Lecture 08
GEE Change Detection:
two-date image differencing

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1. Introduction

2. Case example: detection of a wild fire
    1. Select pre/post-event images
    2. Preprocess images
    3. Compute change map
    4. Analyze change map

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⇒ **Change detection** in remote sensing consists in *capturing differences in images acquired at different times in order to assess how landscape conditions have changed*. Examples:

- changes in land cover → e.g., deforestation, urban sprawl, desertification, polar ice loss, etc.
- changes after natural disasters → e.g., floods, fires, eruptions, etc.

⇒ Questions which can be addressed:

- has a change occurred?
- what area is affected?
- what is the nature/severity of the change?

⇒ Challenges which arise: separate the "changes of interest" from the "other changes"

- changes related to *seasonal conditions*
- changes related to *image acquisition conditions*:
  - scene illumination (e.g., sun angle, sensor position)
  - atmospheric effects (e.g., clouds)
  - sensor health and processing algorithm (e.g., leading to radiometric inconsistencies)

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Naive method: two-date image differencing

⇒ Easiest way to detect changes is to perform *image differencing* between two images (pre- and post-event), by simply subtracting the spectral bands values (or spectral indices values) of the pre-image from that of the post-image, pixel by pixel.

⇒ The exercise here consists in detecting the changes related the wild fires which affected the region of Palermo in July 2023. The workflow will be as followed:

1. Select images
2. Preprocess images
3. Compute change map
4. Analyze change map

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Step 1: Select pre/post-event images

1. Select two images (before/after the event), trying to minimize the impact of:
   - *seasonal conditions*: select images acquired during the same season
     ⇒ use `.filter(ee.Filter.calendarRange(<start>, <end>, 'month')`
   - *atmospheric conditions*: select images with the *least cloud cover* possible
     ⇒ Simple approach: use metadata `CLOUD_COVER` to select the least clouded image

     NB: sorting the collection using the metadata `CLOUD_COVER` can help to select the least clouded image. However, keep in mind that this metadata corresponds to a percentage of the cloud cover computed over the entire image footprint ⇒ this might not reflect the cloud cover in your area of interest.

     ⇒ Advanced approach: compute a *cloud score* on the area of interest using band 'QA60'

     NB: the band name 'QA60' is specific to GEE, but is derived from ESA's cloud masks 'MSK_CLOUDS' subtypes "OPAQUE" & "CIRRUS"

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Step 1: Select pre/post-event images

1. Select two images (before/after the event):
   ⇒ Simple approach: select pre-event image using metadata `CLOUD_COVER`

```
# Select image collection and bands
image_collection = (ee.ImageCollection('COPERNICUS/S2_HARMONIZED')
                        .select(
                            ['B2', 'B3', 'B4', 'B8', 'B11', 'B12'],              # selected bands
                            ['blue', 'green', 'red', 'nir', 'swir1', 'swir2']     # renamed bands (for convenience)
                        ))

# Select pre-event image
point = ee.Geometry.Point([13.33, 38.13])    # select region of interest
ti, tf = '2019-01-01', '2022-01-01'          # select time interval
ti_month, tf_month = 8, 10                   # select month interval (season)

image_pre = (image_collection
                 .filterBounds(point)
                 .filterDate(ti, tf)
                 .filter(ee.Filter.calendarRange(ti_month, tf_month, 'month'))
                 .sort('CLOUD_COVER')     # sort collection by cloud cover
                 .first())                # select least clouded image
image_pre_date = ee.Date(image_pre.get('system:time_start')).format('YYYY-MM-dd').getInfo()
```

