CASA 0023 Learning Diary

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Table of contents

1 Sneak Peak

This is a Quarto book to document my learning journey in **Remote Sensing Cities and Environments** course during my time at CASA UCL 24/25, offering insights learned, its applications, and my own reflections. The module is based on Dr Andrew Maclachlan github page [here]. For those of you who also want to learn Geographic Information Science beyond 'typical GIS' Software, as in use R-Studio, you could also visit his other github page [here].

The lecturers in this course are Dr. Andrew Maclachlan—referred to Andy in this learning diary—and Dr. Ollie Ballinger—referred to as Ollie.

1.1 Introduction

Hi, I'm Nooriza Maharani, a student currently pursuing a Master's degree in Urban Spatial Science at UCL. I graduated with a degree in Geography, specializing in Regional Development Studies. Over the past five years, I have worked as a technical consultant for various governments in Indonesia, both local or ministry level, ensuring that their decision-making is data-driven. Although the results often need to pass through political and budgeting reviews, that's essentially what I do. Over the years, I have assisted local governments in Indonesia managing and utilizing spatial data to support various agendas, including land management, land consolidation, disaster risk assessment, accessibility analysis, and the development of both basic and thematic databases.

Honestly, I don't have a specific topic of interest to add here because I have many! From health to art, from sport analytic to social analytic. I love to connect them all with spatial. That's why I chose an interdisciplinary course at CASA. One thing for sure is that I love doing analytics for social good. I love to look beyond tools and methodologies, focusing instead on the challenges we can address using these methods. In the end, all the sophisticated methodologies and cutting-edge technical tools are meaningful when we use them to address challenges and solve problems, right?

1.2 Why do I choose this module?

The reason I choose remote sensing is because I want to use its vast open resources to analysis various topics. I had learned the foundations during my undergraduate degree but I haven't delved further into it and haven't got any experience to use GEE yet. Thus, I hope at the end of this class, I will get knowledge on to get alternative of spatial data using remote sensing plus analyse various topic across different scale using GEE.

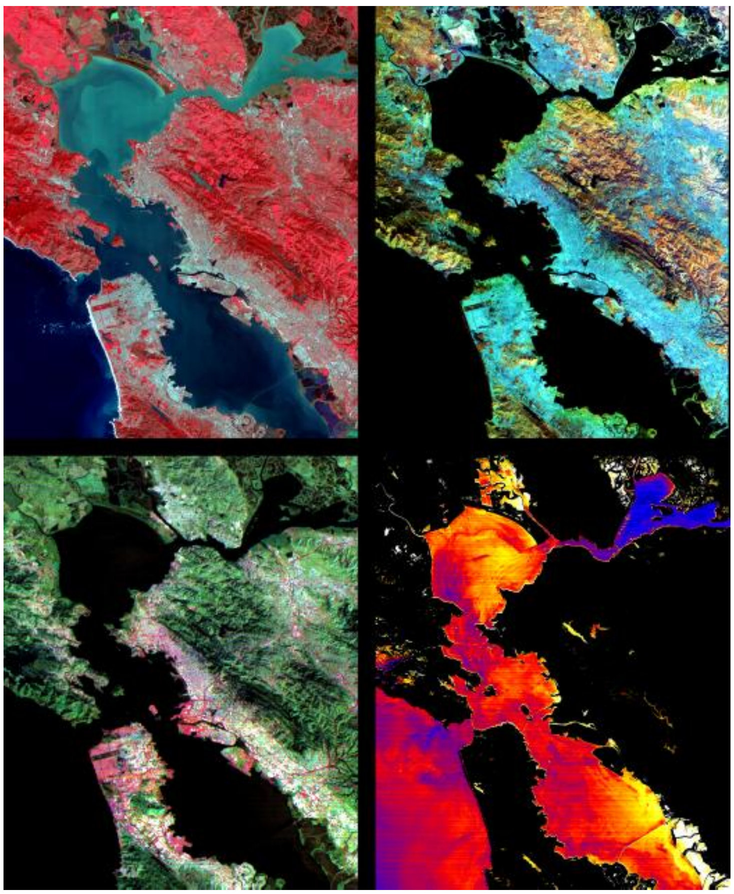
Remote sensing is also an interesting field as it could produce wealth of information without direct contact. Don't you think learning remote sensing makes us have the eye of the bird even beyond? I mean we agree that remote sensing offers perspectives far beyond what our human eyes can naturally perceive such as *allowing* to *see things from above and to see the unseen with the naked eye.*

Figure 1: Seeing things from above. source : Chirps Nature Centre

For example, see the ASTER images of San Fransisco Bay below it highlights different object such as vegetation (upper left); soil & rocks in mountainous area (upper right); urban materials (lower left) ; and water temperature (lower right). All from one image…that's cool !

Figure 1 : ASTER images of San Fransisco. source : NASA/JPL

Practically, learning this course will, hopefully, help me address the challenges I faced during my previous work in Indonesia. For example, while working on a project focused on healthcare accessibility across hundreds of small islands, we struggled to obtain latest data to identify which islands were inhabited and which were not. Additionally, we faced challenges in determining which islands had ports suitable for docking ships. I believe that applying remote sensing data is both cost- and time-efficient in helping the government maintain more precise



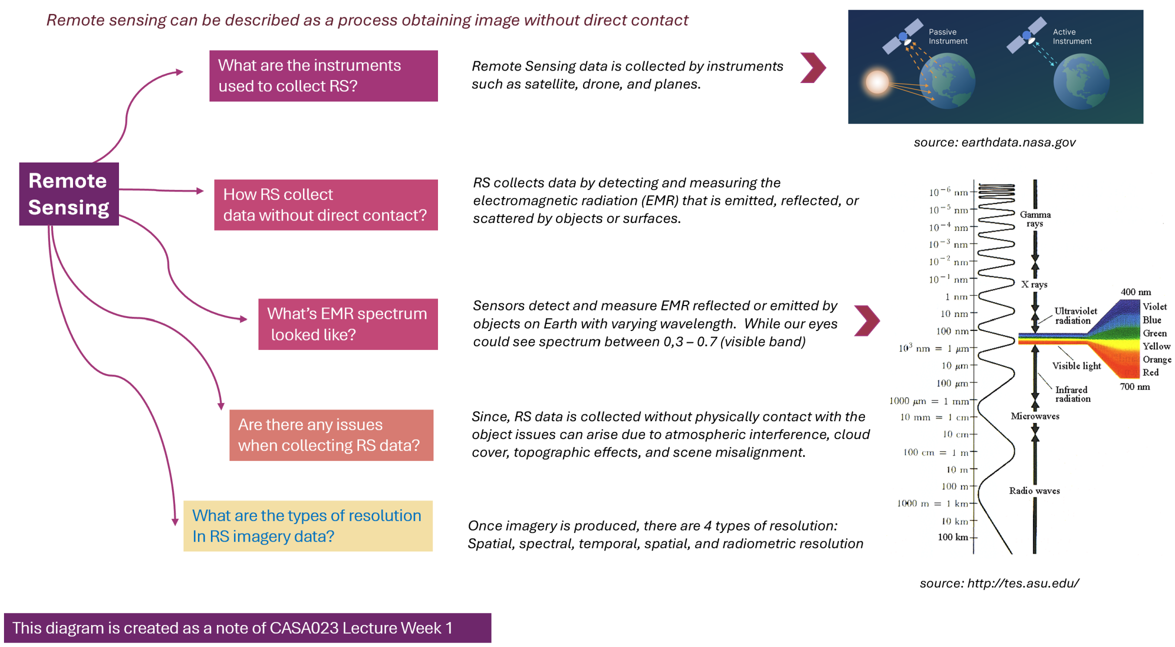
and up-to-date data, which is particularly important in world's largest archipelago country like Indonesia.

Feel free to explore my site to learn more about my learning experience. Hope it helps!

2 Getting to Know Remote Sensing

2.1 Summary

This week, the lecture covers an introduction of remote sensing, such as its vast application, instruments, collection method, and things we have to consider when we deal with remote sensing data. I tried to make the summary using visualization below to make it easier to understand.



During the practical, we explore several tools to deal with remote sensing data such as SNAP (Sentinel Application Platform) and R-studio to plot spectral signature. We are also introduced with 2 imagery : Sentinel-2A and Landsat-8. It is interesting how this two imagery has a global coverage and for FREE. Both of them has spectral bands that could be useful for vegetation monitoring, land cover classification, and agricultural applications. We could benefit from Sentinel-2 frequent observations to monitor rapid changes. Meanwhile, Landsat data allows us to do large areas and long-term vegetation monitoring as it has extensive historical archive and consistent global coverage. Below I discussed the application of both Landsat and Sentinel in a vegetation analysis.

2.2 Application

Landsat for monitoring accross vast region : Detecting of vegetation evolution across China Urban Development

- When I mentioned Landsat have a vast amount of historical data, Han et al. (2025) explores this historical archive of 30 years Landsat data (spanning of landsat 5 to 8) on 2.125 city to monitor the vegetation evolution, using reflective bands such as Blue, green, red, NIR and SWIR (1 and 2) and highlighting vegetation characteristics using NDVI, EVI, and OSAVI. The NDVI and RGB bands were further processed to derive texture variables, including variance, contrast, entropy, angular second moment, and correlation. These texture metrics capture spatial patterns and fine-scale structural details of urban vegetation that may not be visible through spectral bands alone. The findings will classify vegetation in urban area, whether it is decreasing or increasing over time.

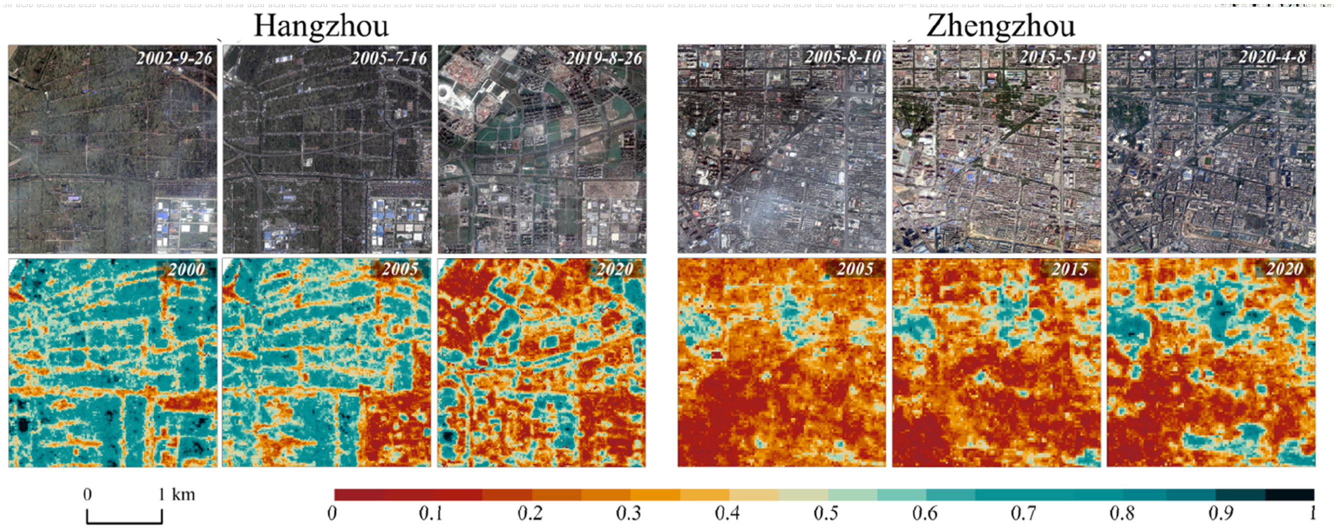


Figure 1: A sample result shows urban vegetation degradation in Hangzhou and an increase in vegetation in Zhengzhou. source : (Han et al. 2025).

