In [2]:
```
import numpy as np
import xarray as xr
import matplotlib.pyplot as plt
import geopandas as gpd
from shapely.geometry import Polygon
from shapely.geometry import box
```

In [3]:
```
data = xr.open_dataset("geospatial_test_datacube.nc") # Loading geospatia
```

In [4]:
```
data
```

Out[4]:

xarray.Dataset

▶ Dimensions: (**time**: 23, **y**: 227, **x**: 304)

▼ Coordinates:

time	(time)	datetime64[ns]	2021-04-09 ... 2021-11-...
y	(y)	float32	45.23 45.23 45.23 ... 45...
x	(x)	float32	-69.95 -69.95 ... -69.92...

▼ Data variables:

S2_RED	(time, y, x)	float32	...
S2_GREEN	(time, y, x)	float32	...
S2_BLUE	(time, y, x)	float32	...
S2_NIR	(time, y, x)	float32	...

▼ Attributes:

transform :	[8.98405270e-05 0.00000000e+00 -6.99499045e+01 0.00000000e+00 -9.04387077e-05 4.52332071e+01]
crs :	+init=epsg:4326
res :	[8.98405270e-05 9.04387077e-05]
descriptions :	['RED', 'GREEN', 'BLUE', 'NIR']
AREA_OR_POI...	Area
_FillValue :	nan
s2_data_lineage :	{"Data origin": "S3 bucket (ARN=arn:aws:s3:::sentinel-cogs-inventory)"}
ulx, uly :	[-69.94990454 45.23320715]

In [5]:
```
data.variables # Get to know our variables
```

Out[5]:
```
Frozen({'time': <xarray.IndexVariable 'time' (time: 23)>
array(['2021-04-09T00:00:00.000000000', '2021-04-14T00:00:00.000000000',
       '2021-04-27T00:00:00.000000000', '2021-05-07T00:00:00.000000000',
       '2021-05-19T00:00:00.000000000', '2021-05-24T00:00:00.000000000',
       '2021-05-29T00:00:00.000000000', '2021-06-18T00:00:00.000000000',
       '2021-07-28T00:00:00.000000000', '2021-08-10T00:00:00.000000000',
       '2021-08-12T00:00:00.000000000', '2021-08-25T00:00:00.000000000',
       '2021-09-04T00:00:00.000000000', '2021-09-16T00:00:00.000000000',
       '2021-09-19T00:00:00.000000000', '2021-09-21T00:00:00.000000000',
       '2021-10-06T00:00:00.000000000', '2021-10-09T00:00:00.000000000',
       '2021-10-29T00:00:00.000000000', '2021-11-05T00:00:00.000000000',
       '2021-11-20T00:00:00.000000000', '2021-11-23T00:00:00.000000000',
       '2021-11-25T00:00:00.000000000'], dtype='datetime64[ns]'), 'S2_RE
D': <xarray.Variable (time: 23, y: 227, x: 304)>
[1587184 values with dtype=float32]
Attributes:
    transform:             [ 8.98405270e-05  0.00000000e+00 -6.99499045e
+01  ...
    crs:                   +init=epsg:4326
    res:                   [8.98360017e-05 9.04414549e-05]
    descriptions:
    AREA_OR_POINT:         Area
    band_wavelength:       665 nm
    scene_id:              S2A_19TDL_20210409_0_L2A
    scene_classification:  {"water": 0.7, "not_vegetated": 24.98, "sno
w": 0.0..., 'S2_GREEN': <xarray.Variable (time: 23, y: 227, x: 304)>
[1587184 values with dtype=float32]
Attributes:
    transform:             [ 8.98405270e-05  0.00000000e+00 -6.99499045e
+01  ...
    crs:                   +init=epsg:4326
    res:                   [8.98360017e-05 9.04414549e-05]
    descriptions:
    AREA_OR_POINT:         Area
    band_wavelength:       560 nm
    scene_id:              S2A_19TDL_20210409_0_L2A
    scene_classification:  {"water": 0.7, "not_vegetated": 24.98, "sno
w": 0.0..., 'S2_BLUE': <xarray.Variable (time: 23, y: 227, x: 304)>
[1587184 values with dtype=float32]
Attributes:
    transform:             [ 8.98405270e-05  0.00000000e+00 -6.99499045e
+01  ...
    crs:                   +init=epsg:4326
    res:                   [8.98360017e-05 9.04414549e-05]
    descriptions:
    AREA_OR_POINT:         Area
    band_wavelength:       490 nm
    scene_id:              S2A_19TDL_20210409_0_L2A
    scene_classification:  {"water": 0.7, "not_vegetated": 24.98, "sno
w": 0.0..., 'S2_NIR': <xarray.Variable (time: 23, y: 227, x: 304)>
[1587184 values with dtype=float32]
Attributes:
    transform:             [ 8.98405270e-05  0.00000000e+00 -6.99499045e
+01  ...
    crs:                   +init=epsg:4326
    res:                   [8.98360017e-05 9.04414549e-05]
    descriptions:
    AREA_OR_POINT:         Area
    band_wavelength:       842 nm
    scene_id:              S2A_19TDL_20210409_0_L2A
```

```
    scene_classification:  {"water": 0.7, "not_vegetated": 24.98, "sno
w": 0.0..., 'y': <xarray.IndexVariable 'y' (y: 227)>
array([45.233162, 45.233074, 45.232983, ..., 45.212906, 45.212814, 45.21
2723],
      dtype=float32)
Attributes:
    axis:           Y
    long_name:      latitude
    standard_name:  latitude
    units:          degrees_north, 'x': <xarray.IndexVariable 'x' (x: 30
4)>
array([-69.94986, -69.94977, -69.94968, ..., -69.92282, -69.92273, -69.9
2264],
      dtype=float32)
Attributes:
    axis:           X
    long_name:      longitude
    standard_name:  longitude
    units:          degrees_east})
```

