ecmw...
          history:
```

This looks a bit overwelming but it nice way to store gridded data. Below is a schematic of what an xarray data structure represents.

```
[17]: # Print the time period of the data
print('The data ranges from %s to %s' %(xds['t2m']['time'].values.min(),

→xds['t2m']['time'].values.max()))
```

```
The data ranges from 2020-01-01T00:00:00.000000000 to 2020-12-31T18:00:00.000000000
```

So we know the data spans one year but there are 1464 dimensions in the time variable. This means that the reanalysis data must have a temporal resolution of 6 hours. So before we continue we will resample to daily temporal resolution.

```
[18]: xds_daily = xds.resample(time='1D').mean()
xds_daily
```

```
[18]: <xarray.Dataset>
    Dimensions: (time: 366, longitude: 233, latitude: 99)
    Coordinates:
```

```
* time (time) datetime64[ns] 2020-01-01 2020-01-02 ... 2020-12-31

* longitude (longitude) float32 -125.0 -124.8 -124.5 ... -67.5 -67.25 -67.0

* latitude (latitude) float32 49.24 48.99 48.74 48.49 ... 25.24 24.99 24.74

Data variables:

t2m (time, latitude, longitude) float32 280.6 281.4 ... 296.3 296.2

tcc (time, latitude, longitude) float32 0.9765 0.8814 ... 0.2124
```

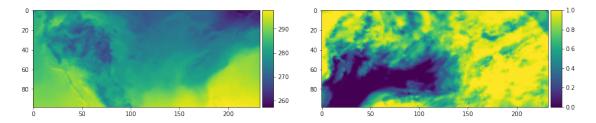
## 0.4.1 Plot climate reanalysis data for January 31, 2020

Now each layer in the dataset corresponds to a single day. Let's plot the air temperature and cloud cover for the day which the Landsat image was acquired (January 31, 2020 - which is DOY 31).

```
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=(16,6))
im1 = ax1.imshow(xds_daily['t2m'][31,:,:])
divider = make_axes_locatable(ax1)
cax = divider.append_axes('right', size='5%', pad=0.05)
fig.colorbar(im1, cax=cax, orientation='vertical')

im2 = ax2.imshow(xds_daily['tcc'][31,:,:])
divider = make_axes_locatable(ax2)
cax = divider.append_axes('right', size='5%', pad=0.05)
fig.colorbar(im2, cax=cax, orientation='vertical')
```

#### [19]: <matplotlib.colorbar.Colorbar at 0x1c57fad46d0>



C:\Users\brdeh\anaconda3\envs\lab4\lib\site-packages\xarray\core\indexes.py:234:
FutureWarning: Passing method to Float64Index.get\_loc is deprecated and will
raise in a future version. Use index.get\_indexer([item], method=...) instead.
 indexer = self.index.get\_loc(
C:\Users\brdeh\anaconda3\envs\lab4\lib\site-packages\xarray\core\indexes.py:234:
FutureWarning: Passing method to Float64Index.get\_loc is deprecated and will
raise in a future version. Use index.get\_indexer([item], method=...) instead.
 indexer = self.index.get\_loc(

# 0.4.2 1a) the air temperature (in F) and cloud cover (in %) in Florence, OR (in 2020) on January 31, 2020?

```
[21]: # Note: Jan 31 is DOY 31

print('Cloud cover in Florence on Jan 31, 2020 = %.2f %%' %

→(florence_weather['tcc'][30].values * 100))
```

Cloud cover in Florence on Jan 31, 2020 = 99.98 %

```
[22]: fahrenheit = (florence_weather['t2m'][30].values - 273.15) * 9/5 + 32 print('Air temperature in Florence on Jan 31, 2020 = %.2f F' % (fahrenheit))
```

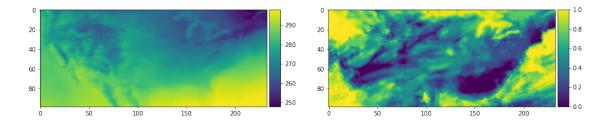
Air temperature in Florence on Jan 31, 2020 = 53.82 F

# 0.4.3 1b) the air temperature (in F) and cloud cover (in %) in Eugene, OR (in 2020) on February 15, 2020?

