land_cover_classification

October 27, 2019

In [13]:
```
import pandas as pd
import os
import yaml
from sentinelsat import SentinelAPI, geojson_to_wkt
import osmnx as ox
```

In [14]:
```
import geopandas as gpd
import numpy as np
import matplotlib.pyplot as plt
import os
from osgeo import gdal
import rasterio
from rasterio.plot import show_hist
from rasterio.plot import show
from rasterio.mask import mask
from shapely.geometry import box
from fiona.crs import from_epsg
```

In [15]:
```
from shapely.geometry import box
```

In [16]:
```
with open("auth.yaml", 'r') as ymlfile:
    auth = yaml.safe_load(ymlfile)
```

In [17]:
```
api = SentinelAPI(auth['copernicus_open_access_hub']['username'],
                  auth['copernicus_open_access_hub']['password'],
                  'https://scihub.copernicus.eu/dhus')
```

In [18]:
```
# this is the place where I was born and grew up
# I chose to use the image from this place because it would be
# easier to label the clusters since I am closely familiar with the area
place_name='Gelendzhik, Russia'
```

In [19]:
```
# will return either polygon or point (in GeodatFrame format) if boundaries of the pl
place = ox.gdf_from_place(place_name)
```

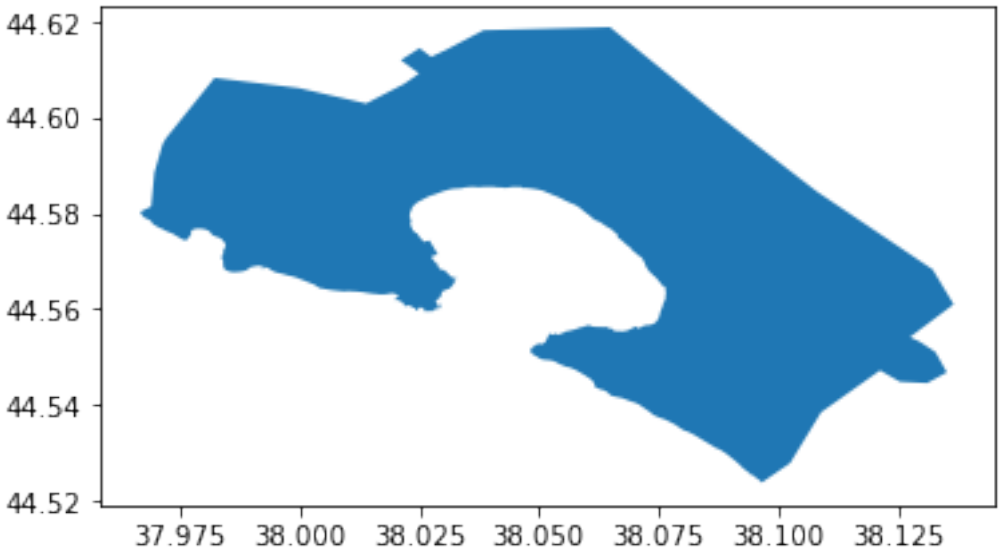
In [161]:
```
place
```

Out[161]:
```
                                            geometry  \
0  POLYGON ((37.9666898 44.5802578, 37.9668569 44...
```

```
                                                  place_name  bbox_north  bbox_south  \
0  Gelendzhik,    , Krasnod...   44.618823   44.523708

   bbox_east  bbox_west
0  38.136722   37.96669
```

In [158]:
```
place.plot()
```

Out[158]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1626f26a0>
```



In [20]:
```
place.crs
```

Out[20]:
```
'+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs'
```

In [21]:
```
query_box=box(minx=place.bbox_west.values[0],
    miny=place.bbox_south.values[0],
    maxx=place.bbox_east.values[0],
    maxy=place.bbox_north.values[0])
```

In [22]:
```
# 3-month period to search for scenes with less than 6% cloud coverage where bounding
# of interest is within the image (that is image contains the bounding box)
products = api.query(query_box.wkt,
                     area_relation='Contains',
                     date = ('20190601', '20190926'),
                     platformname = 'Sentinel-2',
                     processinglevel = 'Level-2A',
                     cloudcoverpercentage = (0,5))
```

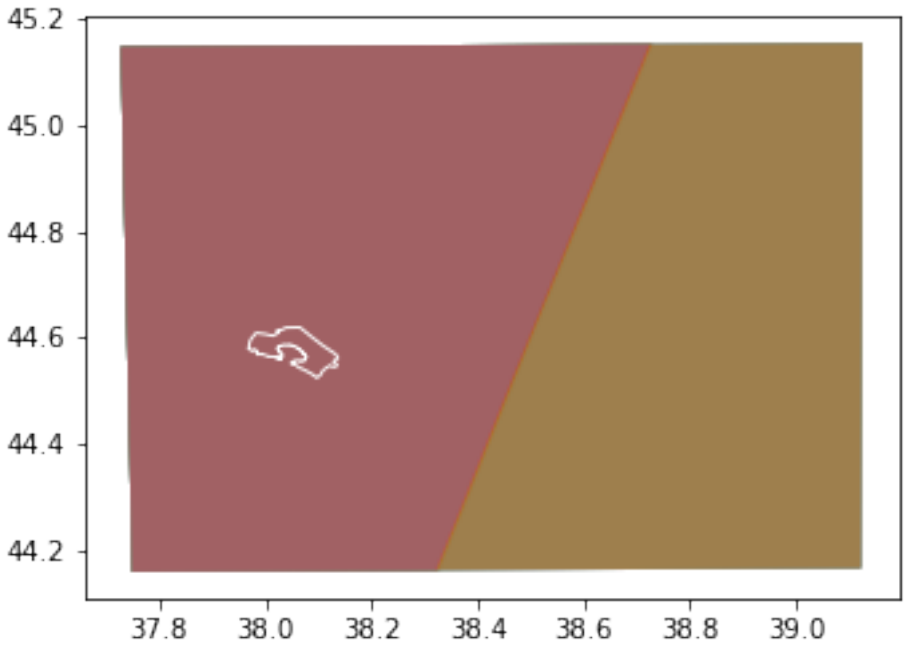
```
In [23]: products_gdf = api.to_geodataframe(products)

In [24]: if not products_gdf.empty:
             products_gdf_sorted = products_gdf.sort_values(['cloudcoverpercentage'], ascending
         else:
             print ('No records scences found for the filtered parameters')

In [162]: products_gdf_sorted.head()

