# Time Series Analisys on Geoespatial Data with Python

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#### First instructions:

Access the link to join our private WhatsApp community for students: https://chat.whatsapp.com/EPn27ZqR07IF3e1vnj8Fil

It is important to access the Whatsapp Group to get the Colab Notebooks, as the PDF files are protected from text copying.

## Chapter 4 - Working with image time series with GEE

Let's start by importing the libraries

```
In []: import ee
   import matplotlib.pyplot as plt
   import numpy as np
   import pandas as pd
   import geemap
   import geopandas as gpd
   import warnings
   warnings.filterwarnings('ignore')
```

Let's authenticate and initialize the GEE library

```
In [ ]: ee.Authenticate()
    ee.Initialize(project='my-project-1527255156007')

In [ ]: from google.colab import drive
    drive.mount('/content/drive')
```

Mounted at /content/drive

We select our analysis area and convert it to a FeatureCollection:

Link to Dataset:

https://drive.google.com/drive/folders/1B2O\_kfc\_Ntfu2eeNVFBHdPPhH8iI\_VDy?usp=sharing

```
In [ ]: path_aoi_soja = '/content/drive/MyDrive/Datasets_TS/AOI_cana/cana_lotes.shp'
In [ ]: gdf_soja = gpd.read_file(path_aoi_soja)
        gdf_soja
In [ ]:
Out[]:
              id
                                                   geometry
         0 NaN POLYGON ((-47.93468 -21.13461, -47.9334 -21.13...
           NaN POLYGON ((-47.93154 -21.13705, -47.92954 -21.1...
         2 NaN POLYGON ((-47.9231 -21.13705, -47.92215 -21.13...
         3 NaN POLYGON ((-47.93712 -21.13007, -47.93579 -21.1...
           NaN POLYGON ((-47.94116 -21.12812, -47.94111 -21.1...
         5 NaN POLYGON ((-47.92352 -21.14178, -47.92319 -21.1...
In [ ]: gdf_soja.boundary.plot()
Out[ ]: <Axes: >
       -21.128
        -21.130
        -21.132
        -21.134
        -21.136
        -21.138
        -21.140
        -21.142
                                                                      -47.920
                                                                                  -47.915
                    -47.940
                                -47.935
                                             -47.930
                                                         -47.925
In [ ]: fc = geemap.geopandas_to_ee(gdf_soja)
In [ ]: fc
Out[ ]:
          ► FeatureCollection (6 elements, 1 column)
         Let's get an ImageCollection of Sentinel 2 from 2017 to 2024:
In [ ]: S2_coll = ee.ImageCollection("COPERNICUS/S2_SR_HARMONIZED").filter(ee.Filter.lt(
```

```
In [ ]: print('Total number of images :', S2_coll.size().getInfo())
       Total number of images : 162
        We will create a folder to store the images:
In [ ]:
        !mkdir sentinel_2_by_year
        First we define a function to generate an image for each year:
In [ ]: def create_image_collection_by_year(image_collection, fc, start_year, end_year):
          years = ee.List.sequence(start_year, end_year)
           def create_yearly_composite(year):
             start_date = ee.Date.fromYMD(year, 1, 1)
             end_date = ee.Date.fromYMD(year, 12, 31)
            year_image = image_collection \
                 .filterDate(start_date, end_date) \
                 .reduce(ee.Reducer.median()) \
                 .set({'year': year})
             return year_image.clip(fc)
          yearly_composites = ee.ImageCollection.fromImages(
              years.map(create_yearly_composite))
           return yearly_composites
        Then we apply it to our ImageCollection:
In [ ]: | start_year = 2019
        end_year = 2023
        yearly_s2_collection = create_image_collection_by_year(S2_coll, fc, start_year,
        print('Total number of images :', yearly_s2_collection.size().getInfo())
       Total number of images : 5
        Let's visualize the results:
In [ ]: Map = geemap.Map()
        Map.centerObject(fc)
        # Function to display an image on the map
        def display_image(image):
          vis_params = {
               'bands': ['B4_median', 'B3_median', 'B2_median'],
               'min': 0,
               'max': 3000,
               'gamma': 1.4
          Map.addLayer(image, vis_params, str(image.get('year').getInfo()))
        # Iterate through the yearly image collection and display each image
        for i in range(yearly_s2_collection.size().getInfo()):
             image = ee.Image(yearly_s2_collection.toList(yearly_s2_collection.size()).ge
```