```
[23]: # Plot data for Feb 15th 2020
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=(16,6))
im1 = ax1.imshow(xds_daily['t2m'][45,:,:])
divider = make_axes_locatable(ax1)
cax = divider.append_axes('right', size='5%', pad=0.05)
fig.colorbar(im1, cax=cax, orientation='vertical')

im2 = ax2.imshow(xds_daily['tcc'][45,:,:])
divider = make_axes_locatable(ax2)
cax = divider.append_axes('right', size='5%', pad=0.05)
fig.colorbar(im2, cax=cax, orientation='vertical')
```

[23]: <matplotlib.colorbar.Colorbar at 0x1c50192c2e0>



C:\Users\brdeh\anaconda3\envs\lab4\lib\site-packages\xarray\core\indexes.py:234:
FutureWarning: Passing method to Float64Index.get\_loc is deprecated and will
raise in a future version. Use index.get\_indexer([item], method=...) instead.
indexer = self.index.get\_loc(

C:\Users\brdeh\anaconda3\envs\lab4\lib\site-packages\xarray\core\indexes.py:234:
FutureWarning: Passing method to Float64Index.get\_loc is deprecated and will
raise in a future version. Use index.get\_indexer([item], method=...) instead.
 indexer = self.index.get\_loc(

Cloud cover in Eugene on Feb 15, 2020 = 99.99 %

```
[26]: fahrenheit = (eugene_weater['t2m'][45].values - 273.15) * 9/5 + 32 print('Air temperature in Eugene on Feb 15, 2020 = %.2f F' % (fahrenheit))
```

Air temperature in Eugene on Feb 15, 2020 = 42.00 F

### 0.5 Question 2 (20 points):

Find the following grid cells in the climate reanalysis dataset and provide the lat/lons **and** a rough location of where they are located.

- a) Highest average air temperature (i.e. hottest place)
- b) Lowest average air temperature (i.e. coldest place)
- c) Highest average cloudiness (i.e. cloudiest place)
- d) Lowest average cloudiest (i.e. least cloudy place)
- e) Place with highest range in daily air temperature
- f) Place with the absolute coldest temperature on a single day

You can copy and paste the lat/lons into Google Maps to find a rough location of where these places are.

#### 0.5.1 Question 2a) Highest average air temperature (i.e. hottest place)

```
hot_long = xds_daily.longitude[index_hot[1]]
print('The hottest place on average in this region was %.2f F on average and_\(\text{\text{\text{\text{orange}}}}\) \( \delta \) \( \delta \)
```

The hottest place on average in this region was 79.07~F on average and located at lat: 28.99~,long: -111.25~

The hottest place on average was Sonora Mexico.

### 0.5.2 Question 2b) Lowest average air temperature (i.e. coldest place)

The coldest place on average in this region was 29.18 F on average and located at lat: 43.99 ,long: -109.75

The coldest place on average was in Park County WY

(0, 0)

#### 0.5.3 Question 2c) Highest average cloudiness (i.e. cloudiest place)

The cloudiest place on average in this region was 77.15 percent coverage on average and located at lat: 49.24,long: -125.00

The cloudiest place was sproat lake BC, Canada.

#### 0.5.4 Question 2d) Lowest average cloudiest (i.e. least cloudy place)

The clearest place on average in this region was 16.89 on average and located at lat: 31.49, long: -114.75

The clearest place on average was in the **Gulf of CA**.

#### 0.5.5 Question 2e) Place with highest range in daily air temperature

<xarray.DataArray 't2m' ()>
array(443, dtype=int64)