Out[162]:                                                                                  ti
          a0355a57-a5eb-452d-a248-0bbdf44f463c  S2B_MSIL2A_20190916T082559_N0213_R021_T37TDK_2
          f04131c5-10a4-4321-82db-9eb7c0a6bde1  S2B_MSIL2A_20190827T082609_N0213_R021_T37TDK_2
          0806a7e1-325b-40fa-9ef1-813d82ea89c5  S2B_MSIL2A_20190903T081609_N0213_R121_T37TDK_2
          c01a3c5c-5554-4015-b671-64ed4e9380a7  S2A_MSIL2A_20190901T082601_N0213_R021_T37TDK_2
          c4cfd524-135d-4163-96c8-07a89d1ea907  S2A_MSIL2A_20190812T082611_N0213_R021_T37TDK_2

                                                                                             li
          a0355a57-a5eb-452d-a248-0bbdf44f463c  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          f04131c5-10a4-4321-82db-9eb7c0a6bde1  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          0806a7e1-325b-40fa-9ef1-813d82ea89c5  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          c01a3c5c-5554-4015-b671-64ed4e9380a7  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          c4cfd524-135d-4163-96c8-07a89d1ea907  https://scihub.copernicus.eu/dhus/odata/v1/Pro

                                                                                  link_alternati
          a0355a57-a5eb-452d-a248-0bbdf44f463c  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          f04131c5-10a4-4321-82db-9eb7c0a6bde1  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          0806a7e1-325b-40fa-9ef1-813d82ea89c5  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          c01a3c5c-5554-4015-b671-64ed4e9380a7  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          c4cfd524-135d-4163-96c8-07a89d1ea907  https://scihub.copernicus.eu/dhus/odata/v1/Pro

                                                                                       link_ic
          a0355a57-a5eb-452d-a248-0bbdf44f463c  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          f04131c5-10a4-4321-82db-9eb7c0a6bde1  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          0806a7e1-325b-40fa-9ef1-813d82ea89c5  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          c01a3c5c-5554-4015-b671-64ed4e9380a7  https://scihub.copernicus.eu/dhus/odata/v1/Pro
          c4cfd524-135d-4163-96c8-07a89d1ea907  https://scihub.copernicus.eu/dhus/odata/v1/Pro

                                                                                          summa
          a0355a57-a5eb-452d-a248-0bbdf44f463c  Date: 2019-09-16T08:25:59.024Z, Instrument: MS
          f04131c5-10a4-4321-82db-9eb7c0a6bde1  Date: 2019-08-27T08:26:09.024Z, Instrument: MS
          0806a7e1-325b-40fa-9ef1-813d82ea89c5  Date: 2019-09-03T08:16:09.024Z, Instrument: MS
          c01a3c5c-5554-4015-b671-64ed4e9380a7  Date: 2019-09-01T08:26:01.024Z, Instrument: MS
          c4cfd524-135d-4163-96c8-07a89d1ea907  Date: 2019-08-12T08:26:11.024Z, Instrument: MS

                                                          beginposition  \
          a0355a57-a5eb-452d-a248-0bbdf44f463c 2019-09-16 08:25:59.024
          f04131c5-10a4-4321-82db-9eb7c0a6bde1 2019-08-27 08:26:09.024
          0806a7e1-325b-40fa-9ef1-813d82ea89c5 2019-09-03 08:16:09.024
```

```
c01a3c5c-5554-4015-b671-64ed4e9380a7 2019-09-01 08:26:01.024
c4cfd524-135d-4163-96c8-07a89d1ea907 2019-08-12 08:26:11.024

                                          endposition  \
a0355a57-a5eb-452d-a248-0bbdf44f463c 2019-09-16 08:25:59.024
f04131c5-10a4-4321-82db-9eb7c0a6bde1 2019-08-27 08:26:09.024
0806a7e1-325b-40fa-9ef1-813d82ea89c5 2019-09-03 08:16:09.024
c01a3c5c-5554-4015-b671-64ed4e9380a7 2019-09-01 08:26:01.024
c4cfd524-135d-4163-96c8-07a89d1ea907 2019-08-12 08:26:11.024

                                    ingestiondate  orbitnumber  \
a0355a57-a5eb-452d-a248-0bbdf44f463c 2019-09-16 20:24:18.384        13203
f04131c5-10a4-4321-82db-9eb7c0a6bde1 2019-08-27 17:07:30.465        12917
0806a7e1-325b-40fa-9ef1-813d82ea89c5 2019-09-03 17:24:45.057        13017
c01a3c5c-5554-4015-b671-64ed4e9380a7 2019-09-01 14:47:50.800        21897
c4cfd524-135d-4163-96c8-07a89d1ea907 2019-08-12 17:44:07.657        21611

                                    relativeorbitnumber  ...  \
a0355a57-a5eb-452d-a248-0bbdf44f463c                  21  ...
f04131c5-10a4-4321-82db-9eb7c0a6bde1                  21  ...
0806a7e1-325b-40fa-9ef1-813d82ea89c5                 121  ...
c01a3c5c-5554-4015-b671-64ed4e9380a7                  21  ...
c4cfd524-135d-4163-96c8-07a89d1ea907                  21  ...

                                    processingbaseline  processinglevel  \
a0355a57-a5eb-452d-a248-0bbdf44f463c               02.13         Level-2A
f04131c5-10a4-4321-82db-9eb7c0a6bde1               02.13         Level-2A
0806a7e1-325b-40fa-9ef1-813d82ea89c5               02.13         Level-2A
c01a3c5c-5554-4015-b671-64ed4e9380a7               02.13         Level-2A
c4cfd524-135d-4163-96c8-07a89d1ea907               02.13         Level-2A

                                    producttype  platformname        size  \
a0355a57-a5eb-452d-a248-0bbdf44f463c     S2MSI2A    Sentinel-2   600.05 MB
f04131c5-10a4-4321-82db-9eb7c0a6bde1     S2MSI2A    Sentinel-2   592.07 MB
0806a7e1-325b-40fa-9ef1-813d82ea89c5     S2MSI2A    Sentinel-2  1016.59 MB
c01a3c5c-5554-4015-b671-64ed4e9380a7     S2MSI2A    Sentinel-2   597.63 MB
c4cfd524-135d-4163-96c8-07a89d1ea907     S2MSI2A    Sentinel-2   593.56 MB