In [6]:
```python
data_aoi = gpd.read_file('geospatial_sub_aoi.geojson') # Loading the geos
```

In [7]:
```python
data_aoi.head()
```

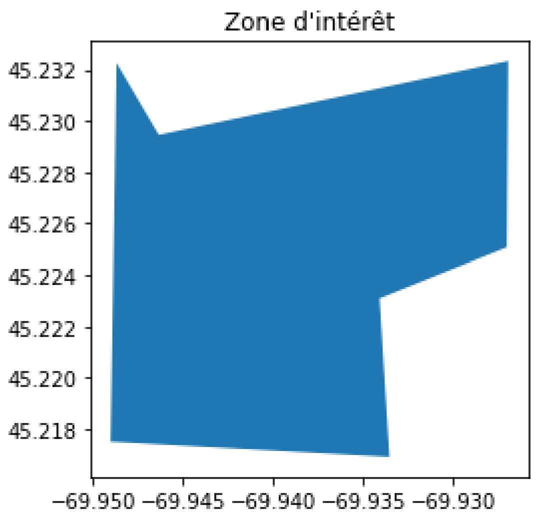
Out[7]:

	geometry
0	POLYGON ((-69.94867 45.23227, -69.94900 45.217...

In [8]:
```python
data_aoi.geometry.head()
```

Out[8]:
```
0    POLYGON ((-69.94867 45.23227, -69.94900 45.217...
Name: geometry, dtype: geometry
```

In [9]:
```python
# Viewing the area of interest
data_aoi.plot()
plt.title('Zone d\'intérêt')
plt.show()
```



In [10]:
```python
# Checking for the presence of NaN values in a spectral band
def verif_nan(bande):
    nb_nan = data[bande].isnull().sum()
    print("Nombre de valeurs NaN dans la bande {}: {}".format(bande, nb_n
```

In [11]:
```
verif_nan('S2_RED')
```

```
Nombre de valeurs NaN dans la bande S2_RED: 0
```

In [12]:
```
verif_nan('S2_BLUE')
```

```
Nombre de valeurs NaN dans la bande S2_BLUE: 0
```

In [13]:
```
verif_nan('S2_GREEN')
```

```
Nombre de valeurs NaN dans la bande S2_GREEN: 0
```

Question 1

In [14]:
```
ndvi_data = (data['S2_NIR'] - data['S2_RED']) / (data['S2_NIR'] + data['S
```

