

Satellite Image Analysis with Earth Engine and Python Open Source Packages

This exercise introduces Google Earth Engine and raster satellite image analysis and visualization. Working with data from the Sentinel-2 satellite system:

- Assemble images around a specific location and within a specified time period
 - Query metadata information about the images
- View an image statically and with an interactive map
- Calculate a 'spectral indice'
- Calculate change between two images
- Classify an image into statistical clusters
- Create a time series dataset from single location from the images
 - Visualize the time series with an interactive map

The exercise can be run without any knowledge of coding, but for some background, you might want to run through the following coloboratory notebooks:

1. Earth Engine Python API Colab Setup <https://colab.research.google.com/github/google/earthengine-api/blob/master/python/examples/ipynb/ee-api-colab-setup.ipynb>
2. Google Earth Engine with Python - Developer's Guide
https://colab.research.google.com/github/csaybar/EEwPython/blob/dev/1_Introduction.ipynb#scrollTo=5AkUqloUQpXv

▼ Set up the analysis environment

The basic steps to get things set up, using 'python' scripting jargon, are:

1. Install packages
2. Import modules
3. 'Authenticate' earth engine
4. Define functions

Colaboratory comes with a variety of standard scientific computing 'libraries', and many others can be installed fairly easily. This exercise will use the 'earth engine api', the 'geemap' library for visualizing earth engine data, and a variety of libraries to plot results.

```
# install dependencies into virtual machine
!pip install geemap
#!pip install ee
#!pip install earthengine-api
!pip install geopandas
#!pip install altair
```

```
Collecting geemap
  Downloading https://files.pythonhosted.org/packages/c1/f1/50dc342f3c2844353652d5df007ca
    |██████████| 389kB 5.3MB/s
Collecting ipynb-py-convert
  Downloading https://files.pythonhosted.org/packages/43/90/37ff1b9f553583e60c327e1ea8cbf
Collecting mss
  Downloading https://files.pythonhosted.org/packages/d7/5f/77dece686b8d08a17430e169e9367
    |██████████| 81kB 8.8MB/s
Collecting bqplot
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    |██████████| 983kB 14.6MB/s
Collecting folium>=0.11.0
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    |██████████| 102kB 9.5MB/s
Collecting ipyfilechooser
  Downloading https://files.pythonhosted.org/packages/f7/4f/e8d949a6395b6079fe81bf728e5cb
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from gee
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from gee
Collecting voila
  Downloading https://files.pythonhosted.org/packages/50/7d/ef470f3d3c574162bb8705b264f4c
    |██████████| 1.9MB 19.5MB/s
Collecting colour
  Downloading https://files.pythonhosted.org/packages/74/46/e81907704ab203206769dee1385dc
Requirement already satisfied: pillow in /usr/local/lib/python3.6/dist-packages (from gee
Collecting ipyleaflet>=0.13.3
  Downloading https://files.pythonhosted.org/packages/a0/9d/f411b8a9522f1710f278c60b2cd8d
    |██████████| 5.1MB 45.1MB/s
Collecting geocoder
  Downloading https://files.pythonhosted.org/packages/4f/6b/13166c909ad2f2d76b929a4227c95
    |██████████| 102kB 10.6MB/s
Collecting geeadd>=0.5.1
  Downloading https://files.pythonhosted.org/packages/53/3e/98e4d21b5d06a670a6692272a89cb
Requirement already satisfied: click in /usr/local/lib/python3.6/dist-packages (from gee
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (from Gee
Collecting pyshp
  Downloading https://files.pythonhosted.org/packages/ca/1f/e9cc2c3fce32e2926581f8b690583
```

| [██████████] | 225kB 44.9MB/s

Collecting whitebox

 Downloading <https://files.pythonhosted.org/packages/9e/80/72ddfe55b9fad2909c3befb6360c3>

| [██████████] | 71kB 8.1MB/s

Requirement already satisfied: earthengine-api>=0.1.230 in /usr/local/lib/python3.6/dist-packages

Collecting ipytree

 Downloading <https://files.pythonhosted.org/packages/36/2f/f93092e485afc384b4cc39f17ff1c>

| [██████████] | 1.1MB 46.0MB/s

Collecting ffmpeg-python

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Requirement already satisfied: ipywidgets>=7.5.0 in /usr/local/lib/python3.6/dist-packages

Collecting traitlets>=0.0.6

 Downloading <https://files.pythonhosted.org/packages/9c/d1/8d5bd662703cc1764d986f6908a60>

Requirement already satisfied: traitlets>=4.3.0 in /usr/local/lib/python3.6/dist-packages

Requirement already satisfied: branca>=0.3.0 in /usr/local/lib/python3.6/dist-packages (from traitlets>=4.3.0)

Requirement already satisfied: jinja2>=2.9 in /usr/local/lib/python3.6/dist-packages (from traitlets>=4.3.0)

Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from traitlets>=4.3.0)

Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from traitlets>=4.3.0)

Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.6/dist-packages

Collecting jupyter-client<7,>=6.1.3

 Downloading <https://files.pythonhosted.org/packages/dc/41/9fa443d5ae8907dd8f7d12146cb00>

| [██████████] | 112kB 49.3MB/s

Collecting nbconvert<7,>=6.0.0

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| [██████████] | 552kB 44.0MB/s

Requirement already satisfied: nbclient<0.6,>=0.4.0 in /usr/local/lib/python3.6/dist-packages

Collecting jupyter-server<2.0.0,>=0.3.0

 Downloading <https://files.pythonhosted.org/packages/7f/0d/1eafbdca04feecdf596382d077660>

| [██████████] | 204kB 40.3MB/s

Collecting ratelim

 Downloading <https://files.pythonhosted.org/packages/f2/98/7e6d147fd16a10a5f821db6e25f19>

Requirement already satisfied: future in /usr/local/lib/python3.6/dist-packages (from ratelim)

Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from ratelim)

Collecting beautifulsoup4>=4.9.0

 Downloading <https://files.pythonhosted.org/packages/d1/41/e6495bd7d3781cee623ce23ea6ac7>

| [██████████] | 122kB 50.0MB/s

```
Collecting logzero>=1.5.0
```

```
  Downloading https://files.pythonhosted.org/packages/7e/f7/369920be5b4e9c1a05f5e10bae62b
```

```
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from logzero>=1.5.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: google-auth>=1.4.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: httplib2<1dev,>=0.9.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: google-auth-httplib2>=0.0.3 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: nbformat>=4.2.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: ipython>=4.0.0; python_version >= "3.3" in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: ipykernel>=4.5.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: widgetsnbextension~=3.5.0 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: urllib3!=1.25.0,!<1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: bleach in /usr/local/lib/python3.6/dist-packages (from nbsphinx>=0.8.0)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.6/dist-packages (from logzero>=1.5.0)
Requirement already satisfied: async-generator in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: terminado>=0.8.3 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: prometheus-client in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: soupsieve>1.2; python_version >= "3.0"
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Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3" in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: setuptools>=40.3.0 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: google-resumable-media<0.5.0dev,>=0.3.1 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/python3.6/dist-packages
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Requirement already satisfied: pexpect; sys_platform != "win32" in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: pickleshare in /usr/local/lib/python3.6/dist-packages (from notebook)
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Requirement already satisfied: packaging in /usr/local/lib/python3.6/dist-packages (from notebook)
Requirement already satisfied: ptyprocess; os_name != "nt" in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: pyasn1>=0.1.3 in /usr/local/lib/python3.6/dist-packages (from notebook)
Requirement already satisfied: google-api-core<2.0.0dev,>=1.14.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: wcwidth in /usr/local/lib/python3.6/dist-packages (from notebook)
Requirement already satisfied: googleapis-common-protos<2.0dev,>=1.6.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: protobuf>=3.4.0 in /usr/local/lib/python3.6/dist-packages
Building wheels for collected packages: ipynb-py-convert, pyshp
  Building wheel for ipynb-py-convert (setup.py) ... done
  Created wheel for ipynb-py-convert: filename=ipynb_py_convert-0.4.6-cp36-none-any.whl size=36216 sha256=12a32
  Stored in directory: /root/.cache/pip/wheels/80/dc/7c/a7279f7726d66951fe48d5af45247bcf
  Building wheel for pyshp (setup.py) ... done
  Created wheel for pyshp: filename=pyshp-2.1.2-cp36-none-any.whl size=36216 sha256=12a32
  Stored in directory: /root/.cache/pip/wheels/96/6c/53/4112475adf3b831da97f083163d0f38ee
Successfully built ipynb-py-convert pyshp
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have folium 0.11.0 which is required by this application.
Installing collected packages: ipynb-py-convert, mss, traitypes, bqplot, folium, ipyfile
  Found existing installation: folium 0.8.3
  Uninstalling folium-0.8.3:
```

```
Successfully uninstalled folium-0.8.3
Found existing installation: jupyter-client 5.3.5
Uninstalling jupyter-client-5.3.5:
    Successfully uninstalled jupyter-client-5.3.5
Found existing installation: nbconvert 5.6.1
Uninstalling nbconvert-5.6.1:
    Successfully uninstalled nbconvert-5.6.1
Found existing installation: beautifulsoup4 4.6.3
Uninstalling beautifulsoup4-4.6.3:
    Successfully uninstalled beautifulsoup4-4.6.3
Successfully installed beautifulsoup4-4.9.3 bqplot-0.12.19 colour-0.1.5 ffmpeg-python-0.2
Collecting geopandas
    Downloading https://files.pythonhosted.org/packages/f7/a4/e66aafbefcbb717813bf3a355c8c4
    |██████████| 972kB 4.1MB/s
Collecting pyproj>=2.2.0
    Downloading https://files.pythonhosted.org/packages/e4/ab/280e80a67fcf109d15428c0ec5639
    |██████████| 6.5MB 21.7MB/s
Requirement already satisfied: pandas>=0.23.0 in /usr/local/lib/python3.6/dist-packages (from geopandas)
Requirement already satisfied: shapely in /usr/local/lib/python3.6/dist-packages (from geopandas)
Collecting fiona
    Downloading https://files.pythonhosted.org/packages/37/94/4910fd55246c1d963727b03885ead
    |██████████| 14.8MB 328kB/s
Requirement already satisfied: certifi in /usr/local/lib/python3.6/dist-packages (from fiona)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.6/dist-packages (from fiona)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from fiona)
Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.6/dist-packages (from fiona)
Requirement already satisfied: six>=1.7 in /usr/local/lib/python3.6/dist-packages (from fiona)
Requirement already satisfied: attrs>=17 in /usr/local/lib/python3.6/dist-packages (from fiona)
Collecting click-plugins>=1.0
    Downloading https://files.pythonhosted.org/packages/e9/da/824b92d9942f4e472702488857914
Collecting munch
    Downloading https://files.pythonhosted.org/packages/cc/ab/85d8da5c9a45e072301beb37ad7f8
Collecting cligj>=0.5
    Downloading https://files.pythonhosted.org/packages/ba/06/e3440b1f2dc802d35f329f299ba96
Requirement already satisfied: click<8,>=4.0 in /usr/local/lib/python3.6/dist-packages (from cligj)
Installing collected packages: pyproj, click-plugins, munch, cligj, fiona, geopandas
```