                                                                        filena
a0355a57-a5eb-452d-a248-0bbdf44f463c  S2B_MSIL2A_20190916T082559_N0213_R021_T37TDK_2
f04131c5-10a4-4321-82db-9eb7c0a6bde1  S2B_MSIL2A_20190827T082609_N0213_R021_T37TDK_2
0806a7e1-325b-40fa-9ef1-813d82ea89c5  S2B_MSIL2A_20190903T081609_N0213_R121_T37TDK_2
c01a3c5c-5554-4015-b671-64ed4e9380a7  S2A_MSIL2A_20190901T082601_N0213_R021_T37TDK_2
c4cfd524-135d-4163-96c8-07a89d1ea907  S2A_MSIL2A_20190812T082611_N0213_R021_T37TDK_2

                                                                  level1cpdiidentifi
a0355a57-a5eb-452d-a248-0bbdf44f463c  S2B_OPER_MSI_L1C_TL_SGS__20190916T121753_A0132
f04131c5-10a4-4321-82db-9eb7c0a6bde1  S2B_OPER_MSI_L1C_TL_EPAE_20190827T111401_A0129
```

```
                                    0806a7e1-325b-40fa-9ef1-813d82ea89c5  S2B_OPER_MSI_L1C_TL_EPAE_20190903T111337_A0130
                                    c01a3c5c-5554-4015-b671-64ed4e9380a7  S2A_OPER_MSI_L1C_TL_SGS__20190901T103223_A0218
                                    c4cfd524-135d-4163-96c8-07a89d1ea907  S2A_OPER_MSI_L1C_TL_SGS__20190812T121250_A0216

                                                                                                                identif
                                    a0355a57-a5eb-452d-a248-0bbdf44f463c  S2B_MSIL2A_20190916T082559_N0213_R021_T37TDK_2
                                    f04131c5-10a4-4321-82db-9eb7c0a6bde1  S2B_MSIL2A_20190827T082609_N0213_R021_T37TDK_2
                                    0806a7e1-325b-40fa-9ef1-813d82ea89c5  S2B_MSIL2A_20190903T081609_N0213_R121_T37TDK_2
                                    c01a3c5c-5554-4015-b671-64ed4e9380a7  S2A_MSIL2A_20190901T082601_N0213_R021_T37TDK_2
                                    c4cfd524-135d-4163-96c8-07a89d1ea907  S2A_MSIL2A_20190812T082611_N0213_R021_T37TDK_2

                                                                                                          uuid  \
                                    a0355a57-a5eb-452d-a248-0bbdf44f463c  a0355a57-a5eb-452d-a248-0bbdf44f463c
                                    f04131c5-10a4-4321-82db-9eb7c0a6bde1  f04131c5-10a4-4321-82db-9eb7c0a6bde1
                                    0806a7e1-325b-40fa-9ef1-813d82ea89c5  0806a7e1-325b-40fa-9ef1-813d82ea89c5
                                    c01a3c5c-5554-4015-b671-64ed4e9380a7  c01a3c5c-5554-4015-b671-64ed4e9380a7
                                    c4cfd524-135d-4163-96c8-07a89d1ea907  c4cfd524-135d-4163-96c8-07a89d1ea907

                                                                                                                geome
                                    a0355a57-a5eb-452d-a248-0bbdf44f463c  (POLYGON ((37.74888294664043 44.15851530960486
                                    f04131c5-10a4-4321-82db-9eb7c0a6bde1  (POLYGON ((37.74888294664043 44.15851530960486
                                    0806a7e1-325b-40fa-9ef1-813d82ea89c5  (POLYGON ((37.74888294664043 44.15851530960486
                                    c01a3c5c-5554-4015-b671-64ed4e9380a7  (POLYGON ((37.74888294664043 44.15851530960486
                                    c4cfd524-135d-4163-96c8-07a89d1ea907  (POLYGON ((37.74888294664043 44.15851530960486

                                    [5 rows x 35 columns]
```

In [26]:
```
ax=products_gdf_sorted.plot(column='uuid', cmap=None, alpha=0.5)
place.plot(ax=ax, edgecolor="white", facecolor='None')
```

Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12386f320>
```




```
In [27]: # this is the scene ID needed to to call download fucntion
         uuid=products_gdf_sorted.index.to_list()[0]

In [28]: # this is the name that will be given by default to a folder in which data will be do
         title=products_gdf_sorted.loc[uuid].title

In [71]: api.download(uuid, directory_path='./imagery')

Downloading: 100%|| 629M/629M [01:23<00:00, 7.57MB/s]
MD5 checksumming: 100%|| 629M/629M [00:01<00:00, 397MB/s]


Out[71]: {'id': 'a0355a57-a5eb-452d-a248-0bbdf44f463c',
          'title': 'S2B_MSIL2A_20190916T082559_N0213_R021_T37TDK_20190916T130703',
          'size': 629254856,
          'md5': 'D81389A9DA283099896F26EEEAD287D8',
          'date': datetime.datetime(2019, 9, 16, 8, 25, 59, 24000),
          'footprint': 'POLYGON((38.732885529268415 45.151802429452395,38.679186431583965 45.0
          'url': "https://scihub.copernicus.eu/dhus/odata/v1/Products('a0355a57-a5eb-452d-a248
          'Online': True,
          'Creation Date': datetime.datetime(2019, 9, 16, 20, 25, 14, 987000),
          'Ingestion Date': datetime.datetime(2019, 9, 16, 20, 24, 18, 384000),
          'path': './imagery/S2B_MSIL2A_20190916T082559_N0213_R021_T37TDK_20190916T130703.zip'
          'downloaded_bytes': 629254856}

In [72]: import zipfile
         with zipfile.ZipFile(f"imagery/{title}.zip","r") as zip_ref:
             zip_ref.extractall("imagery")
```

