Introduction to Google Earth Engine

CoPhil EO AI/ML Training - Day 1, Session 4

Stylianos Kotsopoulos
EU-Philippines CoPhil Programme

Welcome to Session 4

Final Session of Day 1!

Google Earth Engine

Planetary-scale geospatial analysis in the cloud

Duration: 2 hours (Hands-on with Python API)

Learning Objectives

By the end of this session, you will be able to:

1. Understand what GEE is and why it's powerful
2. Authenticate and initialize GEE Python API
3. Access Sentinel-1 and Sentinel-2 imagery
4. Filter image collections (spatial, temporal, property)
5. Apply cloud masking to Sentinel-2
6. Create temporal composites (median, mean)
7. Calculate spectral indices (NDVI, NDWI)
8. Visualize results with geemap
9. Export data for further analysis

Session Roadmap

Time	Topic	Duration
00-15 min	GEE Overview & Authentication	15 min
15-55 min	Core Concepts & Sentinel Access **(HANDS-ON)**	40 min
55-60 min	☕ **Break**	**5 min**
60-110 min	Processing & Visualization **(HANDS-ON)**	50 min
110-120 min	Export & Summary	10 min

Part 1: Google Earth Engine Overview

What is Google Earth Engine?

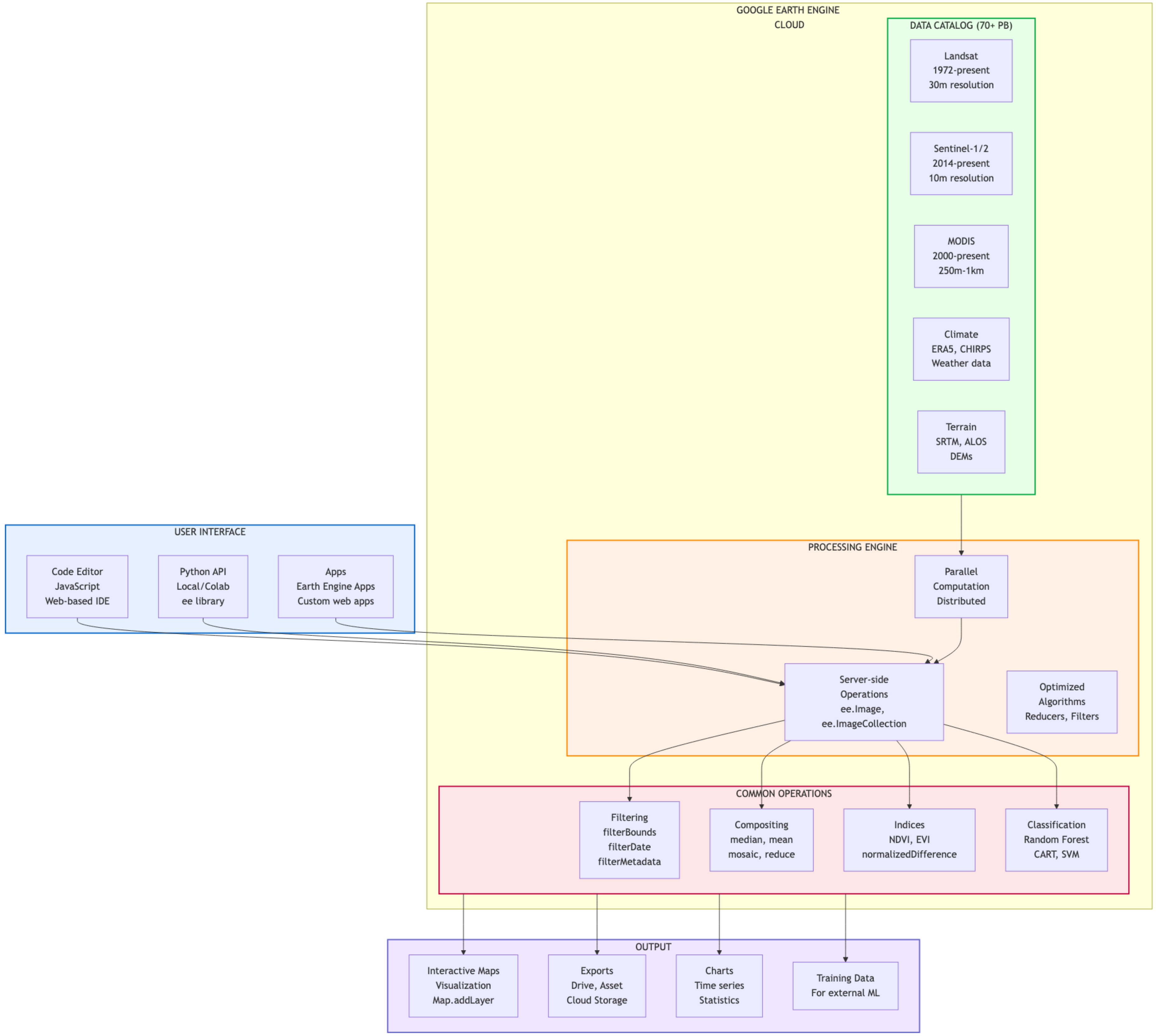
Cloud-Based Platform for Geospatial Analysis

Google Earth Engine

- **Massive data catalog** (petabytes)
- **Powerful compute** (Google’s infrastructure)
- **Free for research & education**
- **No download needed**
- **Process at scale**

“Planetary-scale geospatial analysis”

GEE Architecture and Workflow



Google Earth Engine complete architecture showing User Interface, Cloud Processing, Data Catalog, and Outputs

Why GEE for This Training?

Addresses Key Challenges:

- ❌ **Traditional:** Download 100s of GB of Sentinel data
- ✅ **GEE:** Access entire archive without downloading
- ❌ **Traditional:** Need powerful computer for processing
- ✅ **GEE:** Google's infrastructure does the work
- ❌ **Traditional:** Complex cloud masking & preprocessing
- ✅ **GEE:** Built-in algorithms & analysis-ready data
- ❌ **Traditional:** Time-series analysis is painful
- ✅ **GEE:** Designed for temporal analysis

Perfect for Philippine-scale analysis!

GEE Data Catalog

Datasets Available:

Satellite Imagery:

- Sentinel-1, 2, 3, 5P
- Landsat (entire archive!)
- MODIS
- Planet, SkySat (some)
- Many more…

Geophysical:

- Climate data
- Elevation (SRTM, ASTER)
- Weather data
- Population datasets
- Land cover products

Browse: https://developers.google.com/earth-engine/datasets

Python API vs JavaScript Code Editor

JavaScript Code Editor

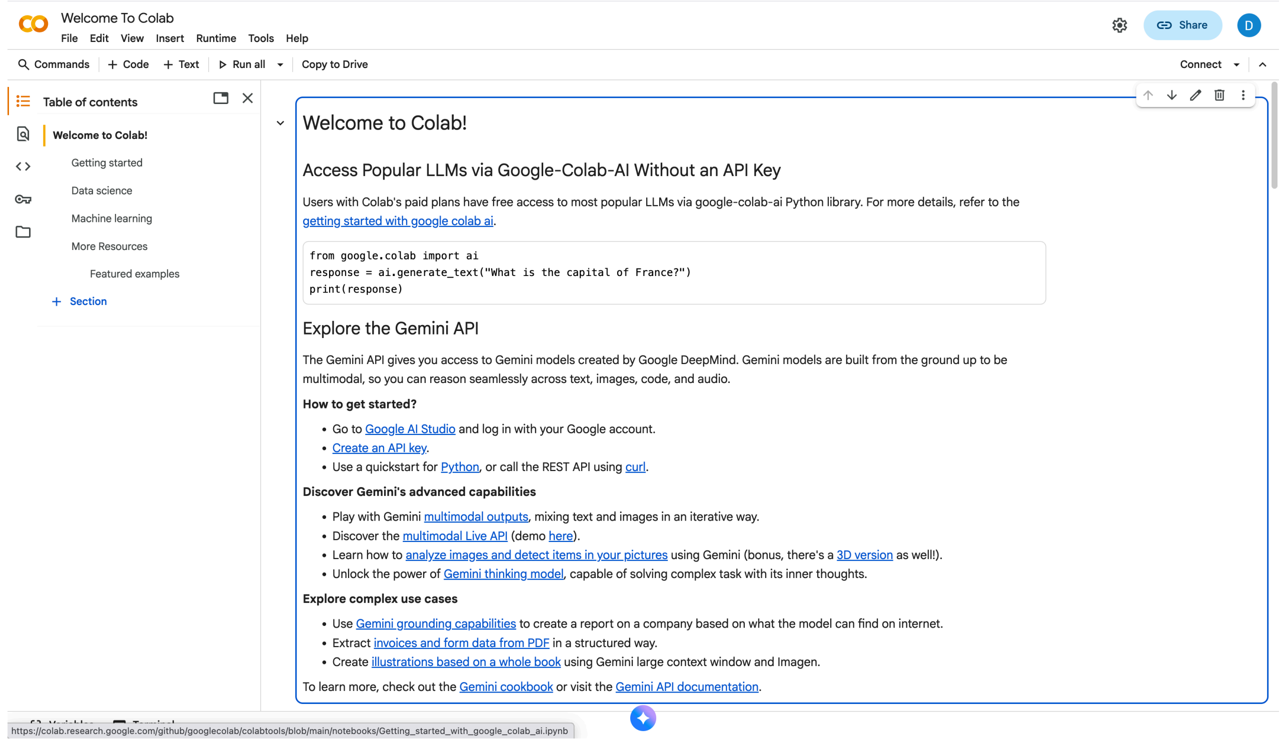
- Web-based IDE
- Interactive visualization
- Quick prototyping
- Built-in examples

Python API (Our Focus)

- Jupyter notebooks
- Integration with ML libraries
- Familiar Python ecosystem
- **geemap** package for visualization

Today: Python-only approach using **geemap**

geemap Package



Python package for interactive GEE mapping

- Built on ipyleaflet
- Interactive map visualization
- Layer controls
- Inspector tool
- Split-panel comparison
- Export functionality
- **Makes Python GEE as easy as Code Editor**

GEE Authentication

Sign Up for GEE

Before We Code

You need a Google Earth Engine account!

Sign up: https://earthengine.google.com/signup

Steps:

1. Visit signup page
2. Use Gmail account
3. Select "Research/Education"
4. Wait for approval (usually instant)

Already have account? Great! Let's authenticate.

Authentication Process

83d Open Notebook: `Day1_Session4_Google_Earth_Engine.ipynb`

Authentication Code:

```python
import ee
import geemap

# Authenticate (first time only)
ee.Authenticate()

# Initialize
ee.Initialize()

print("GEE Initialized Successfully!")
```

Part 2: Core GEE Concepts

Key GEE Objects

ee.Image

- Single raster image
- Multiple bands
- Properties (metadata)

ee.ImageCollection

- Stack of images
- Time series
- Filter and reduce

ee.Geometry

- Points, lines, polygons
- Define areas of interest

ee.Feature / FeatureCollection

- Vector data with attributes
- Shapefiles, GeoJSON

Everything is server-side! Code describes operations, execution happens on Google’s servers.

Server-Side vs Client-Side

Server-Side (ee.*):

```python
# Runs on Google servers
image = ee.Image('COPERNICUS/S2/...')
ndvi = image.normalizedDifference(['B8', 'B4'])
mean_ndvi = ndvi.reduceRegion(
    reducer=ee.Reducer.mean(),
    geometry=aoi,
    scale=10
)
```

Fast, scalable

Client-Side (Python):

```python
# Runs on your computer
result = mean_ndvi.getInfo()
print(result)  # Downloads result

# Visualization
Map = geemap.Map()
Map.addLayer(ndvi)
Map  # Display
```

For viewing results

Filtering

Three main filter types:

1. Spatial (filterBounds):

```
aoi = ee.Geometry.Rectangle([120.5, 14.5, 121.0, 15.0])  # Metro Manila
images = collection.filterBounds(aoi)
```

2. Temporal (filterDate):

```
images = collection.filterDate('2024-01-01', '2024-12-31')
```

3. Property (filter):

```
# Cloud cover < 20%
images = collection.filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
```

Chain filters together!

Reducers

Aggregate data across space or time:

Temporal Reduction:

```python
# Median composite
median = collection.median()

# Mean
mean = collection.mean()

# Max NDVI
max_ndvi = collection.max()
```

Most common: Median composite to remove clouds

Spatial Reduction:

```python
# Mean value in region
mean_val = image.reduceRegion(
    reducer=ee.Reducer.mean(),
    geometry=aoi,
    scale=10
)
```

Sentinel Data in GEE

Accessing Sentinel-2

83dLive Coding Exercise 1

```
# Define area of interest (Palawan)
aoi = ee.Geometry.Rectangle([118.0, 8.0, 120.5, 11.5])

# Load Sentinel-2 collection
s2 = ee.ImageCollection('COPERNICUS/S2_SR_HARMONIZED') \\
    .filterBounds(aoi) \\
    .filterDate('2024-01-01', '2024-12-31') \\
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))

# Print collection info
print('Number of images:', s2.size().getInfo())

# Get first image
first_image = s2.first()
print('Bands:', first_image.bandNames().getInfo())
```

Visualizing Sentinel-2

83dLive Coding Exercise 2

```
# Create map
Map = geemap.Map(center=[9.5, 118.5], zoom=8)

# Visualization parameters - True Color
vis_params_rgb = {
    'bands': ['B4', 'B3', 'B2'],
    'min': 0,
    'max': 3000,
    'gamma': 1.4
}

# Add layer
Map.addLayer(first_image, vis_params_rgb, 'Sentinel-2 True Color')
Map
```

False Color Composite

83dLive Coding Exercise 3

```python
# False color (vegetation = red)
vis_params_false = {
    'bands': ['B8', 'B4', 'B3'],  # NIR, Red, Green
    'min': 0,
    'max': 3000
}

Map.addLayer(first_image, vis_params_false, 'False Color')
```

Vegetation appears bright red!

Accessing Sentinel-1

83dLive Coding Exercise 4

```
# Load Sentinel-1 collection
s1 = ee.ImageCollection('COPERNICUS/S1_GRD') \\
    .filterBounds(aoi) \\
    .filterDate('2024-01-01', '2024-12-31') \\
    .filter(ee.Filter.eq('instrumentMode', 'IW')) \\
    .filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VV')) \\
    .filter(ee.Filter.eq('orbitProperties_pass', 'DESCENDING'))

# Get median composite
s1_median = s1.select('VV').median()

# Visualize
vis_params_s1 = {'min': -25, 'max': 0}
Map.addLayer(s1_median, vis_params_s1, 'Sentinel-1 VV')
```

☕ 5-Minute Break

Stretch Break

Stand up • Grab water • Back in 5 minutes

Part 3: Processing & Analysis

Cloud Masking

83dLive Coding Exercise 5

```
def maskS2clouds(image):
    """Mask clouds using QA60 band"""
    qa = image.select('QA60')

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

    # Both flags should be zero (clear)
    mask = qa.bitwiseAnd(cloudBitMask).eq(0) \\
        .And(qa.bitwiseAnd(cirrusBitMask).eq(0))

    return image.updateMask(mask)

# Apply to collection
s2_masked = s2.map(maskS2clouds)

# Create cloud-free composite
```

Understanding Bitwise Operations

How QA60 Band Stores Cloud Information:

```
QA60 value = 1024 (binary: 10000000000)
                             ↑
                         Bit 10 set → Cloud present

Bit mask operation:
cloud_bit_mask = 1 << 10  # Shift 1 left by 10 = 1024
qa.bitwiseAnd(cloud_bit_mask)  # Extract bit 10
```

Why Bitwise?

- Efficient storage (multiple flags in one band)
- Bit 10 = Opaque clouds
- Bit 11 = Cirrus clouds
- Can check multiple conditions

QA60 Bit Flags:

Bit	Flag
10	Opaque clouds
11	Cirrus clouds

Example Values:

- 0 = Clear (00000000000)
- 1024 = Clouds (10000000000)
- 2048 = Cirrus (100000000000)
- 3072 = Both (110000000000)

Advanced Cloud Masking: SCL Band

Scene Classification Layer (SCL) - More Detailed Classification:

```python
def mask_s2_clouds_scl(image):
    """Advanced cloud masking using SCL band"""
    scl = image.select('SCL')

    # SCL Classification Values:
    # 3 = Cloud shadows
    # 4 = Vegetation
    # 5 = Bare soil
    # 6 = Water
    # 8 = Cloud medium probability
    # 9 = Cloud high probability
    # 10 = Thin cirrus
    # 11 = Snow/ice

    # Keep only clear land/water pixels
    mask = scl.eq(4).Or(scl.eq(5)).Or(scl.eq(6))

    return image.updateMask(mask).divide(10000)
```

SCL vs QA60: SCL provides more granular classification but requires loading additional band

Calculating NDVI

83dLive Coding Exercise 6

```python
# Calculate NDVI
ndvi = composite.normalizedDifference(['B8', 'B4']).rename('NDVI')

# Visualization parameters
ndvi_vis = {
    'min': -0.2,
    'max': 0.8,
    'palette': ['brown', 'yellow', 'green', 'darkgreen']
}

Map.addLayer(ndvi, ndvi_vis, 'NDVI')
```

Dark green = healthy vegetation

Other Indices

83dLive Coding Exercise 7

```
# NDWI (water)
ndwi = composite.normalizedDifference(['B3', 'B8']).rename('NDWI')

# NDBI (built-up)
ndbi = composite.normalizedDifference(['B11', 'B8']).rename('NDBI')

# Add to map
Map.addLayer(ndwi, {'min': -0.5, 'max': 0.5, 'palette': ['white', 'blue']}, 'NDWI')
Map.addLayer(ndbi, {'min': -0.5, 'max': 0.5, 'palette': ['green', 'gray']}, 'NDBI')
```

Temporal Compositing

Compare different time periods:

```
# Dry season (Jan-Mar)
dry = s2_masked.filterDate('2024-01-01', '2024-03-31').median()

# Wet season (Jul-Sep)
wet = s2_masked.filterDate('2024-07-01', '2024-09-30').median()

# Calculate NDVI for both
ndvi_dry = dry.normalizedDifference(['B8', 'B4'])
ndvi_wet = wet.normalizedDifference(['B8', 'B4'])

# Difference
ndvi_change = ndvi_wet.subtract(ndvi_dry)

Map.addLayer(ndvi_change, {'min': -0.5, 'max': 0.5,
                            'palette': ['red', 'white', 'green']},
             'NDVI Change')
```

Green = vegetation increase, Red = vegetation decrease

Composite Methods Comparison

Different ways to create composites:

1. Median Composite

```
composite = collection.median()
```

- Most common
- Reduces outliers
- Good for cloud removal

2. Mean Composite

```
composite = collection.mean()
```

- Average of all values
- Smooth results
- Can blur features

3. Greenest Pixel

```
def add_ndvi(img):
    ndvi = img.normalizedDifference(['B8','
    return img.addBands(ndvi.rename('NDVI')

composite = collection.map(add_ndvi).qualit
```

- Maximum NDVI pixel
- Best vegetation condition
- Ideal for crop mapping

Greenest Pixel Composite Example

Philippine Rice Monitoring Application:

```python
# Define Central Luzon rice area
rice_aoi = ee.Geometry.Rectangle([120.5, 15.0, 121.5, 16.0])

# Load Sentinel-2 for growing season
s2_rice = (ee.ImageCollection('COPERNICUS/S2_SR')
    .filterBounds(rice_aoi)
    .filterDate('2024-06-01', '2024-10-31')  # Main rice season
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 30))
    .map(maskS2clouds))

# Add NDVI band to each image
def add_ndvi_band(image):
    ndvi = image.normalizedDifference(['B8', 'B4']).rename('NDVI')
    return image.addBands(ndvi)

s2_with_ndvi = s2_rice.map(add_ndvi_band)

# Create greenest pixel composite
```

Result: Captures peak rice biomass across entire growing season

Time Series Analysis

Extract time series at a point:

```python
# Define point (Manila)
point = ee.Geometry.Point([121.0, 14.6])

# Function to add date and NDVI
def addNDVI(image):
    ndvi = image.normalizedDifference(['B8', 'B4']).rename('NDVI')
    return image.addBands(ndvi).set('date', image.date().format('YYYY-MM-dd'))

# Add NDVI to collection
s2_ndvi = s2_masked.map(addNDVI)

# Extract time series
ts = s2_ndvi.select('NDVI').getRegion(point, 10).getInfo()

# Convert to pandas DataFrame
import pandas as pd
df = pd.DataFrame(ts[1:], columns=ts[0])
print(df.head())
```

Philippine Example: Rice Monitoring

83dLive Coding Exercise 8 - Complete Workflow

```
# Rice growing area (Central Luzon)
rice_aoi = ee.Geometry.Rectangle([120.5, 15.0, 121.0, 15.5])

# One year of data
rice_s2 = ee.ImageCollection('COPERNICUS/S2_SR_HARMONIZED') \\
    .filterBounds(rice_aoi) \\
    .filterDate('2024-01-01', '2024-12-31') \\
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 30)) \\
    .map(maskS2clouds)

# Monthly composites
def monthlyComposite(month):
    start = ee.Date.fromYMD(2024, month, 1)
    end = start.advance(1, 'month')
    return rice_s2.filterDate(start, end).median() \\
        .set('month', month)

# Create 12 monthly NDVI composites
```

Part 4: Export & Integration

Exporting Data

Export to Google Drive:

```
# Export image
task = ee.batch.Export.image.toDrive(
    image=composite,
    description='Palawan_S2_Composite',
    folder='GEE_Exports',
    region=aoi,
    scale=10,
    crs='EPSG:4326',
    maxPixels=1e9
)

# Start task
task.start()

# Check status
print('Task Status:', task.status())
```

Find exported file in Google Drive!

Export Options

Export Types:

- `toDrive()` - Google Drive
- `toAsset()` - GEE Asset (reuse in GEE)
- `toCloudStorage()` - Google Cloud Storage

Data Types:

- Image (raster)
- Table (vector)
- Video (time series animation)

Best Practices:

- Set appropriate `scale` (resolution)
- Define `region` (don't export globally!)
- Use `maxPixels` wisely
- Check `crs` matches your needs
- Monitor tasks in Code Editor

Integration with ML Workflows

GEE → Python ML Pipeline:

```
# 1. Process in GEE (fast, scalable)
composite = s2_masked.median()
ndvi = composite.normalizedDifference(['B8', 'B4'])

# 2. Sample training data
training = ndvi.sampleRegions(
    collection=training_polygons,
    scale=10
)

# 3. Export to Drive
ee.batch.Export.table.toDrive(
    collection=training,
    description='training_data',
    fileFormat='CSV'
).start()

# 4. Download and use in scikit-learn/TensorFlow (Day 2!)
```

geemap Advanced Features

Split-panel comparison:

```
left_layer = geemap.ee_tile_layer(dry, vis_params, 'Dry Season')
right_layer = geemap.ee_tile_layer(wet, vis_params, 'Wet Season')

Map = geemap.Map()
Map.split_map(left_layer, right_layer)
Map
```

Time slider:

```
Map.add_time_slider(monthly_ndvi, vis_params, date_format='YYYY-MM')
```

Interactive charting, legends, colorbars, and more!

Philippine Case Studies

Case Study 1: Typhoon Impact Assessment

Scenario: Assess vegetation damage from Typhoon Odette (Rai) - December 2021

```
# Define affected region (Bohol & Cebu)
visayas_aoi = ee.Geometry.Rectangle([123.5, 9.5, 125.0, 11.0])

# Pre-typhoon (November 2021)
pre_typhoon = (ee.ImageCollection('COPERNICUS/S2_SR')
    .filterBounds(visayas_aoi)
    .filterDate('2021-11-01', '2021-11-30')
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 30))
    .map(maskS2clouds)
    .median())

# Post-typhoon (January 2022)
post_typhoon = (ee.ImageCollection('COPERNICUS/S2_SR')
    .filterBounds(visayas_aoi)
    .filterDate('2022-01-15', '2022-02-15')
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 30))
    .map(maskS2clouds)
    .median())
```

Analysis:

- Red areas = severe damage
- Yellow = moderate damage
- Coastal coconut plantations heavily affected
- Rapid assessment for disaster response

Output: Damage map for NDRRMC

Case Study 2: Manila Bay Water Quality

Scenario: Monitor turbidity and suspended sediment in Manila Bay

```
# Define Manila Bay AOI
manila_bay = ee.Geometry.Polygon([
    [[120.7, 14.4], [120.95, 14.4], [121.0, 14.65],
     [120.75, 14.75], [120.7, 14.4]]
])

# Load Sentinel-2 (dry season 2024)
s2_manila = (ee.ImageCollection('COPERNICUS/S2_SR')
    .filterBounds(manila_bay)
    .filterDate('2024-02-01', '2024-04-30')
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
    .map(maskS2clouds)
    .median())

# Calculate Turbidity Index (Red/Green ratio)
turbidity = s2_manila.select('B4').divide(s2_manila.select('B3'))

Map.addLayer(turbidity,
```

Application: Monitor rehabilitation progress, identify pollution sources

Case Study 3: Rice Paddy Phenology (Sentinel-1)

Scenario: Track rice growth stages using SAR in Central Luzon

```
# Define rice area (Nueva Ecija)
rice_region = ee.Geometry.Rectangle([120.8, 15.3, 121.3, 15.8])

# Load Sentinel-1 time series (wet season 2024)
s1_rice = (ee.ImageCollection('COPERNICUS/S1_GRD')
    .filterBounds(rice_region)
    .filterDate('2024-06-01', '2024-11-30')
    .filter(ee.Filter.eq('instrumentMode', 'IW'))
    .select('VH'))  # VH sensitive to rice canopy

# Create time series chart
chart = geemap.image_series_by_region(
    s1_rice, rice_region, reducer='mean',
    scale=100, x_property='system:time_start'
)
chart
```

Phenology Pattern:

- **Low VH** = flooding/transplanting
- **Rising VH** = vegetative growth
- **Peak VH** = heading/flowering
- **Declining VH** = maturity/harvest

Case Study 4: Mangrove Monitoring in Palawan

Scenario: Map and monitor mangrove forest extent in Puerto Princesa

```
# Define Palawan coastal area
palawan_coast = ee.Geometry.Rectangle([118.7, 9.5, 119.0, 10.0])

# Load recent Sentinel-2
s2_mangrove = (ee.ImageCollection('COPERNICUS/S2_SR')
    .filterBounds(palawan_coast)
    .filterDate('2024-01-01', '2024-12-31')
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
    .map(maskS2clouds)
    .median())

# Mangrove index: NDVI + NDWI combination
ndvi = s2_mangrove.normalizedDifference(['B8', 'B4'])
ndwi = s2_mangrove.normalizedDifference(['B3', 'B8'])

# Simple mangrove classifier
mangrove_mask = ndvi.gt(0.3).And(ndwi.gt(-0.1))

```

Philippine Applications Summary

What GEE Enables for Philippines:

Disaster Response: - Flood mapping during typhoons - Damage assessment - Recovery monitoring

Agricultural Monitoring: - Rice area mapping (PRiSM program) - Crop health assessment - Yield prediction

Environmental Management: - Forest cover change - Mangrove monitoring - Water quality assessment

Urban Planning: - Land cover mapping - Urban expansion tracking - Infrastructure development

All at national scale, updated regularly, cloud-free!

Session Summary

What You've Learned:

✅ GEE platform & Python API authentication ✅ Core concepts: Image, ImageCollection, filtering, reducing ✅ Accessing Sentinel-1 and Sentinel-2 data ✅ Cloud masking (QA60 bitwise operations & SCL band) ✅ Calculating spectral indices (NDVI, NDWI, NDBI) ✅ Temporal compositing (median, mean, greenest pixel) ✅ Time series analysis and multi-temporal comparison ✅ Visualization with geemap ✅ Exporting data for ML workflows ✅ Philippine case studies (typhoon, water quality, rice, mangroves)

Q&A

Common Questions:

- GEE free tier limits?
- JavaScript vs Python trade-offs?
- How to handle large exports?
- Best practices for efficiency?
- Working with Landsat data?
- Custom algorithms in GEE?
- Integration with QGIS?
- Where to learn more?

Resources

Official Documentation:

https://developers.google.com/earth-engine

Python API:

https://geemap.org

Tutorials:

https://developers.google.com/earth-engine/tutorials

Community:

https://groups.google.com/forum/#!forum/google-earth-engine-developers

Awesome GEE:

https://github.com/giswqs/Awesome-GEE

Day 1 Complete!

Amazing Progress Today!

You've mastered:

1. ✅ Copernicus & Philippine EO ecosystem
2. ✅ AI/ML fundamentals for EO
3. ✅ Python geospatial libraries (GeoPandas, Rasterio)
4. ✅ Google Earth Engine Python API

Tomorrow: Apply these skills to real ML problems!

Day 2 Preview

Machine Learning for Earth Observation

Morning: - Random Forest classification - Training data preparation - Model evaluation - **Palawan land cover mapping**

Afternoon: - Deep learning introduction - CNN for imagery - Transfer learning - **Building damage assessment**

See you tomorrow! 🚀

Thank You!

Excellent Work Today!

Rest well.

Tomorrow we build AI models!