- You may have now have to `RESTART RUNTIME` (with a button in the output above) to properly import the modules in the next step

▼ Import modules

Plotting, visualization, and data analysis tools

```
# earth engine and statistical analysis
from IPython.display import Image
import ee, datetime
import pandas as pd
from pylab import *
import seaborn as sns

# file management
import os
import glob

# geospatial and plotting modules
# import geopandas as gpd
import geemap.eefolium as geemap

import folium
import matplotlib.pyplot as plt
%matplotlib inline

import altair as alt
```

▼ Authenticate earth engine

Since earth engine requires a login, to use it with colaboratory requires 'authenticating' an analysis session. That is, giving permission via a google account. Rinning the cell below will provide a link to a google authentication website, which will ask your permission and then provide a verification code to paste into a box - then hit enter to finish the process.

```
# Trigger the authentication flow.  
ee.Authenticate()
```

To authorize access needed by Earth Engine, open the following URL in a web browser and f

https://accounts.google.com/o/oauth2/auth?client_id=517222506229-vsmmajv00ul0bs7p89v5

The authorization workflow will generate a code, which you should paste in the box below.

Successfully saved authorization token.

Once it has successfully saved authorization token the session can be 'initialized'

```
# start up the session  
ee.Initialize()
```

▼ Define Functions

Functions do something with information. Here are functions to *mask* out clouds and cloud shadows, and to calculate a variety of *spectral indices* from the image data. Sentinel-2 and Landsat 8 satellite image data are used.

- Landsat 8 data is called with `ee.ImageCollection("LANDSAT/LC08/C01/T1_SR")` in the script and described here: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C01_T1_SR
- The functions for masking are adapted from here: https://code.earthengine.google.com/?scriptPath=Examples:Datasets/LANDSAT_LC08_C01_T1_SR
- Sentinel-2 data is called with `ee.ImageCollection("COPERNICUS/S2_SR")` and described here: https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2

Sentinel-2 image bands used in the functions are:

- Band 4 = red
- Band 8 = NIR
- at 10m pixel resolution

Landsat 8 bands used are:

- Band 4 = red
- Band 5 = NIR
- at 30m pixel resolution

The exercise uses Sentinel-2 data, and can be adapted to work with Landsat 8.

▼ Cloudmask functions

These will mask clouds from the image collections to help improve analysis results of the time series data.

```
#function to use QA band to filter clouds
#Landsat 8 sr data
def maskL8sr(image):
    #Bits 3 and 5 are cloud shadow and cloud, respectively.
    cloudShadowBitMask = (1 << 3)
    cloudsBitMask = (1 << 5)
    # Get the pixel QA band.
    qa = image.select('pixel_qa')
    # Both flags should be set to zero, indicating clear conditions.
    mask = qa.bitwiseAnd((cloudShadowBitMask).eq(0)).bitwiseAnd((cloudsBitMask).eq(0))
    return image.updateMask(mask)
```

```
#function to use QA band to filter clouds
#Sentinel 2 data
def maskS2clouds(image):
    qa = image.select('QA60')

    #Bits 10 and 11 are clouds and cirrus, respectively.
    cloudBitMask = 1 << 10
    cirrusBitMask = 1 << 11

    #Both flags should be set to zero, indicating clear conditions.
    mask = qa.bitwiseAnd(cloudBitMask).eq(0)
    mask2 = qa.bitwiseAnd(cirrusBitMask).eq(0)
    mask3 = qa.bitwiseAnd(cloudBitMask).eq(0).bitwiseAnd(cirrusBitMask).eq(0)
    #cloud_img = image.updateMask(mask)
    #cir_img = cloud_img.updateMask(mask2)
```

```
return image.updateMask(mask).updateMask(mask2)
#return image.updateMask(mask)
```

▼ Spectral indices and transformations

Spectral indices are designed to combine different wavelengths of energy in order to highlight some materials or features of interest.

Code for the Landsat 8 indices was adapted from [renelikestacos](#) on github. There are quite a few here, and many more have been created.

This exercise uses the *NDVI* (*Normalized Difference Vegetation Index*) as an example. NDVI is [described here](#) in the context of the MODIS sensor system - this exercise uses Sentinel-2 imagery which has 10 meter size pixels.

Other indices are described here:

- [Landsat 8 Spectral Indices](#)
- [Sentinel-2 indices](#) On first look-over I thought there was one for "Macaroni" but I misread the table.

```
# Landsat 8 indices
def NDVI(image):
    return image.normalizedDifference(['B5', 'B4'])

def SAM(image):
    band1 = image.select("B1")
    bandn = image.select("B2", "B3", "B4", "B5", "B6", "B7", "B8", "B9");
    maxObjSize = 256;
    b = band1.divide(bandn);
    spectralAngleMap = b.atan();
```

```

spectralAngleMap_sin = spectralAngleMap.sin();
spectralAngleMap_cos = spectralAngleMap.cos();
sum_cos = spectralAngleMap_cos.reduce(ee.call("Reducer.sum"));
sum_sin = spectralAngleMap_sin.reduce(ee.call("Reducer.sum"));
return ee.Image.cat(sum_sin, sum_cos, spectralAngleMap_sin, spectralAngleMap_cos);

#Enhanced Vegetation Index
def EVI(image):
    # L(Canopy background)
    # C1,C2(Coefficients of aerosol resistance term)
    # GainFactor(Gain or scaling factor)
    gain_factor = ee.Image(2.5);
    coefficient_1 = ee.Image(6);
    coefficient_2 = ee.Image(7.5);
    l = ee.Image(1);
    nir = image.select("B5");
    red = image.select("B4");
    blue = image.select("B2");
    evi = image.expression(
        "Gain_Factor*((NIR-RED)/(NIR+C1*RED-C2*BLUE+L))",
        {
            "Gain_Factor":gain_factor,
            "NIR":nir,
            "RED":red,
            "C1":coefficient_1,
            "C2":coefficient_2,
            "BLUE":blue,
            "L":l
        }
    )
    return evi

#Atmospherically Resistant Vegetation Index

```

```
#AEROSPATIALLY RESISTANCE VEGETATION INDEX
```

```
def ARVI(image):
    red = image.select("B4")
    blue = image.select("B2")
    nir = image.select("B5")
    red_square = red.multiply(red)
    arvi = image.expression(
        "NIR - (REDsq - BLUE)/(NIR+(REDsq-BLUE))",
        {
            "NIR": nir,
            "REDsq": red_square,
            "BLUE": blue
        }
    )
    return arvi
```

```
#Leaf Area Index
```

```
def LAI(image):
    nir = image.select("B5")
    red = image.select("B4")
    coeff1 = ee.Image(0.0305);
    coeff2 = ee.Image(1.2640);
    lai = image.expression(
        "((NIR/RED)*COEFF1)+COEFF2",
        {
            "NIR":nir,
            "RED":red,
            "COEFF1":coeff1,
            "COEFF2":coeff2
        }
    )
    return lai
```

This exercise demonstrates the use of Sentinel-2 image data, so these indices need to be adapted to the different band names in the dataset.

```
# adapted to Sentinel-2

# NDVI for Sentinel-2 bands
def senNDVI(image):
    return image.normalizedDifference(['B8', 'B4'])
```

▼ Create target areas for analysis

A single point will be used to set the initial data search.

