

**Initial**

T X

2023/1/19

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1 — #jupyter: python3 #—

# Preface

This is a Quarto book.

To learn more about Quarto books visit <https://quarto.org/docs/books>.

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## 2 Introduction

This is a book created from markdown and executable code.

See for additional discussion of literate programming.

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# 3 Week 1

## 3.1 Summary

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

Passive data: Energy usually in electromagnetic 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

### 3.1.1 remotely-sensed data usually comes in

Raster: file

types: BIL, BSQ, BIP, GeoTIFF

### 3.1.2 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 bands of city to identify who has access to vegetation)

Radiometric resolution: resolution of cell's value

Temporal resolution: usually inversely related to pixel size (spatial)

MODIS

### 3.1.3 Practical

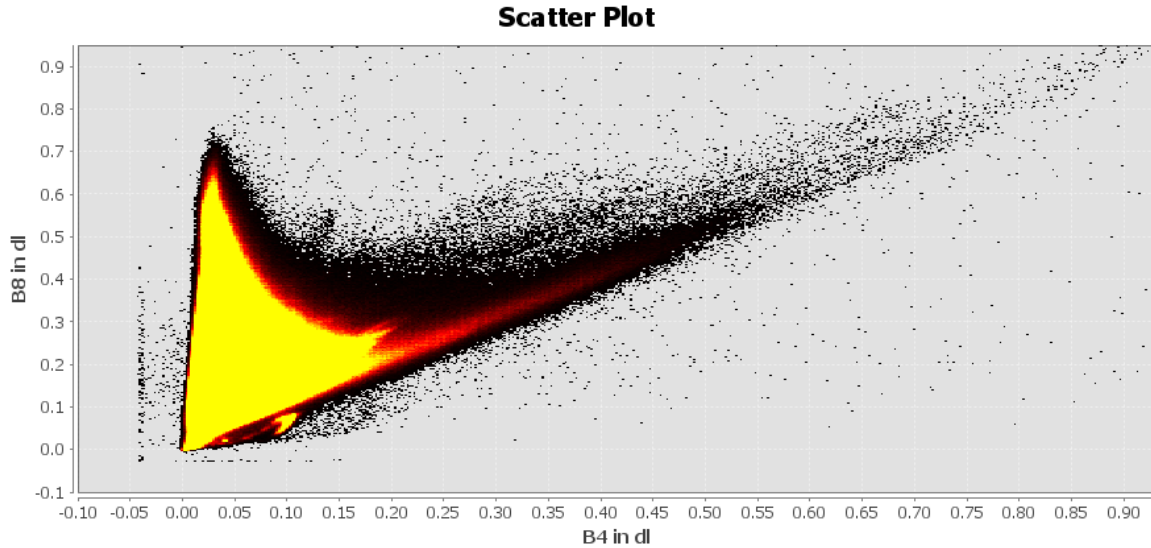


Figure 3.1: Spectral Feature Space, Vegetation On Bands B04 and B08

## 3.2 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 3.1, 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.

### **3.3 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

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# 5 Week 3 - Remote sensing data