However, Landsat is an optical imaging system that is often **susceptible to cloud cover** and has limitations in distinguishing different vegetation types based solely on spectral characteristics. Imagine studying a mountainous region where cloud cover is persistent—using optical images like Landsat for vegetation monitoring and identification would be challenging. To address this issue, Li et al. (2023) utilized Sentinel-1, which operates with C-band Synthetic Aperture Radar (SAR), enabling vegetation mapping under all weather conditions. The SAR data from Sentinel-1, when combined with the optical imagery of Sentinel-2, allows for the production of high-resolution maps that effectively differentiate bamboo forests from other vegetation types. This integration helps overcome the limitations of optical data in vegetation monitoring, where mixed spectral characteristics often lead to uncertainty in distinguishing bamboo from other forest types.

During my time understanding this paper, I was thinking that Landsat's vast amount of historical data has the potential to serve as a framework for evaluating the effectiveness of the **government's long-term** plan on urban greening. t must be challenging for the current government to evaluate which planning schemes have led to present conditions without access to extensive historical data. As a result, assessing the effectiveness of previous plans, identifying trends, and making informed adjustments for future development becomes difficult. For instance, in my country, Indonesia, we have long-term regional planning spanning 20 years, with reviews every five years. However, making accurate projections over such a long period can be challenging, even with periodic reviews. By utilizing Earth observation and historical imagery, we can improve our ability to project urban greenery developments and implement more realistic and measurable strategies

2.3 Reflection

Remote sensing provides diversity in data source, but…. will the implementation be easy?

After exploring the application of the two selected satellites during practical this week, I have concluded that remote sensing data is particularly effective for analyzing large-scale and long-term variations. It can help to mitigate the high costs of manual data collection across vast regions. This insight made me reflect a lot on a similar challenge in my country. We often have challenges to find dataset for spatial analysis as we rely much on vector data, if any it would be outdated. Using remote sensing data not only allows us to have more updated data but also allows us to explore various potential variables derived from satellite imagery. However I must admit despite the potential of remote sensing, its adoption in the government sector—especially at the local level—remains limited. From my experience, this is largely due to a lack of human resources with the skills to process and analyze remote sensing data. For end users, the adoption of remote sensing is heavily linked with the information they can bring on the table, and often might depend on the leadership, budgetary constraints, procedures and personal capacity (National Academy of Sciences. 2003).

Future Applications: I want to use remote sensing to map and analyze how river meandering evolves after the rainy season in my hometown. I have wanted to do this mini-project for years, but since I have not yet fully understood the methods and applications of remote sensing, I have not been able to accomplish it. This interest stems from my childhood observations—back then, the distance between the settlement and the river felt quite far. However, in recent years, I have noticed that the river has become visible from just a kilometer away from my house. In fact, around 2022, during a particularly heavy rainy season, the embankment collapsed, causing a house to be swept away into the river. Honestly, that accident often haunts me when the rainy season arrives. I just want to verify if my observations are accurate through remote sensing analysis and understand the potential risks for future precautions

2.4 References

3 Xaringan and Quarto Book

Lecture this week reminded me of one of powerful figure in Uchiha Clan, the one who can manipulate reality once he activates this-so-called Xaringan. Well, but this Xaringan is not related to figures in Konoha's world but related to a certain library in R Studio that enable us to create neat HTML slides in R.

I think a presentation is basically a way to communicate insights to the audience, and a great presentation may even "hypnotize" the audience. Is that one of reasons it called Xaringan?

3.1 Summary

```
xaringanExtra::embed_xaringan(url = "https://nooriza16.github.io/Xaringan/Xaringan.html",
```

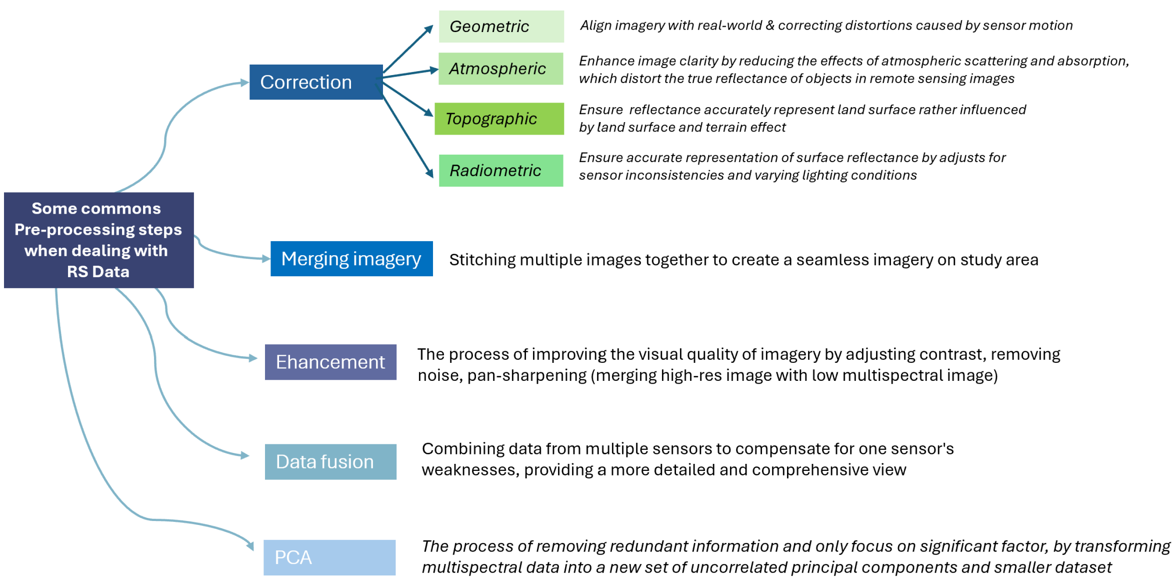
3.2 Reflections

For someone who is not familiar with html, learning Xaringan is definitely challenging compared to powerpoint, as we just usually click tabs on power point. Honestly, I still consider power point provides more themes and more visualization effects that is easily to access compared to Xaringan. However, as I delved further I realize that using Xaringan is providing us with flexibility even such as positioned our picture. So far, I feel like Xaringan is best at incorporating snippet code on presentation or interactive features that usually too heavy to load in power point. Besides, it helps me to give a sense of what html look like.

4 Image Correction

4.1 Summary

Here is my note based on this week's lecture that explores steps people usually do in image correction. Although sometimes we get a "ready-to-use data" without the need to going through all of these process, having the basic understandings of these steps would help us understand the quality our data.



This diagram is created as a note of CASA023 Lecture Week 3

I also add several new terminologies, based on my own note during the lecture, related to image processing during this week's summary

Reflectance and radiance Reflectance is basically the amount of light when a surface reflect the light, while radiance is the amount of light captured by sensor after interacting with Earth's surface

Digital Number	A raw value for a given pixel that represents the intensity of radiation received in a specific spectral band. Digital number is important because it serves as a basis for image classification, for example digital number close to 0 represents object that absorbs much incoming light (low reflectance) such as water bodies or shadows.
Digital Object Substraction (DOS)	DOS is an atmospheric correction method that subtracts pixel values based on the amount of difference between digital values of dark objects (usually water bodies) with their corresponding reflectance
Collection, level, and tier	I will use the Landsat case to explain this terminology. In Landsat the collection would be named as Collection 1 and 2, it represents the sequence of launching time and their mission : Landsat 2 is the latest. Level 1 is a scaled digital number, while level 2 is further processed data. Meanwhile, tier 1 is the highest quality data from Landsat and suitable for time series analysis. source: https://www.usgs.gov/landsat-missions/landsat-collection-2-level-1-data

4.2 Application

In this week application, I would like to explore the application of remote sensing on my favorite topic : data unavailability. In developing countries like Indonesia, maintaining updated and comprehensive data is challenging due to time and cost constraints. A study in Pakistan also mentioned similar challenges, particularly data related to socioeconomic condition that often limited and sporadic (Arshad et al. 2023). Honestly, this topic piques my interest because Bill Gates came across an article in The Washington Post and seems fascinated with the idea of using remote sensing to identify poverty, as he shared on X.

Figure 1 : Tweet about satellite imagery on detecting poor region. Source : Twitter

Arshad et al. (2023) addressed those challenges by deriving information through satellite imagery. They use publicly accessible high-resolution satellite imagery (Google Maps API with 16 zoom) and Landsat 7 (low resolution data). Google Maps API provides high-resolution imagery to identify man-made features like buildings and highway which are indicators of development levels meanwhile Landsat 7 is used to train Convolutional Neural Networks (a method of feature extraction from imagery in Machine Learning) in identifying nightlight bin (low to high). Areas with higher levels of economic activity and development tend to have more lights at night. This method will produce a map that indicates a poverty and development level compared to poverty line. The results are then validated using actual socioeconomic data from surveys. Below is a map where each point represents a poverty clusters (10x10 km area), comparing predicted and actual data. Green points indicate clusters above the poverty line, while red points indicates the opposite.

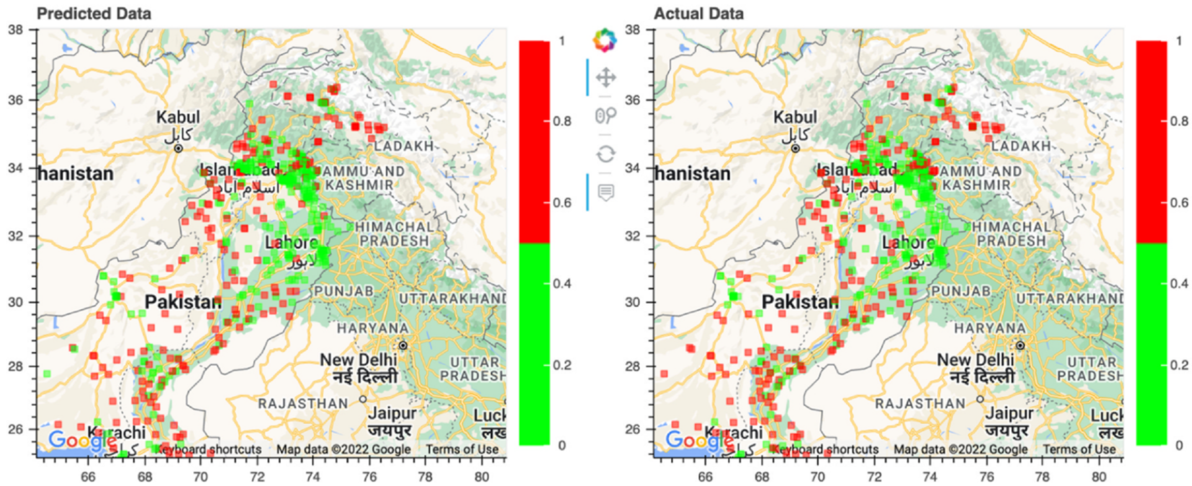


Figure 2 : Socioeconomic conditions compared to poverty line in Pakistan. Source : (Arshad et al. 2023).