2.1. Select pre/post-event images

⇒ advanced approach: select pre-event image using cloud score computed on the area of interest

```
# Function to add cloud bands from QA60 band
def add_cloud_bands(image):
    cloud_bit_mask = 1 << 10    # = 1024   (opaque cloud)
    cirrus_bit_mask = 1 << 11   # = 2048   (cirrus cloud)
    cloud_opaque = image.select('QA60').eq(cloud_bit_mask).rename('cloud_opaque')
    cloud_cirrus = image.select('QA60').eq(cirrus_bit_mask).rename('cloud_cirrus')
    cloud_free = image.select('QA60').eq(0).rename('cloud_free')
    cloud_opaque_and_cirrus = cloud_opaque.Or(cloud_cirrus).rename('cloud_opaque_and_cirrus') # cloud+cirrus
    return image.addBands([cloud_opaque, cloud_cirrus, cloud_free, cloud_opaque_and_cirrus]) # add bands to image

# Function to calculate mean value of 'cloud_opaque_and_cirrus' band in aoi
def get_cloudscore_aoi(image):
    mean_value = image.select('cloud_opaque_and_cirrus').reduceRegion(reducer=ee.Reducer.mean(), geometry=aoi_geometry)
    return image.set('cloud_score_aoi', mean_value.get('cloud_opaque_and_cirrus')) # add 'cloud_score_aoi' as property

aoi_geometry = ee.Geometry.Rectangle(coords=Map.user_roi_coords())  # Geometry from rectangle drawn on map
image_collection = (ee.ImageCollection('COPERNICUS/S2_HARMONIZED')
                    .filterBounds(point)
                    .filterDate(ti, tf)
                    .filter(ee.Filter.calendarRange(ti_month, tf_month, 'month'))
                    .map(add_cloud_bands) # add cloud bands derived from 'QA60'
                    .map(get_cloudscore_aoi) # compute cloud score for each image and return as property 'cloud_score_aoi'
                    .select(['B2', 'B3', 'B4', 'B8', 'B11', 'B12'], ['blue', 'green', 'red', 'nir', 'swir1', 'swir2'])
                    .sort('cloud_score_aoi')
                    )
image_pre = image_collection.first() # = image with lowest cloud score on aoi
```

Step 1: Select pre/post-event images

1. Select two images (before/after the event)
2. Clip region of interest (optional)
   NB: use `clip` with parsimony as it increases computation time (see Coding Best Practices)

```
# Clip region of interest
lon_min, lon_max = 12.9597, 13.6091
lat_min, lat_max = 37.9648, 38.2878
roi = ee.Geometry.Rectangle([lon_min, lat_min, lon_max, lat_max])

image_pre = image_pre.clip(roi)
image_post = image_post.clip(roi)
```

Step 1: Select pre/post-event images

1. Select two images (before/after the event)
2. Clip region of interest (optional)
3. Display result

```
Map = geemap.Map()
Map.centerObject(point, 11)
Map.addLayerControl()

vis_params = {'bands': ['red', 'green', 'blue'], 'min': 0, 'max': 2000}
Map.addLayer(image_pre, vis_params, f'Pre-event ({image_pre_date})')
Map.addLayer(image_post, vis_params, f'Post-event ({image_post_date})')
Map
```

Step 1: Select pre/post-event images

Pre-event image
(2019-08-01)

Post-event image
(2023-08-03)

Step 2: Preprocess images

⇒ *image preprocessing* should be achieved on images before continuing the *change detection* workflow, in order to ensure that each pixel records the same type of measurement at the same location over time.

This typically includes:

- *image co-registration*
  ⇒ ensures that images are in the same projection and have the same pixel size (resampling)
- *radiometric and atmospheric corrections*
  ⇒ ensures that the pixel values are comparable (e.g., convert digital numbers (DN) to reflectance values, calculated either at the *top of the atmosphere* (TOA) or at the *surface*, with or without *atmospheric correction*)
- *illumination correction*
  ⇒ correct *local solar incidence* (depends on sensor inclination + sun elevation/azimuth + terrain slope/aspect) → see Canty (2019) Chapter 5
  *NB: notice the **sunglint** in the post-event image, caused by the specular reflection of sunlight off the water surface directly towards the satellite sensor, which results in bright silvery pixels. (The MSI instrument onboard Sentinel-2 has different detectors which acquire the scene with slightly different viewing angles, thereby resulting in different sunglint patterns. Metadata stores information on sensor/sun viewing angles).*
- *cloud and shadow masking*
  ⇒ remove pixels affected by clouds/shadows

Step 2: Preprocess images

⇒ luckily, the most important preprocessing steps have been applied to the images available in GEE. EX:

- **Sentinel-2** (MSI)
  - Top-of-Atmosphere Reflectance: `'COPERNICUS/S2_HARMONIZED'`
    = Level 1-C processing
    = *top-of-atmosphere reflectance* (TOA), orthorectified, harmonized[1]
  - Surface Reflectance: `'COPERNICUS/S2_SR_HARMONIZED'`
    = Level 2-A processing
    = *surface reflectance*, orthorectified, atmospherically corrected, harmonized[1]
- **Sentinel-1** (SAR)
  - Ground Range Detected SAR (log-scaling): `'COPERNICUS/S1_GRD'`
    = Level 1 GRD processing
    = *backscattered intensity with log scaling* ($I_{dB} = 10 * log_{10}(I)$), single-polarization (VV or VH), sampled in ground range, orthorectified (terrain corrected using DEM), calibrated (thermal noise removal + radiometric calibration)
  - Ground Range Detected SAR (log-scaling): `'COPERNICUS/S1_GRD_FLOAT'`
    = same as `'COPERNICUS/S1_GRD'` but without log scaling

[1] The "*harmonized*" designation means that the band-dependent offset added to reflectance bands (affecting data after 2022/01/24, processing baseline 04.00) has been removed.

Step 3: Compute change map

⇒ the "naive approach" to computing *change maps* is to *substract bands* (or *substract band compositions* such as spectral indices) between the pre-event and post-event images.

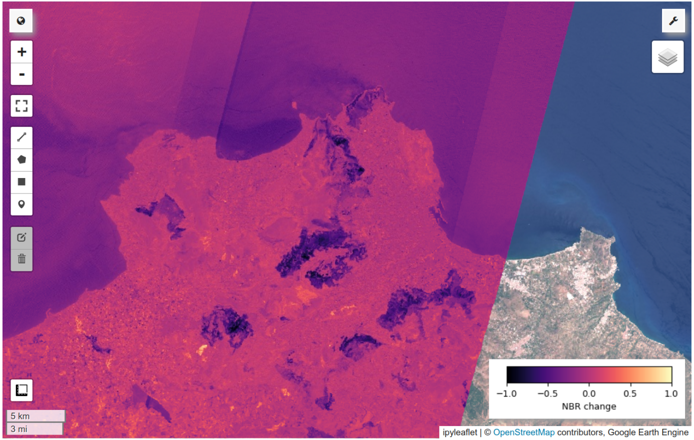
⇒ the choice of the bands (or band compositions) to substract greatly depends on the type of change to detect (i.e. flooding, fire, urban sprawl, etc.)

⇒ in this example we want to detect a *wild fire*, so we will substract the *NBR* (Normalized Burn Ratio) between the pre-event and post-event images, where $NBR = \frac{NIR - SWIR}{NIR + SWIR}$

```
# Calculate Normalized Burn Ratio (NBR) for pre-event and post-event images
nbr_pre = image_pre.normalizedDifference(['nir', 'swir2']).rename('nbr_pre')
nbr_post = image_post.normalizedDifference(['nir', 'swir2']).rename('nbr_post')

# Calculate difference between pre-event and post-event NBR
img_change = nbr_post.subtract(nbr_pre).rename('change')

# Display result
vis_params = {'palette': 'magma', 'min': -1, 'max': 1}
Map.addLayer(img_change, vis_params, 'Change map')
Map.add_colorbar(vis_params, label="NBR change", layer_name='Change map')
```

Step 3: Compute change map

Change map (dNBR)



Step 4: **Analyze change map**

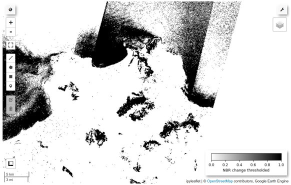
⇒ The goal here is to isolate the regions of the change map that correspond to the burned area

⇒ This can be achieved by:

1. **threshold** the change map
   ⇒ select threshold to binarize image in burned/non-burned areas
2. **mask** the thresholded map
   ⇒ make pixels with value $= 0$ invalid (i.e. not burned)
3. **update** the burned mask
   ⇒ exclude from the mask the pixels corresponding to water bodies (e.g. lakes, rivers, etc.)
4. **analyze** the burned mask!
   4.1 get the *severity map* of the burned regions
   ⇒ mask the change map using the burned mask and scale colormap to min/max values
   4.2 get the *area* of the burned regions
   ⇒ sum the pixel areas of the burned mask
   4.3 get the *contour* of the burned regions
   ⇒ reduce mask to vector

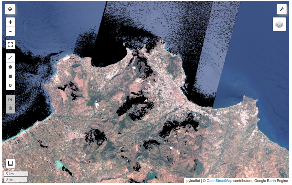
Step 4: Analyze change map

1. Thresholded change map




```
# Threshold change map
lt_threshold, lt_newval = -0.25, 1  # select threshold and new value = 1 (= valid)
img_change_thresh = ee.Image(0)     # create image filled with 0 (= invalid)
img_change_thresh = img_change_thresh.where(img_change.lte(lt_threshold), lt_newval)
Map.addLayer(img_change_thresh, {'palette':['white', 'black']}, 'Change map thresholded')
```

2. Mask of burned area



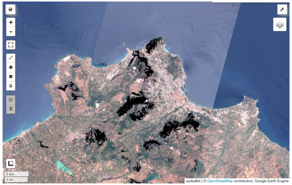

```
# Get mask of burned area
mask_burned = img_change_thresh.selfMask()  # make pixels with value = 0 invalid
Map.addLayer(mask_burned, {'palette':['white', 'black']}, 'Burned mask')
```

2.4. Analyze change map

3.1 Water mask

```python
# Get water bodies (to exclude from burned mask)
water_mask = (ee.Image("JRC/GSW1_1/GlobalSurfaceWater")
              .select('occurrence') # frequency with which water was present (since 1984)
              .gte(50)
             )  # pixel values: 1=water / None=not-water
Map.addLayer(water_mask, {'palette':['white', 'blue']}, 'water')
```

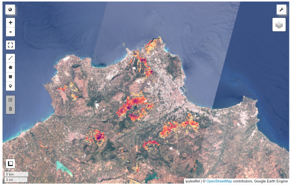
3.2. Updated burned mask



```python
# Exclude water bodies from burned mask
# => need to invert water mask (we need invalid values (= 0) where water is):
#    .unmask => converts None values to 0
#    .eq(0)  => tests if pixel=0 => where water used to be (=1), sets False (=0=invalid)
water_mask_invert = water_mask.unmask(0).eq(0)
mask_burned = mask_burned.updateMask(water_mask_invert) # Update mask
Map.addLayer(mask_burned, {'palette':['white', 'black']}, 'Burned mask (water excluded)')
```

2.4. Analyze change map

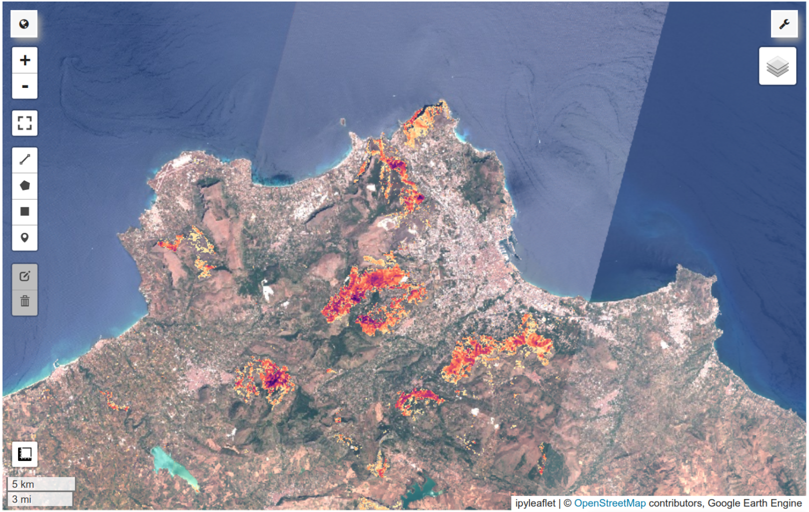
4.1 Burned regions severity



```
# Get burn severity
# => mask `change map` using mask `mask_burned`
burned_severity = img_change.updateMask(mask_burned)

# Get min/max in burned_severity masked image
minMax = burned_severity.reduceRegion(
    reducer=ee.Reducer.minMax(),
    geometry=burned_severity.geometry(),
    maxPixels=1e10,
)
min = minMax.get('change_min').getInfo()    # property name = <band_name>_min
max = minMax.get('change_max').getInfo()    # property name = <band_name>_max
vis_params = {'palette':'magma', 'min':min, 'max':max}
Map.addLayer(burned_severity, vis_params, 'Burned regions severity')
```

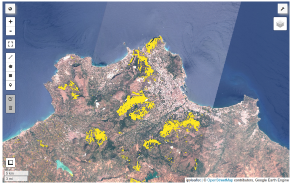
2.4. Analyze change map

Burned regions severity



2.4. Analyze change map

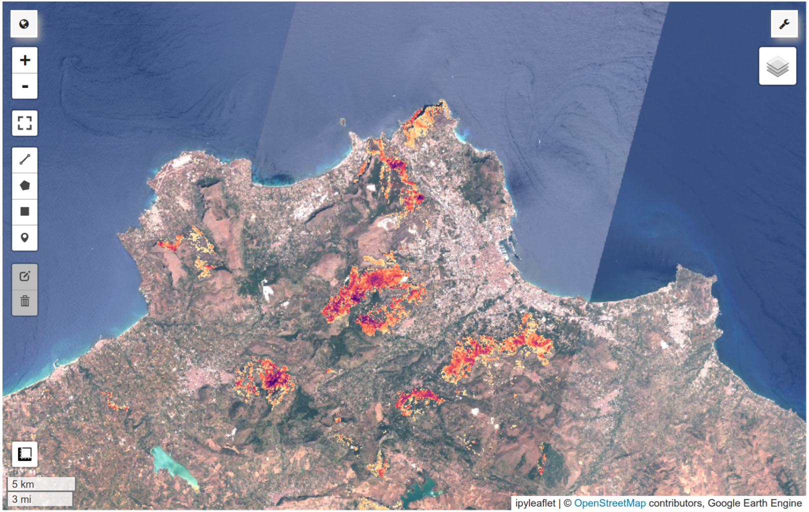
4.2. Compute burned area



```
# Create a pixel area image in which pixel value = pixel area in m2
# NB: the returned image has a single band called "area"
# NB: you'll notice that the pixel area value changes with the zoom level
#      => need to specify pixel scale when performing computation with ee.reduceRegion
#      => specify parameter "scale" (or "crs"/"crsTransform")
img_pixArea = ee.Image.pixelArea()
mask_area = img_pixArea.updateMask(mask_burned)

# Sum the area of burned pixels
area = mask_area.reduceRegion(
    reducer=ee.Reducer.sum(),
    geometry=roi,    # clipped region where to compute area,
    scale=10,        # nominal scale in meters of the projection to work in
    maxPixels=1e10
)

# Fetch summed aimg_pixArearea property
square_meters = area.getNumber('area').round()
hectares = square_meters.divide(10000).round()   # 1 hectare = 100x100m = 10,000 m2
print('Burned area = {} Ha'.format(hectares.getInfo()))

# Add layer with pixel area
Map.addLayer(mask_area, {'palette':'viridis', 'min':0, 'max':3000}, 'pixel area (masked)')
```

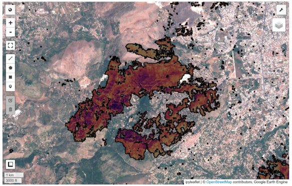
2.4. Analyze change map

Burned regions severity



2.4. Analyze change map

4.3. Contour burned area




```
fc_burn = mask_burned.reduceToVectors(
    geometry=roi,
    scale=30
).filterMetadata("label", "equals", 1)
Map.addLayer(fc_burn, {}, 'Burned contour in aoi')
```