display\_image(image)

```
Мар
In [ ]: start_year = 2019
        end_year = 2023
        This way we can export the images:
In [ ]: geemap.ee_export_image_collection(
            yearly_s2_collection,
            out_dir="./sentinel_2_by_year",
            scale=20,
            crs='EPSG:4326',
            region=fc.geometry(),
            filenames= yearly_s2_collection.aggregate_array("year").getInfo(),
            file_per_band=False,
            timeout=300,
            proxies=None
        Now we install rasterio to open the downloaded images and display them:
In [ ]: !pip install rasterio
       Collecting rasterio
         Downloading rasterio-1.4.3-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_
       64.whl.metadata (9.1 kB)
       Collecting affine (from rasterio)
         Downloading affine-2.4.0-py3-none-any.whl.metadata (4.0 kB)
       Requirement already satisfied: attrs in /usr/local/lib/python3.11/dist-packages
       (from rasterio) (25.3.0)
       Requirement already satisfied: certifi in /usr/local/lib/python3.11/dist-packages
       (from rasterio) (2025.4.26)
       Requirement already satisfied: click>=4.0 in /usr/local/lib/python3.11/dist-packa
       ges (from rasterio) (8.2.0)
       Collecting cligj>=0.5 (from rasterio)
         Downloading cligj-0.7.2-py3-none-any.whl.metadata (5.0 kB)
       Requirement already satisfied: numpy>=1.24 in /usr/local/lib/python3.11/dist-pack
       ages (from rasterio) (2.0.2)
       Collecting click-plugins (from rasterio)
         Downloading click_plugins-1.1.1-py2.py3-none-any.whl.metadata (6.4 kB)
       Requirement already satisfied: pyparsing in /usr/local/lib/python3.11/dist-packag
       es (from rasterio) (3.2.3)
       Downloading rasterio-1.4.3-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_6
       4.whl (22.2 MB)
                                                  - 22.2/22.2 MB 53.6 MB/s eta 0:00:00
       Downloading cligj-0.7.2-py3-none-any.whl (7.1 kB)
       Downloading affine-2.4.0-py3-none-any.whl (15 kB)
       Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
       Installing collected packages: cligj, click-plugins, affine, rasterio
       Successfully installed affine-2.4.0 click-plugins-1.1.1 cligj-0.7.2 rasterio-1.4.
       3
In [ ]: import rasterio
        import matplotlib.pyplot as plt
```

image\_dir = './sentinel\_2\_by\_year'

import os

```
for filename in os.listdir(image_dir):
    if filename.endswith('.tif'):
        filepath = os.path.join(image_dir, filename)

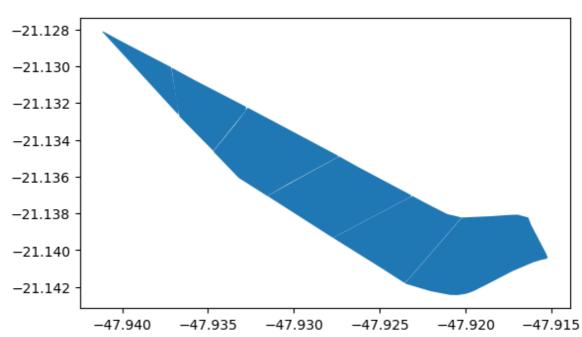
with rasterio.open(filepath) as src:
        R = src.read(4)  # Band 4 (Red)
        G = src.read(3)  # Band 3 (Green)
        B = src.read(2)  # Band 2 (Blue)

        rgb = np.dstack((R, G, B))
        rgb = (rgb / 4000)

plt.figure(figsize=(10, 10))
        plt.imshow(rgb)
        plt.title(filename)
        plt.axis('off')
        plt.show()
```

```
In [ ]: gdf_soja.plot()
```

```
Out[]: <Axes: >
```



Let's now extract information from the polygons and images:

```
In [ ]: import json
    import rasterio
    from rasterio.mask import mask

In [ ]: total_gdf = gdf_soja.dissolve()
```

We start with NDVI information by year and for the entire area:

```
In [ ]:
    ndvi_data = []
    for year in range(start_year, end_year + 1):
        src_img = rasterio.open(f'./sentinel_2_by_year/{year}.tif')
        for feat in json.loads(total_gdf.to_json())['features']:
```

```
out_img, _ = mask(dataset=src_img, shapes=[feat['geometry']], crop=True, nod

nir = out_img[8, :, :]

red = out_img[4, :, :]

#Calculate NDVI, handling potential division by zero

ndvi = np.where(red != 0, (nir - red) / (nir + red), np.nan)

# Exclude nodata values (-9999) and NaN values when calculating mean

valid_pixels = ndvi[ndvi != -9999]

valid_pixels = valid_pixels[~np.isnan(valid_pixels)]

mean_ndvi = np.nanmean(valid_pixels)

print(f"Mean NDVI for year {year}: {mean_ndvi}")

ndvi_data.append({'year': year, 'mean_ndvi': mean_ndvi}))

ndvi_df = pd.DataFrame(ndvi_data)
```