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

## 5.1 Summary:

### 5.1.1 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

### 5.1.2 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

### 5.1.3 Atmospheric 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.

#### 5.1.4 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).

#### 5.1.5 Radiometric 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.

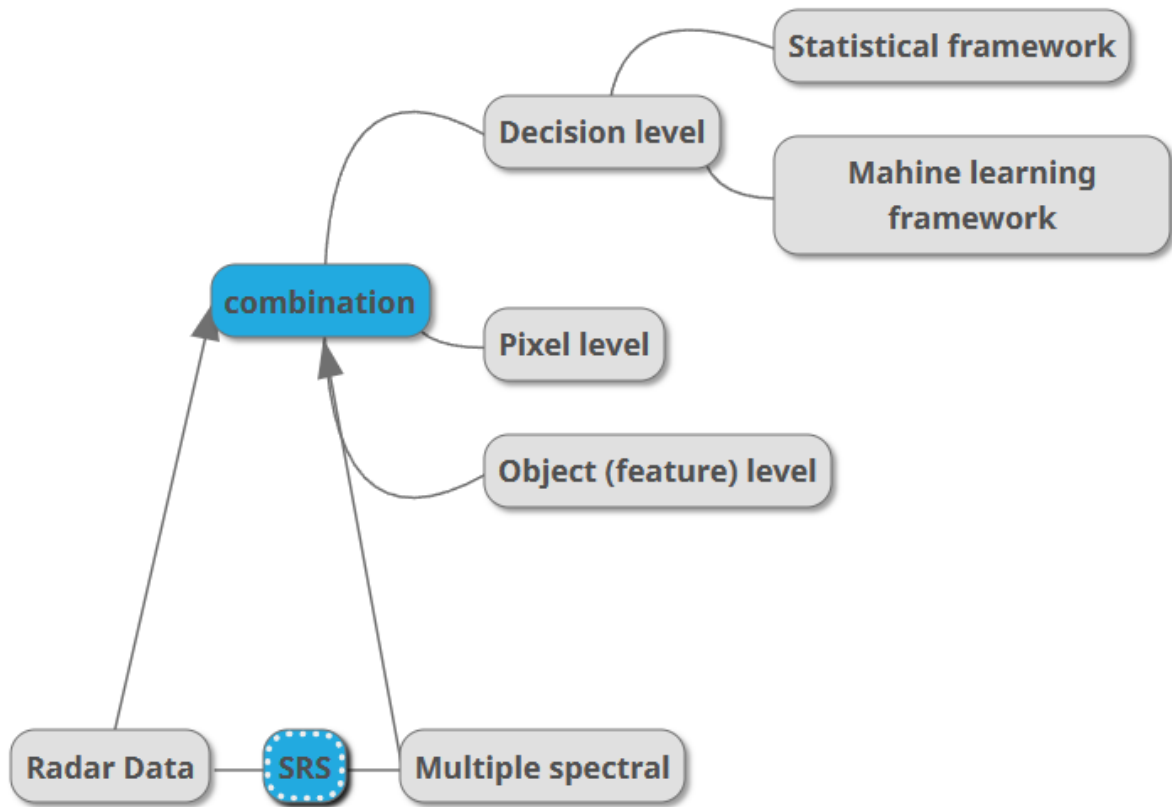
#### 5.1.6 Joining data sets

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

#### 5.1.7 Image Enhancements

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

## 5.2 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. @Better together: Integrating and fusing multispectral and radar satellite imagery to inform biodiversity monitoring, ecological research and conservation science.