Note that this is 'x, y' style (longitude, latitude)

- Deschutes National Forest: [-121.2611, 44.0916]

```
# use the Deschutes National Forest point
rnapoint = [-121.2611, 44.0916]

# Create earth engine point
point = {'type': 'Point', 'coordinates': rnapoint}
```

▼ Create image collection

An 'image collection' is a group (or filtered group) of related imagery or other data.

- [ImageCollection Overview](#)

Images in earth engine are described here.

- [Image Overview](#)

Collections can be vast, so commonly they are filtered by a geographic area or time period.

▼ Set time period

This exercise uses data from early 2015 to the October 10, 2020. The Sentinel-2 image collection frequency increases over this time as a second sensor comes into use.

Landsat 8 dataset availability is from April 2013 onwards, so a longer time period could be analysed with this data.

```
# Set start and end date
startTime = datetime.datetime(2015, 3, 28)
# endTime = datetime.datetime.now()
endTime = datetime.datetime(2020, 11, 9)
```

▼ Load Sentinel-2 image collection

```
# Create Sentinel-2 image collection
collection = ee.ImageCollection("COPERNICUS/S2").filterDate(startTime, endTime).filterBounds(p

# Create Landsat 8 image collection
#lsCollection = ee.ImageCollection("LANDSAT/LC08/C01/T1_SR").filterDate(startTime, endTime).fi
```

```
PROJECTION = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR').select(['SR_B1','SR_B2','SR_B3','SR_B4','SR_B5','SR_B6','SR_B7']).filterDate(datetime.datetime(2015, 1, 1),
```

▼ Image Collection Information and Metadata

It is usually a good idea to examine the data in the collections created.

```
# Get the number of images.  
count = collection.size()  
print('Count: ', str(count.getInfo())+'\n')
```

```
Count: 599
```

```
# Get the date range of images in the collection.  
drange = collection.reduceColumns(ee.Reducer.minMax(), ["system:time_start"])  
mindate = (ee.Date(drange.get('min')).getInfo())  
maxdate = (ee.Date(drange.get('max')).getInfo())  
print(f'Sentinel 2 Date range: {mindate} to {maxdate}')  
  
Sentinel 2 Date range: {'type': 'Date', 'value': 1442602882000} to {'type': 'Date', 'valu
```

Those dates look a little odd - they are a timestamp (in milliseconds) from Jan 1, 1970 - this is 'UNIX epoch time.' We can convert back to a more human-readable format this way:

```
# divide by 1000 to convert from milliseconds  
datetime.datetime.fromtimestamp(0/1000)  
  
datetime.datetime(1970, 1, 1, 0, 0)
```

So the date / time of the oldest image in this particular collection is:

```
datetime.datetime.fromtimestamp(1445454617457/1000)  
  
datetime.datetime(2015, 10, 21, 19, 10, 17, 457000)
```

There are many other types of information about the images in the metadata.

```
#Get a list of all metadata properties.  
properties = collection.propertyNames()  
print('Metadata properties: '+str(properties.getInfo())) # ee.List of metadata properties  
  
Metadata properties: ['date_range', 'period', 'system:visualization_0_min', 'type_name',
```

▼ Metadata for the first image in the collection

'Metadata' or standarized information about a dataset, is useful both for human-understanding of the usefulness (or not) of a particular dataset. More information about getting metatdata can be found at these links:

- https://developers.google.com/earth-engine/ic_info
- https://samapriya.github.io/gee-py/projects/collection_meta/

```
# sort the collection by time of image acquisition  
sorted = collection.sort("system:time_start");
```

```
# Get the first (oldest) image.
scene = sorted.first()

#properties of the image
properties = scene.propertyNames()
print('Metadata properties: '+str(properties.getInfo())) # ee.List of metadata properties

Metadata properties: ['DATATAKE_IDENTIFIER', 'SPACECRAFT_NAME', 'FORMAT_CORRECTNESS_FLAG']

#Get the 'tile' location identifier
target = 'MGRS_TILE'
meta = scene.get(target).getInfo()
print('{} = {}'.format(target, meta))

MGRS_TILE = 10TFP

#Get the data id
target = 'GRANULE_ID'
meta = scene.get(target).getInfo()
print('{} = {}'.format(target, meta))

GRANULE_ID = L1C_T10TFP_A001254_20150918T190122

#Get estimated cloud cover
target = 'CLOUD_COVERAGE_ASSESSMENT'
meta = scene.get(target).getInfo()
print('{} = {}'.format(target, meta))

CLOUD_COVERAGE_ASSESSMENT = 2.0484
```

```
#Get the timestamp and convert it to a date.  
date = ee.Date(scene.get('system:time_start')). getInfo()  
# print(date['value'])  
x=date['value']  
print(datetime.datetime.fromtimestamp(x/1000))
```

2015-09-18 19:01:22

```
oldest = collection.sort('system:time_start').limit(1)  
scene = oldest.first()  
#Get a specific metadata property.  
target = 'system:time_start'  
meta = scene.get(target).getInfo()  
print('{} = {}'.format(target, meta))
```

```
#Get the timestamp and convert it to a date.  
date = ee.Date(scene.get('system:time_start')).getInfo()  
# print(date['value'])  
x=date['value']  
print(datetime.datetime.fromtimestamp(x/1000))
```

system:time_start = 1442602882000
2015-09-18 19:01:22

▼ Assignment: Geog 485

What does the “MGRS_TILE” metadata mean in the context of the Sentinel-2 image collection - how do we interpret the value ‘10TEP’? Describe how the Sentinel-2 tile system works.

Here is the code cell again...

```
#Get the 'tile' location identifier
target = 'MGRS_TILE'
meta = scene.getInfo()
print('{} = {}'.format(target, meta))

MGRS_TILE = 10TFP
```

▼ Assignment: Geog 491

What data type are the `mindate` and `maxdate` variables? How could the output of the code below be made to print the following:

```
Sentinel 2 Date range: 1445454617457 to 1604430749547
```

instead of:

```
# Sentinel 2 Date range: {'type': 'Date', 'value': 1445454617457} to {'type': 'Date', 'value': 1604862

# this is the code below, mentioned above
# Get the date range of images in the collection.
drange = collection.reduceColumns(ee.Reducer.minMax(), ["system:time_start"])
mindate = (ee.Date(drange.get('min')).getInfo()['value']) # datatype is dict so provide the re
```

```
maxdate = (ee.Date(drangef.get('max')).getInfo()['value']) # datatype is dict so provide the re
print(f'Sentinel 2 Date range: {mindate} to {maxdate}')

Sentinel 2 Date range: 1442602882000 to 1604862742204
```

▼ Assignment: Geog 491

Write a function to convert a timestamp from a date, given a ee image.

Adapt the code below, so that given an image, the output will be the date/time in a more human readable format.