WARNING:rasterio.\_env:CPLE\_AppDefined in 2019.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe l. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2020.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2021.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2022.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

```
Mean NDVI for year 2019: 0.11235534825508786
Mean NDVI for year 2020: 0.12091211683305336
Mean NDVI for year 2021: 0.10815726939512024
```

WARNING:rasterio.\_env:CPLE\_AppDefined in 2023.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

Mean NDVI for year 2022: 0.09125206936978875 Mean NDVI for year 2023: 0.10601139752554287

```
In [ ]: ndvi_df
```

# Out[]: year mean\_ndvi 0 2019 0.112355 1 2020 0.120912 2 2021 0.108157 3 2022 0.091252 4 2023 0.106011

We can also generate information by year and by polygon:

```
In [ ]: ndvi_by_polygon = []
    for year in range(start_year, end_year + 1):
        src_img = rasterio.open(f'./sentinel_2_by_year/{year}.tif')
        for feat in json.loads(gdf_soja.to_json())['features']:
        out_img, _ = mask(dataset=src_img, shapes=[feat['geometry']], crop=True, nod
```

```
nir = out_img[8, :, :]
red = out_img[4, :, :]

#Calculate NDVI, handling potential division by zero
ndvi = np.where(red != 0, (nir - red) / (nir + red), np.nan)

# Exclude nodata values (-9999) and NaN values when calculating mean
valid_pixels = ndvi[ndvi != -9999]
valid_pixels = valid_pixels[~np.isnan(valid_pixels)]
mean_ndvi = np.nanmean(valid_pixels)
ndvi_by_polygon.append({'year': year, 'mean_ndvi': mean_ndvi, 'id_polygon':
ndvi_polygon_df = pd.DataFrame(ndvi_by_polygon)
```

WARNING:rasterio.\_env:CPLE\_AppDefined in 2019.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2020.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2021.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2022.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2023.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe 1. Defining non-color channels as ExtraSamples.

```
In [ ]: ndvi_polygon_df
```

Out[	]:		year	mean_ndvi	id_polygon
		0	2019	0.211833	0
		1	2019	0.222753	1
		2	2019	0.215872	2
		3	2019	0.243543	3
		4	2019	0.102792	4
		5	2019	0.271991	5
		6	2020	0.243169	0
		7	2020	0.253338	1
		8	2020	0.248999	2
		9	2020	0.227691	3
		10	2020	0.089343	4
		11	2020	0.279476	5
		12	2021	0.222637	0
		13	2021	0.229863	1
		14	2021	0.221499	2
		15	2021	0.218580	3
		16	2021	0.083739	4
		17	2021	0.233424	5
		18	2022	0.199790	0
		19	2022	0.211180	1
		20	2022	0.200020	2
		21	2022	0.164285	3
		22	2022	0.061607	4
		23	2022	0.172599	5
		24	2023	0.210022	0
		25	2023	0.217239	1
		26	2023	0.207668	2
		27	2023	0.197545	3
		28	2023	0.085981	4
		29	2023	0.259470	5

And finally we will create some spectral indices and obtain the information by year and by plot:

```
In [ ]: ndvi_ndre_ndwi_by_polygon = []
        for year in range(start_year, end_year + 1):
          src_img = rasterio.open(f'./sentinel_2_by_year/{year}.tif')
          for feat in json.loads(gdf_soja.to_json())['features']:
            out_img, _ = mask(dataset=src_img, shapes=[feat['geometry']], crop=True, nod
            nir = out_img[8, :, :]
            red = out_img[4, :, :]
            re = out_img[5, :, :]
            green = out_img[3, :, :]
            #Calculate NDVI
            ndvi = np.where(red != 0, (nir - red) / (nir + red), np.nan)
            #Calculate NDRE
            ndre = np.where(nir != 0, (nir - re) / (nir + re), np.nan)
            #Calculate NDWI
            ndwi = np.where((green + nir) != 0, (green - nir) / (green + nir), np.nan)
            # Exclude nodata values (-9999) and NaN values when calculating mean
            valid_pixels_ndvi = ndvi[ndvi != -9999]
            valid_pixels_ndvi = valid_pixels_ndvi[~np.isnan(valid_pixels_ndvi)]
            mean_ndvi = np.nanmean(valid_pixels_ndvi)
            valid_pixels_ndre = ndre[ndre != -9999]
            valid_pixels_ndre = valid_pixels_ndre[~np.isnan(valid_pixels_ndre)]
            mean_ndre = np.nanmean(valid_pixels_ndre)
            valid_pixels_ndwi = ndwi[ndwi != -9999]
            valid_pixels_ndwi = valid_pixels_ndwi[~np.isnan(valid_pixels_ndwi)]
            mean_ndwi = np.nanmean(valid_pixels_ndwi)
            ndvi_ndre_ndwi_by_polygon.append({'year': year, 'mean_ndvi': mean_ndvi, 'mea
        ndvi_ndre_ndwi_polygon_df = pd.DataFrame(ndvi_ndre_ndwi_by_polygon)
```