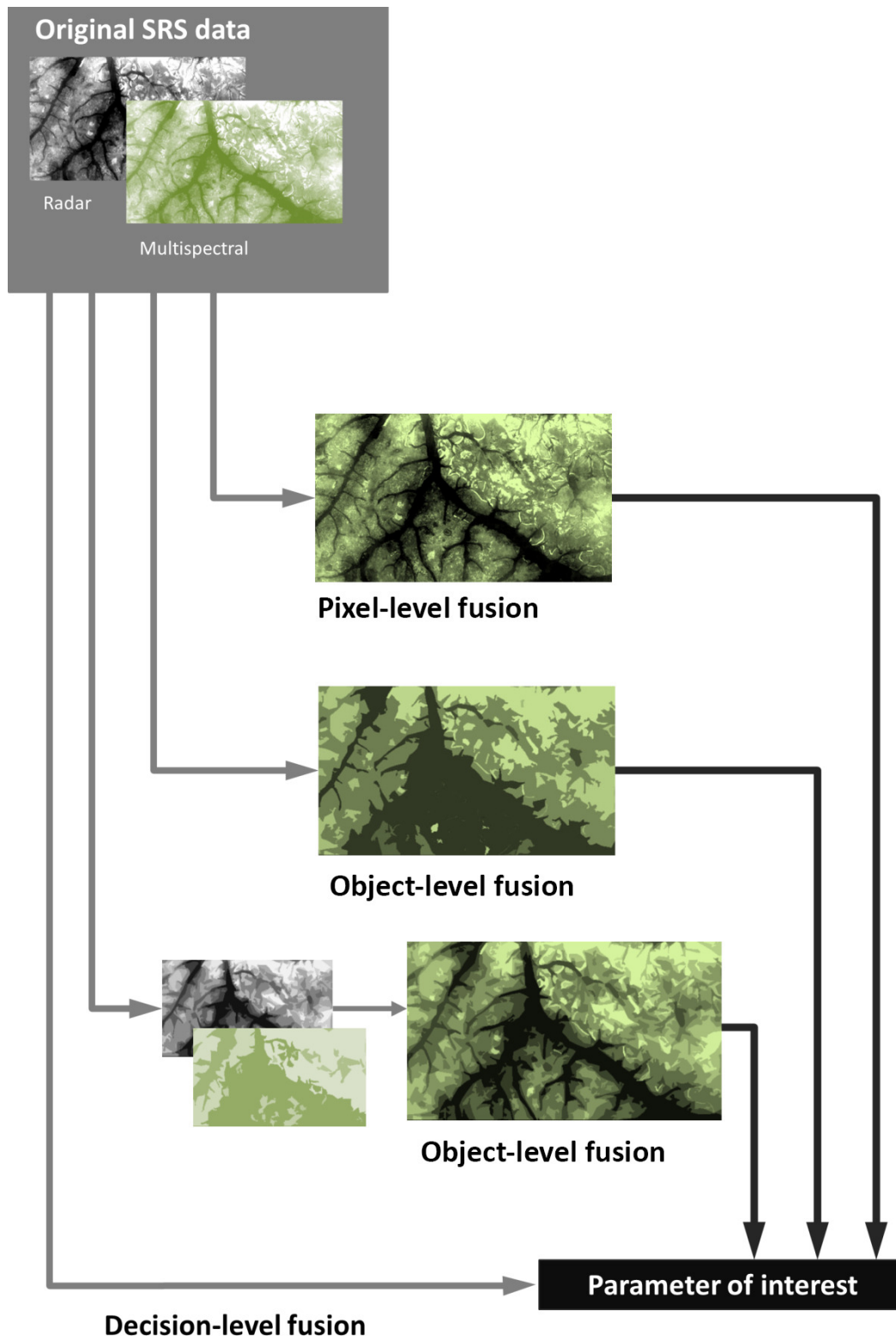
Satellite remote sensing (SRS) can be derived from Multispectral sensors and radar sensors.

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

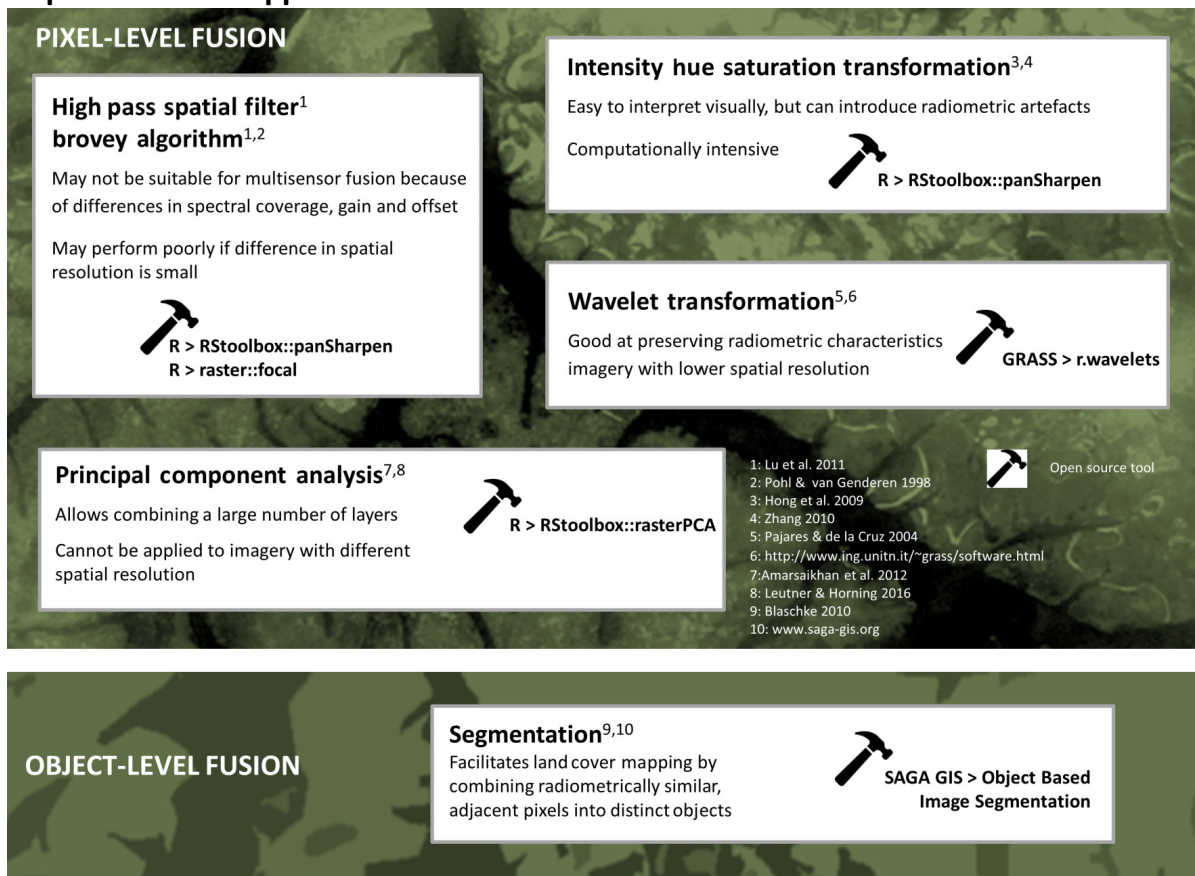
### 5.2.1 Image fusion:

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 as 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)

### 5.2.2 Implementation approach



#### *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.

**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.

## 5.3 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 exciting 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.

## **6 Week4 - Policy applications**

### **6.1 Summary**

#### **6.1.1 Sensor Data**

# 7 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.

## 7.1 Summary

### 7.1.1 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.

### 7.1.2 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

### 7.1.3 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

#### 7.1.4 Limitations

No support for phase data, needs SNAP.

## 7.2 Application

## 7.3 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 were 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.



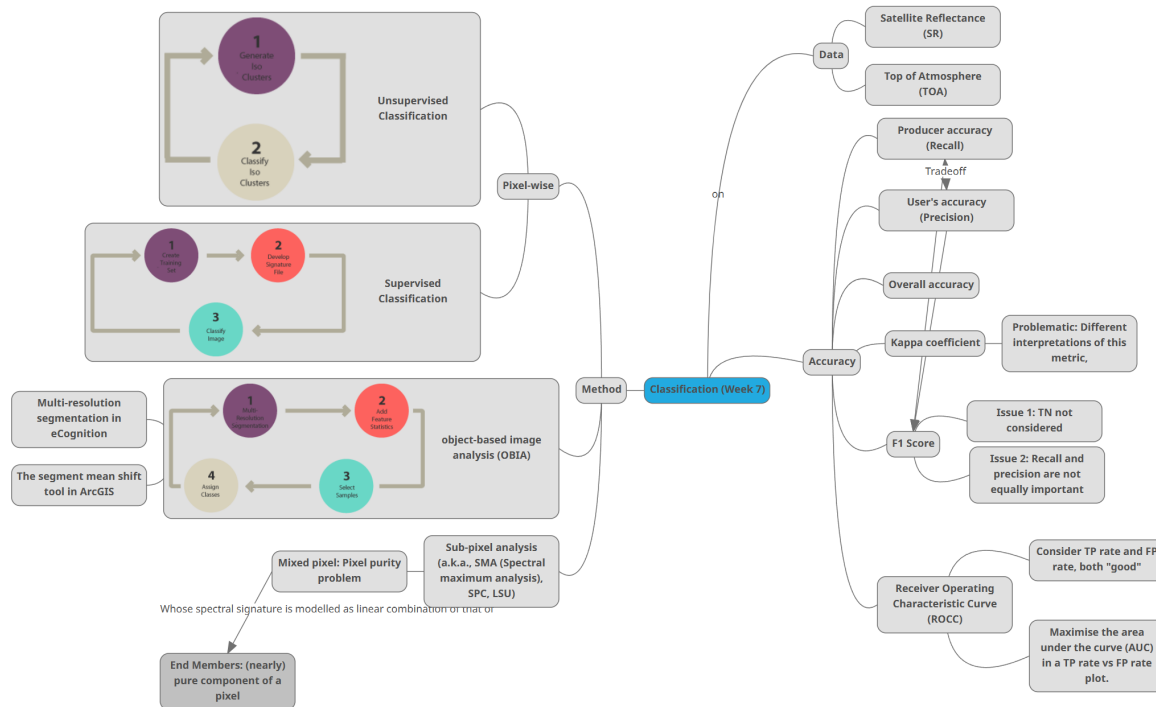
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# 9 Week7 - Classification and Accuracy

This week's learning diary continues that from Week 6 in addressing the big problem in Remote Sensing, i.e. classification within Earth Observation data. Also, accuracy metrics are discussed.