The function could start something like this:

```
def ts_toDate(scene):
    # your function here
```

and end up printing output such as:

```
2015-10-21 19:10:17.457000
```

```
def ts_toScene(scene):
    #Get the timestamp and convert it to a date.
    date = ee.Date(scene.get('system:time_start')).getInfo()
    # print(date['value'])
    x=date['value']
    print(datetime.datetime.fromtimestamp(x/1000))

ts_toScene(scene)
```

--_-----,----,

2015-09-18 19:01:22

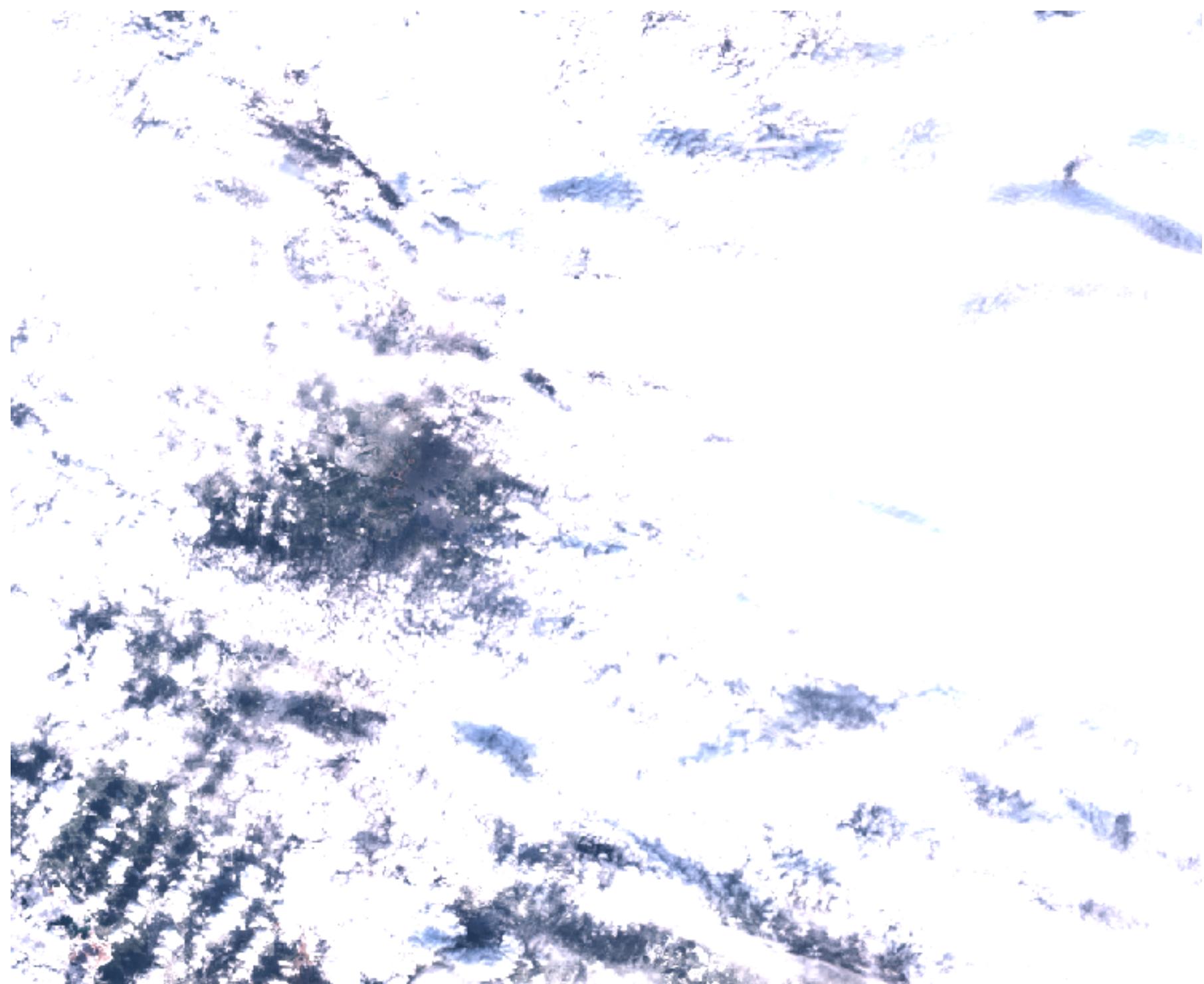
▼ View the most recent image

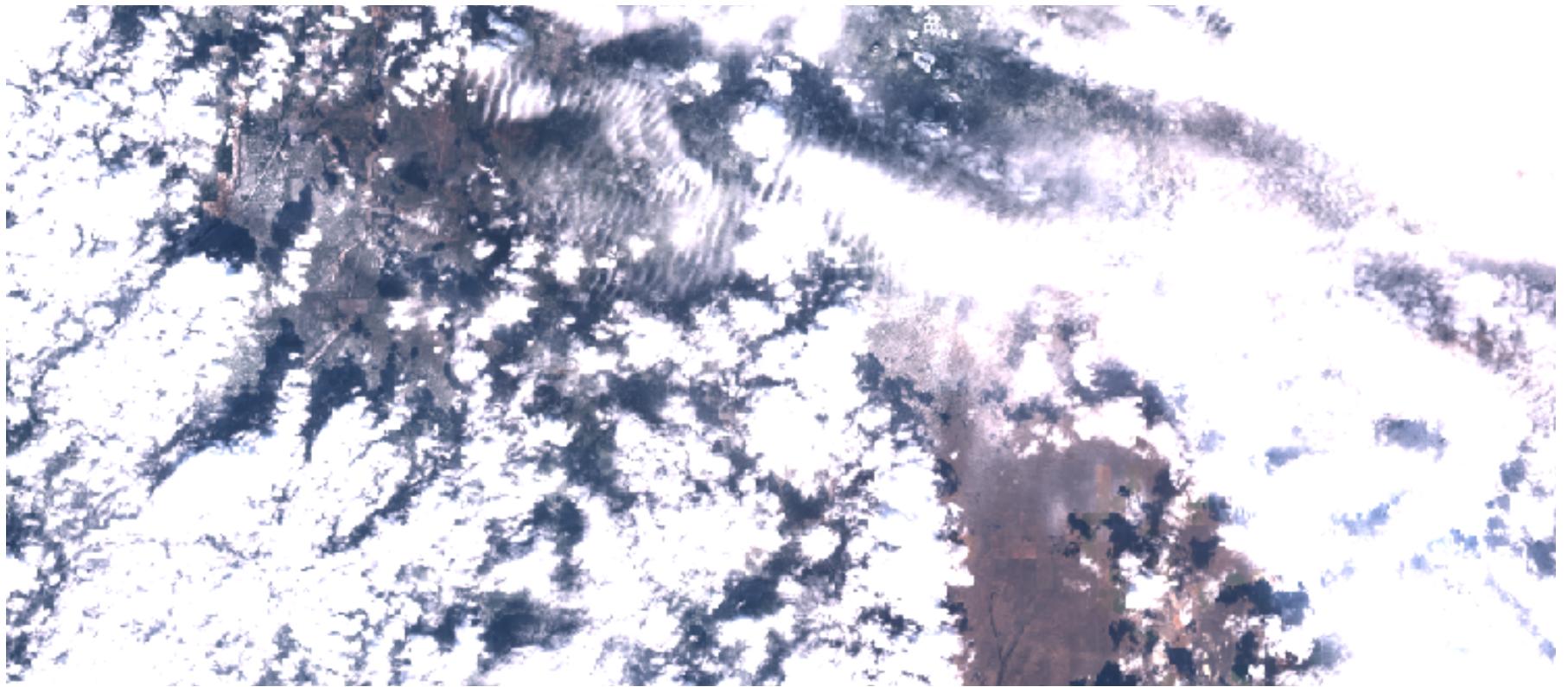
The data can be viewed as a static image or with an interactive map. First, the static image - these are handy because you can copy and paste them directly into another document

```
# Limit the collection to the 1 most recent images.
recent = collection.sort('system:time_start', False).limit(1)
# pull the image from the collection
image = recent.first()
print('Recent images: '+str(recent.getInfo())+'\n')

Recent images: {'type': 'ImageCollection', 'bands': [], 'id': 'COPERNICUS/S2', 'version': 1, 'system:time_start': '2015-09-18T19:01:22Z', 'system:id': 'COPERNICUS/S2:20150918T190122Z'}
# set the visualization parameters for the output
visParams = {'bands': ['B4', 'B3', 'B2'], 'max': 3000, 'dimensions':1000 }

# create image thumbnail in earth engine and view
thumbnail = image.getThumbUrl(visParams)
Image(url=thumbnail)
```





It is a bit cloudy as of this run. The 'least cloudy' images - there are probably many, can be pulled from the collection using the Quality Assurance band

▼ Get the least cloudy image

The metadata for the collection allows the sorting by estimated cloud cover - for now, limit it to the ten least cloudy images

```
sorted = collection.sort('CLOUD_COVERAGE_ASSESSMENT').limit(10)

# Get the first (least cloudy) image.
image = sorted.first();
```

```
# Get the number of images.  
count = sorted.size()  
print('Count: ', str(count.getInfo())+'\n')  
  
# Get the date range of images in the collection.  
drange = sorted.reduceColumns(ee.Reducer.minMax(), ["system:time_start"])  
print('Sentinel 2 Date range: ', str(ee.Date(drange.get('min')).getInfo()), str(ee.Date(drange.get('max')).getInfo()))
```

Count: 10

Sentinel 2 Date range: {'type': 'Date', 'value': 1443466882000} {'type': 'Date', 'value': 1443466882000}

```
#Get the timestamp and convert it to a date.
```