In [15]:
```
ndvi_data
```

Out[15]: xarray.DataArray (**time**: 23, **y**: 227, **x**: 304)

```
array([[[0.62311345, 0.62311345, 0.6612276 , ..., 0.738523  ,
         0.7610312 , 0.7610312 ],
        [0.78484946, 0.78484946, 0.7461864 , ..., 0.729616  ,
         0.7360574 , 0.7360574 ],
        [0.7316661 , 0.7316661 , 0.6671105 , ..., 0.62512076,
         0.78181815, 0.78181815],
        ...,
        [0.6911272 , 0.48504552, 0.48504552, ..., 0.5377561 ,
         0.47117797, 0.5424836 ],
        [0.6953793 , 0.5753992 , 0.5753992 , ..., 0.37571156,
         0.5851346 , 0.7231702 ],
        [0.7114915 , 0.66701144, 0.66701144, ..., 0.5881436 ,
         0.77481365, 0.7161048 ]],

       [[0.44147158, 0.44147158, 0.54115593, ..., 0.7959596 ,
         0.78008753, 0.78008753],
        [0.7433155 , 0.7433155 , 0.75518537, ..., 0.77339894,
         0.782801  , 0.782801  ],
        [0.75450593, 0.75450593, 0.7139296 , ..., 0.74929094,
         0.7554786 , 0.7554786 ],
...
        [0.63016534, 0.551181  , 0.551181  , ..., 0.73238176,
         0.655527  , 0.75266325],
        [0.7659138 , 0.60186625, 0.60186625, ..., 0.69435215,
         0.6860171 , 0.7511521 ],
        [0.8212407 , 0.6822595 , 0.6822595 , ..., 0.6744809 ,
         0.827792  , 0.8098721 ]],

       [[0.6601942 , 0.6601942 , 0.59090906, ..., 0.8777293 ,
         0.9566983 , 0.9566983 ],
        [0.7951604 , 0.7951604 , 0.7686291 , ..., 0.8796993 ,
         0.9171742 , 0.9171742 ],
        [0.80886245, 0.80886245, 0.70818067, ..., 0.86597943,
         0.8496733 , 0.8496733 ],
        ...,
        [0.66309774, 0.59760153, 0.59760153, ..., 0.66493595,
         0.60098314, 0.69693094],
        [0.6629002 , 0.5866314 , 0.5866314 , ..., 0.6846325 ,
         0.71889406, 0.7132915 ],
        [0.76829267, 0.6347826 , 0.6347826 , ..., 0.7311089 ,
         0.8158915 , 0.7271214 ]]], dtype=float32)
```

▼ Coordinates:

time	(time)	datetime64[ns]	2021-04-09 ... 2021-11-25

y	(y)	float32	45.23 45.23 45.23 ... 45.21 ...	
x	(x)	float32	-69.95 -69.95 ... -69.92 -69...	

▶ Attributes: (0)

In [16]:
```
data['NDVI'] = ndvi_data # Add NDVI layer to existing data cube
```

In [17]:
```
# Save the updated data cube in a new netCDF file
data.to_netcdf('sentinel2_datacube_avc_ndvi.nc')
```

In [ ]:
```

```

In [19]:
```
data1 = xr.open_dataset("sentinel2_datacube_avc_ndvi.nc")
```

In [20]:
```
data1
```

Out[20]: xarray.Dataset

▶ Dimensions: (**time**: 23, **y**: 227, **x**: 304)

▼ Coordinates:

time	(time)	datetime64[ns]	2021-04-09 ... 2021-11-...
y	(y)	float32	45.23 45.23 45.23 ... 45...
x	(x)	float32	-69.95 -69.95 ... -69.92...

▼ Data variables:

S2_RED	(time, y, x)	float32	...
S2_GREEN	(time, y, x)	float32	...
S2_BLUE	(time, y, x)	float32	...
S2_NIR	(time, y, x)	float32	...
NDVI	(time, y, x)	float32	...

▼ Attributes:

transform :	[8.98405270e-05 0.00000000e+00 -6.99499045e+01 0.00000000e+00 -9.04387077e-05 4.52332071e+01]
crs :	+init=epsg:4326
res :	[8.98405270e-05 9.04387077e-05]
descriptions :	['RED', 'GREEN', 'BLUE', 'NIR']
AREA_OR_POI...	Area
_FillValue :	nan
s2_data_lineage :	{"Data origin": "S3 bucket (ARN=arn:aws:s3:::sentinel-cogs-inventory)"}
ulx, uly :	[-69.94990454 45.23320715]

Question 1 b

In [21]:
```
date_exemple = '2021-04-09' # Select a specific date to create the RGB im
```