When reflecting on the map above, I would prefer to visualize the classification results as polygon rather than points, as they were more intuitive. Additionally, it would be nice to map the difference across the years, Ben Abbes et al. (2024) just do this ! They use multispectral images (Landsat 5, 7,8) and Nightlight images (from Defense Meteorological Satellite Program (DMSP) and the Visible Infrared Imaging Radiometer Suite (VIIRS)) in Southeast Brazil. The classification result is represented using an estimated wealth index, and it can even map socioeconomic transformation over 10 years in a single map! I think the map is quite brilliant. He takes the delta between the latest and past data and visualizes it with a gradual color scale. The stronger the hue, the larger the margin

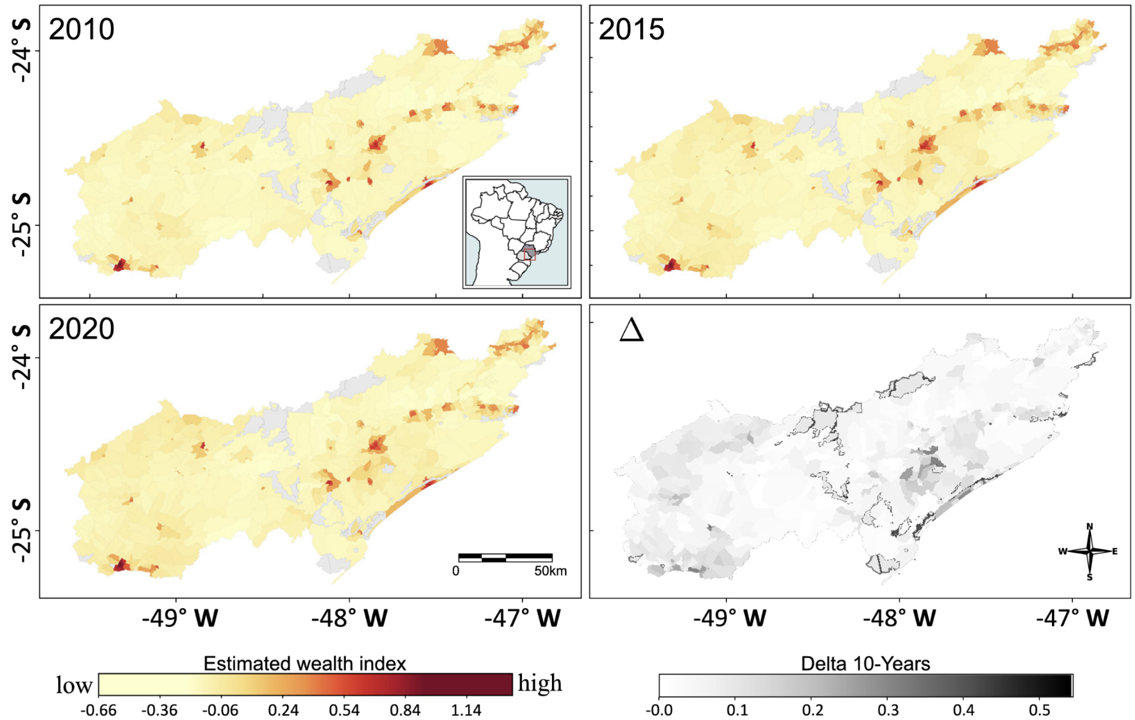


Figure 3 : Spatio-temporal mapping of wealth index estimations in Southeast Brazil. Source : Ben Abbes et al. (2024).

4.3 Reflection

I think performing Remote Sensing correction on R Studio is quite challenging, as I become more used to using 'button' in Remote Sensing application such as ENVI or SNAP. After this week's lecture, I genuinely think that Remote Sensing is quite complex as it is not only an image but beyond the imagery each pixel is composed by digital number and it could be linked and better interpreted using regression too. Understanding the image classification using machine learning is also quite challenging for me, as they use new terminologies that I haven't heard before such as convolutional neural network, epoch, and data training.

Honestly, remote sensing combined with machine learning quite scare me off. However, I try to look beyond the methodology instead focusing on how explanatory remote sensing can be when combined with classification and prediction task, tasks machine learning good at. I think looking beyond the methodology and focusing on the exciting application has also helped me me thrive on managing challenge during this Master's. After reading the paper, I tried to delve further into the combination of remote sensing and machine learning. If I could turn back the time, I would like to deploy this combination to make my works faster. I recalled during my works years ago, the project needed to identify thousand ports across hundred of islands in Indonesia, and we did that manually ! If I understand correctly, I could combine image classification techniques, such as convolutional neural networks, with high-resolution imagery to detect local ports used for docking ship (typically made of wood or cement) in the ocean.

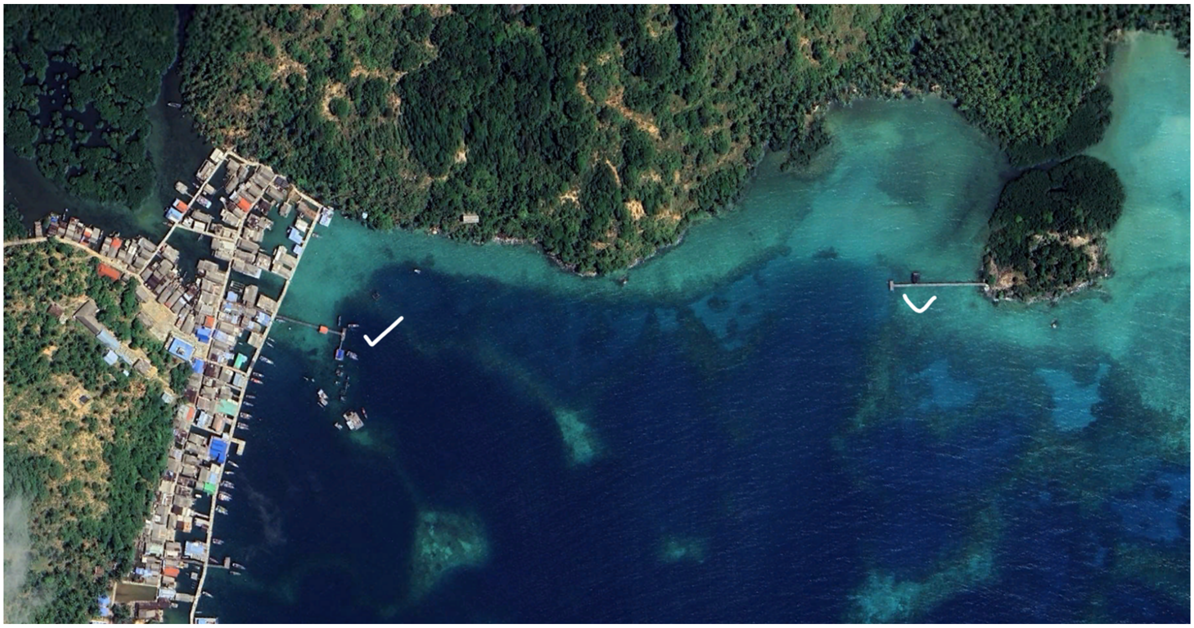
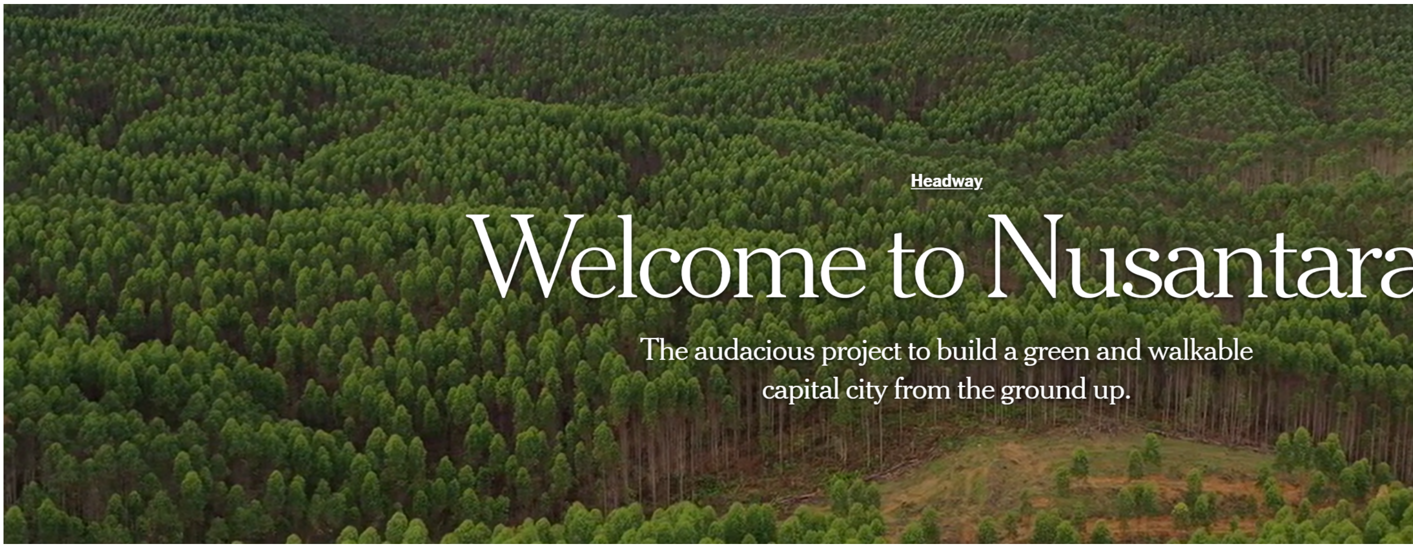


Figure 3 : Google Earth Imagery portraying local ports in Anambas Islands. Source : Google Earth, 2024

4.4 References

5 Policy

Project Case : A New Relocated Capital City of Indonesia ; From Jakarta to Nusantara



Source : www.nytimes.com

5.1 Summary

Recently Indonesia planned to move its capital city from Jakarta (in Java islands) into Penajam Paser Utara City (Borneo Islands), as the current capital city, Jakarta, faced an issue of sinking, land subsidence, overcrowding, low air and water quality (Bappenas 2021). The term Nusantara is used to name this new capital city, symbolizing the varied geographic settings and cultural diversities of Indonesia.

As for the time this published, Nusantara Development is on the phase 2 (2025-2029) that involved strengthening core area (housing, office, commercial zone). Thus, in the time being, Jakarta will still remain the capital of Indonesia until the Presidential Decree on the transfer of the capital to Nusantara is issued. The issuance of this decree will depend on the readiness of the new capital city, including the preparation of all supporting systems such as infrastructure, human resources, and governance systems.