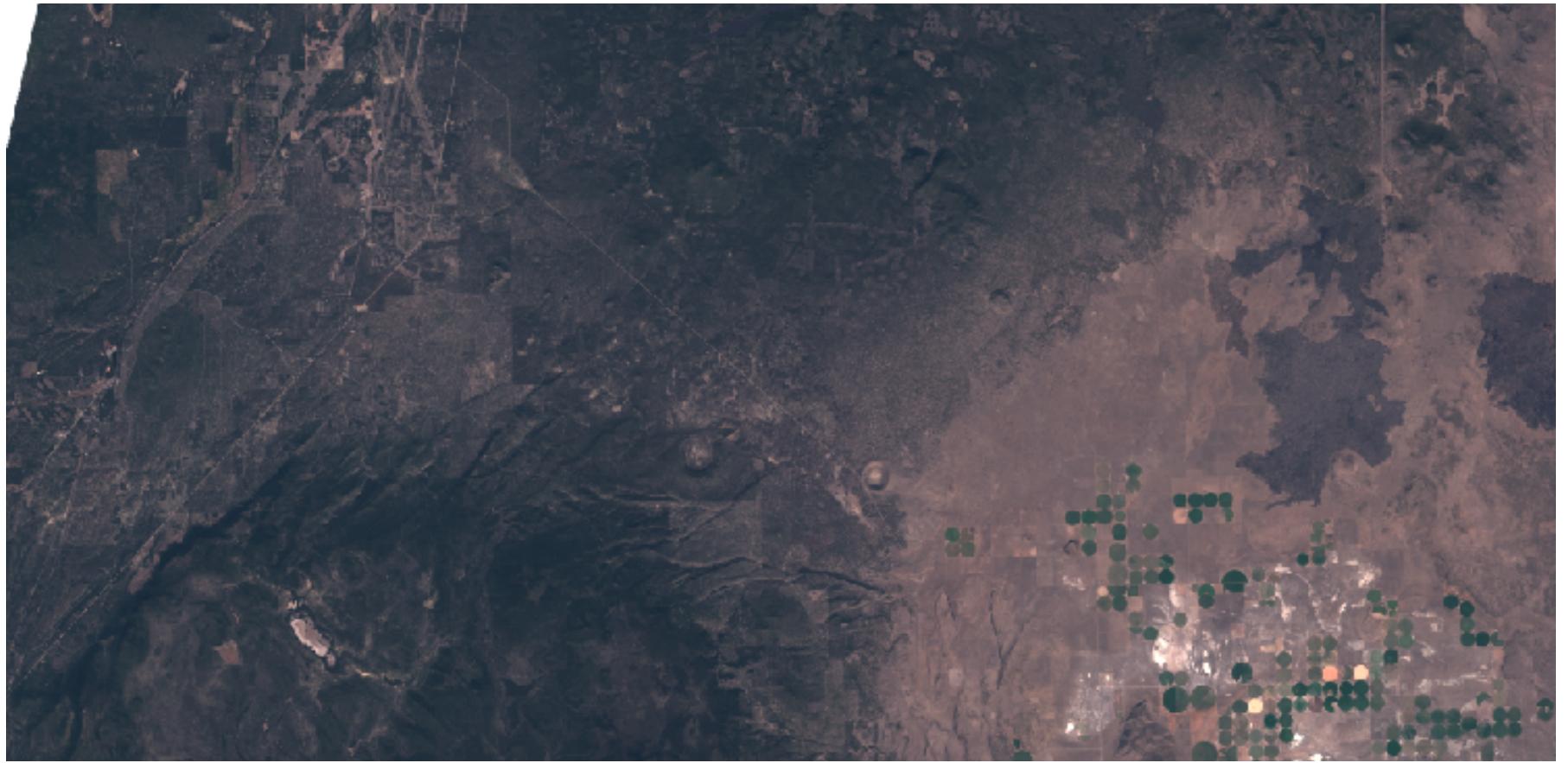
```
date = ee.Date(image.get('system:time_start')).getInfo()  
# print(date['value'])  
x=date['value']  
print(datetime.datetime.fromtimestamp(x/1000))
```

2015-09-28 19:01:22

An image from July 2, 2017. View this 'least cloudy' image.

```
visParams = {'bands': ['B4', 'B3', 'B2'], 'max': 3000, 'dimensions':1000}  
thumbnail = image.getThumbUrl(visParams)  
Image(url=thumbnail)
```





▼ Calculate and view NDVI

This image is much better.

The NDVI is calculated with a ratio of two wavelengths of reflected energy - 'red' and 'near-infrared'.

Higher NDVI values should correspond to larger amounts of green vegetation. To calculate this, run the Sentinel-2 NDVI function made earlier in the exercise on the existing image.

```
# run the sentinel NDVI function  
sndvi = senNDVI(image)
```

```
# change visualization setting for the NDVI data
visParams = {'min':0, 'max': 1, 'dimensions':1000}
thumbnail = sndvi.getThumbUrl(visParams)
Image(url=thumbnail)
```



Brighter areas in the image should represent areas with higher amounts of growing green vegetation.

▼ View scene interactively

To examine whether NDVI is actually showing growing vegetation more closely, an interactive map is useful.

The *folium* python library can be used to view this same data on an interactive map. Multiple layers and other graphics can also be viewed, and the visualization saved as an .html file.

First, let's get the parameters for visualization set up.

```
# visualization settings
rgbParams = {'bands': ['B4', 'B3', 'B2'], 'max': 3000, 'gamma': [1.4, 1.2, 1.4]}
ndviParams = {'min': 0, 'max': 1}
```

```
# flip the point coordinate to be lat, long (y, x) for folium
f = folium.Figure(width=800, height=600)
Map = geemap.Map(center=rnapoint[::-1], zoom= 12).add_to(f)
Map.addLayer(image, rgbParams, 'Natural Color Sentinel-2');
Map.addLayer(sndvi, ndviParams, 'NDVI')
Map.addLayerControl()
f
```



- ▼ Find the least cloudy recent image and examine

Now, to compare the above image (from 2017) with a more recent, relatively cloud free image.



```
# Limit the collection to the 10 most recent images.  
recent = collection.sort('system:time_start', False).limit(10)  
  
sorted = recent.sort('CLOUD COVERAGE ASSESSMENT')
```

```
# Get the first (least cloudy) image.  
recentqa = sorted.first()  
  
recentndvi = senNDVI(recentqa)  
  
#Get the timestamp and convert it to a date.  
date = ee.Date(recentqa.get('system:time_start')). getInfo()  
# print(date['value'])  
x=date['value']  
print(datetime.datetime.fromtimestamp(x/1000))
```

2020-10-29 19:12:23.587000

▼ An image from October 9, 2020

In this run, it is Oct. 9th, 2020.

Lets look at this data, and add the point used to 'filter' the collection geographically as well.

```
# flip the point coordinate to be lat, long (y, x) for folium  
f = folium.Figure(width=800, height=600)  
Map = geemap.Map(center=rnapoint[::-1], zoom= 12).add_to(f)  
Map.addLayer(image, rgbParams, 'Before Natural Color')  
Map.addLayer(recentndvi, ndviParams, 'NDVI recently')  
Map.addLayer(sndvi, ndviParams, 'NDVI before')  
Map.addLayerControl()  
folium.Marker(rnapoint[::-1], popup='<i>Deschutes National Forest</i>').add_to(Map) # marker
```

f



▼ Use image math to compare the images

Compute a difference image of NDVI between the two dates.

Image math is relatively straightforward with earth engine (and it could also be calculated outside earth engine with the 'numpy' and related modules.



```
# create image expression
# the 'subtract()' mathematical operator could also be used
# dif = recentndvi.subtract(sndvi)
dif = image.expression('new-old', {'new': recentndvi, 'old': sndvi})
difParams = {'min':-1, 'max': 1, 'palette': ['red', 'grey', 'green']}
```



Examine the result - redder areas have less green vegetation recently compared to 2017, while green areas have more.



```
# plot the difference image along with the other layers
f = folium.Figure(width=800, height=600)
# flip the point coordinate to be lat, long (y, x) for folium
Map = geemap.Map(center=rnapoint[::-1], zoom= 11).add_to(f)
Map.addLayer(image, rgbParams, 'Before Natural Color')
Map.addLayer(recentqa, rgbParams, 'Recent Natural Color')
Map.addLayer(recentndvi, ndviParams, 'NDVI recently')
Map.addLayer(sndvi, ndviParams, 'NDVI before')
Map.addLayer(dif, difParams, 'dif')
Map.addLayerControl()
```

[Folium Map](#) | [Download Notebook](#) | [Natural Color](#) | [NDVI](#) | [Add to Map](#)

```
    folium.Marker([mapPointL[0], mapPointL[1]], popup= '<u>Deschutes National Forest</u>').add_to(map)
```

```
f
```



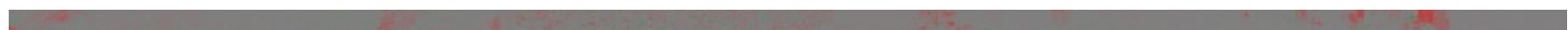
▼ Assignment: Geog 485

What explains the changes visible in the NDVI difference image?