## 9.1 Summary

The summary of lecture content as well as practical outcomes. See [?@fig-mindmap](#) for an overview. If certain words are intelligible due to resolution issues, hopefully you can right click and "open in new page" to get a better view since this is a .SVG file.



### 9.1.1 Data

- Surface Reflectance (SR)
- Top of Atmosphere (TOA)

A mixed way of doing urban recognition

### 9.1.2 OBIA (object-based image analysis)

Instead of a per-pixel approach, we adopt an object-based image analysis (OBIA), where you have to manually create objects.

SLIC (*Simple Linear Iterative Clustering*) (2012): No ground truth

Descent, similarity (Homogeneity)

### 9.1.3 Sub-pixel analysis

SMA (Spectral maximum analysis), SPC, LSU

Through a series of manipulation of material, we acquire a list describing the broken-down land cover of that pixel

#### 9.1.3.1 Pixel purity

**Endmember:** an important concept in spectral mixture analysis

In remote sensing, an end member refers to a pure or nearly pure material or component that is present within a mixed pixel.

In spectral mixture analysis, the spectral signature of a mixed pixel is modelled as a linear combination of the spectral signatures of the constituent endmembers, with each end member being assigned a proportion or fraction that represents its contribution to the overall reflectance or radiance of the mixed pixel.

#### 9.1.4 Accuracy assessment

- Producer accuracy: Recall
- User's accuracy: Precision
- Overall accuracy: not equivalent to F1
- Kappa coefficient:  $[0, 1]$ , measures how good the classification is compared to random distribution e.g. Poisson. Different interpretations of this metric, problematic

Make a tradeoff between Producer accuracy and User accuracy, by shifting the decision boundary.

- F1: issue: TN not considered; Recall and precision are not equally important yet equally weighted in F1
- Receiver Operating Characteristic Curve: True positive rate and false positive rate are all good. We want to maximise the area under the curve in a True positive rate vs false positive rate plot.

#### 9.1.5 Workflow

- (Potentially use unsupervised classification to understand your data)
- Class definition (Potentially use unsupervised classification)
- Preprocessing
- Training
- Pixel Assignment
- Accuracy assessment

Pseudo-invariant features to be trained on to make your model robust to time-space changes

Pseudo-invariant features are often used as reference targets or calibration sites in remote sensing to account for changes in sensor or atmospheric conditions and to reduce the effects of noise and calibration drift on image data. These features have relatively constant spectral properties over time and space, and can therefore serve as a stable reference for monitoring changes in other features or materials within an image or scene.

A flow chart can be seen in [Figure 9.1](#) :