Figure 1: The Relocation Settings and Vision. source: (Capital Authority 2024)

The new capital city, Nusantara, is designed as a **forest city**, with 75% of its designated area being green space. This design aims to create a harmonious blend of urban development and biodiversity hotspots (Borneo Island, where Nusantara is located, is famous for its tropical rainforests). However, the design of being a forest city, its proximity to the rainforest, and its drive on landscape change would present significant **challenges**. One of the major concerns is the increasing likelihood of mosquito-borne diseases (such as **malaria**) spreading in the new capital, which are prevalent in tropical regions (Surendra et al. 2024). Since malaria is both a global and local challenge, certain goals should be considered to support Nusantara's sustainability, such as:

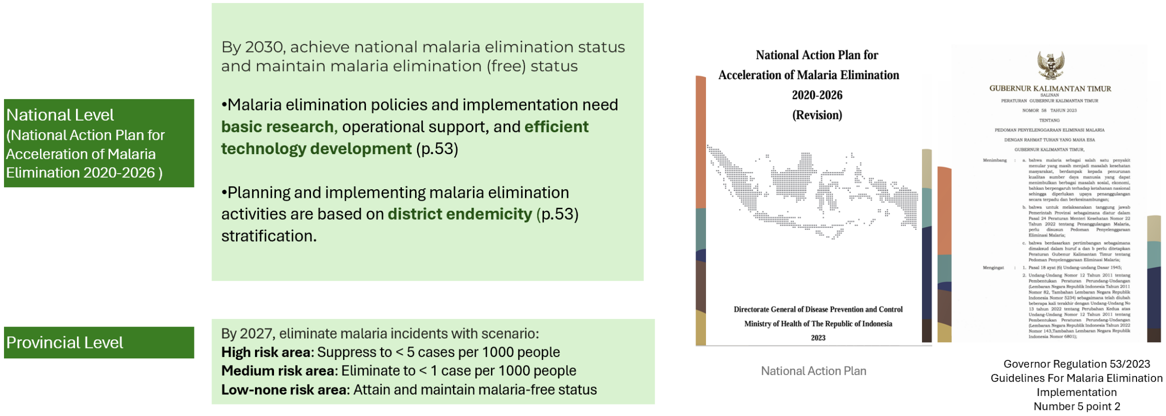
5.1.1 Policy

A. Global Goals : Sustainable Development Goals (SDGs) 3.3 : Fight Communicable Diseases

The SDGs propose achievable global in combating malaria with target that in include reducing incident, mortality rates, eliminate malaria in 35 countries by 2030 and prevent resurgence of the disease in a malaria-free country. Meanwhile, Indonesia's estimated malaria incidence per 1000 population at risk is still on range between 1-50 incidents per 1000 population in 2023. To achieve target of Global Goals, (WHO 2021) have launched global technical strategy for malaria with framework such as:

Figure 2 : SDGs Goal and WHO Technical Strategy

B.National Level : National Action Plan for Acceleration of Malaria Elimination 2020-2026



5.2 Application

Remote Sensing as Baseline for detecting malaria hotspot

In malaria elimination projects, remote sensing can serve as a crucial baseline data source for mapping malaria hotspots by integrating climatic and land-use factors. @wimberly2021 proposed a framework that leverages Earth observation products to identify mosquito habitats based on climate conditions, human activities, and specific land-use patterns.

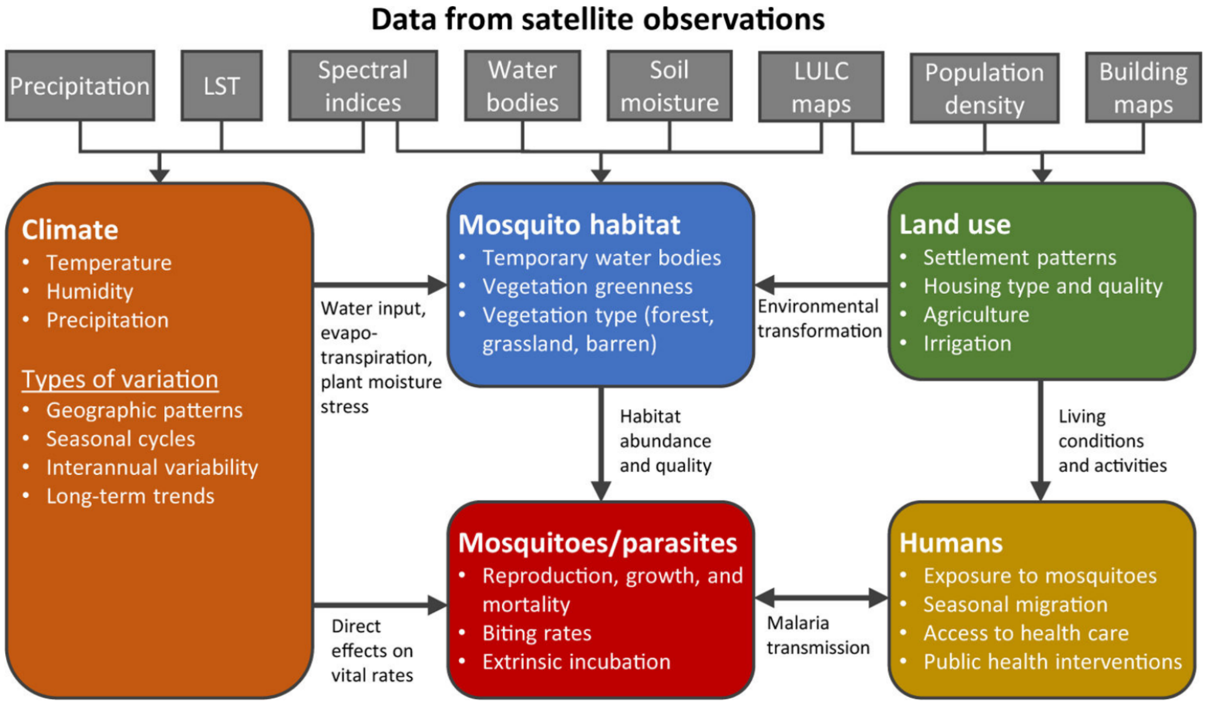


Figure 2: Framework in which Remote Sensing used in Malaria studies. source : Wimberly et al. (2021).

To address policy mentioned in section 2, I underlined some dataset that could be used to the analysis:

Data	Purpose
• **Sentinel-2 (rainy season)**	*Highlight water bodies and wetlands* – These serve as proxies for mosquito breeding sites. *Vegetation and land cover* – Provides insight into potential mosquito habitats. *Surface temperature* – Acts as a proxy for mosquito activity.
• **Digital Elevation Model (DEM) Data/Topography**	Helps to provide topografy to identify potential inundation areas, which could influence mosquito breeding patterns.

Data	Purpose
• **Microsoft Open Buildings**	Useful as a proxy for human settlements and potential exposure risk.
• **Rainfall Data**	The rainfall season can be considered as a timeframe for analysis. However, if locally recorded rainfall data from the Indonesian Climatic Institution is available, it could help refine the identification of rainfall patterns, allowing for a more informed selection of the time series.

5.3 Reflections

During this week, I got a lot of reflections as I finally found lecture that explicitly bridging the gap of 'academics' to real-world policy. My reflections would be:

1. Combining remote sensing with GIS

   Since Nusantara is still uninhabited, we could model nearby settlements to investigate the remote sensing framework. By combining the results with malaria incident data, we can validate our classification—analyzing what percentage of high-risk areas have recorded incidents and which have not. While global and local malaria elimination frameworks mention aggregating incident data and risk levels, they do not explicitly emphasize mapping. Using maps, we can overlay malaria hotspots with incident data, land use, and socio-economic factors. As Naserrudin, Yong, et al. (2023) notes, people are exposed to malaria due to professions that require them to venture deeper into the forest.

2. Remote Sensing and GIS is good, but enriching the analysis with **affected communities** make it better

   Beyond remote sensing data, incorporating local knowledge can improve the analysis. Understanding how affected communities respond to malaria provides insight into the effectiveness of mitigation efforts (Naserrudin, Lin, et al. 2023). These communities have lived near rainforests for generations and are directly affected, making their experiences valuable for practical prevention strategies.

3. Implementation challenges, the need for collaboration

   One the most important key-takeaway from the lecture is that "some academics papers are too technical, without clearly addressed policy; some policy don't include academic findings they could benefit for." This condition lead to a gap between academics and urban governance. However, in my observation during my work with the government the potential cause is human resources (make the adoption of academics finding hard to implement), annual budget cycles (governments prioritize immediate results and may be reluctant to invest in the long-term experimental processes typical of academia). Bridging the gap on malaria prevention requires collaboration and commitment not only between epidemiologists, healthcare, and geospatial analysts but with the governments to ensure research translates into actionable policies.

5.4 References

6 Introduction to GEE

6.1 Summary

This week's material is all about GEE (Google Earth Engine). In a simple definition, GEE is a cloud platform that allows us to access satellite imagery for the whole world and spatial-computation on Google for free. GEE hosts massive amounts of satellite imagery and we as a user request their imagery data and analyse it on the cloud-platform without have to worry about the capability of our local machine. Basically, GEE has an architecture that collects user input (client side) and then process this input (server side). In GEE we could manage both raster and feature (vector) data. We input command on GEE mostly using Java Script programming language. As someone enthusiastic with GEE, the need to learn 'a new' programming language almost discourages me, as I worry that I might mix up all the programming languages I have learnt before.However, when I looked at the way GEE articulates data structures, I found it quite similar to Python, with just a few additional keywords, such as 'var' to denote variable. Below are some basic pieces of information from Andy's lecture about the GEE language that GEE starters need to know. Check out this introduction from Google if you're still unconvinced

```javascript
// All the javascript you need to know (almost)

var number = 1

var string = 'Hello, World!'

var list = [1.23, 8, -3]
print(list[2])

var dictionary = {
  a: 'Hello',
  b: 10,
  c: 0.1343,
  d: list
}

print(dictionary.b)
print(number, string, list, dictionary)
```

Figure 1 : Basic javascript in GEE. source : Andrew Maclachan Github

When I was first introduced to the idea that GEE is efficient in managing raster data, I was curious about how this efficiency works. For example, if I want to use Landsat 8 (30 m resolution) to analyze the whole UK, it would require processing every 30 m pixel across the whole region, which I assumed would take longer time. However, what makes GEE faster dealing with those data actually because there is a pyramid of reduced resolution in GEE, which able to optimizes performance using lower-resolution versions of the data when full detail is not necessary and also resampling method to adapt the analysis requirement. Thus when performing analysis, GEE does not just take the original image resolution, but GEE adjusts image resolution based on our output needs. In summary, when you are zooming out and zooming in, GEE retrieves different resolution of imagery.

As a starter GEE interface is a bit too much, like where should I focus on because there are 3 main parts of it. Two years ago I even tried to write my first script on console panel :) because I thought it would be similar with R Studio. Come to think back on it, GEE has already put the 'section to code' intuitively in a centre called code editor. See the picture of GEE interface below, if you are like me a starter in GEE the very first thing that anyone should notice the most is code editor : a space to write our code and for the other parts let our self become adjust to it along the time.