Greener areas are estimated to have more growing green vegetation recently, while redder areas are estimated to have less. Think about the time difference between the images as well.

- seasonality,
- atmosphere,
- solar orientation,
- actual LULC change

There is likely more than one factor at play - don't forget to look at the images from the two dates in addition to the NDVI difference image for your answer - and to examine the entire image area using the zoom and pan tools.



▼ Time Series Analysis

Since the collection has hundreds of images of this area since 2015, this data can be used to look at the variation of NDVI over a single point as a time series.

▼ Retrieve information over the collection time period

The point used to geographically limit the image collection can be used to gather information from a single area over the entire time period. The code for this is described [here](#).

```
info = collection.getRegion(point,10). getInfo()
```

▼ mask clouds to create a filtered collection

We can use the cloud mask function created earlier to remove data that has been identified as cloudy in the collection, to compare with the data above.

This new result will be called `dataset`

```
# apply the cloud mask to the collection  
maskeddata = collection.map(masks2clouds)
```

Get information about the filtered collection

```
# get the data for a specific area  
info_filt = maskeddata.getRegion(point,10). getInfo()
```

▼ Compare the unfiltered and the filtered collection

Plot the data by turning it into a pandas dataframe and using the seaborn package to visualize it

unfiltered

```
# plot the ndvi
data = info

# Reshape image collection
header = data[0]
data = array(data[1:])

iTIme = header.index('time')
time = [datetime.datetime.fromtimestamp(i/1000) for i in (data[0:,iTIme].astype(int))]

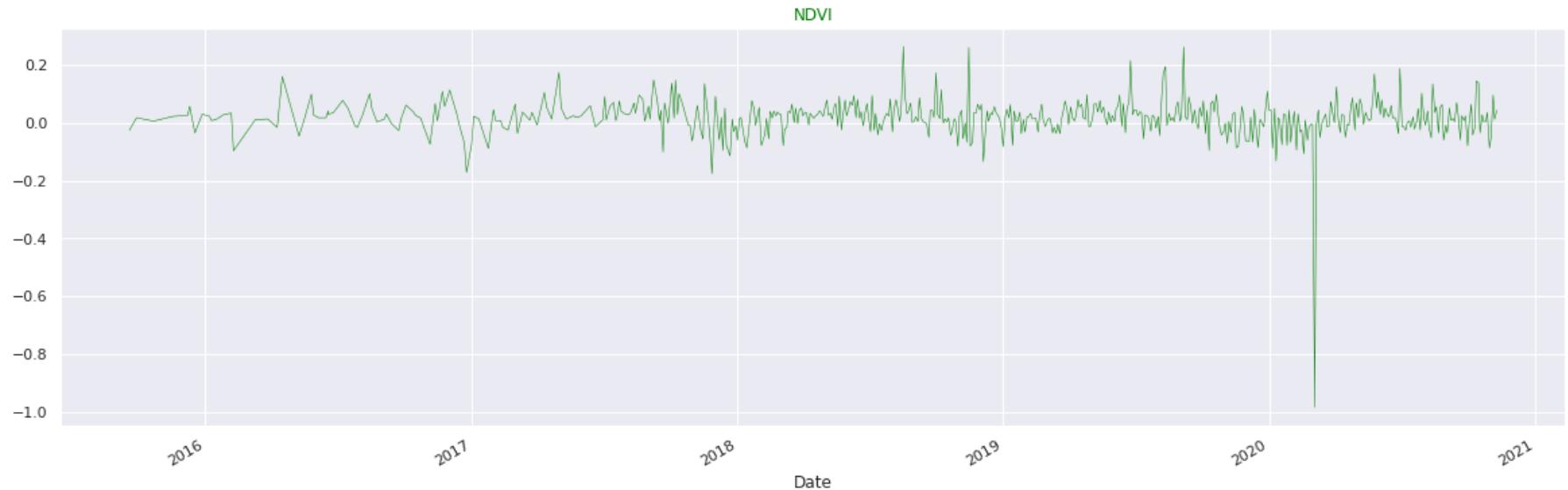
# List of used image bands
#band_list = [ 'RED',u'NIR']
band_list = [ 'B4',u'B8']

iBands = [header.index(b) for b in band_list]
yData = data[0:,iBands].astype(np.float)

# Calculate NDVI
red = yData[:,0]
nir = yData[:,1]
ndvi = (nir - red) / (nir + red)

# reshape NDVI into Pandas
df = pd.DataFrame(data=ndvi, index=list(range(len(ndvi))), columns=[ 'NDVI'])
df = df.interpolate()
df['Date'] = pd.Series(time, index=df.index)
df = df.set_index(df.Date)
df.index = pd.to_datetime(df.index)
df['NDVI']=df[ 'NDVI'].fillna(0)
```

```
sns.set(rc={'figure.figsize':(20, 6)})  
df['NDVI'].plot(linewidth=0.5, color="green")  
plt.title('NDVI', color='green')  
  
Text(0.5, 1.0, 'NDVI')
```



Lots of spikiness - much of it related to cloudy pixels

▼ Plot the filtered data

```
## plot the ndvi
```

```
data = info_filt

# Reshape image collection
header = data[0]
data = array(data[1:])

iTTime = header.index('time')
time = [datetime.datetime.fromtimestamp(i/1000) for i in (data[0:,iTTime].astype(int))]

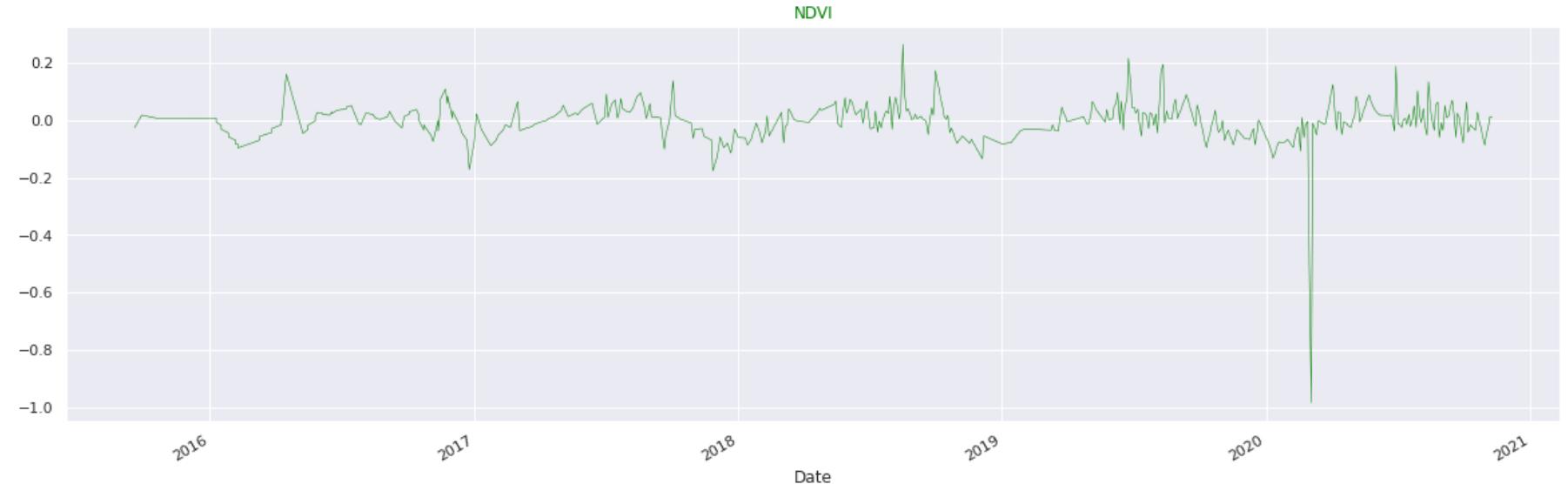
# List of used image bands
#band_list = [ 'RED',u'NIR']
band_list = [ 'B4',u'B8']

iBands = [header.index(b) for b in band_list]
yData = data[0:,iBands].astype(np.float)

# Calculate NDVI
red = yData[:,0]
nir = yData[:,1]
ndvi = (nir - red) / (nir + red)
# reshaoe NDVI into Pandas
df = pd.DataFrame(data=ndvi, index=list(range(len(ndvi))), columns=[ 'NDVI'])
df = df.interpolate()
df['Date'] = pd.Series(time, index=df.index)
df = df.set_index(df.Date)
df.index = pd.to_datetime(df.index)
df['NDVI']=df[ 'NDVI'].fillna(0)

sns.set(rc={'figure.figsize':(20, 6)})
df['NDVI'].plot(linewidth=0.5, color="green")
plt.title('NDVI', color='green')
```

```
Text(0.5, 1.0, 'NDVI')
```