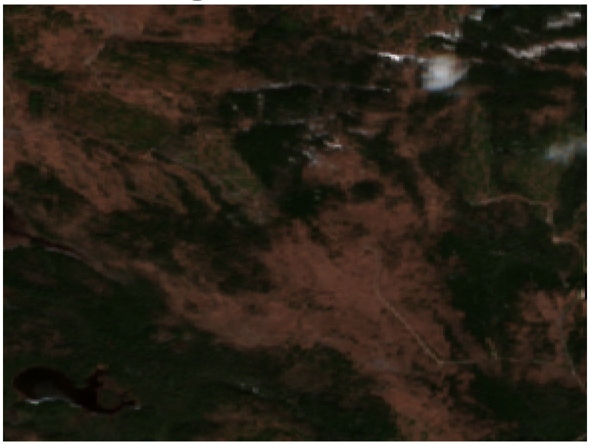
In [22]:
```
# Select red, green and blue stripes for this date
bande_rouge = data1['S2_RED'].sel(time=date_exemple)
bande_verte = data1['S2_GREEN'].sel(time=date_exemple)
bande_bleue = data1['S2_BLUE'].sel(time=date_exemple)
```

In [23]:
```
rgb_image = np.stack([bande_rouge, bande_verte, bande_bleue], axis=-1) #
```

In [24]:
```
rgb_image = rgb_image / rgb_image.max() # Normalize pixel values to the r
```

In [25]:
```
# Display RGB image
plt.imshow(rgb_image)
plt.title('Image RGB - {}'.format(date_exemple))
plt.axis('off')
plt.show()
```

Image RGB - 2021-04-09



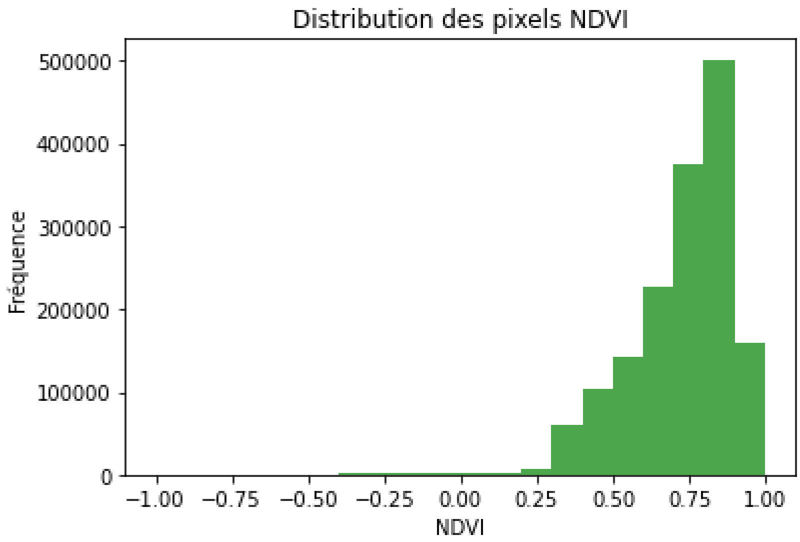
Question 1 c

In [29]:
```
ndvi_all_dates = data1['NDVI'] # Select NDVI layer for all dates
```

In [30]:
```
ndvi_val = ndvi_all_dates.values.flatten() # Stack NDVI values for all da
```

In [31]:
```
ndvi_val = ndvi_val[~np.isnan(ndvi_val)] # Delete NaN values
```

In [32]:
```
# Display histogram of NDVI values
plt.hist(ndvi_val, bins=20, color='green', alpha=0.7)
plt.title('Distribution des pixels NDVI')
plt.xlabel('NDVI')
plt.ylabel('Fréquence')
plt.show()
```



Question 1 d

In [33]:
```
ndvi_all_dates = data1['NDVI'] # Select NDVI layer for entire data cube
```

In [34]:
```
num_times = ndvi_all_dates.sizes['time'] # Extract dimensions from the da
```