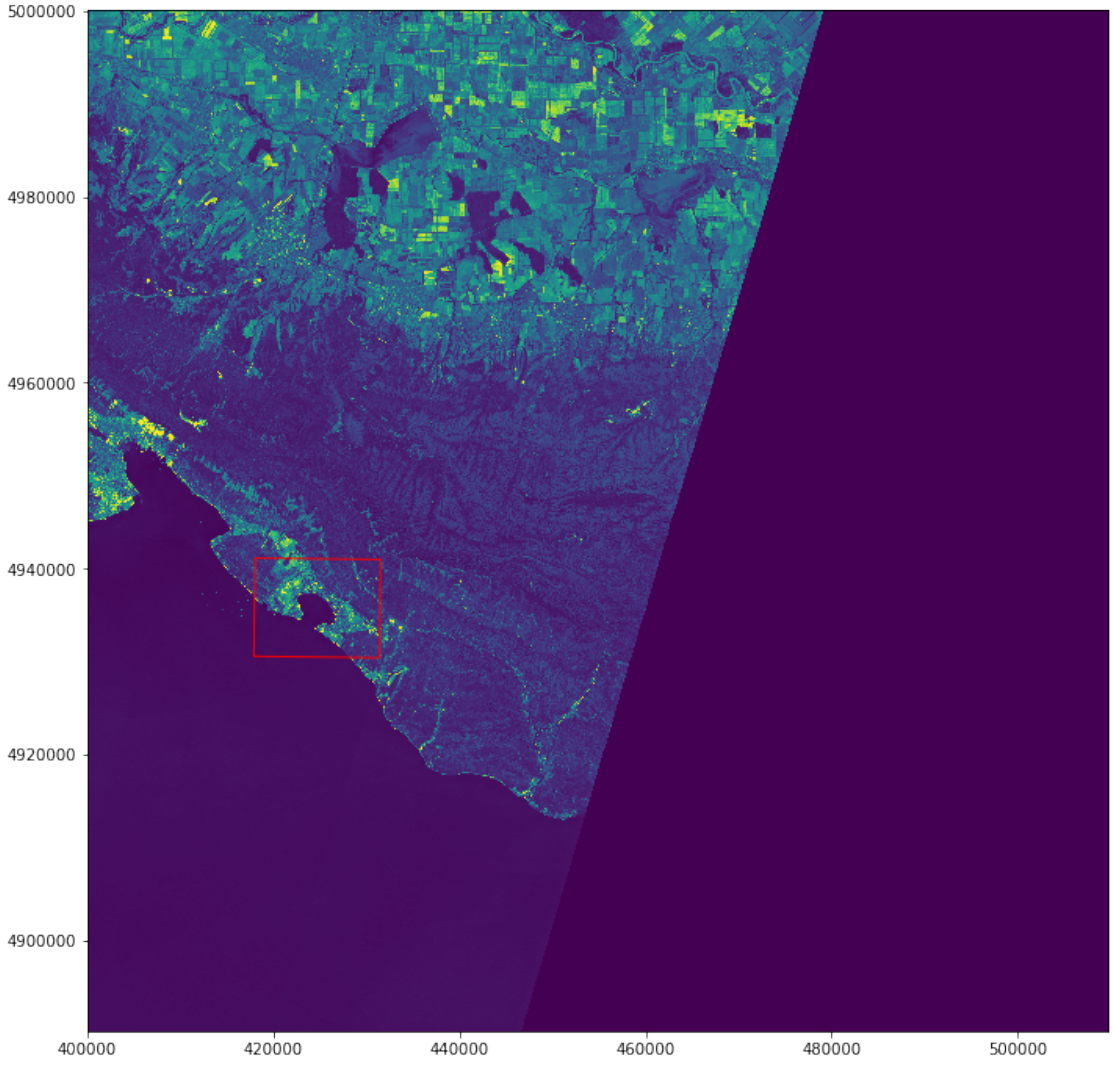
```
In [144]: # clean-up
          if os.path.exists(f"imagery/{title}.zip"):
              os.remove(f"imagery/{title}.zip")

In [29]: # there is lots of folders that get downloaded, actual images is in the GRANULE/IMG_D
         sentinel_folder=os.listdir(os.path.join('imagery', f'{title}.SAFE', 'GRANULE'))[0]

In [30]: sentinel_folder

Out[30]: 'L2A_T37TDK_A013203_20190916T083039'

In [31]: os.listdir(os.path.join('imagery', f'{title}.SAFE', 'GRANULE', sentinel_folder))

Out[31]: ['MTD_TL.xml', 'IMG_DATA', 'QI_DATA', 'AUX_DATA']

In [32]: # one folder for each of the 13 spectral bands--they are in different resolutions
         os.listdir(os.path.join('imagery', f'{title}.SAFE', 'GRANULE', sentinel_folder, 'IMG_

Out[32]: ['R60m', 'R20m', 'R10m']

In [33]: folder=os.path.join('imagery', f'{title}.SAFE', 'GRANULE', sentinel_folder, 'IMG_DATA

In [34]: os.listdir(folder)

Out[34]: ['R60m', 'R20m', 'R10m']

In [35]: for sub_folder in os.listdir(folder):
             print (f'{sub_folder} :', )
             for file in os.listdir(os.path.join(folder, sub_folder)):
                 print (file)

R60m :
T37TDK_20190916T082559_B07_60m.jp2
T37TDK_20190916T082559_B8A_60m.jp2
T37TDK_20190916T082559_WVP_60m.jp2
T37TDK_20190916T082559_TCI_60m.jp2
T37TDK_20190916T082559_B06_60m.jp2
T37TDK_20190916T082559_B04_60m.jp2
T37TDK_20190916T082559_B05_60m.jp2
T37TDK_20190916T082559_AOT_60m.jp2
T37TDK_20190916T082559_B09_60m.jp2
T37TDK_20190916T082559_B01_60m.jp2
T37TDK_20190916T082559_B11_60m.jp2
T37TDK_20190916T082559_SCL_60m.jp2
T37TDK_20190916T082559_B03_60m.jp2
T37TDK_20190916T082559_B02_60m.jp2
T37TDK_20190916T082559_B12_60m.jp2
R20m :
T37TDK_20190916T082559_B06_20m.jp2
T37TDK_20190916T082559_TCI_20m.jp2
```

```
T37TDK_20190916T082559_WVP_20m.jp2
T37TDK_20190916T082559_B07_20m.jp2
T37TDK_20190916T082559_B8A_20m.jp2
T37TDK_20190916T082559_AOT_20m.jp2
T37TDK_20190916T082559_B05_20m.jp2
T37TDK_20190916T082559_B04_20m.jp2
T37TDK_20190916T082559_SCL_20m.jp2
T37TDK_20190916T082559_B11_20m.jp2
T37TDK_20190916T082559_B02_20m.jp2
T37TDK_20190916T082559_B12_20m.jp2
T37TDK_20190916T082559_B03_20m.jp2
R10m :
T37TDK_20190916T082559_AOT_10m.jp2
T37TDK_20190916T082559_B04_10m.jp2
T37TDK_20190916T082559_WVP_10m.jp2
T37TDK_20190916T082559_TCI_10m.jp2
T37TDK_20190916T082559_B02_10m.jp2
T37TDK_20190916T082559_B03_10m.jp2
T37TDK_20190916T082559_B08_10m.jp2
```

