Learning Diary - CASA0023

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2023/3/16

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Preface

Introduction

Welcome to my learning diary page of Remote Sensing Cities and Environment (CASA0023)! This diary is made for the content taught at 2022-2023.

I'm a current Master of Science student at Bartlett Centre for Advanced Spatial Analysis

1 Week 1

1.1 Summary

This section summarises the lecture content and a graph of feature space derived from practical in SNAP operations.

Passive data: Energy usually in eletcromagnetic form e.g., human eyes

Active data: Energy in addition in illumination . e.g., radar.

How EM waves interact with Earth's surface and atmosphere: Reflection, scattering, absorption

single

dual

quad

1.1.1 remotely-sensed data usually comes in

Raster: file

types: BIL, BSQM BIP, GeoTIFF

1.1.2 Four resolutions:

Spatial: ranging from 10 cm to several kilos

Spectral: How many different spectral bands are there? (Every feature on earth has a unique spectral signature)

(Atmospheric windows:)

(Vegetation: red edge -- infra bands. APP: look at the infra band s of city to identify who has access to vegetation)

Radiometric resolution: resolution of cell's value

Temporal resolution: ussualy inversly relate3 to pixel size (spatial)

MODIS

1.1.3 Practical

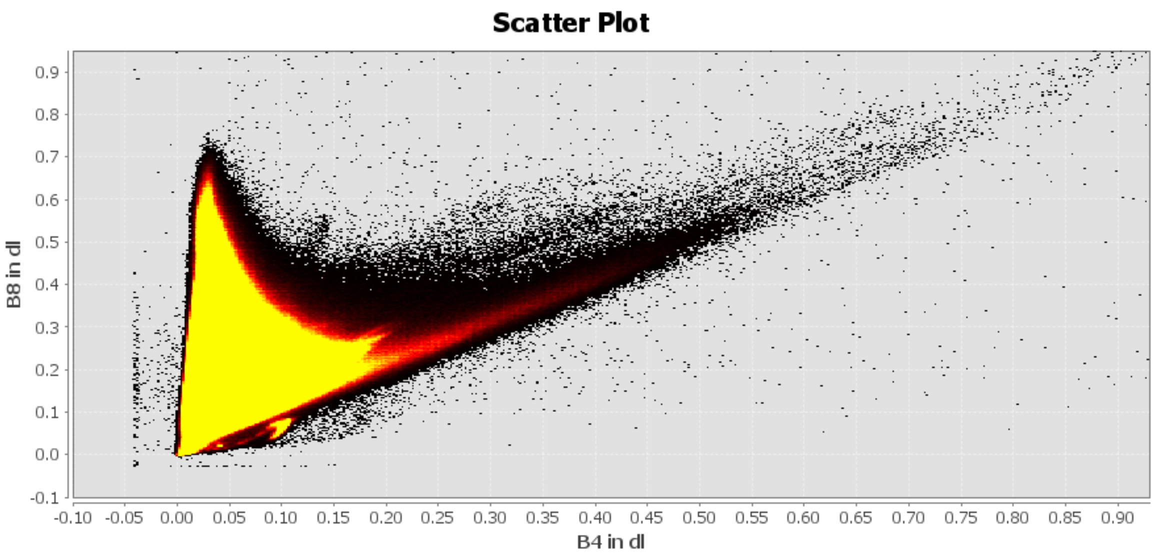


Figure 1.1: Spectral Feature Space, Vegetation On Bands B04 and B08

1.2 Application:

"Spectral Feature Space, Vegetation On Bands B04 and B08"

One of the applications really attracted me was the spatial signature of vegetation on the terra, as we could assign features to each end of the spatial signature area see Figure **??**, such as bare land on the right end of the triangle-like area where red light captured are dense while near-infrared level is low. Heavy vegetation are witnessed at the upper end of the triangle-like area where red light low and near-infrared is high, indicating heavy biomass. As for the left-down corner where both red and near-infrared are low, we can identify wet lands. This is integrated in the NDVI (Normalized Difference Vegetation Index) to estimate vegetation cover.

Spatial signatures can also be used to monitor the health of vegetation by identifying patterns of quavariation in spectral reflectance that are indicative of stress or disease. For example, vegetation that is stressed or diseased may have a different spectral reflectance signature than healthy vegetation, which can be identified using spatial signatures.

In addition, spatial signatures can be used to monitor the growth and distribution of vegetation over time by comparing satellite imagery from different dates. This can be useful for understanding the impacts of land use changes, climate change, and other factors on vegetation.

Overall, spatial signatures are a powerful tool for vegetation monitoring, as they can be used to identify and classify different types of vegetation, monitor vegetation health, and track vegetation changes over time.

1.3 Reflection

just state what interest you and why, as well as the application. Application: Context matters. Why useful? What had it assisted achieving. Mind map of concepts, to show understanding of data and workflow

One of the challenges I encountered is to navigate the complexities of the interface of SNAP and QGIS. It becomes clear to me that yes implementing several functions in code can be challenging, but a software with collective functions as a whole can be mindblowing even when with decent GUIs. Specifically, finding which function falling under which menu consumes a lot of time, and figuring out filling parameters to carry the analysis also took some efforts of iterative validation.

When doing the operation in R on a script level, it becomes confusing where I put the data

2 2. Week 2 - Portfolio

3 Week 3 - Remote sensing data

In this week's learning diary, we try to handle

3.1 Summary:

3.1.1 Different Sensors

Across track scanners: Mirror reflects light onto 1 detector. For example, Landsat dataset are captured by this sort

Along track scanners: Basically several detectors pushed along. E.g., Quickbird, SPOT

3.1.2 Geometric Correction

RS data could include image distortions introduced by: View angle, topography, wind and rotation of the earth

We identify Ground Control Points (GCP) in distorted data to match them with local map, correct image, or GPS data from handheld device, but these reference images could also contain distortions and imprecisions.

RMSE is adopted here to measure fitness between images. Use GCPs to minimise RMSE.

Doing geometric correction can shift the original image, so we want to re-sample the final raster by using Nearest Neighbour, Linear, Cubic, Cubic spline re-samplers

3.1.3 Atmosphric Correction

According to Jensen (1986), two factors contribute to environmental attenuation: Atmospheric scattering, topographic attenuation.

There are unnecessary and necessary atmospheric corrections:

necessary ones are:

- Biophysical parameters needed (e.g. temperature, leaf area index, NDVI)

- E.g. .. .NDVI is used in the Africa Famine Early Warning System and Livestock Early Warning System
- Using spectral signatures through time and space

Absorption and scattering can create the haze, i.e. reduces contrast of image.

Scattering can create the “adjacency effect”, radiance from pixels nearby mixed into pixel of interest.

3.1.4 Orthorectification Correction

This is a subset of georectification, i.e. giving coords to an image. Particularly Orthorectification means removing distortion so pixels can appear being viewed at nadir (straight down). This requires the support of an Elevation Model to calculate the nadir view for each pixel on a sensor geometry.

To do this: cosine correction, Minnaert correction, Statistical Empirical correction, C Correction (advancing the Cosine). Need radiance (DN to TOA) from sloped terrain, Sun’s zenith angle, Sun’s incidence angle - cosine of the angle between the solar zenith and the normal line of the slope. Latter two found in angle coefficient files (e.g. Landsat data ANG.txt).

3.1.5 Rdiometric Correction

Corrections to raw satellite imagery can be performed using a method called Dark Object Subtraction (DOS). The logic is that the darkest pixel in the image should be 0 and any value it has is due to the atmosphere. To remove the atmospheric effect, the value from the darkest pixel is subtracted from the rest of the pixels in the image. The calculation involves converting the Digital Number (DN) to radiance, computing the haze value for each band (but not beyond NIR), and subtracting the 1% reflectance value from the radiance. The calculation requires values such as mean exoatmospheric irradiance, solar azimuth, Earth-sun distance, and others, which can be found in sources such as Landsat user manuals.

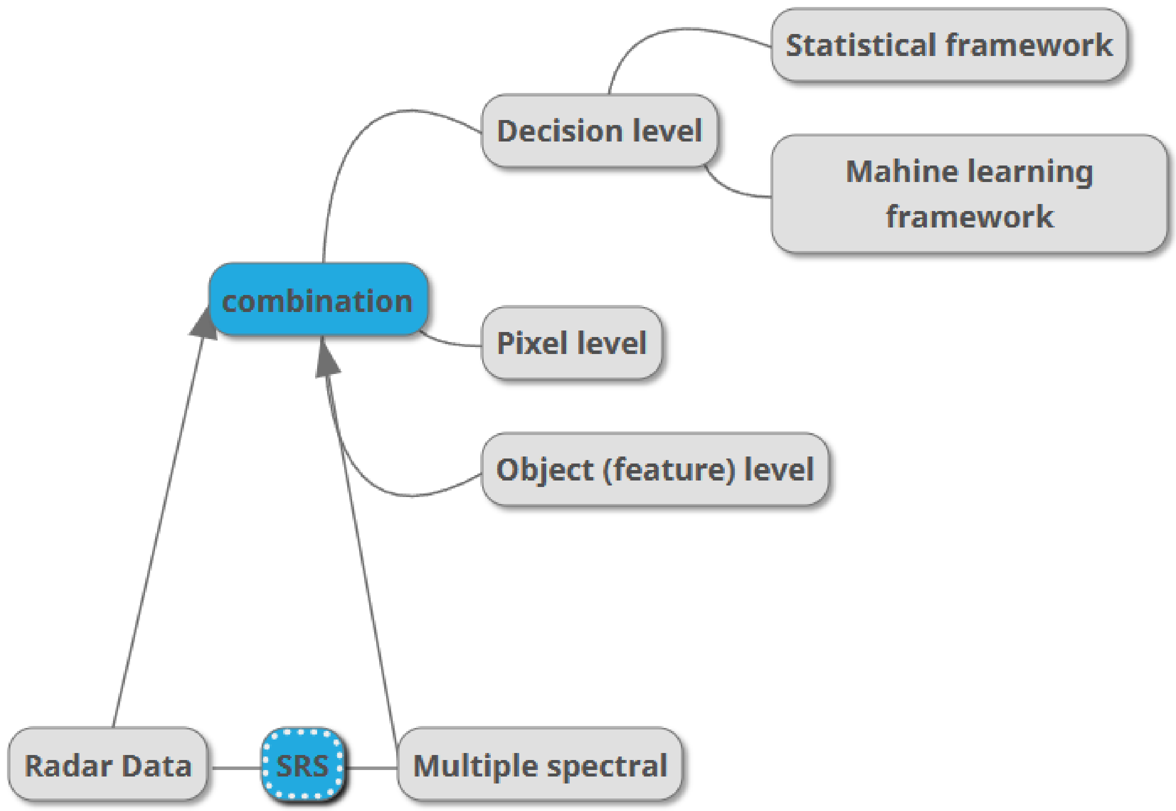
3.1.6 Joining data sets

Also known as Mosaicking: We feather two images, creating a seamless mosaic, where the diving lien is called seamline.

3.1.7 Image Enhancements

Image stretch, Band ratioing, Normalised Burn Ratio, Edge enhancement, Filtering, PCA, Image fusion (see application) etc.

3.2 Application - Discussing image fusion in one literature



From literature we delve in the nuances of levels on which we perform image fusion to acquire better results. The integration methods vary as the levels vary (Schulte to Bühne and Pettorelli 2018).

Satellite remote sensing (SRS) can be derived from Multispectral sensors and radar sensors.

Multispectral sensors are passive, merely receiving electromagnetic waves reflected from surface, usually used to reflect chemical properties (such as nitrogen or carbon content and moisture). Usually produces data with comparatively low spatial resolution

Radar ones emit electromagnetic radiation and measure the returning signal, responding to the three-dimensional structure of objects, being sensitive to their orientation, volume and surface roughness. Usually produces data with comparatively high spatial resolution

3.2.1 Image fusion:

1. **decision-level** (SRS integration), where separate predictors are used to estimate a parameter of interest.

2. **object-level (feature-level).** unit: multi-pixel objects. (1) using radar and multispectral imagery is input into an object-based image segmentation algorithm, or (2) segmenting each type of imagery separately before combining them. multi-pixel objects

3. **pixel-level (Observation-level)**, where pixel values are combined to derive a fused image with new pixel values, either in the spatial or the temporal domain.

(2. and 3. derive entirely new predictors.)

Schematic overview of multispectral-radar SRS data fusion techniques. The parameter of interest can be a categorical variable, like land cover, or a continuous variable, like species richness. In pixel-level fusion, the original pixel values of radar and multispectral imagery are combined to yield new, derived pixel values. Object-based fusion refers to (1) using radar and multispectral imagery is input into an object-based image segmentation algorithm, or (2) segmenting each type of imagery separately before combining them. Finally, decision-level fusion corresponds to the process of quantitatively combining multispectral and radar imagery to derive the parameter of interest (by e.g. combining them in a regression model, or classification algorithm)

3.2.2 Implementation Approaches

pixel-level

1. Component substitution techniques: such as principal component analysis (PCA), Intensity-hue-saturation (IHS).

2. PCA is the only pixel-level image fusion technique that cannot be applied to imagery with different spatial resolutions, and the only that allows unlimited image numbers.

3. IHS fusion. Three images with lower spatial resolution (typically multispectral data) are integrated with a single image with high spatial resolution (typically radar) to retain the radiometry but increase the spatial resolution of the former. Facilitate visual interpretation by combining resulting images into a single RGB image.

4. Multi-resolution analysis, such as **Wavelet transformation. Decompose multispectral and radar imagery into their respective low- and high-frequency components

5. Arithmetic fusion techniques: such as the Brovey transform algorithm. Unlikely to be appropriate for multispectral-radar SRS image fusion.

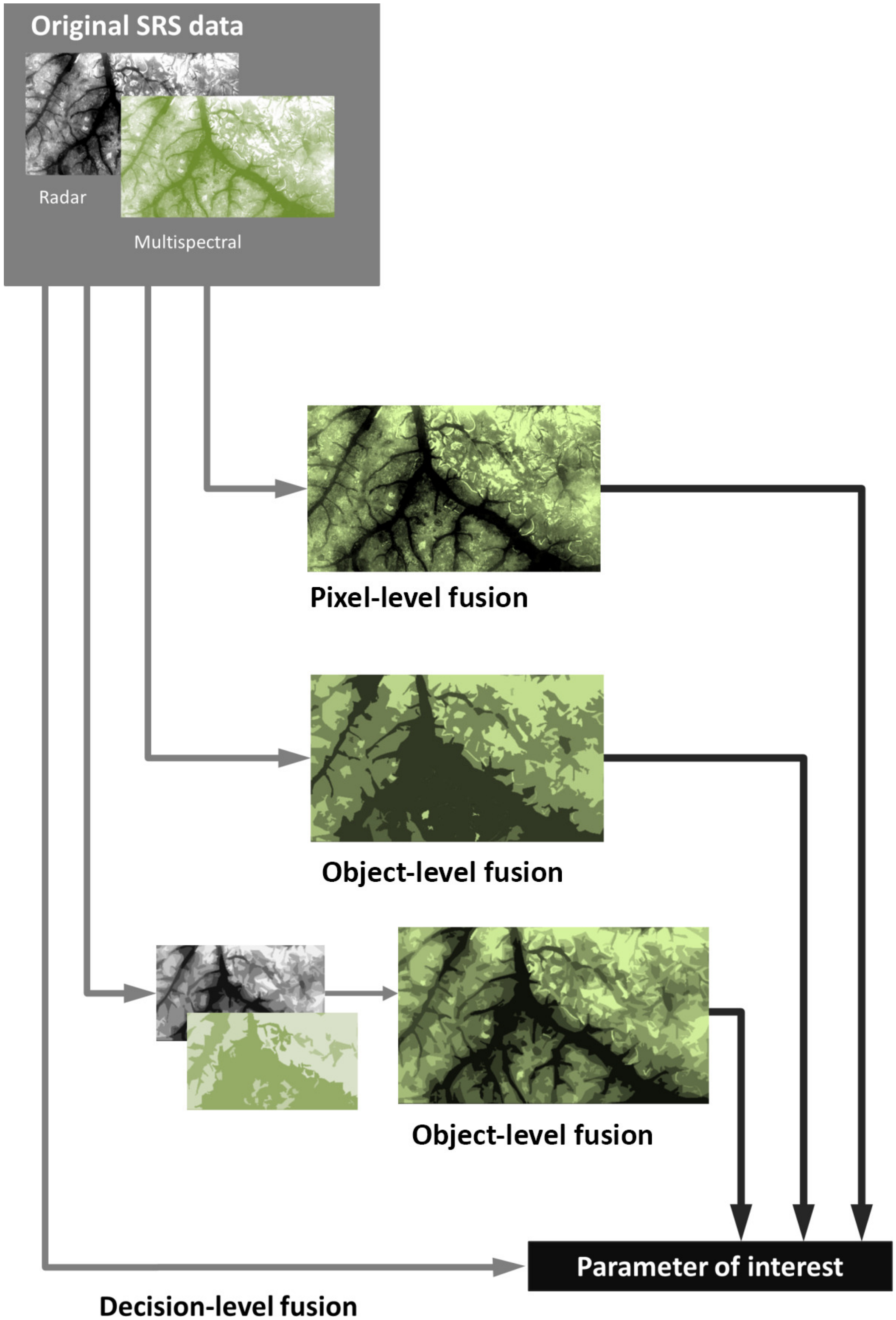


Figure 3.1: Credit: Schulte to Bühne and Pettorelli (2018)

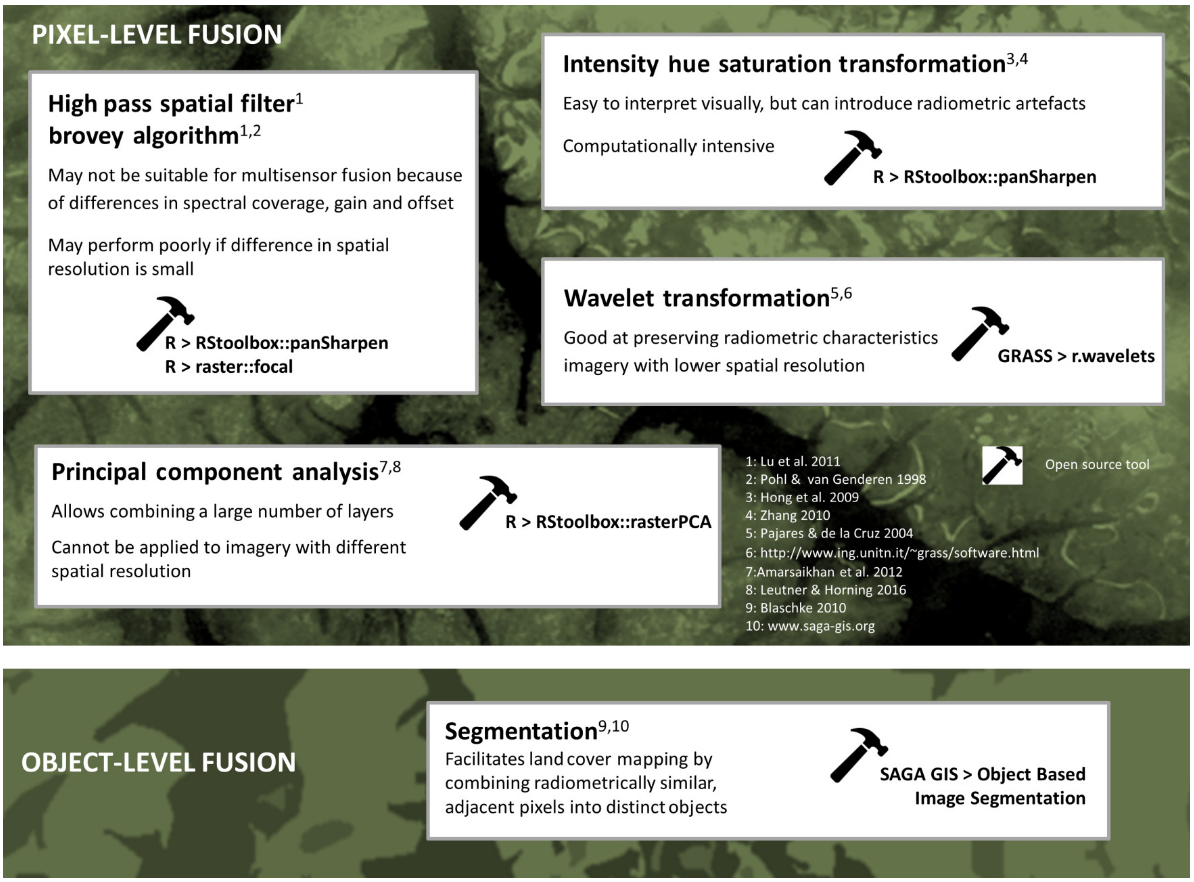


Figure 3.2: Credit: Schulte to Bühne and Pettorelli (2018)

Object-level: Based on brightness and intensity values of each pixel, as well as its spatial context, objects such as lines, shapes or textures are extracted.

1. **image segmentation:** Demands that multispectral and radar SRS images are with the same spatial resolution

2. *extracting objects separately and combining in a feature map*

Object-based fusion reduces all multispectral and radar information into a single layer of discrete objects, which are often relatively easy to relate to ecological features.

Decision-level fusion: Quantitative decision-making frameworks—such as a regression, a quantitative model or a classification algorithm.

3.3 Reflection

Data correction, Data fusion and Image enhancement SRS data fusion can increase the quality of SRS (Satellite Remote sensing)-derived parameters for application in terrain detection, urban analysis, ecology and conservation (Schulte to Bühne and Pettorelli 2018). It is thus important to explore how best to capitalise on recent technological developments and changes in SRS data availability. It is exctiing to apply solid machine learning methods to this area and it is marvelous to see the progress reflected by the increasing number of software supporting this application. The improvement of image quality enables new research designs in ecology and conservation areas and reignite previously greyed-out options.

The application of data correction, data fusion, and image enhancement techniques to SRS data can greatly improve the accuracy and reliability of SRS-derived parameters, which can then be used in various fields, including terrain detection, urban analysis, ecology, and conservation. With the rapid advancements in technology and the increasing availability of SRS data, there is a growing opportunity to leverage the latest machine learning techniques in this area. The development of new software tools to support these applications is a testament to the progress being made in this field. By enhancing the quality of the SRS data, researchers are able to design more robust and informative studies, unlocking new insights and avenues for exploration in ecology and conservation. This, in turn, has the potential to lead to breakthroughs and innovations in these fields, making a significant impact on the world around us.

4 Week4 - Policy applications

4.1 Summary

4.1.1 Sensor Data

5 Week 5 - An introduction to Google Earth Engine

This week introduces **Google Earth Engine (GEE)**, a geospatial processing service that allows for planetary scale analysis of massive datasets in seconds.

Basics:

- The set up of GEE, its terms and jargon, and client vs server side operations, see Table 1
- How GEE uses Javascript and how mapping functions are used instead of loops
- The concept of scale in GEE, which refers to both the volume of analysis and pixel resolution
- How GEE aggregates the image to fit a 256x256 grid.

Objects and methods in GEE are introduced:

- E.g. geometries, features, feature collections, and
- Various data reduction techniques (e.g., reducing images, reducing images by region(s), reducing images by neighborhood).

Also, the types of analyses that can be performed in GEE are briefly covered.

5.1 Summary

5.1.1 GEE Basics

JavaScript, where objects are dictionaries:

- We have ee (EarthEngine), a powerful package. Anything starting with ee (proxy objects) are stored on the server.
- Problems:
    - We don't iterate the data on the server; instead, we map (using a mapping function) them into objects (variables) so we only load them once.
    - There are also some sort of server-wide functions.

- Avoid using loops in GEE on the server-side, as mapping can automatically detect the number of loops needed.

Scale:

- Pixel resolution, set by the output.
- GEE does resampling, aggregating your input to a 256*256, mainly down-sampling.

Table 1: Terms and Jargon Related to Google Earth Engine

Term	Definition
Google Earth Engine	A geospatial processing service that allows geospatial analysis at scale.
Image	Refers to raster data in GEE and has bands.
Feature	Refers to vector data in GEE and has geometry and attributes.
ImageCollection	A stack of images in GEE.
FeatureCollection	A stack of features (lots of polygons) in GEE.
Proxy objects	GEE objects that are stored on the server and have no data in the script.

Table 2: Differences between Client and Server Side in Google Earth Engine

Aspect	Definition
Client Side	Refers to the browser side of GEE.
Server Side	Refers to the side of GEE where data is stored.
Earth Engine Objects	Objects in GEE starting with "ee".
Looping	Looping is not recommended for objects on the server side.
Mapping	Instead of loops, mapping is used in GEE to apply a function to everything on the server.
Scale	Scale refers to pixel resolution in GEE. The scale is set by the output, not the input, and Earth Engine selects the pyramid with the closest scale to analysis.

5.1.2 GEE Objects

Objects:

- Images (Rasters), geometry, ImageCol, features, featureCol, joins, arrays, chart.

Table 3: Geometry Types and Features

Type of Geometry	Description
Point	A single location represented by its longitude and latitude
Line	A series of connected points representing a linear feature
Polygon	A closed shape with three or more sides, represented by a series of connected lines forming a closed loop
MultiPolygon	A collection of polygons, where each polygon is represented as a list of coordinate tuples defining its vertices
MultiGeometry	A collection of different types of geometries

5.1.3 GEE Processes and Applications/Outputs

GEE applications:

- Reducing types.
- Different to filterBounds() that filters the area of interest, to do zonal statistics, we have reduceRegion(), where regions are subcategories of the area of interest.
- Also, we have reduceNeighborhood(), which is a bit like a kind of image enhancement.