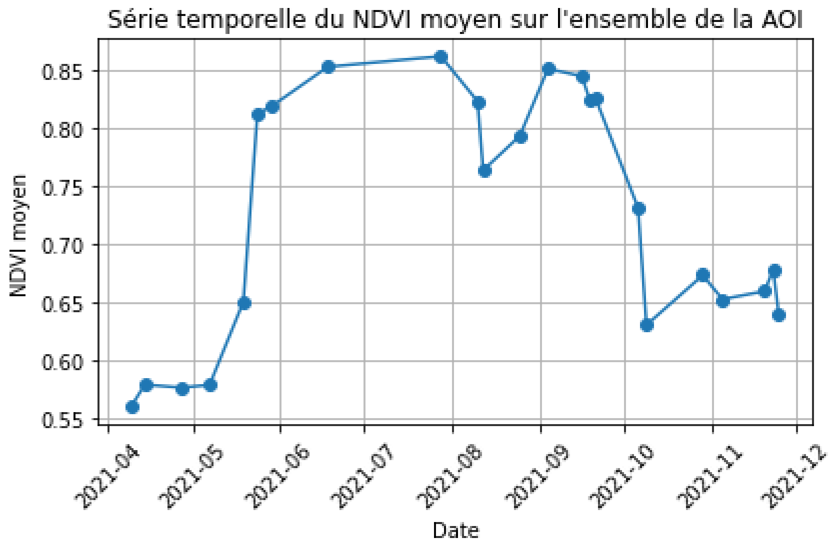
In [35]:
```
ndvi_moy = [] # Initialize a list to store NDVI averages for each date
```

In [36]:
```
# Loop on each date to calculate the average NDVI over the entire AOI
for i in range(num_times):
    ndvi_date = ndvi_all_dates.isel(time=i)
    ndvi_mean = ndvi_date.mean()
    ndvi_moy.append(ndvi_mean)
```

In [37]:
```
ndvi_moy = np.array(ndvi_moy) # Convert the list into a NumPy array
```

In [38]:
```
dates = ndvi_all_dates.time.values # Create a date table for the x axis
```

In [39]:
```
# Plot the time series of mean NDVI over the entire AOI
plt.plot(dates, ndvi_moy, marker='o', linestyle='-')
plt.title('Série temporelle du NDVI moyen sur l\'ensemble de la AOI')
plt.xlabel('Date')
plt.ylabel('NDVI moyen')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



Question 2

Interpretation of spatial distribution and NDVI/vegetation trends

Spatial distribution of NDVI:

The histogram of NDVI pixels shows that the area is dominated by vegetation, with varying levels of cover density. The RGB image allows us to visualize and understand how vegetation is distributed in space. The presence of non-vegetated areas, such as bare soil, in the RGB image is correlated with low NDVI values.

Temporal evolution of NDVI:

The mean NDVI time series shows a seasonal pattern, with higher values in spring and summer when vegetation is actively growing, and lower values in autumn and winter when vegetation is dormant.

Question 3

In [41]:
```
aoi_limites = data_aoi.geometry.total_bounds # Extracting AOI limits
```

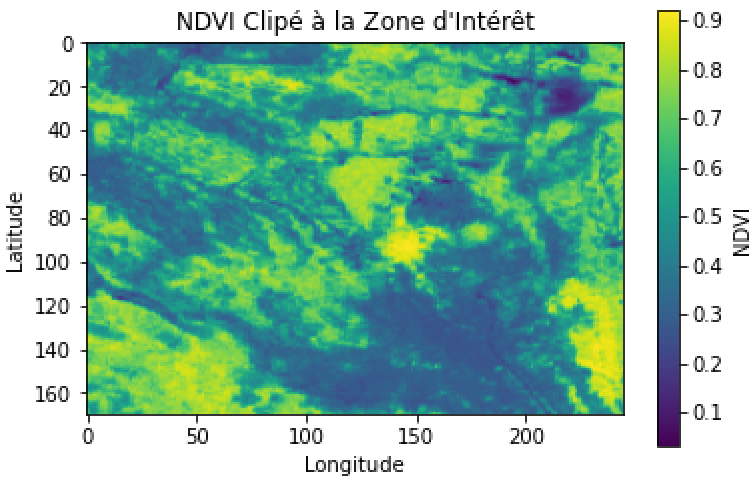
In [42]:
```
aoi_box = box(*aoi_limites) # Create bounding box geometry from AOI bound
```

In [43]:
```
x_min, y_min, x_max, y_max = aoi_limites # Select the x and y coordinates
```

In [44]:
```
ndvi_clipper = data1['NDVI'].sel(x=slice(x_min, x_max), y=slice(y_max, y_
```

In [45]:
```
# Display clipped NDVI
plt.imshow(ndvi_clipper[0], cmap='viridis')
plt.colorbar(label='NDVI')
plt.title('NDVI Clipé à la Zone d\'Intérêt')
plt.xlabel('Longitude')
```

```
plt.ylabel('Latitude')
plt.show()
```



In [ ]:

Lien vers un travail de géolocalisation fait en salle de classe

Github

In [ ]: