Cairo University
Faculty of Engineering
Computer Engineering Dept

CMPELEC7 — RSSI

Lab Requirement 0

8 Feb 2026 • Introduction to Spatial Data

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Here we go again!

INTRODUCTION

This course is designed to transition the student from a passive observer of maps to an active engineer of spatial data.

While the context is ”Remote Sensing,” the core methodology is **Applied Problem Solving**. Students will encounter complex, unstructured datasets (satellite imagery) and must employ algorithmic thinking to extract meaningful patterns. The skills developed here—manipulating multi-dimensional arrays, understanding signal processing in the frequency/spectral domain, and automating feature extraction—are universal. They form the backbone of modern Computer Vision, Machine Learning pipelines, and Big Data analytics.

The goal is not merely to learn ”where things are,” but to mathematically prove ”what things are.”

DATA STRUCTURES

To manipulate satellite imagery programmatically, the underlying data structure must be understood.

Raster vs. Vector

Spatial data is generally categorized into two types:

- **Vector Data:** Represents discrete objects (Points, Lines, Polygons) using mathematical coordinates. This is similar to SVG graphics or Object-Oriented definitions.
- **Raster Data:** Represents continuous fields (Temperature, Elevation, Reflectance) using a fixed grid of pixels. This is the primary format for satellite imagery.

File Formats

Standard image formats like JPEG or PNG are insufficient for scientific analysis because they are ”lossy” (compressed) and lack spatial context. In this course, the **GeoTIFF** format is maybe encountered in this course project.

- **TIFF (Tagged Image File Format):** A container that supports high-bit-depth data (e.g., 16-bit integers or 32-bit floats) and lossless compression, ensuring the raw sensor values are preserved.
- **Geo-Tags:** A GeoTIFF embeds metadata tags that map the pixel grid to specific Earth coordinates (Latitude/Longitude). This allows the software to know that Pixel $(0, 0)$ corresponds to a specific physical location.

CASE STUDY

To illustrate the power of multispectral analysis, consider the problem of identifying the mineral **Kaolinite**.

The Power of Pixel Manipulation

Before analyzing complex satellite data, the concept of channel manipulation can be understood through standard RGB photography.
Consider the detection of a river. Even in a simple image, different features manifest differently across color channels. By isolating specific channels—for example, the Blue channel—water bodies may appear distinctively darker or have a different contrast profile compared to the surrounding terrain. This logic of "isolating a channel to find a feature" is the fundamental basis of Remote Sensing.

Figure 1: Pixel manipulation in standard imagery: isolating channels to detect features like rivers.

The Physics of Light

To perform this detection scientifically, we must understand the "ingredients" of the image. The colors we see are simply reflections of light. By understanding how different wavelengths combine, we can reverse-engineer the process to highlight specific materials.

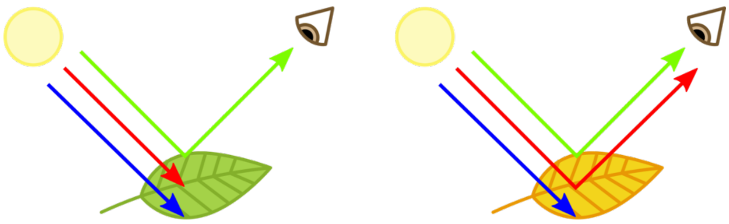

Figure 2: The combination of light: understanding how reflected wavelengths create the colors we see.

The Kaolinite Spectral Signature

In our specific case, Kaolinite appears identical to common white soil in the visible spectrum. However, to a sensor, it has a unique fingerprint.

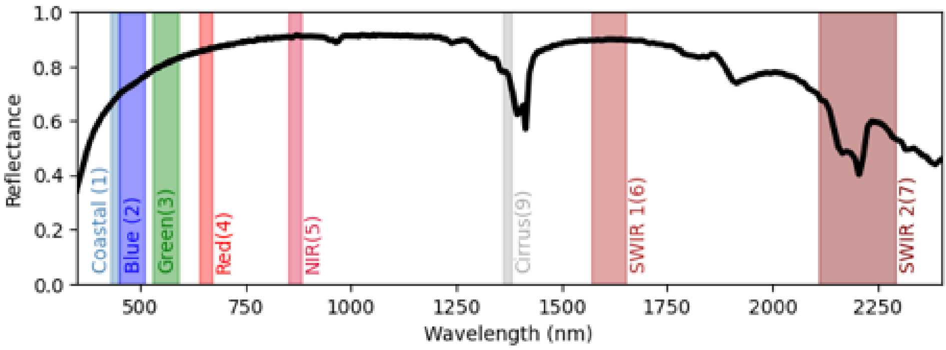

Figure 3: The Spectral Signature of Kaolinite. Note the distinct absorption and reflection peaks.

As shown in the plot above:

- Kaolinite **Reflects** strongly in the SWIR 1 band (Band 6).
- Kaolinite **Absorbs** strongly in the SWIR 2 band (Band 7).
- Kaolinite **Reflects** visible Red light (Band 4).

The Result: False Color Composite

We exploit this signature by mapping the invisible bands to the visible display channels:

- **Red Channel** $\leftarrow$ SWIR 2 (Band 7).
- **Green Channel** $\leftarrow$ SWIR 1 (Band 6).
- **Blue Channel** $\leftarrow$ Red Light (Band 4).

When **Low Red** + **High Green** + **High Blue** are mixed, the resulting color is **Cyan**. Thus, any pixel that appears Cyan is effectively "flagged" as Kaolinite.

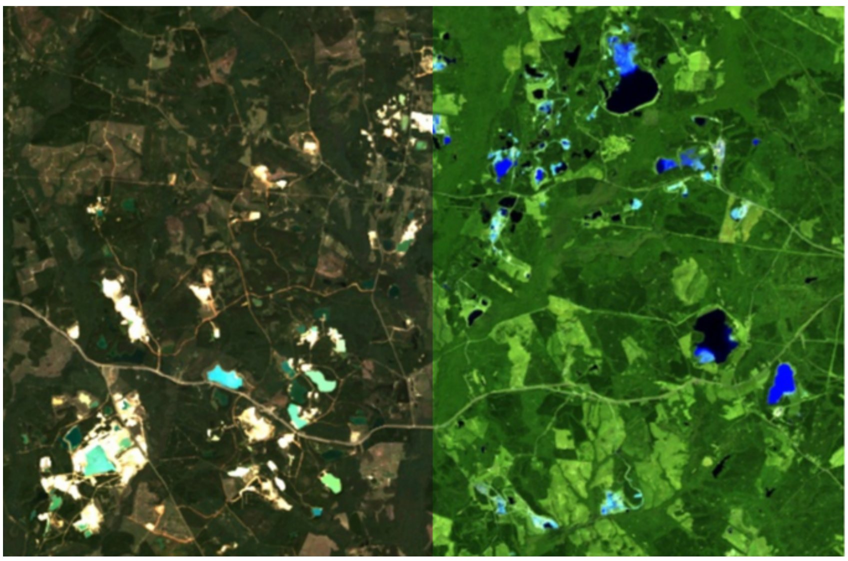

Figure 4: The final output. The Cyan pixels reveal the hidden Kaolinite deposits.

LAB NOTEBOOK

The conceptual framework established above requires a computational tool for implementation. In this lab, the `multispectral_images.ipynb` notebook serves as the primary workbench. This notebook demonstrates the fundamental operations required to manipulate high-dimensional raster data using Python.

Library Ecosystem

While this notebook uses **EarthPy** for its simplicity in handling stacks, it is important to be aware of the broader Python ecosystem for geospatial analysis:

- **GDAL:** The underlying C++ engine that powers almost all geospatial software. It is powerful but complex to use directly.
- **Rasterio:** A "Pythonic" wrapper around GDAL. It is the industry standard for reading and writing raster data in production environments.
- **SatPy:** A specialized library for meteorological data, excellent for creating RGB composites from raw satellite instrument files.

Notebook Overview

The code provides a hands-on example of:

1. **Ingestion:** Loading `.tiff` files and converting them into NumPy arrays.
2. **Stacking:** Combining individual 2D band arrays into a single 3D Data Cube.
3. **Visualization:** Using `matplotlib` to render specific band combinations.

Standard Band Combinations

The notebook moves beyond the Kaolinite case study to implement industry-standard band combinations. By altering the RGB mapping, specific physical properties of the terrain can be highlighted.
The following configurations are implemented using the `earthpy` and `matplotlib` libraries. The interpretations below serve as a key for analysis:

- **Color Infrared (CIR):** Mapping (NIR, Red, Green) $\rightarrow$ (R, G, B).
  - **Red:** Indicates healthy vegetation. Chlorophyll reflects Near-Infrared light strongly. The brighter the red, the healthier the density.
  - **Cyan/Grey:** Indicates urban areas, concrete, or bare ground.
  - **Dark Blue/Black:** Indicates clear water, which absorbs NIR light.

- **Short-Wave Infrared (SWIR):** Mapping (SWIR2, NIR, Red) $\rightarrow$ (R, G, B).
  - **Bright Green:** Indicates dense vegetation.
  - **Pink/Magenta:** Indicates bare earth or soil. This contrast makes it excellent for distinguishing between planted and fallow fields.
  - *Note:* SWIR radiation penetrates atmospheric haze better than visible light.
- **Agriculture Composite:** Mapping (SWIR1, NIR, Blue) $\rightarrow$ (R, G, B).
  - **Vibrant Green:** Indicates healthy crops.
  - **Brown/Orange:** Indicates senescing (dying) plants or timber.
  - *Note:* This combination is specifically tuned to monitor crop stages and detect harvest readiness.
- **Geology Composite:** Mapping (SWIR2, SWIR1, Blue) $\rightarrow$ (R, G, B).
  - *Interpretation:* This composition relies on texture and subtle color variations rather than a single dominant hue. It highlights differences in rock mineralogy and soil types that are invisible in standard imagery.
- **Bathymetric:** Mapping (Red, Green, Coastal Aerosol) $\rightarrow$ (R, G, B).
  - **Blue/Turquoise gradients:** Highlight sediment suspension and water depth variations in near-shore environments.

Spectral Indices

Unlike False Color Composites, which are for visualization, **Spectral Indices** are mathematical ratios calculated per pixel to quantify a specific phenomenon. These result in a single-channel image where pixel values range from -1 to +1.

- **Vegetation Index (NDVI):** Calculated as $\frac{B8-B4}{B8+B4}$.
  - **Value $\approx$ +1.0:** Indicates dense, healthy green vegetation (high chlorophyll).
  - **Value $\approx$ 0.0:** Indicates bare soil or rock.
  - **Negative Values:** Indicate water bodies.
- **Moisture Index (NDMI):** Calculated as $\frac{B8A-B11}{B8A+B11}$.
  - **Value $\approx$ +1.0:** Indicates high moisture content (no water stress).
  - **Low/Negative Values:** Indicate dry soil, stressed vegetation, or barren land.

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