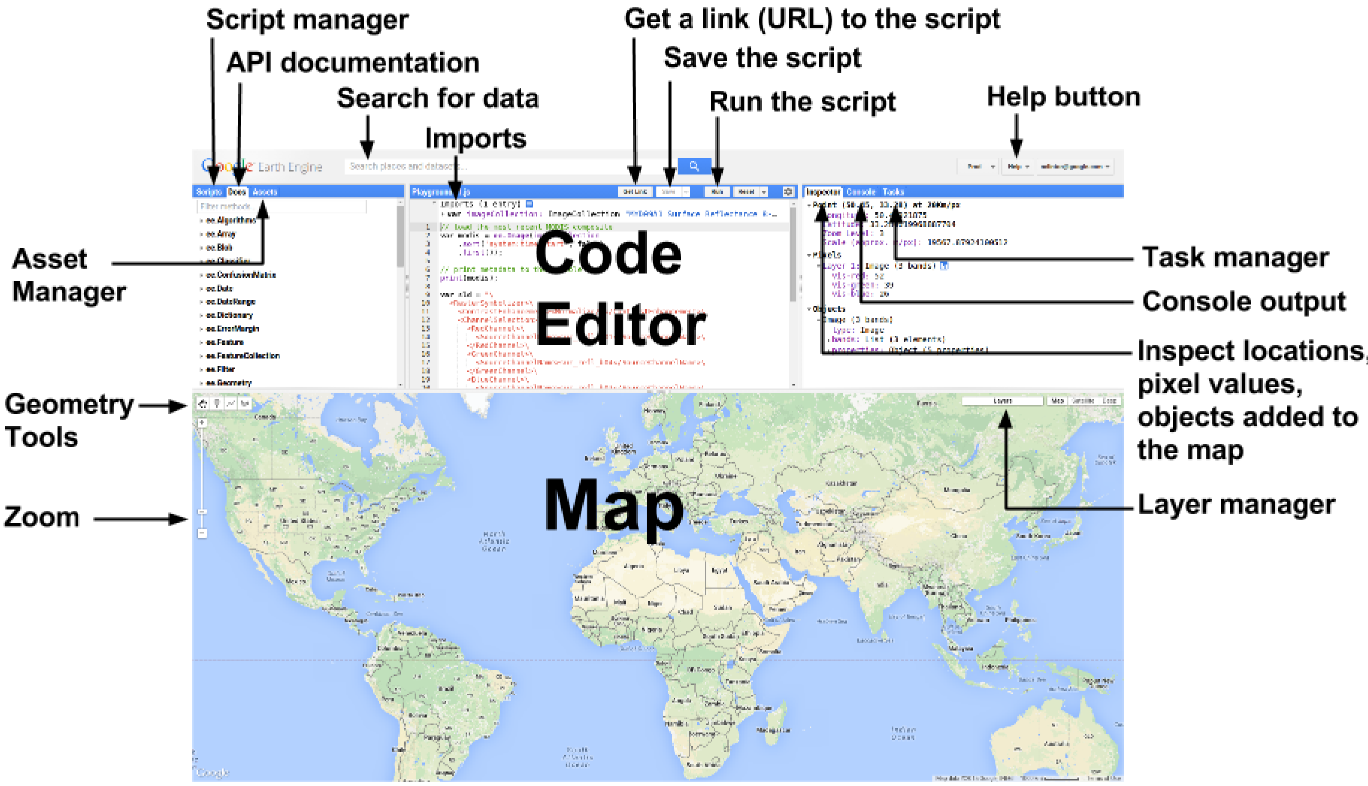


Figure 2 : GEE Interface. source : [GEE Beginer cookbook]

6.2 Application

» >"*We might not be able to turn back time, but well..... we sure can look back using Landsat"*«

In this section, I would like to explore the **GEE strength on providing vast archive** of imagery to investigate unplanned settlements during urban transformation projects. The vast historical of imagery enables researcher to look back at various critical date for development plans. @yilmaz2024 used collection of Landsat data (Landsat 5, 6,7) from March 1983 to February 2007 to compare land use before and after urban renewal project happen. When I pondered upon this it is like investigating planning product in a sense of is it *planning to fail or failing to plan?*

With analysis of temporal imagery, the result show a contrasting initial condition of urban renewal's targetted area and its projection. For instance, in Gaziosmanpasa district it is projected to be a forested area in the future, however after looking back up to one year before the approval of the development plans turns out it is highly urbanized area. The contrasting initial condition and urban renewal project in this area will present challenge to the success of the plan, as the development of greening area will fiercely compete with massively built up area.

This finding also underlined the *issues* that projected plan is not carefully consider the dominant land use of the area, which will most likely shape the future land use. As a planner, it is not easy to make sure the execution of plannings we made although we have risk mitigation in our proposed plan. However, after reading this paper I realize that we can utilize the historical archive of satellite imagery in GEE to monitor land use growth pattern before projecting its future planning target, especially to target building green space or open space among the growing built up areas.

LULC status of urban renewal project areas before development plans and planning activities in project areas.

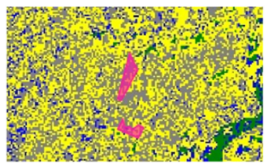
Project	1980 Metropolitan Land Use Plan planned land use type	LULC maps before development plans (Frames refer to urban renewal project areas)	Development plan information	
			Spatial plan type	Acceptance date/Planned use
Gaziosmanpasa Sarıgöl I	Current Residential Area		Slum reclamation and prevention binding implementation plan	January 21, 1987 Area to be afforested
Gaziosmanpaşa Sarıgöl II	Current Residential Area		Slum reclamation and prevention binding implementation plan	January 21, 1987 Area to be afforested

Figure 3 : Comparisan of existing land use and its projection. Source : Yılmaz and Alkan (2024)]

The case of comparing urban renewal project with old urban areas is interesting in urban management. However, "Urban Renewal Mapping: A Case Study in Beijing from 2000 to 2020" (n.d.) underlined the challenges to get enough information during the process because **the lack of detection methods framework in urban renewal mapping**. As we can see from the previous paper, they use random forest algorithm to identify urban and non-urban and validate using Kappa coefficients. In this paper, they propose a complete mapping framework including segmentation in detecting temporal information of urban renewal. Some key take away from their proposed framework are:

1. Data Preparation : define the urban scope and limit its boundary combined with image collections to get time series image stacks
2. Identification of old/renewed urban areas : LandTrendr fitting (algorithm to detect inter-annual land cover change) + segmentation of loss/grain (quantifying the dissimilarity) and random forest classification
3. Temporal detection : compare extraction strategy with different loss/grain and combination of NDVI/NDBI/NDMI + validation samples

Oh wait….for someone who is not really interested in remote sensing's application in urban mapping this will be challenging, but maybe the snapshot of the result below can help you grasp the intuition of how those steps yield the result. We can see from the left picture that we could have NDVI index graph to explain the built-up area

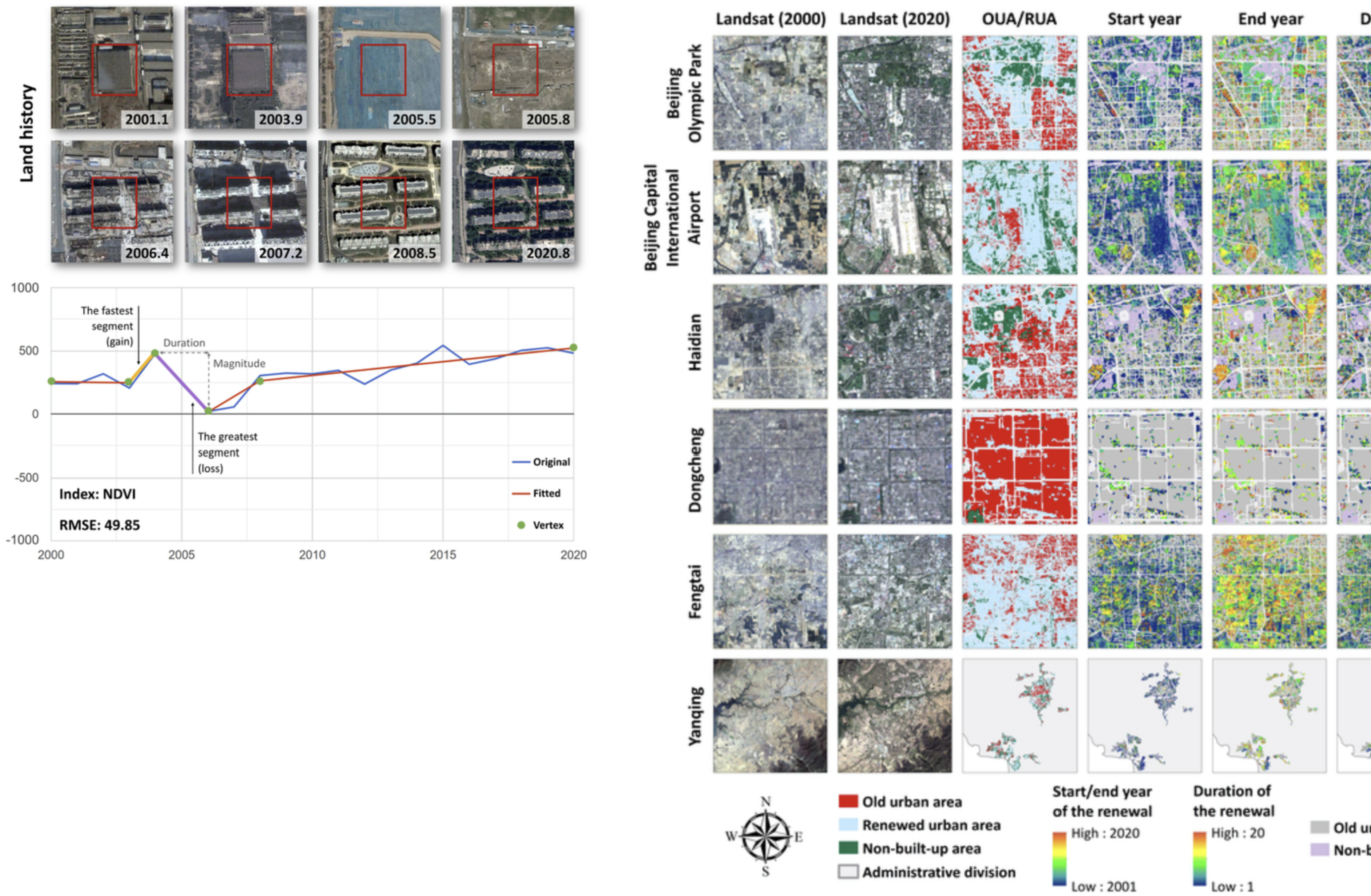


Figure 4 : Left : index of NDVI in time series with curve from LandTrendr ; right : urban renewal and urban old area. Source : (Ni et al. 2023)

6.3 Reflection

The most exciting part of using Google Earth Engine (GEE) for me is the ability to share analysis results through web map applications. Clients are usually more engaged when they can interact with a visual platform that helps them understand the project better. Remote sensing analysis is often more complex than regular vector processing, so I imagine the difficulty on to deliver the results with its key preprocessing step. What makes it even harder is, we often need to switch between remote sensing desktop apps and present the results.

By using a web map, we make it easier for clients, even those without a technical background, to explore and understand the intuition of the analysis : what layers we have, what imagery we use, what imageries we combined. The interactive map will provide a clearer view of the project, allowing clients to see the bigger picture and stay engaged throughout the process. However, I must admit GEE is only a tool to make best use of it we need a prior fundamental concept of remote sensing, such as spectral band, enhancement, fusion, PCA, and other remote sensing pre-processing steps. Because in every script we write there should be a thinking process on why we do reduction, why we do enhancement, basically need our judgement to navigate each steps.

I would also like to highlight the importance of domain knowledge when using remote sensing sources. As I mentioned before GEE is just a tool–its ability to provide remarkable insights truly depend on the person utilizing it. We might use the same satellite imagery, but with domain knowledge the analysis will yield different results. For example, *The Economist* uses satellite data to track conflict in real time (FYI, I come across this in CASA Seminar in 2023 during the time I prepared my graduate's school application), *Pediatrics* use remote sensing to understand the association of air pollution with asthma prevalence. *Archaeologists* can utilize remote sensing alongside other methods to understand landscape of historical sites. There are *tons* of use cases, right?!

If you are having curious mind like me, check Dr Ollie Ballinger's github page here to see how powerful remote sensing can be when combined with domain knowledge. Ah yes, he is also a lecturer in Remote Sensing class.