Band designations are found here:
https://www.usgs.gov/centers/eros/science/usgs-eros-archive-sentinel-2?qt-science_center_objects=0#qt-science_center_objects

```
In [36]: resolution='R20m'

In [37]: os.listdir(os.path.join(folder, resolution))

Out[37]: ['T37TDK_20190916T082559_B06_20m.jp2',
          'T37TDK_20190916T082559_TCI_20m.jp2',
          'T37TDK_20190916T082559_WVP_20m.jp2',
          'T37TDK_20190916T082559_B07_20m.jp2',
          'T37TDK_20190916T082559_B8A_20m.jp2',
          'T37TDK_20190916T082559_AOT_20m.jp2',
          'T37TDK_20190916T082559_B05_20m.jp2',
          'T37TDK_20190916T082559_B04_20m.jp2',
          'T37TDK_20190916T082559_SCL_20m.jp2',
          'T37TDK_20190916T082559_B11_20m.jp2',
          'T37TDK_20190916T082559_B02_20m.jp2',
          'T37TDK_20190916T082559_B12_20m.jp2',
          'T37TDK_20190916T082559_B03_20m.jp2']

In [38]: red=[band for band in os.listdir(os.path.join(folder, resolution)) if 'B04' in band][0
         blue=[band for band in os.listdir(os.path.join(folder, resolution)) if 'B02' in band]
         green=[band for band in os.listdir(os.path.join(folder, resolution)) if 'B03' in band
         nir=[band for band in os.listdir(os.path.join(folder, resolution)) if 'B8' in band][0
         band5=[band for band in os.listdir(os.path.join(folder, resolution)) if 'B05' in band
         band6=[band for band in os.listdir(os.path.join(folder, resolution)) if 'B06' in band
         band7=[band for band in os.listdir(os.path.join(folder, resolution)) if 'B07' in band
```

```
In [43]: # read RGB composite to take a look at what we downloaded
         src=rasterio.open(os.path.join(folder, resolution, 'T37TDK_20190916T082559_TCI_20m.jp

In [47]: data=src.read(1)

In [48]: src.meta

Out[48]: {'driver': 'JP2OpenJPEG',
          'dtype': 'uint8',
          'nodata': None,
          'width': 5490,
          'height': 5490,
          'count': 3,
          'crs': CRS.from_epsg(32637),
          'transform': Affine(20.0, 0.0, 399960.0,
                 0.0, -20.0, 5000040.0)}

In [49]: # make GeodataFrame from the area of interest box
         geo_box = gpd.GeoDataFrame({'geometry': query_box}, index=[0], crs=place.crs)

In [55]: # Vizualize the raster band and the area of interest
         fig, ax = plt.subplots(figsize=(12, 12))
         plt.imshow(data, extent=[src.bounds.left, src.bounds.right, src.bounds.bottom, src.bou
         geo_box.to_crs(src.crs).plot(ax=plt.gca(), edgecolor="red", facecolor="none");
```




```
In [57]: def crop_band(clip_gdf, input_folder, band, output_folder, out_name):
             '''Clip raster band to the area of interest and write out clipped raster (in tif
             Params:
                 clip_gdf (GeodatFrame): Area of interest
                 input_folder (str): Folder with raster band
                 band (str): Name of the band
                 output_folder (str): Folder where clipped features will be stored
                 outname (str): Name for the clipped band
             '''
             import json
             if not os.path.exists(output_folder):
                 os.makedirs(output_folder)
             # this is how the mask function needs the clip feature to be according to the doc
             crop_feature = [json.loads(clip_gdf.to_json())['features'][0]['geometry']]
```

```
            src=rasterio.open(os.path.join(input_folder, band))
            # clip using mask
            out_image, out_transform=mask(src, crop_feature, crop=True)
            # get the metadata of the original raster to use for the output raster
            out_meta=src.meta.copy()
            # update the width an height since they are now (after clipping) they are
            # different from the original raster's dimensions
            out_meta.update({'height': out_image.shape[1],
                             'width':out_image.shape[2],
                             'transform': out_transform})
            # open the new tif file in the writing mode and write out the clipped raster
            with rasterio.open(f'{output_folder}/{out_name}.tif', 'w', **out_meta) as dest:
                dest.write(out_image)
```

```
In [58]: band_names={red:'red',
                    green: 'green',
                    blue: 'blue',
                    nir: 'nir',
                    band5: 'band5',
                    band6: 'band6',
                    band7: 'band7',
                   }
```

```
In [60]: band_names
```

```
Out[60]: {'T37TDK_20190916T082559_B04_20m.jp2': 'red',
          'T37TDK_20190916T082559_B03_20m.jp2': 'green',
          'T37TDK_20190916T082559_B02_20m.jp2': 'blue',
          'T37TDK_20190916T082559_B8A_20m.jp2': 'nir',
          'T37TDK_20190916T082559_B05_20m.jp2': 'band5',
          'T37TDK_20190916T082559_B06_20m.jp2': 'band6',
          'T37TDK_20190916T082559_B07_20m.jp2': 'band7'}
```

```
In [61]: # reproject area of interest to same projection as the imagery
         geo_box=geo_box.to_crs(src.crs)
```

```
In [62]: os.path.join(folder, resolution)
```

```
Out[62]: 'imagery/S2B_MSIL2A_20190916T082559_N0213_R021_T37TDK_20190916T130703.SAFE/GRANULE/L2A
```

```
In [63]: for band, name in band_names.items():
             crop_band(clip_gdf=geo_box,
                       input_folder=os.path.join(folder, resolution),
                       band=band,
                       output_folder='clipped',
                       out_name=name)
```

0.1 Some feature generating to add additional dimension

Normalized Difference Vegetation Index (NDVI) quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs). NDVI always ranges from -1 to +1. But there isn't a distinct boundary for each type of land cover.

For example, when you have negative values, it's highly likely that it's water. On the other hand, if you have a NDVI value close to +1, there's a high possibility that it's dense green leaves.