WARNING:rasterio.\_env:CPLE\_AppDefined in 2019.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe l. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2020.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe l. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2021.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe l. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2022.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe l. Defining non-color channels as ExtraSamples.

WARNING:rasterio.\_env:CPLE\_AppDefined in 2023.tif: TIFFReadDirectory:Sum of Photo metric type-related color channels and ExtraSamples doesn't match SamplesPerPixe

```
In [ ]: ndvi_ndre_ndwi_polygon_df
```

1. Defining non-color channels as ExtraSamples.

]:		year	mean_ndvi	mean_ndre	mean_ndwi	id_polygon
	0	2019	0.211833	0.071175	-0.292873	0
	1	2019	0.222753	0.074579	-0.308874	1
	2	2019	0.215872	0.071267	-0.296813	2
	3	2019	0.243543	0.058453	-0.335602	3
	4	2019	0.102792	0.024878	-0.147474	4
	5	2019	0.271991	0.078054	-0.351619	5
	6	2020	0.243169	0.056209	-0.339234	0
	7	2020	0.253338	0.059032	-0.354262	1
	8	2020	0.248999	0.060208	-0.341119	2
	9	2020	0.227691	0.058162	-0.314856	3
	10	2020	0.089343	0.025259	-0.130339	4
	11	2020	0.279476	0.065116	-0.401848	5
	12	2021	0.222637	0.060281	-0.320042	0
	13	2021	0.229863	0.065044	-0.331048	1
	14	2021	0.221499	0.058338	-0.318446	2
	15	2021	0.218580	0.050339	-0.307804	3
	16	2021	0.083739	0.020576	-0.121875	4
	17	2021	0.233424	0.061486	-0.350738	5
	18	2022	0.199790	0.056870	-0.295521	0
	19	2022	0.211180	0.060725	-0.310015	1
	20	2022	0.200020	0.057007	-0.290526	2
	21	2022	0.164285	0.051227	-0.237701	3
	22	2022	0.061607	0.021142	-0.091213	4
	23	2022	0.172599	0.059635	-0.269935	5
	24	2023	0.210022	0.062079	-0.296140	0
	25	2023	0.217239	0.064826	-0.306923	1
	26	2023	0.207668	0.061425	-0.292091	2
	27	2023	0.197545	0.052667	-0.228555	3
	28	2023	0.085981	0.022509	-0.108081	4
	29	2023	0.259470	0.071183	-0.368327	5

## **Timelapses**

Out[

One feature of the geemap library is the creation of timelapses. Let's create some:

```
In [ ]: Map = geemap.Map()
In [ ]: roi = Map.user_roi
        if roi is None:
            roi = ee.Geometry.BBox(-18.6983, -36.1630, 52.2293, 38.1446)
            Map.addLayer(roi)
            Map.centerObject(roi)
        First one using NDVI from the MODIS satellite
In [ ]: timelapse = geemap.modis_ndvi_timelapse(
            roi,
            out_gif='ndvi.gif',
            data='Terra',
            band='NDVI',
            start_date='2000-01-01',
            end_date='2022-12-31',
            frames_per_second=3,
            title='MODIS NDVI Timelapse',
            overlay_data='countries',
        geemap.show_image(timelapse)
In [ ]: roi = ee.Geometry.BBox(-171.21, -57.13, 177.53, 79.99)
        Map.addLayer(roi)
        Map.centerObject(roi)
        Then the temperature of the oceans:
In [ ]: timelapse = geemap.modis_ocean_color_timelapse(
            satellite='Aqua',
            start_date='2018-01-01',
            end_date='2020-12-31',
            roi=roi,
            frequency='month',
            out_gif='temperature.gif',
            overlay_data='continents',
            overlay_color='yellow',
            overlay_opacity=0.5,
        geemap.show_image(timelapse)
In [ ]: from IPython.display import Image
        Image(filename='temperature.gif')
```

### Thank you! See you in the next Chapter!