6.4 References

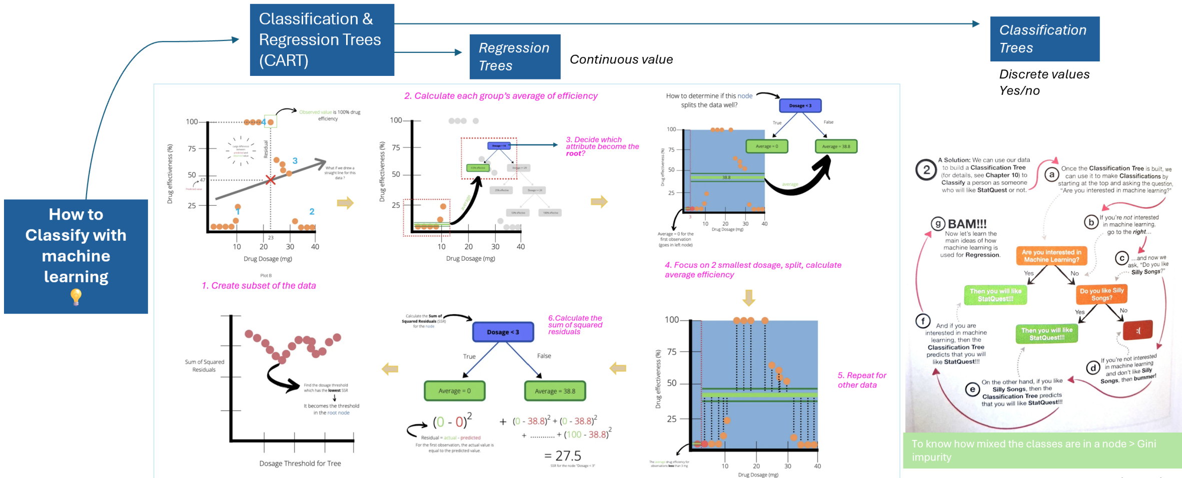
7 Classification I

7.1 Summary

Take a deep breath okaaay? as today's lecture is quite intense ! The lecture is divided into 2 main points: **how classification is used** and **how to do the classifications**. Classification process in remote sensing often applied in several topics, such as:

Topics	Sensor
Urban expansion/sprawl	Landsat
Land Use Changes on driving air pollution	Sentinel 3 : Sea & Land Surface Temperature Sentinel-5: precursors major air pollution
Urban green spaces	Several options such as high, medium resolution imagery ; Lidar-hyperspectral
Monitoring forest and illegal practices	Landsat
Forest fires	Landsat

In practice, classification in remote sensing is combined with machine learning techniques that include training data and testing data. Today's class focus on classification and regression trees (CART). As a visual learner, learning using this diagram make me understand the complex materials better, hope it helps you too.



Source : Luka Beverin (Medium)

Source : Josh Starmer's Book(2022)

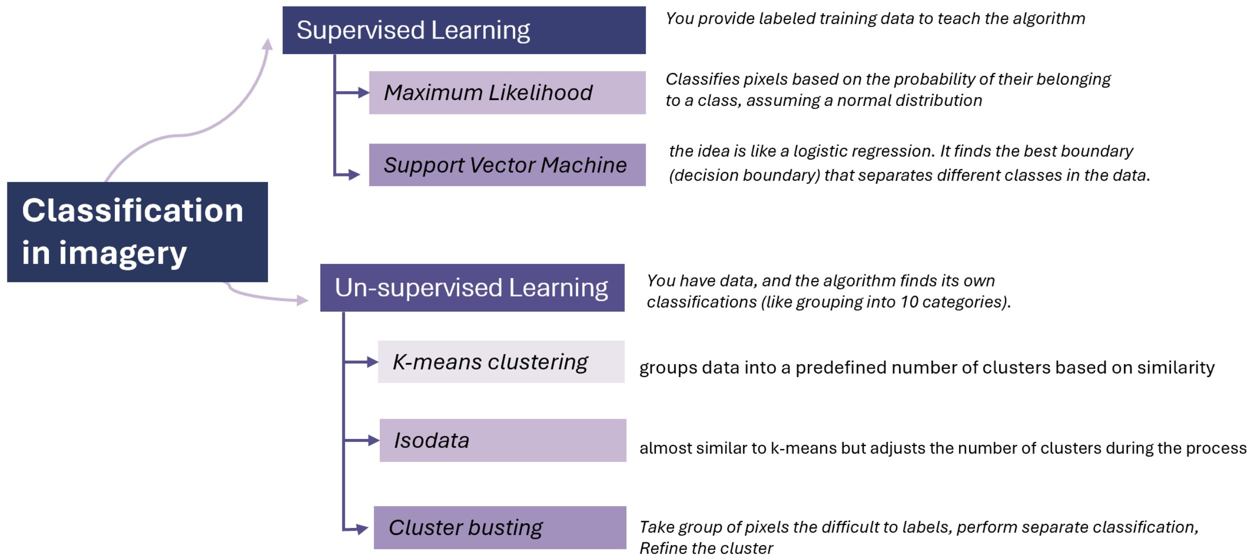
This diagram is created as a note of CASA023 Lecture Week 6

One of the challenge using machine learning is OVERFITTING. In simple terms, overfitting happens when a model fits the training data too well but performs poorly on new data. There are many ways to deal with overfitting, such as : (a) Limit how the tree grows (b) Pruning – Remove unnecessary branches after the tree is built to simplify (c) Pruning with Alpha Regularization – Remove leaves, increase the pruning parameter ( ) and find the lowest tree score. The goal is to keep the tree small without sacrificing performance. (d) Data Splitting – Divide data into training (to build the tree) and testing (to evaluate performance) sets and find the lowest sum residuals in regression tasks

One more thing, as decision tree is not good with new data we could use another method called random forest. I like to use the Chatgpt analogy on this: a Decision Tree is like asking one expert for advice meanwhile a Random Forest is like asking 100 experts, each with a unique take, then averaging their answers.

How does it apply to imagery?

The idea is to turn each pixel in an image into a specific category, you'd use image segmentation, which labels each pixel based on predefined categories. This applies to both of supervised or unsupervised learning.



This diagram is created as a note of CASA023 Lecture Week 6

7.2 Application

In my understanding, classification in remote sensing will be easier if object detected having a stark difference. The more differ the object the easier the detection would be. Then I was thinking about **dense object with high irregular shape**, such as informal settlement. How does the classification work? It must be posing a unique challenge. Thus, I want to explore how the classification of informal settlement in small town of Cape Town, South Africa.

Apparently,machine learning with its ability to detect pattern or by grouping similar area together is really helpful on this. Chamunorwa, Shoko, and Magidi (2024) tried to compare 4 machine learning algorithm to detect sparse informal settlement using Gradient Boost, KNN, Random Forest, and Support Vector Machine [SVM] with data extracted from cloud computing repositories.

KNN is valued because its simplicity in classification tasks (effective for well-defined clusters). Gradient Boosting is valued for its ability to improve performance through the sequential combination of weak models, (capturing complex interactions within the data). Meanwhile, Random Forest : an ensemble method, is good at managing high-dimensional data and deal with overfitting. SVM is strong in classifying data with clear margins by creating optimal decision boundaries. Overall, the Random Forest and Gradient Boosting models were found to be the most effective for delineating informal settlements with accuracy of 89.07 % for RF and 89.05 for Gradient Boosting. It is amazing to see how this machine learning can capture the different cluster of informal settlements.

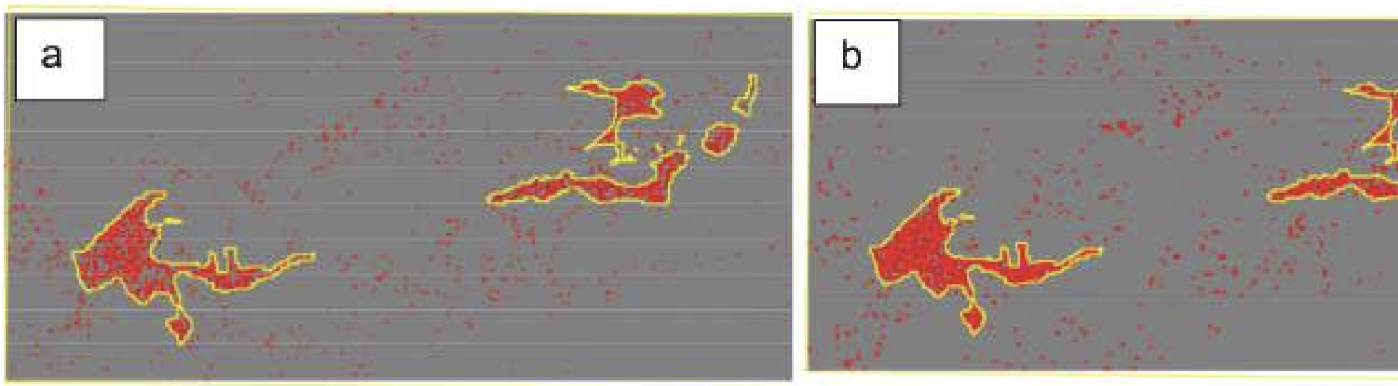


Figure 1 RF (left) and KNN (left) predicted outcome

I wondered if this same algorithms **applied to** urban area with **different morphology** what will happen, will it maintain its accuracy or declining. Because we know that each city experiences different processes and mechanisms, resulting in unique urban conditions and morphology. It's even molded with different policy and government's agenda that might shape them into what they are today.

The answer is yes, it can be ! Although they come from different process Ibrahim et al. (2019) highlight that informal settlements still have unique identifier that make them distinguishable from formal settlements. However, they also mentioned that accuracy tends to improve when the model is trained in areas close to the prediction site.

7.3 Reflection

I know that machine learning is really helpful in automation in classification, however I must admit that it will take time for me to fully understand what and why of its underlying process. The complexity of its process and even the interpretation can be overwhelming without foundation in the principles behind them. Nonetheless, with continuous learning, exposure, and practice my understanding will gradually develop, hopefully!

Future applications : I would love to apply classification techniques to quantify the actual proportion of greenery in urban areas, both planned greenery or unplanned one. This proportion will then be compared to the designated urban greenery targets. I am particularly interested in this because, in my country, local governments are required to allocate at least 30% of their total area to green spaces. This analysis will help answer important questions such as: Have the governments achieved this target? If so, to what extent? This approach demonstrates how data-driven decision-making can lead to more informed judgments.

7.4 References

8 Classification II

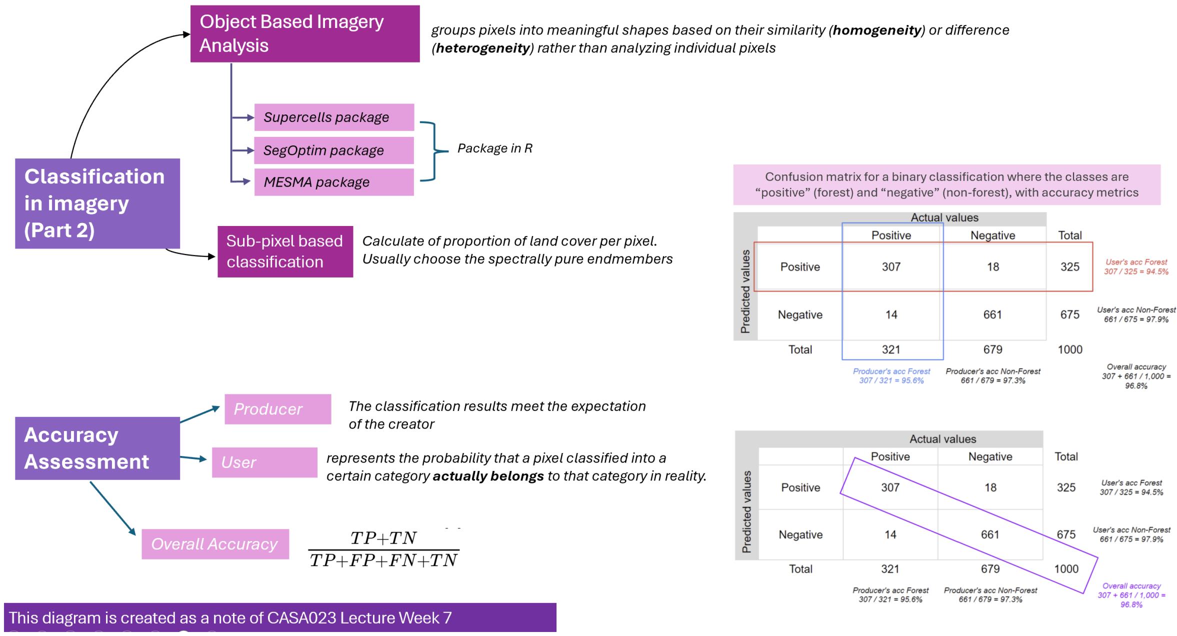
Before summarizing everything, I need to bring this to my self when reflecting back to all the materials for this past 2 weeks.