But when NDVI is close to zero, there isn't green leaves and it could even be an urbanized area.

https://gisgeography.com/ndvi-normalized-difference-vegetation-index/
$NDVI = \frac{NIR-RED}{NIR+RED}$

```
In [64]: # write the function to calculate NDVI
         def calculate_ndvi(red, nir):
             ''' Given Red and NIR bands as input,
             calcuates NDVI'''

             # beacase division will unlikely result in integers
             # change the datatype of our arrays from integer to float
             red=red.astype(float)
             nir=nir.astype(float)

             # since we have 0 values
             # we need to mask them out, so that they don't participate in the calculations
             masked_red=np.ma.masked_where(red==0, red)
             masked_nir=np.ma.masked_where(nir==0, nir)

             # NDVI formula
             ndvi=(masked_nir-masked_red)/(masked_nir+masked_red)
             ndvi=ndvi.filled(fill_value=-1)
             return ndvi
```

```
In [65]: tifs=[tif for tif in os.listdir('./clipped') if tif.endswith('.tif')]
```

```
In [66]: red=rasterio.open(os.path.join('./clipped', 'red.tif')).read(1)
         blue=rasterio.open(os.path.join('./clipped', 'blue.tif')).read(1)
         green=rasterio.open(os.path.join('./clipped', 'green.tif')).read(1)
         nir=rasterio.open(os.path.join('./clipped', 'nir.tif')).read(1)
         band5=rasterio.open(os.path.join('./clipped', 'band5.tif')).read(1)
         band6=rasterio.open(os.path.join('./clipped', 'band6.tif')).read(1)
         band7=rasterio.open(os.path.join('./clipped', 'band7.tif')).read(1)
```

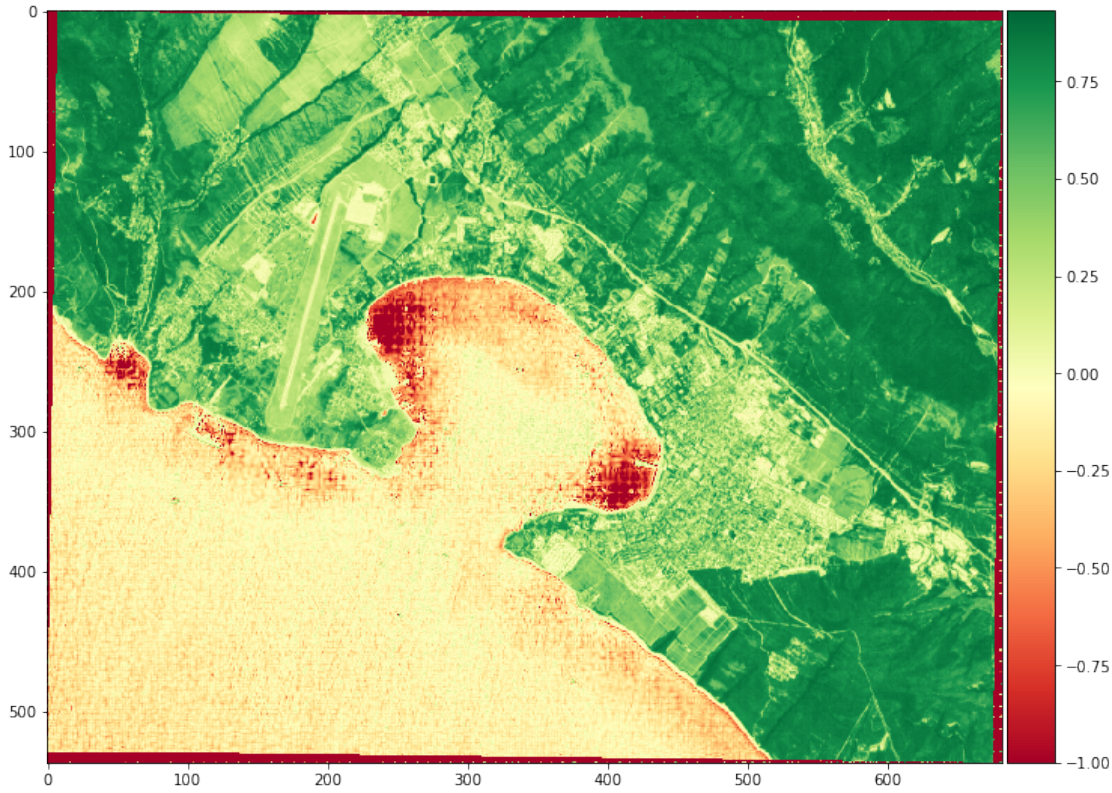
```
In [67]: red.shape
```

```
Out[67]: (537, 682)
```

```
In [68]: ndvi=calculate_ndvi(red, nir)
```

```
In [79]: from mpl_toolkits.axes_grid1 import make_axes_locatable
```

```
In [81]: fig, ax = plt.subplots(figsize=(12, 12))
         im=plt.imshow(ndvi, cmap=plt.get_cmap('RdYlGn'))
         divider = make_axes_locatable(ax)
         cax = divider.append_axes("right", size="5%", pad=0.05)
         plt.colorbar(im, cax=cax);
```




```
In [100]: from sklearn import cluster

In [101]: all_bands=np.dstack([red.ravel(),
                               green.ravel(),
                               blue.ravel(),
                               nir.ravel(),
                               ndvi.ravel(),
                               band5.ravel(),
                               band6.ravel(),
                               band7.ravel()])

In [102]: all_bands.shape[1:]

Out[102]: (366234, 8)

In [103]: X = all_bands.reshape(all_bands.shape[1:])
```

```
In [104]: X.shape
```

```
Out[104]: (366234, 8)
```

```
In [105]: k_means = cluster.KMeans(n_clusters=6, random_state=123)
          k_means.fit(X)
```

```
Out[105]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
                 n_clusters=6, n_init=10, n_jobs=None, precompute_distances='auto',
                 random_state=123, tol=0.0001, verbose=0)
```

```
In [88]: X_cluster = k_means.labels_
```

```
In [89]: set(k_means.labels_)
```