```
<xarray.DataArray 't2m' ()>
     array(57.7585, dtype=float32)
     (1, 210)
[36]: \max_{\text{valueF}} = \text{np.max}(\text{np.max}(\text{np.max}(\text{xds\_daily}['t2m'], axis = 0) - 273.15) * 9/5_{\text{L}}
       4+32) - (((np.min(xds_daily['t2m'], axis = 0)) - 273.15) * 9/5 + 32))
      print(max valueF)
      range_lat = xds_daily.latitude[index_range[0]]
      range_long = xds_daily.longitude[index_range[1]]
      print('The highest range in temp in this region was %.2f F on average and ⊔
       →located at lat: %.2f ,long: %.2f' % ((max_valueF,range_lat,range_long)))
     <xarray.DataArray 't2m' ()>
     array(133.04608231)
     The highest range in temp in this region was 133.05 F on average and located at
     lat: 48.99 ,long: -72.50
     The largest range in daily air temps was in QC, Canada.
     0.5.6 Question 2f) Place with the absolute coldest temperature on a single day
[37]: min_value = np.min(xds_daily['t2m'], axis = 0).argmin()
      print(min_value)
     <xarray.DataArray 't2m' ()>
     array(521, dtype=int64)
[38]: # convert 1D index to 2D coords
      min_indx = np.unravel_index(min_value, np.min(xds_daily['t2m'], axis =0).shape)
      print(min_indx)
     (2, 55)
[39]: cold = np.min(xds_daily['t2m'][:, min_indx[0], min_indx[1]], axis =0)
      cold_lat = xds_daily.latitude[min_indx[0]]
      cold_long = xds_daily.longitude[min_indx[1]]
      print('Coldest place on Earth for a single day was was %.2f F at lat: %.2f L
       →,long: %.2f' % (((cold - 273.15) * 9/5 + 32), cold_lat, cold_long))
     Coldest place on Earth for a single day was was -24.57 F at lat: 48.74 ,long:
     -111.25
```

## 0.6 Question 3 (20 points):

Display the Landsat image of Florence, OR as:

- a) an **NDVI** image (i.e. (Band 5 Band 4) / (Band 5 + Band 4))
- b) a color infrared composite (i.e. bands 5, 4, 3)

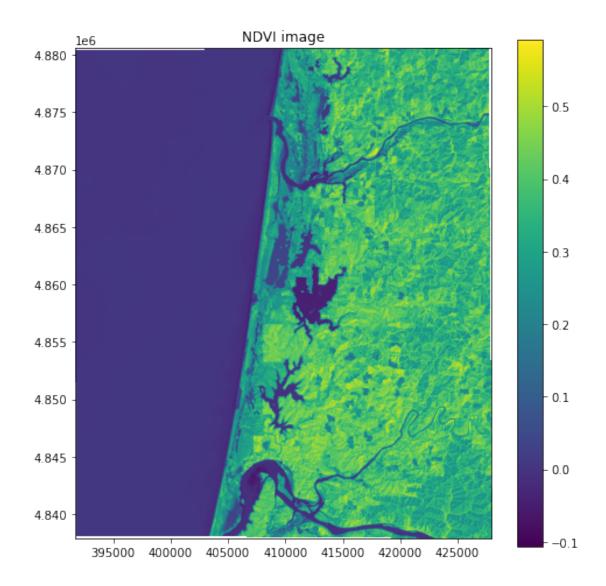
0.6.1 3a) an NDVI image (i.e. (Band 5 - Band 4) / (Band 5 + Band 4))

We can compute a Normalized Difference Vegetation Index (NDVI) using the Green and NIR bands.

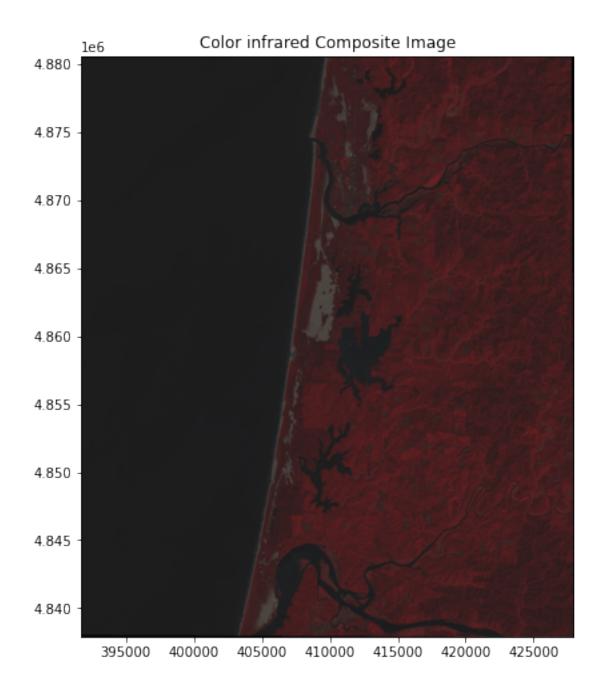
```
NDWI = (Band 5 - Band 4) / (Band 5 + Band 4)
```

Remember that arrays are zero indexed, so the first layer is corresponds to all\_bands[:,:,0]. Also note that we have to make sure our bands are converted to float datatypes.