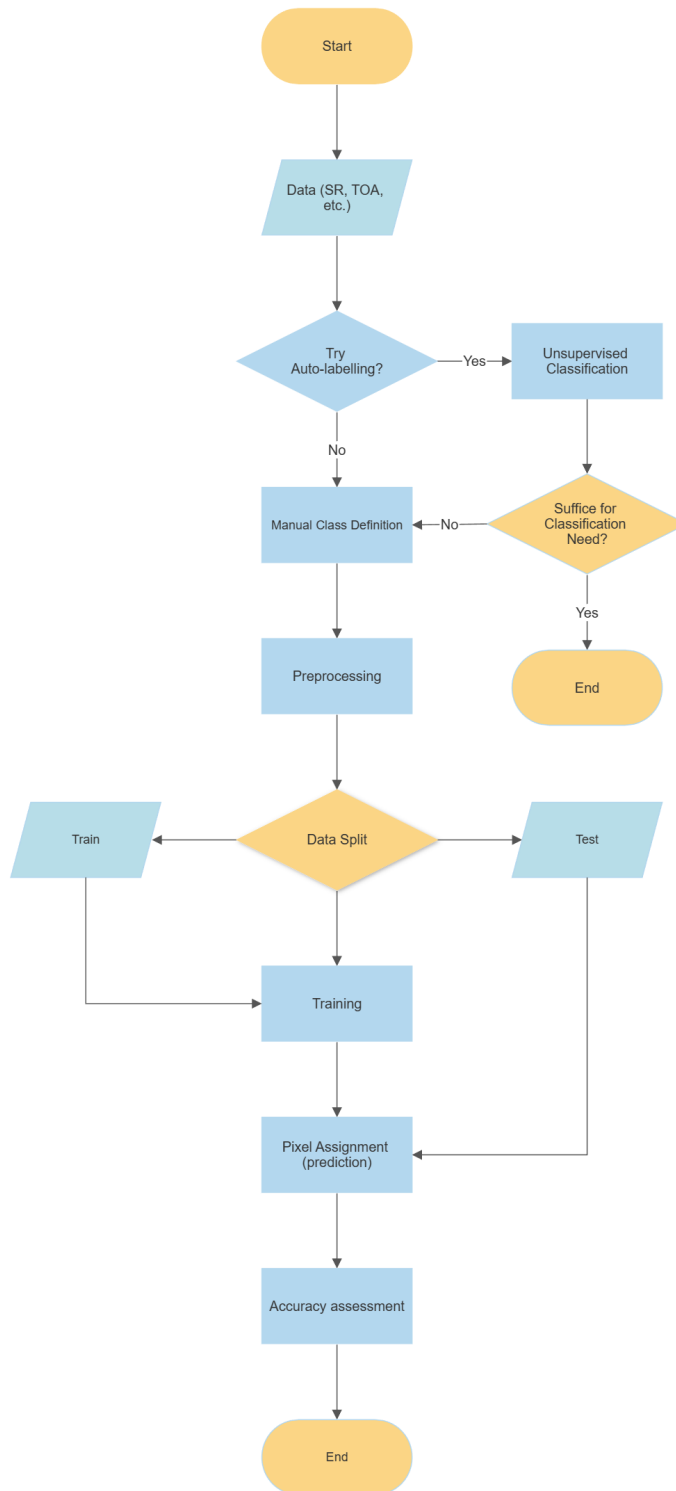


Figure 9.1: Classification Workflow, courtesy: myself

### **9.1.6 A “Sneak preview” (Analogous to Data Leakage in ML)**

Waldo Tobler’s first law of geography indicates that if training and testing are spatially close, the training can cause the problem of a sneak preview.

#### **9.1.6.1 Spatial Cross Validation**

Similar to cross-validation but adds clustering to folds.

In spatial cross-validation, the data are split into spatially contiguous blocks or subsets, rather than randomly shuffled subsets as in traditional cross-validation. This is done to ensure that the model is tested on data that are spatially distinct from the data used to train the model and to account for spatial autocorrelation and other spatial dependencies in the data.

### **9.1.7 Approaches to deal with Spatial Autocorrelation**

Object-based image classification

Moran’s I (Spatial Cross Validation)

## **9.2 Application - to be completed**

In remote sensing, it is often challenging to accurately classify mixed pixels, which contain a combination of different materials or components. Endmembers refer to pure or nearly pure materials that are present within a mixed pixel. By modelling the spectral signature of a mixed pixel as a linear combination of the spectral signatures of the constituent endmembers, we can determine the contribution of each endmember to the overall reflectance or radiance of the mixed pixel.

This approach can be very useful in urban recognition, where it is essential to accurately classify the different land covers present within a pixel. Furthermore, it can also help us to understand the composition of the land cover in a given area, which can have important implications for environmental monitoring and management. This approach has been applied in various studies to estimate urban land cover, such as the work by Zhang et al. (2018) that utilised endmember extraction to detect urban impervious surfaces.

### 9.3 Reflection

The workflow of Classification of Surface Reflectance and Top of Atmosphere data intrigues me, as it differs from, yet shares certain features with traditional computer vision tasks like image classification and object detection (in regards of treating pixels as objects/units). Alternatively, Surface Reflectance Classification can be treated as a downstream task for both aforementioned ML tasks, due to its uniqueness in dealing with high-precision satellite data and unseparability (worth debating) from EO processing workflow (calibration etc.). Also, uncertainty of classification genres derived from unsupervised labelling can also be an issue.