If you're someone who doesn't know much about ML, here's what Andrew Ng's got to say:

Source : Medium

8.1 Summary

This week continues last week's topic on classification in remote sensing and explores method to assess the accuracy of our classification results. Here they are.....and again with easy-to-digest diagram.



Note : Confusion Matrix's source : https://google-earth-engine.com/

8.2 Applications

This week I will explore the application of classification technique I am quite interested in : Object Based Imagery Analysis (OBIA). I am interested in OBIA because there is a segmentation part in generating the result. The reason I am interested in OBIA because to me this method is more human-like classification. It processes image based on meaningful objects rather than individual pixels. Cool isn't it? So how does it fit into informal settlements detection?

OBIA need information about relevant bands (such as RGB, NIR, SWIR) and indices (such as NDVI, NDBI, NDWI) to process the algorithm. In GEE, an algorithm called simple non-iterative clustering (SNIC) was used to segment image into super pixels (called it a group of similar pixels) based on color and spatial coordinates. Then, calculated contextual characteristics (height, shape, size, texture) afterwards. The combined spectral and contextual information was used to classify the land cover using machine learning algorithm such as Random Forest. Gxokwe and Dube (2024) applied this combined with ground truth and Sentinel 2 to map informal settlement in Capetown Metropolitan Area, and the result is shown below, with distribution quite scattered at different places.

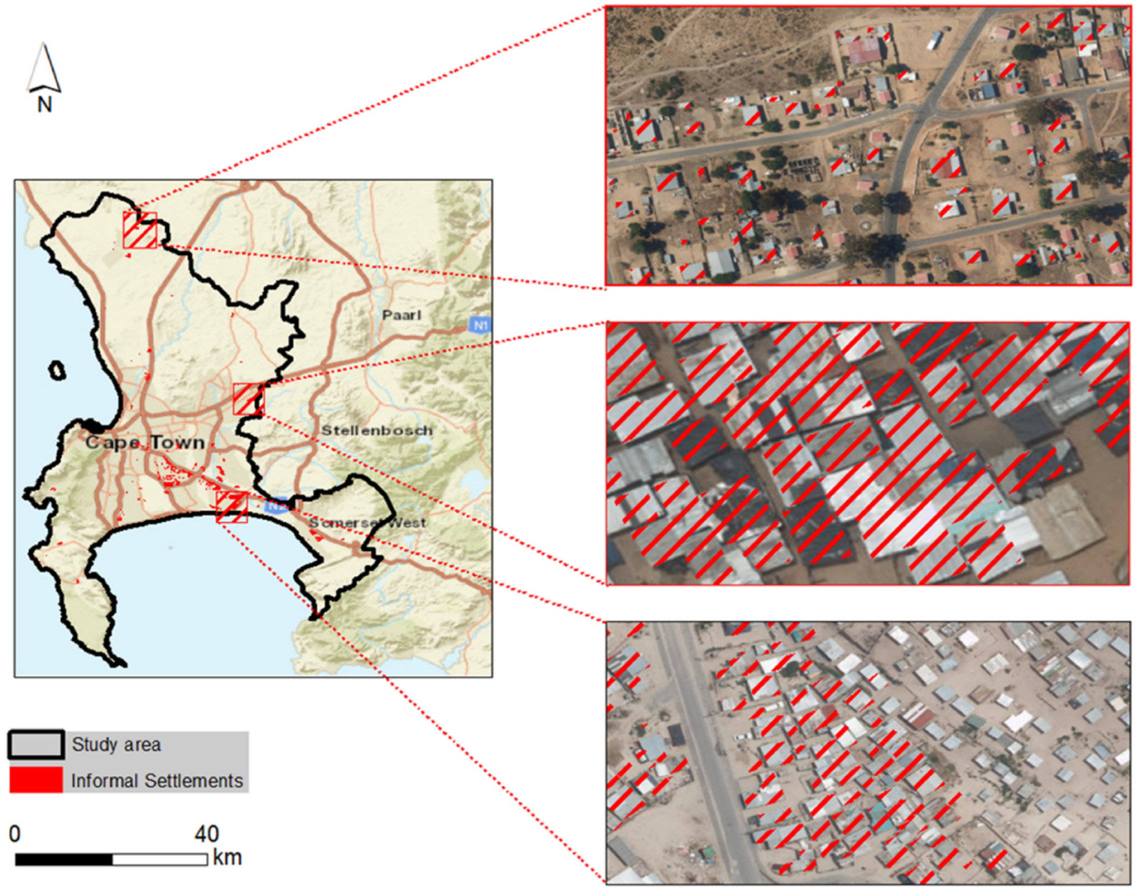


Fig 2. Distribution of informal settlement using Random Forest

In their publication, they mentioned that there are also misclassification between formal and informal settlements due to similar spectral values as well as it occupies small area between formal settlements. This spectral confusion make the producer and user accuracy lower. I also ponder the same way seeing the result in Figure 2, because even with my own interpretation the predicted informal and formal doesn't have distinct feature, except the building's density. Thus, they suggest using SAR (Synthetic Aperture Radar) to **improve deliniation** of informal settlements. Basically, SAR is effective in this setting because it is sensitive to physical characteristics (orientation, shape, and distribution) due to its ability to capture backscatter Gibson, Engelbrecht, and Rush (2019). (Gibson, Engelbrecht, and Rush 2019) use SAR to complement their analysis on detecting before and after fire in informal settlements. I will write this-SAR thing on next week.

During my time studying informal settlement topics, I have become more aware of the various challenges linked to these settlements and how remote sensing can help capture at least some of these challenges. One significant issue is the dynamic nature of informal settlements, where buildings are frequently constructed, demolished, or altered. With Sentinel-1 and Sentinel-2's revisit time of less than 5-6 days, incorporating temporal mapping becomes highly beneficial in effectively monitoring these constant changes in informal settlements.

8.3 Reflection

Remote sensing is interesting but also complex at the same time for me. It often widens the gap between my willingness to learn and my understanding of the subject. I'm not sure how to build the confidence to execute these methodologies when the interpretation and analysis process is left entirely in my hands. During practical sessions, I can ask the lecturer, but when I'm out in the real world, people might ask me questions. "Am I ready?" or "Do I have a solid foundation to justify what I'm doing with remote sensing and machine learning?" Actually, I have a love-hate relationship with regression, I'm sure machine learning will join that club too. However, thinking about the potential insights I can gain from these methods does soothe the hard feelings I have toward these advanced methodologies.

Future application : I genuinely believe that mapping informal settlements using open-source data from Sentinel-1 and Sentinel-2 presents an opportunity for valuable analysis. For example, questions like: How does their spatial distribution look? Do they grow rapidly over time? What are the building materials? We can link this analysis to risk mitigation for fire brigades. Because in Global South country, privatization of public lands is common occurrence Bon (2021), and public land is potential areas for growing informal settlement . As it is unplanned, there might be no adequate access into this informal settlements. Additionally, the semi-permanent materials will expose them vulnerable to fire incidents. Thus, it is interesting to link the finding in informal settlement mapping with its mitigation risk. We know that Government also needs to be responsible when this happened, even when the informal settlements become challenge for their urban planning projects.

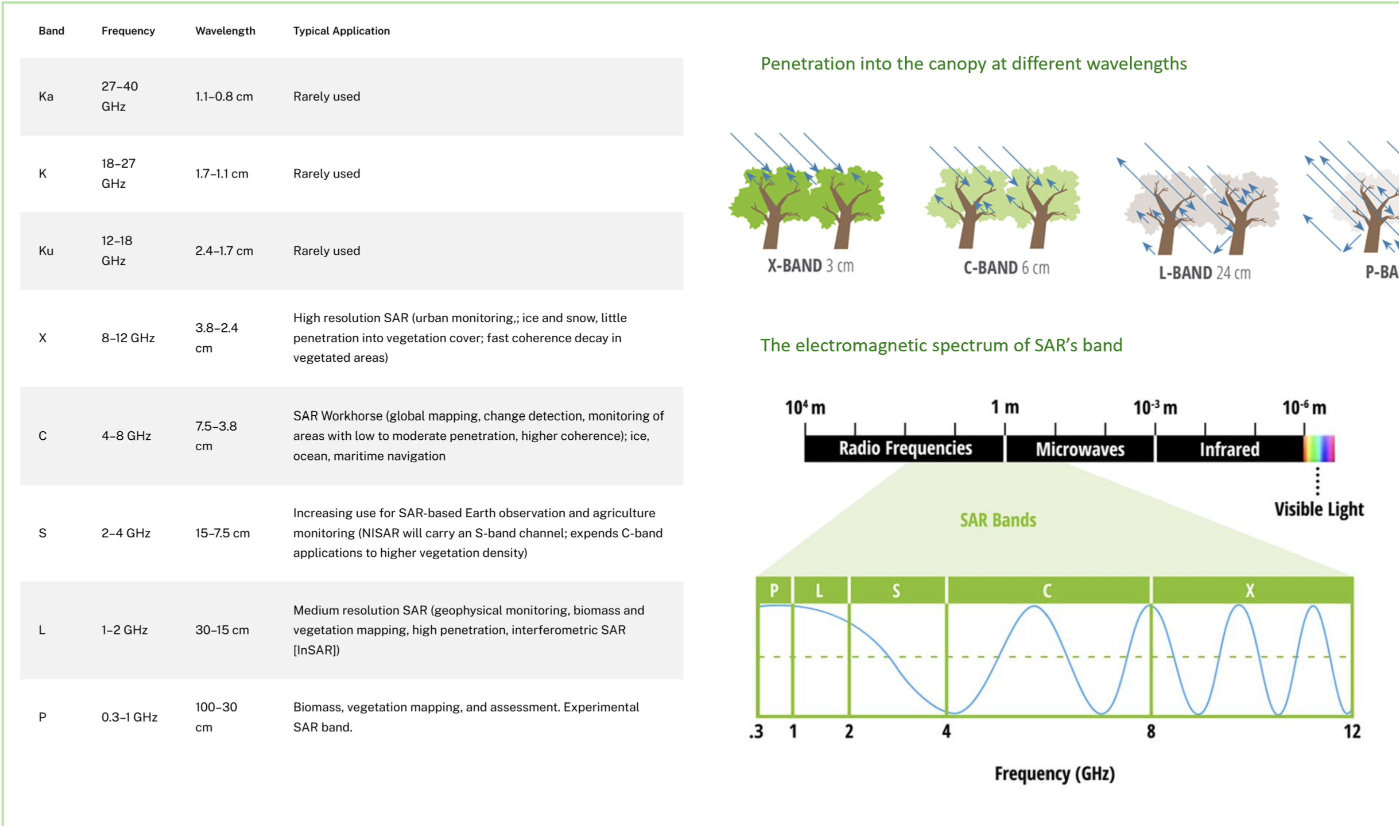
8.4 References

9 Synthetic Aperture Radar

9.1 Summary

Today's lecture explores sensor imagery called Synthetic Aperture Radar (SAR). Well the name sounds complicated :) The only word that unfamiliar for me is 'aperture', after asking Chatgpt with prompt of 'concise and explain to 15 years old', I learned that aperture is like the opening of camera, the wider the aperture the less focus the image captured and the more light it lets in. Meanwhile, radar is an active sensor that emits energy for illumination. Due to its longer wavelength, it can penetrate clouds or dust and capture images at night.