Linear Regressions:

- In a scenario of visualising precipitation, we can do a multivariate multiple linear regression where both independent variables (time) and dependent (precip, temp) variables are multiple.
- Something about constant bound.

Joins:

- In GEE, everything, e.g. within a buffer, intersect, etc. needs the mediation of Join (apply()).
- To perform joins, we need to put data into Filter().

Classifiers:

- Per-pixel
- sub-pixel

Table 4: GEE Processes and Applications/Outputs

Process	Description
Geometry operations	Spatial operations such as union, intersection, buffer, and distance analysis
Joins	Combining two feature collections based on a shared attribute value
Zonal statistics	Computing statistics for a region or set of regions such as mean, median, and mode of pixel values within a feature or a collection of features
Filtering	Filtering of images or specific values based on criteria such as date range, location, and attribute value
Machine learning	Using statistical and machine learning algorithms for classification, clustering, and prediction tasks
Deep learning	A subset of machine, using Deep Neural Networks

5.1.4 Limitations

No support for phase data, needs SNAP.

5.2 Application

5.3 Reflection

GEE-using skills can be a valuable asset for a spatial data scientist, as it allows for complex spatial analysis at scale. Traditional GIS software is eclipsed when it comes to both efficiency and scale.

GEE's unique and efficient way of conducting analysis flows is interesting, such as the introduction of concepts like client vs server-side operations and data reduction techniques. These was required by GEE's feature of carrying out analyses on massive datasets (Gorelick et al. 2017). For those interested in BigData technology, the strategies (server/client split, no looping on server, etc.) applied by Google here is a very resourceful one and worth learning. The user end also has to learn to adopt good practices for reducing data range, which has been simplified to a series of reduction and filtering functions, e.g. `ImageCollection.filterDate()`, `image.reduceNeighborhood()`(Google 2023b).

GEE's combination with machine learning is also promising in regard of automating complex analysis tasks, as Machine Learning APIs offered by GEE support Supervised and Unsupervised Classification, and Regression (Google 2023a). According to Saad El Imanni et al. (2023), as a subtask of intelligent agriculture, weeds detection task sees an impressive performance (overall accuracy reached 96.87%) when GEE and Machine learning are combined.

6 Wk6 Classification

6.1 Summary

Information	Summary
Purpose of classification	To subset data into classes or values, such as landcover or estimating values like GCSE scores or pollution.
Different classification methods	Essentially slice the data in different ways.
Complexity of classification methods	They can often be made to appear more complicated than they are.
Controlling classifiers	Can be done using hyperparameters.
Desired outcome of classifiers	Can range from a single tree to a decision hyperplane boundary in multiple dimensions.

6.1.1 ML methods in EO data classification

Table 1: Supervised Classification Methods

Method	Description
Maximum Likelihood	A statistical method used to estimate the parameters of a probability distribution based on observed data.
Support Vector Machines (SVM)	A supervised learning algorithm that finds the best hyperplane to separate data into different classes.

Table 2: Unsupervised Classification Methods

Method	Description
Density Slicing	Divides the range of pixel values into equal intervals and assigns each interval a unique class value.
Parallelpiped	Uses a set of user-defined ranges for each band to define class boundaries in multi-dimensional space.
Minimum Distance to Mean	Assigns each pixel to the class with the closest mean value in multi-dimensional space.
Nearest Neighbor	Assigns each pixel to the class of its nearest neighbor in multi-dimensional space.

Table 3: Other Machine Learning Methods

Method	Description
Artificial Neural Networks (ANN)	A set of algorithms inspired by the structure and function of biological neural networks, used for pattern recognition and prediction tasks.

6.1.2 Pros and cons - Supervised vs. Unsupervised

Table 1: Supervised vs. Unsupervised Classification

Classification Type	Definition	Method
Supervised	Classifier learns patterns in the data and uses that to place labels onto new data. Pattern vector is used to classify the image. Usually, pixels are treated in isolation but as we have seen - contextual (neighboring pixels), objects (polygons), texture.	Pattern recognition or machine learning