Optionally, in supplementation to manual labelling, automated labelling workflow (e.g. roboflow) can be introduced to curtail repeatitive works in image labelling(Nair, Paul, and Jacob 2018). However, manual labelling is not replaceable at current time (Robison 2018) and the pinning down of ground truth seems to always need human intervention in addition to machine automation.

The introduction of production accuracy and user accuracy is also interesting, as these terminologies are designed presupposing a customer/producer split, dwarfing precision-recall in readability. The treadeoff to be made between the two is crucial, and this is problematically handled by introducing F1 score with two competitive components, and improved by introducing Receiver Operating Characteristic Curve (ROCC) with two “good” indicators, true positive rate and false positive rate.

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# 11 Week8 - Temperature and Policy

The “policy” section occupies two weeks, mainly trying to introduce how to fit EO data workflow into current policies. To do this, you have to identify the gaps, e.g., that between the overarching global policies, metropolitan plans and local plans. Or, the gap within policies like missing locations in the Singapore one.

## 11.1 Summary

### 11.1.1 Urban Heating Islands (UHI) problem and plans

#### 11.1.1.1 Causes

Urban areas have comparatively higher atmospheric and surface temperatures than surrounding rural areas, mainly due to

1. More dark surfaces that retain heat
2. Less vegetation that cools the environment

Also, there are other contributors to the heat:

Contributor	Correlation with UHI phenomenon
Sky View Factor (SVF)	Positive
Air speed	Negative
Heavy cloud cover	Positive
Cyclic solar radiation	Positive
Building material type	Varies
Anthropogenic energy	Positive

#### 11.1.1.2 Cost

The cost of the Urban Heat Island can be divided into social, environmental, and economic costs.

Type of Cost	Examples
Social Costs	Population-adjusted excess mortality rates, heat-related deaths
Environmental Costs	Increase in fossil fuel usage
Economic Costs	Loss of Gross Domestic Product (GDP)

For instance, under a low greenhouse gas scenario, the percent GDP lost from UHI is estimated to be 0.71% in 2050.

### 11.1.1.3 Plans

#### 11.1.1.3.1 Global

#### 11.1.1.3.2 Local

City	Initiatives	Technology
Singapore	Green buildings	Urban greenery
Medellin	Green Corridors	Urban greenery
Sydney	Turn Down the Heat Strategy and Action Plan	Reflective roofs/pavements/sidewalks, Cool roads trial in Western Sydney

## 11.2 Application

MacLachlan et al. (2021) The document outlines a sub-city urban planning modeling approach using open-source tools to measure and monitor localised urban heat island (UHI) mitigation targets. The methodology involves comparing temperature dynamics of low- and high-density census areas using Earth observation data and determining optimal placement of greening elements in proposed plans using a data-driven model. The document concludes that this approach can be universally integrated into urban planning regulation frameworks to mitigate the localized UHI effect and ensure long-term city sustainability. Also it discusses the impact of low population density on housing in Perth, Australia, and the resulting need for strategic land zonation and sustainability targets. ##### Why Data-driven approach

### 11.2.1 Policy limitations

- lacking **specificities** for combating adverse temperature effects at the local level (**sub-city**), therefore not planning practicality

- no **consistency** in planning implementation **methodologies** or steps for **assessing** progress toward UHI reduction targets
- lackage of empirical **evidence for optimizing** UHI mitigation strategies

### 11.2.2 Data to drive the new approach

- Earth Observation (**EO**) data can be processed to identify (un)sustainable urban development through aerial assessments of **land cover change**
- temperature
- elevation

### 11.2.3 Advantages for the Data-driven approach

- EO data can produce **consistent information** necessary for restricting unsustainable development
- **monitor** UHI effects based on associated land-temperature dynamics
- Assessment at finer spatial scales (e.g., block subdivisions)

## 11.3 Methodology

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### 11.3.1 Temperature Modeling

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- Modeled temperature every 3 hours using SOLWEIG model between 2008 and 2010
- 

- Inputs generated from meteorological data, land cover, building DSM, ground DTM, and vegetation canopy REM in QGIS
- 