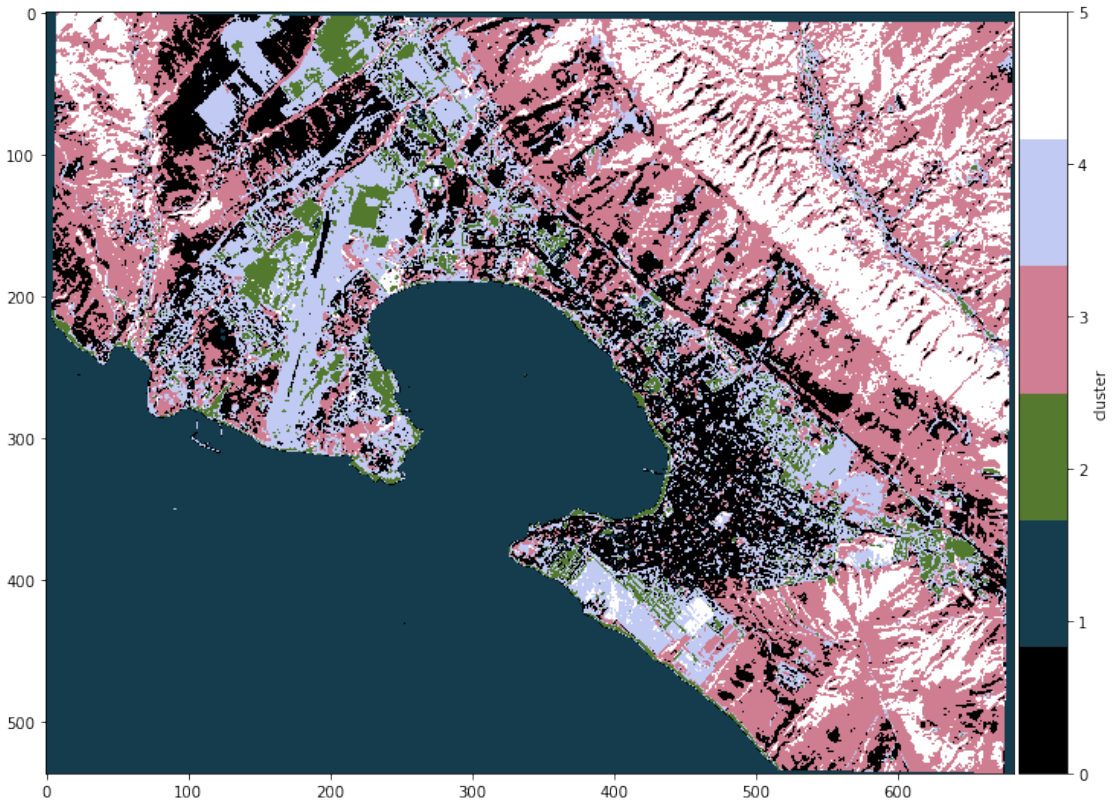
```
Out[89]: {0, 1, 2, 3, 4, 5}
```

```
In [90]: X_cluster.shape
```

```
Out[90]: (366234,)
```

```
In [91]: X_cluster=X_cluster.reshape(red.shape)
```

```
In [94]: plt.figure(figsize=(12, 12))
         ax = plt.gca()
         im=plt.imshow(X_cluster, cmap=plt.cm.get_cmap('cubehelix', 6))
         divider = make_axes_locatable(ax)
         cax = divider.append_axes("right", size="5%", pad=0.05)
         plt.colorbar(ticks=range(6), label='cluster', cax=cax)
         plt.show()
```



In [96]:
```
from PIL import Image
```

In [97]:
```
# I used GoogleEarth to label each cluster
# I zoomed into each area for each cluster to give a meaningful cluster label
image=Image.open(os.path.join('./clipped', 'GoogleEarth.png'))
```

In [99]:
```
fig, ax = plt.subplots(figsize=(11, 11))
ax.imshow(image, interpolation='nearest')
plt.tight_layout()
```

In [106]:
```
labels={
        3: 'trees/dense vegetation',
        1: 'water',
        0: 'residential/roads',
        4: 'grassland',
        2: 'commercial/industrial',
        5: 'sparse vegetaion' ,
    }
```

```
In [107]: bands_df=pd.DataFrame(X, columns=['red', 'green', 'blue', 'nir', 'ndvi', 'band5', 'ba

In [108]: bands_df['cluster'] = k_means.labels_

In [109]: bands_df['labels']=bands_df['cluster'].map(labels)

In [110]: bands_df.sample(20)
```

Out[110]:

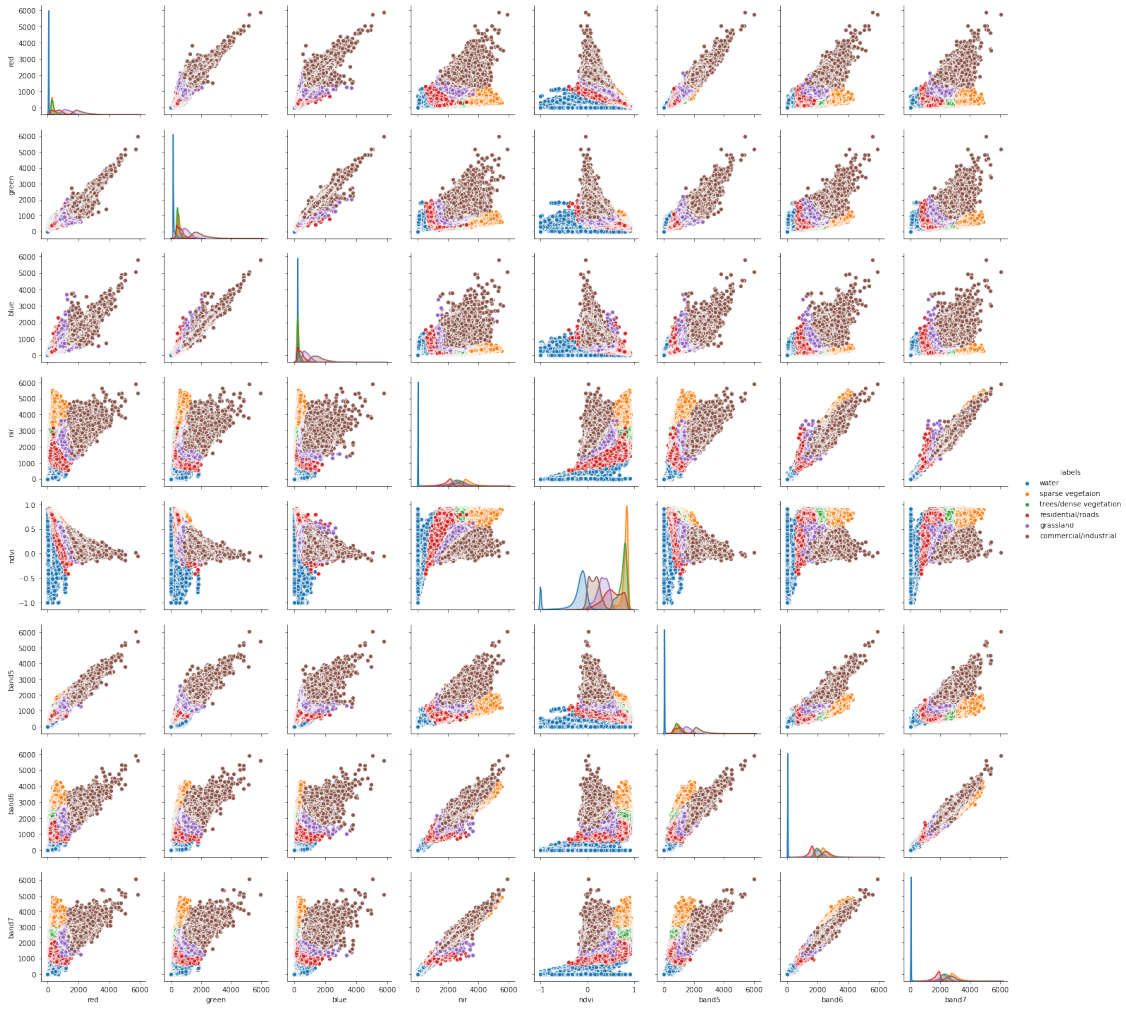
	red	green	blue	nir	ndvi	band5	band6	band7	\
218002	1233.0	1002.0	914.0	1583.0	0.124290	1374.0	1466.0	1633.0	
184279	463.0	530.0	303.0	2325.0	0.667862	983.0	1766.0	2045.0	
173559	88.0	349.0	399.0	58.0	-0.205479	53.0	57.0	63.0	
344326	304.0	453.0	242.0	2485.0	0.782001	787.0	1886.0	2209.0	
357177	69.0	220.0	281.0	40.0	-0.266055	50.0	31.0	47.0	
273148	78.0	210.0	233.0	66.0	-0.083333	62.0	67.0	74.0	
46979	1116.0	956.0	793.0	1784.0	0.230345	1302.0	1487.0	1751.0	
208844	448.0	547.0	416.0	611.0	0.153919	607.0	464.0	723.0	
241644	61.0	152.0	225.0	54.0	-0.060870	43.0	58.0	49.0	
199393	1545.0	1290.0	991.0	2570.0	0.249089	1982.0	2157.0	2391.0	
306152	429.0	688.0	335.0	4003.0	0.806408	1356.0	3017.0	3578.0	
169050	300.0	464.0	293.0	3421.0	0.838753	872.0	2417.0	2944.0	
4248	1649.0	1241.0	934.0	2663.0	0.235158	1978.0	2196.0	2363.0	
184703	162.0	290.0	134.0	2092.0	0.856256	598.0	1552.0	1888.0	
42157	273.0	482.0	188.0	3472.0	0.854206	984.0	2589.0	3126.0	
73958	1853.0	1802.0	1618.0	2189.0	0.083127	1918.0	2121.0	2143.0	
40966	222.0	395.0	198.0	2778.0	0.852000	778.0	2038.0	2499.0	
245152	41.0	159.0	222.0	33.0	-0.108108	38.0	39.0	46.0	
335055	52.0	140.0	218.0	49.0	-0.029703	47.0	48.0	55.0	
49604	426.0	533.0	282.0	2922.0	0.745520	1075.0	2142.0	2437.0	