A little better, now examine the actual filtered data

```
df.head(5)
```

	NDVI	Date
	Date	
2015-09-18 19:01:22.000	-0.025744	2015-09-18 19:01:22.000
2015-09-18 19:01:22.458	-0.025744	2015-09-18 19:01:22.458

▼ Interactive mapping

Make an interactive map with the chart data embedded

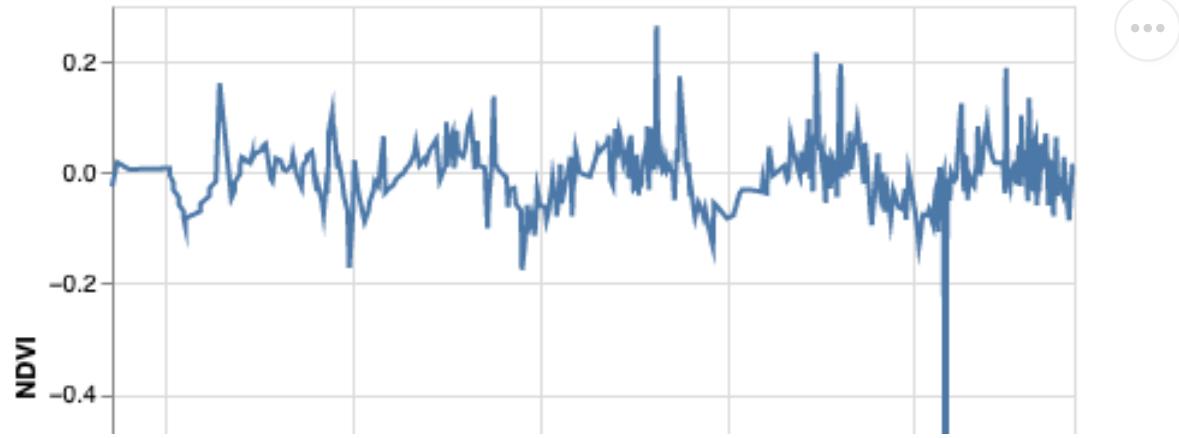
The information we just plotted can be placed onto the interactive map, using the 'Altair' module for plotting.

Altair is designed to quickly make charts that can be displayed online

https://altair-viz.github.io/getting_started/overview.html

Using the "NDVI" and "Date" columns, plot the NDVI over time.

```
chart = alt.Chart(df).mark_line().encode(y='NDVI', x='Date')
chart
```



Fix the size a bit.

Chart Size: https://altair-viz.github.io/user_guide/customization.html#adjusting-chart-size



```
chart = alt.Chart(df).mark_line().encode(y='NDVI', x='Date').properties(width=700, height=200)

chart
```

This is still pretty spiky. Much this is probably due to clouds, haze, smoke, or fog in the atmosphere - or snow on the ground.



▼ Embed the chart onto the folium map

This rendition of the data can be embedded on the map as a pop up for a point.



```
chart = alt.Chart(df).mark_line().encode(y='NDVI', x='Date').properties(width=500, height=150)
vis1 = chart.to_json()

f = folium.Figure(width=800, height=600)
# flip the point coordinate to be lat, long (y, x) for folium
Map = geemap.Map(center=rnapoint[::-1], zoom= 11).add_to(f)
#Map.addLayer(image, rgbParams, 'Before Natural Color')
Map.addLayer(recentqa, rgbParams, 'Recent Natural Color')
#Map.addLayer(recentndvi, ndviParams, 'NDVI recently')
#Map.addLayer(sndvi, ndviParams, 'NDVI before')
Map.addLayer(dif, difParams, 'dif')
Map.addLayerControl()
#folium.Marker(rnapoint[::-1], popup='<i>Research Natural Area</i>').add_to(Map)

# create a marker, with altair graphic as popup
circ_mkr = folium.CircleMarker(
    location=rnapoint[::-1],
    radius=10,
    color='grey',
    fill=True,
    fill_color='red',
    ...
```

```
fillOpacity=1.0,  
opacity=1.0,  
tooltip='NDVI time series',  
popup=folium.Popup().add_child(folium.VegaLite(vis1, width=600, height=200)),  
)  
  
# add to map  
circ_mkr.add_to(Map)  
  
#Map.save('testmap.html')  
f
```



▼ Unsupervised image classification

The image data can also be grouped into clusters based on the spectral similarity of the pixels. One way to do this is with 'Unsupervised Classification' - a common machine learning task.

▀ <https://developers.google.com/earth-engine/guides/clustering>

We will focus the sampling to build the spectral signatures used by the classifier on an area around the Holiday Farm fire of September 2020.



▼ Classify the Data



```
# Define a region in which to generate a sample of the input.  
region = ee.Geometry.Rectangle([-121, 44, -122, 45])  
  
# Make the training dataset.
```

```
#training = recentqa.sample(**{'numPixels':3000})
training = recentqa.sample(**{'region': region, 'scale': 10, 'numPixels':2000})

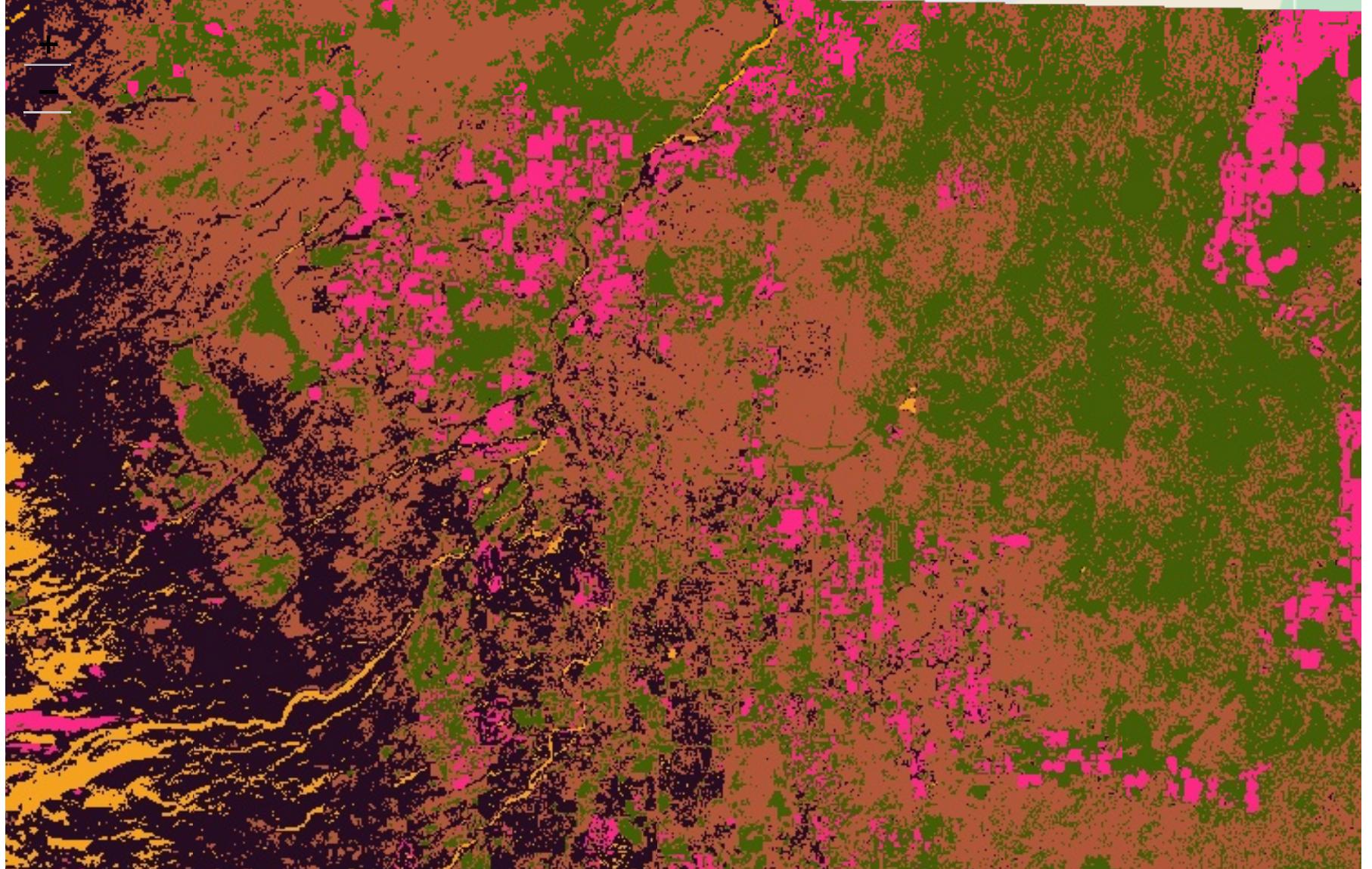
# Instantiate the clusterer and train it to identify 5 classes based on the samples.
clusterer = ee.Clusterer.wekaKMeans(5).train(training);

# Cluster the input using the trained clusterer.
result = recentqa.cluster(clusterer);
```