```
[40]: # Open all bands in a loop
      list_bands = []
      for file in files:
          # Read band
          src = rasterio.open(file)
          band = src.read(1)
          # Append to list
          list_bands.append(band)
      # Convert from list of arrays to n-dimensional array
      all_bands = np.dstack(list_bands)
[41]: all_bands.shape
[41]: (1422, 1208, 9)
[42]: # Convert values to a range of 0-255
      all_bands_image = np.uint8((all_bands / 65536) * 255)
[43]: # Compute NDVI
      ndvi = np.divide((all_bands[:,:,4].astype(float) - all_bands[:,:,3].
       ⇒astype(float)), \
                       (all_bands[:,:,4].astype(float) + all_bands[:,:,3].
       →astype(float)))
     C:\Users\brdeh\AppData\Local\Temp\ipykernel_26676\235523949.py:2:
     RuntimeWarning: invalid value encountered in true_divide
       ndvi = np.divide((all_bands[:,:,4].astype(float) -
     all_bands[:,:,3].astype(float)), \
[44]: # Plot NDVI image
      fig, ax = plt.subplots(figsize=(8,8))
      im = ax.imshow(ndvi, extent=full_extent)
      ax.set title("NDVI image")
      fig.colorbar(im, orientation='vertical')
      plt.show()
```



## 0.6.2 3b) a color infrared composite (i.e. bands 5, 4, 3)



```
[47]: # Write an array as a raster band to a new 8-bit file. For the new file's → profile,

# we start with the profile of the source

profile = src.profile

# And then change the band count to 3, set the dtype to uint8, and specify LZW → compression.

profile.update(dtype=rasterio.uint8, count=3, compress='lzw')
```

```
with rasterio.open(filepath + 'landsat/inf.tif', 'w', **profile) as dst:

# Write array
dst.write(np.rollaxis(inf, axis=2)) # Note that array needs to be in bands,

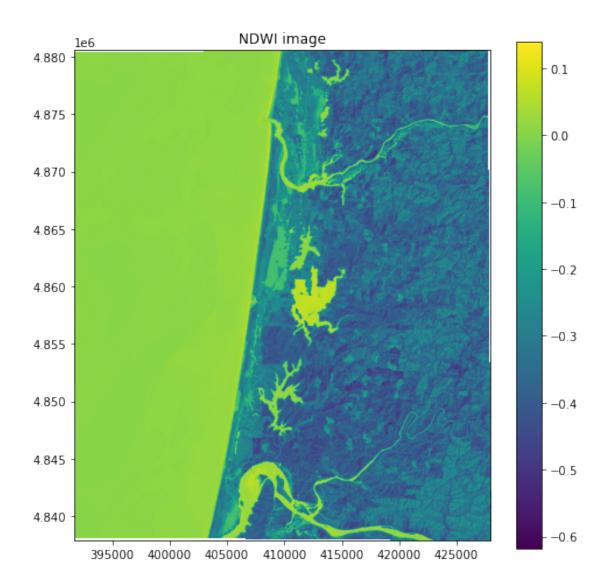
-rows, cols order (z, y, x)
```

## 0.7 Question 4 (for grad students/extra credit)

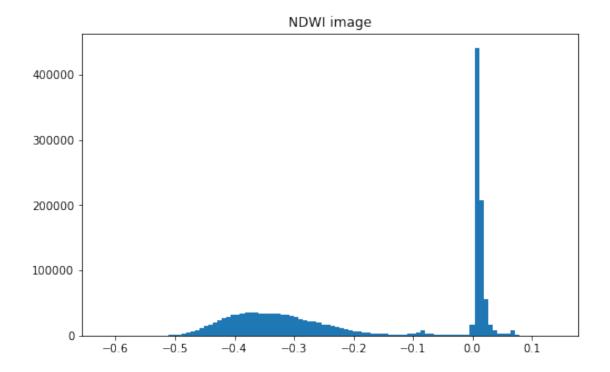
- a) Produce an NDWI histogram for the Landsat image of Florence
- b) Choose a threshold and produce a binary water mask
- c) Compute the area of water in the image (including ocean)

# 0.8 Remember to submit your answers to Questions 1, 2 and 3 by Friday 11:59pm

0.8.1 Question 4a) Produce an NDWI histogram for the Landsat image of Florence



```
[49]: # Insang showed you how to reshape data (collapse into a 1D array)
# flattened_ndwi = np.reshape(ndwi, (ndwi.shape[0] * ndwi.shape[1]))
# #flattened_ndwi
# flattened_ndwi = flattened_ndwi[~np.isnan(flattened_ndwi)]
# #np.isnan(flattened_ndwi)
[50]: # Plot NDWI histogram
fig, ax = plt.subplots(figsize=(8,5))
im = ax.hist(ndwi[~np.isnan(ndwi)], bins =100)
ax.set_title("NDWI image")
plt.show()
```

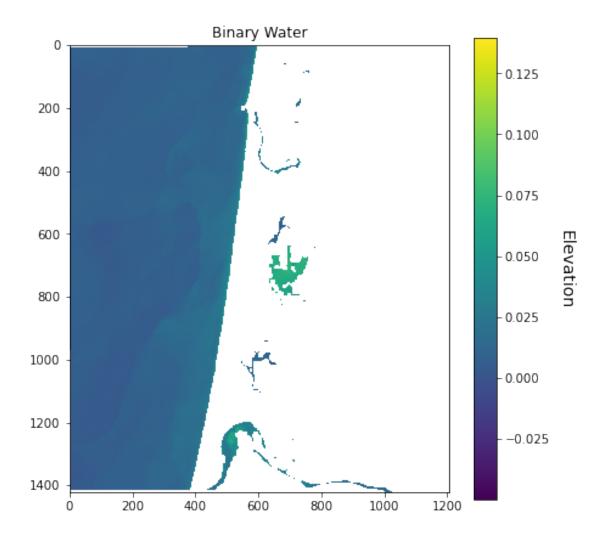


## 0.8.2 Question 4b) Choose a threshold and produce a binary water mask

```
[51]: #Threshold of -0.05
#make a mask
thres_mask = np.ma.masked_array(ndwi, mask =(ndwi < -0.05))

fig, ax = plt.subplots(figsize = (7,7))
im = ax.imshow(thres_mask)
ax.set_title("Binary Water")

cbar = fig.colorbar(im, orientation='vertical')
cbar.ax.set_ylabel('Elevation', rotation=270, fontsize=14)
cbar.ax.get_yaxis().labelpad = 20</pre>
```



## 0.8.3 Question 4c) Compute the area of water in the image (including ocean)

```
[52]: # 30 meter cell size (landsat)

area_m2 = (30*30)*thres_mask.count()

print('The area of water in the image (including the ocean is %.2f km^2'

\( \text{\text{\colored}} \) (area_m2/1000000))
```

The area of water in the image (including the ocean is  $706.21 \, \text{km}^2$