- SVF computed from vegetation canopy REM, building DSM, and ground DTM using UMEP plugin
-

- Building wall heights and aspect generated from DSM and DTM using UMEP plugin
- 

### **11.3.2 Data-Driven Tree Placement**

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- Site selected for modeling temperature in the City of Fremantle
- 
- Three scenarios processed: current urban footprint, proposed changes, and proposed redevelopment with no trees
- 
- Highest temperatures identified and used to redesign tree placement
- 
- 15 trees distributed according to original design aspects
- 
- Updated vegetation canopy REM reflected new tree locations
- 
- Analysis re-run to compare temperature across redevelopment site
- 
- Modeled all scenarios accounting for influence of neighboring landscape features
-

## 11.4 Result

Table 1: Results of assessments of urban design factors on UHI effect in Perth.

Factors assessed	Effect on UHI effect
Vegetation cover	Negative correlation with UHI effect
Canopy cover	Negative correlation with UHI effect
Building density	Positive correlation with UHI effect
Building height	Positive correlation with UHI effect
Albedo	Negative correlation with UHI effect
Land use	Negative correlation with UHI effect
Urban sprawl	Positive correlation with UHI effect

Table 2: Total population and population density per 0.1 km<sup>2</sup> between 2011 and 2016 for Subiaco and Currambine SA1s as defined by the ABS.

SA1	Total Population (2011)	Total Population (2016)	Population Density per 0.1 km <sup>2</sup> (2011)	Population Density per 0.1 km <sup>2</sup> (2016)
Subiaco	N/A	N/A	325	712
Currambine	N/A	N/A	310	324

## 11.5 Reflection

- Case study: Superblocks, Barcelona

Basically about pedestrian economy. Though there have been many retail modes like KFC and other American fast food, the experience from Europe tells that economy vitality can have a boost with pedestrian-dominated areas. See Barcelona

## 12 Summary

In summary, this book has no content whatsoever.

1 + 1

2

# References

- Google. 2023a. “Machine Learning in Earth Engine | Google Earth Engine.” *Google Developers*. <https://developers.google.com/earth-engine/guides/machine-learning>.
- . 2023b. “Reducer Overview | Google Earth Engine.” *Google Developers*. [https://developers.google.com/earth-engine/guides/reducers\\_intro](https://developers.google.com/earth-engine/guides/reducers_intro).
- Gorelick, Noel, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. 2017. “Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone.” *Remote Sensing of Environment*, Big Remotely Sensed Data: Tools, applications and experiences, 202 (December): 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>.
- Jensen, J. Robert. 1986. “Introductory Digital Image Processing: A Remote Sensing Perspective.” In.
- MacLachlan, Andrew, Eloise Biggs, Gareth Roberts, and Bryan Boruff. 2021. “Sustainable City Planning: A Data-Driven Approach for Mitigating Urban Heat.” *Frontiers in Built Environment* 6. <https://www.frontiersin.org/articles/10.3389/fbuil.2020.519599>.
- Nair, Rahul, P. J. Paul, and K. Poulose Jacob. 2018. “Automated Image Annotation: A Survey.” *Journal of Imaging* 4 (3): 37.
- Robison, Keela. 2018. “The Future of Image Annotation: Human in the Loop.” <https://lionbridge.ai/articles/the-future-of-image-annotation-human-in-the-loop/>.
- Saad El Imanni, Hajar, Abderrazak El Harti, El Mostafa Bachaoui, Hicham Mouncif, Fatine Eddassouqui, Mohamed Achraf Hasnai, and Moulay Ismail Zinelabidine. 2023. “Multi-spectral UAV Data for Detection of Weeds in a Citrus Farm Using Machine Learning and Google Earth Engine: Case Study of Morocco.” *Remote Sensing Applications: Society and Environment* 30 (April): 100941. <https://doi.org/10.1016/j.rsase.2023.100941>.
- Schulte to Bühne, Henrike, and Nathalie Pettorelli. 2018. “Better Together: Integrating and Fusing Multispectral and Radar Satellite Imagery to Inform Biodiversity Monitoring, Ecological Research and Conservation Science.” *Methods in Ecology and Evolution* 9 (4): 849–65. <https://doi.org/10.1111/2041-210X.12942>.