▼ Look at the resulting clusters

```
f = folium.Figure(width=800, height=600)
# flip the point coordinate to be lat, long (y, x) for folium
Map = geemap.Map(center=rnapoint[::-1], zoom= 11).add_to(f)

#Map.addLayer(image, rgbParams, 'Before Natural Color')
Map.addLayer(recentqa, rgbParams, 'Recent Natural Color')
#Map.addLayer(recentndvi, ndviParams, 'NDVI recently')
Map.addLayer(result.randomVisualizer(),{}, 'Cluster')
#Map.addLayer(region, {}, 'Polygon')
Map.addLayerControl()
f
```



- ▼ Compare the clusters with the difference image



```
f = folium.Figure(width=800, height=600)
# flip the point coordinate to be lat, long (y, x) for folium
Map = geemap.Map(center=rnapoint[::-1], zoom= 11).add_to(f)
```

```
#Map.addLayer(image, rgbParams, 'Before Natural Color')
Map.addLayer(recentqa, rgbParams, 'Recent Natural Color')
#Map.addLayer(recentndvi, ndviParams, 'NDVI recently')
Map.addLayer(result.randomVisualizer(),{}, 'Cluster')
Map.addLayer(dif, difParams, 'dif')
Map.addLayerControl()

#Map.save('testmap.html')
f
```

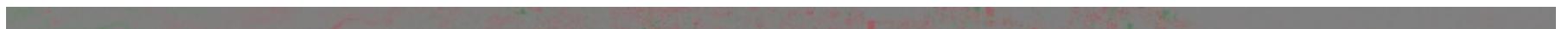


▼ Apply the same cluster groups to the older image

Just for fun, the statistical clusters (training dataset) created from the first image (the 2020 image) can be applied to the older image.



```
# Cluster the older data using the trained clusterer.  
resultOld = image.cluster(clusterer);  
  
f = folium.Figure(width=800, height=600)  
# flip the point coordinate to be lat, long (y, x) for folium  
Map = geemap.Map(center=rnapoint[::-1], zoom= 11).add_to(f)  
Map.addLayer(image, rgbParams, 'Before Natural Color')  
Map.addLayer(recentqa, rgbParams, 'Recent Natural Color')  
#Map.addLayer(recentndvi, ndviParams, 'NDVI recently')  
Map.addLayer(result.randomVisualizer(),{}, 'Cluster')  
Map.addLayer(resultOld.randomVisualizer(),{}, 'ClusterOld')  
  
Map.addLayerControl()
```



f



A difference image between the two classified images can show where the classes have changed.

```
# calculate the difference
difclass = image.expression('recentclass == oldclass', {'recentclass': result, 'oldclass': res
# set colors for difference image: red = expression not true (there is a difference)
difcParams = {'min':0, 'max': 1, 'palette': ['red', 'grey']}
```



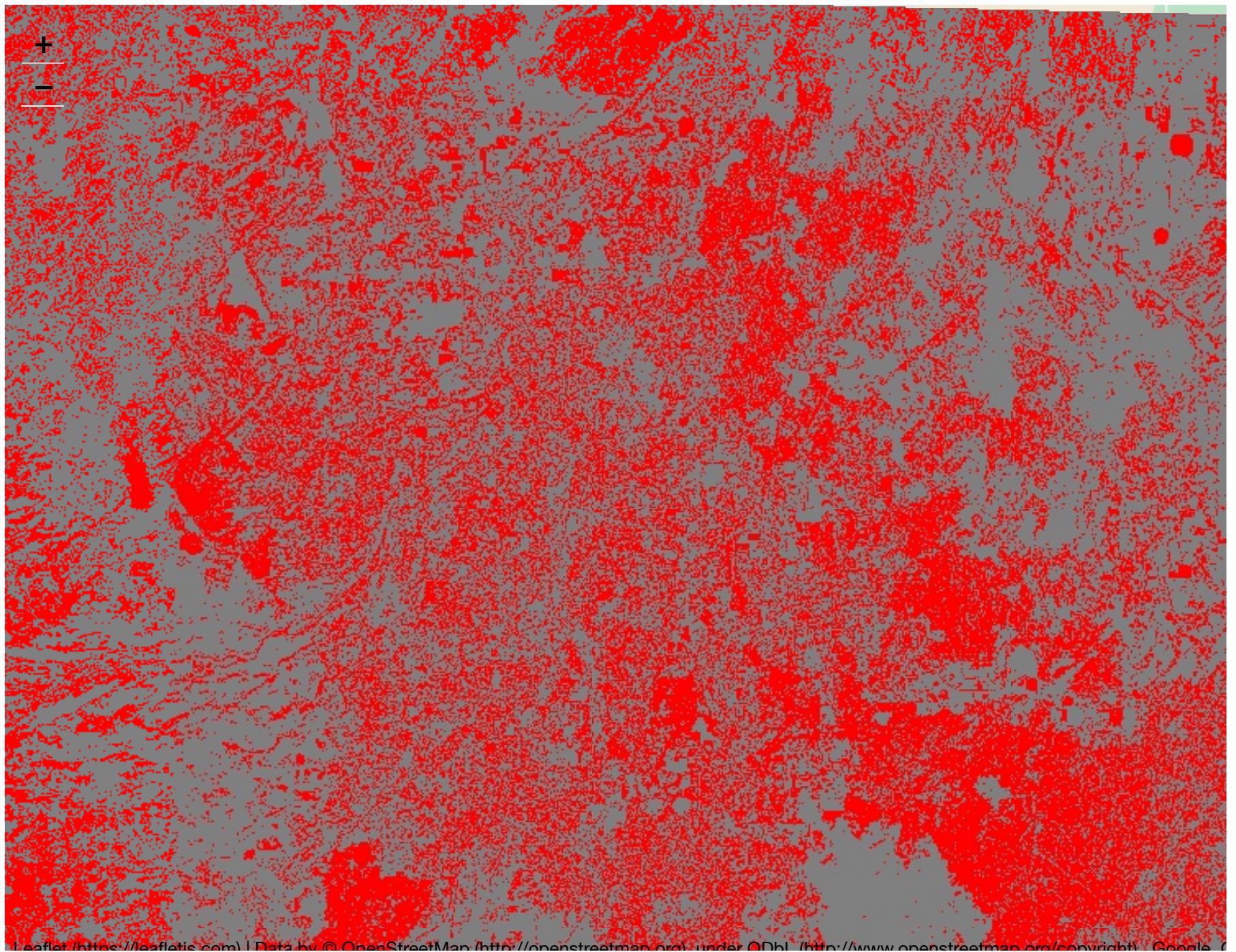
▼ Look at the where the clusters are different

Visualize the result, with red showing areas of difference and grey for unchanged areas.



```
f = folium.Figure(width=800, height=600)
# flip the point coordinate to be lat, long (y, x) for folium
Map = geemap.Map(center=rnapoint[::-1], zoom= 11).add_to(f)
Map.addLayer(image, rgbParams, 'Before Natural Color')
Map.addLayer(recentqa, rgbParams, 'Recent Natural Color')
#Map.addLayer(recentndvi, ndviParams, 'NDVI recently')
Map.addLayer(result.randomVisualizer(),{}, 'Cluster')
Map.addLayer(resultOld.randomVisualizer(),{}, 'ClusterOld')
Map.addLayer(dif, difParams, 'NDVI difference')
Map.addLayer(difclass, difcParams, 'Cluster Difference')
Map.addLayerControl()
```

```
f
```



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The area burned by the Holiday Farm fire seems to be identified, but lots of other areas are marked as different in the image. Basically, it looks like mostly water and shadow is not different classed in the unsupervised signatures.

Assignment: Geog 485

Comment on the classification and the potential issues with this change analysis. Suggest some ways in which the 'classified' change analysis could be improved by modifying the method of classification used, the choice of spectral bands or image dates, or the use of derived bands or other accompanying types of 'ancillary' data.

▼ Assignment Geog 491

Choose 2 of the following three options, and turn in a commented notebook (.ipynb format) and PDF printout of that notebook showing the output for each of the 2 options chosen.

Options:

1. Do the same type of analysis but at another location.
2. Do the same type of analysis, but using the Landsat 8 data collection.
3. Using either Landsat 8 or Sentinel 2 data, add another spectral indice to the time series analysis or change analysis

For each of the 2 options you choose, create a new notebook (you can make a copy of the existing notebook and change the parameters/code). Turn in a copy of each notebook in .ipynb form, and also a PDF printout of each notebook.

Other resources for using Python with Google Earth Engine related to the exercise.

- [ImageCollection Overview](#)
- [Image Overview](#)
- [Google Earth Engine Python API Examples](#)