	cluster	labels
218002	0	residential/roads
184279	3	trees/dense vegetation
173559	1	water
344326	3	trees/dense vegetation
357177	1	water
273148	1	water
46979	0	residential/roads
208844	1	water
241644	1	water
199393	4	grassland
306152	5	sparse vegetaion
169050	5	sparse vegetaion
4248	4	grassland
184703	0	residential/roads
42157	5	sparse vegetaion
73958	2	commercial/industrial
40966	3	trees/dense vegetation
245152	1	water

```
335055         1                    water
49604          3  trees/dense vegetation
```

```
In [111]: import seaborn as sns
```

```
In [112]: sns.pairplot(bands_df.drop('cluster', 1), hue="labels")
          plt.show()
```




```
In [113]: from sklearn.neighbors import KNeighborsClassifier
          from sklearn.model_selection import cross_val_score, GridSearchCV
          from sklearn.preprocessing import StandardScaler
          from sklearn.model_selection import train_test_split
```

```
In [114]: X_bands=bands_df.drop(['labels', 'cluster'], 1)
```

```
In [115]: y=bands_df.cluster
```

```
In [116]: ss=StandardScaler()
```

```
In [117]: Xs = ss.fit_transform(X_bands)

In [119]: X_train, X_test, y_train, y_test=train_test_split(Xs, y)

In [120]: grid_params={'n_neighbors': list(range(3, 50, 4)),
                       'weights': ['uniform', 'distance'],
                       'metric': ['euclidean', 'manhattan']
          }

In [121]: gs=GridSearchCV(KNeighborsClassifier(),
                          grid_params,
                          verbose=1,
                          cv=3,
                          n_jobs=-1
                         )

In [122]: gs_results=gs.fit(X_train, y_train)

Fitting 3 folds for each of 48 candidates, totalling 144 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  3.3min
[Parallel(n_jobs=-1)]: Done 144 out of 144 | elapsed: 18.5min finished


In [137]: gs_results.best_score_

Out[137]: 0.9930608901428961

In [138]: gs_results.best_params_

Out[138]: {'metric': 'manhattan', 'n_neighbors': 39, 'weights': 'distance'}

In [139]: # now train the model using the best parameters returned by Gridsearch
          optimal_knn=KNeighborsClassifier(n_neighbors=gs_results.best_params_['n_neighbors'],
                                           weights=gs_results.best_params_['weights'],
                                           metric=gs_results.best_params_['metric'])

In [140]: optimal_knn.fit(X_train, y_train)

Out[140]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='manhattan',
                               metric_params=None, n_jobs=None, n_neighbors=39, p=2,
                               weights='distance')

In [141]: y_pred=optimal_knn.predict(X_test)

In [142]: from sklearn import metrics

In [143]: # baseline accurace
          y.value_counts() / y.count()
```

```
Out[143]: 1    0.344045
          3    0.229239
          0    0.143236
          4    0.129524
          5    0.119686
          2    0.034270
          Name: cluster, dtype: float64

In [146]: metrics.accuracy_score(y_test, y_pred)

Out[146]: 0.9933048635306196

In [151]: import joblib
          import pickle

In [131]: joblib.dump(optimal_knn, 'KNeighborsClassifier_LandCover.pkl')

Out[131]: ['KNeighborsClassifier_LandCover.pkl']

In [132]: pwd

Out[132]: '/Users/anastasiaclark/GA/land-cover-classification-project'

In [133]: ls

KNeighborsClassifier_LandCover.pkl
Sentinel-2A MSI Spectral Responses.numbers
auth.yaml
classification.ipynb
clipped/
imagery/
land_cover_classification.ipynb
preprocessing_Landsat.ipynb
preprocessing_Sentinel.ipynb


In [157]: # knn_LandCover = joblib.load('KNeighborsClassifier_LandCover.pkl')

In [ ]:
```