If optical images are like our eyes, **SAR is like a bat**, emitting chirps of sounds to locate his prey and other objects. It identifies objects by listening to the reflected signal. The signal that reflects back to the satellite is called backscatter. There will be a low backscatter if the signal hits a flat surface and goes off into space. Meanwhile, it will produce high backscatter when it hits an object and reflects back to the satellite. SAR images are typically grayscale; the more signal returned to the satellite, the brighter (higher value) it appears. I remember that multispectral images have spectral bands, and this also applies to SAR. There are many bands, but the most commonly used is the C band, like the bands in Sentinel-1.



Band	Frequency	Wavelength	Typical Application
Ka	27–40 GHz	1.1–0.8 cm	Rarely used
K	18–27 GHz	1.7–1.1 cm	Rarely used
Ku	12–18 GHz	2.4–1.7 cm	Rarely used
X	8–12 GHz	3.8–2.4 cm	High resolution SAR (urban monitoring,; ice and snow, little penetration into vegetation cover; fast coherence decay in vegetated areas)
C	4–8 GHz	7.5–3.8 cm	SAR Workhorse (global mapping, change detection, monitoring of areas with low to moderate penetration, higher coherence); ice, ocean, maritime navigation
S	2–4 GHz	15–7.5 cm	Increasing use for SAR-based Earth observation and agriculture monitoring (NISAR will carry an S-band channel; expends C-band applications to higher vegetation density)
L	1–2 GHz	30–15 cm	Medium resolution SAR (geophysical monitoring, biomass and vegetation mapping, high penetration, interferometric SAR [InSAR])
P	0.3–1 GHz	100–30 cm	Biomass, vegetation mapping, and assessment. Experimental SAR band.

Figure 1. SAR Bands with frequency and wavelength. Source : NASA

Radar can collect signals with different polarization. Polarization describes the direction in which the plane of a transmitted electromagnetic waves move back and forth. When signal emitted in vertical (V) and received horizontal it indicated V-H, meanwhile when the signal both emitted and received horizontal it indicated H-H. Different surface will respond differently to the polarizations, such as:

Type of Scattering	Occurs when....
Rough surface scattering	signal interact with irregularities of surface and most sensitive to VV scattering (example : bare soil or water)
Volume scattering	signal interacts with multiple scatterer such as leaves in forest, most sensitive to VH or HV
Double bounce scattering	signal reflects off two surfaces before returning back to sensor. This creates strong backscatter and most sensitive to HH. (example : tree and building).

Here's the illustration to understand the type of scattering in radar.

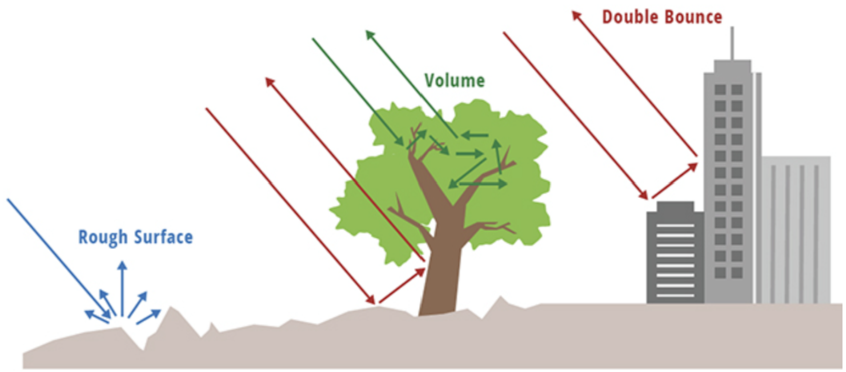


Figure 2 : Type of scattering. Source : NASA

SAR can be useful in our analysis by comparing change between two images. By comparing change between two images, we measure the variance of the appearance over time using 1) standard deviation 2) t-tests 3) combine with optical data (using technique such as PCA, object based image analysis, or intensity fusion). Let's use our dearest Google to get better understanding over this.

9.2 Application

I would like to mention the application of **optical remote sensing versus SAR Imagery** in damage detection during conflict. Emmm.... this topic is slightly unfamiliar to me but but it has become one of my growing interests in recent years. *On that day, as I am curious about this topic I decided to sit in on the practical session of Building Applications with Big Data.*

During conflict, the need to assess building damage is crucial for humanitarian relief efforts. However, in the past the detection depended on **eyewitness reports and manual detection**. We know that time is precious during conflict and humanitarian aids. This calls Mueller et al. (2021) to generate damage monitoring using Very High Resolution (VHR) satellite imagery, good for its resolution and frequency, and using machine learning techniques for automation.

The intuition behind the method is using Convolutional Neural Networks (CNNs) to learns from example of destruction (e.g rubble and bomb raters) to make predictions about other images. Then to address the challenges of limited amount of labeled data (because sometimes the destruction is sparse or only limited buildings destroyed), they use label-augmentation technique which assumed destroyed at a certain time building will remain destroyed in subsequent time. This assumption helps to create additional labels for training dataset. They set a certain threshold to change the continuous prediction into binary classificationsl, The result is shown below, showing damage before and after a heavy weaponry attack in a neighborhood of Aleppo, red : highly predicted as destroyed, while green : low predicted as destroyed.

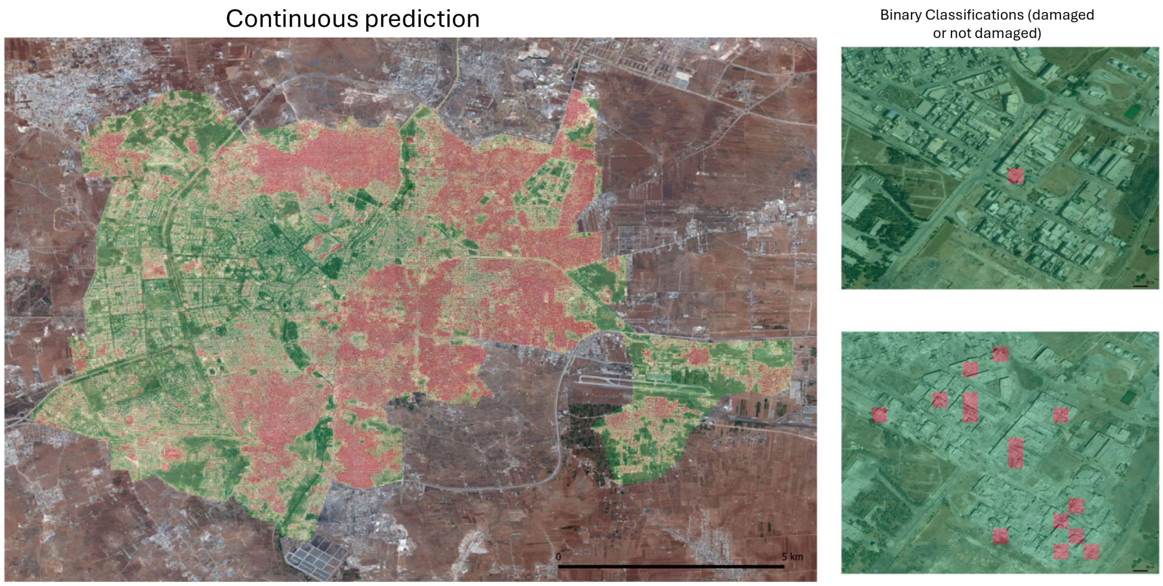


Figure 3 : Damage destruction using optical satellite data. Source : Mueller et al. (2021).

However, I pondered upon the use of VHR imagery in the analysis as it must be **financially expensive,** thus not everyone can get the access into it. It must be nice to have the open access data for this damage detection, right? and Ollie, our Remote Sensing lecturer, has **found the solution !** He managed to find a new method for building damage detection using Pixel-Wise T-test (PWTT) and SAR in Sentinel 1. Yes, you read that right– it's sentinel 1— which means it is open access ! Using this algorithm, he could achieve building-level accuracy higher than deep learning + VHR method (Ballinger 2024). He uses SAR imagery because it emits a pulse towards the earth and then measure its return signal, enabling the analysis of how different textural surface respond differently.

> *Hang in there with me, this next paragraph gets a little bit technical. I know it might be a lot, but my curiosity just won't let this go.*

The intuition behind the methodology is that he investigates how much of the radar signal is reflected back to the satellite, which called backscatter amplitude. Basically, building and rubble will reflected the radar signal differently. The algorithm then compares the backscatter amplitude of each pixel during period before the conflict and after the conflict. To determine, the change in backscatter is significant enough to be classified as damage, he uses T-test to know how much the variation over time and take the largest T-value detected as a potential damage in that pixel. T-test allows us to compare the means joined by its standard deviation and the sample number. See the figure 2 below, the green shows condition before invasion while the red is after invasion. Meanwhile, the dashed line showed the average backscatter amplitude with ± 1 standard deviation before and after the building's destruction.

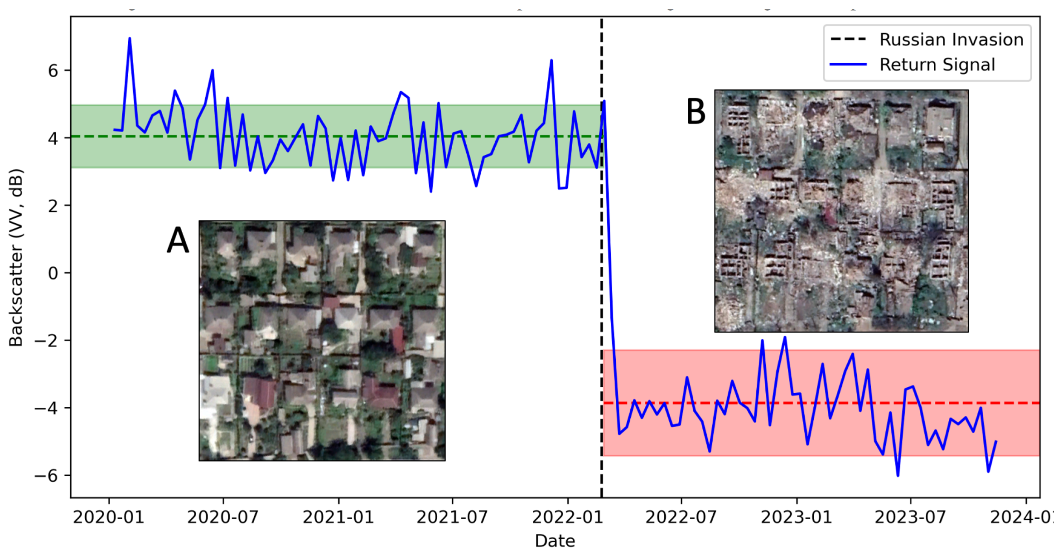


Figure 4 : Backscatter comparation before and after destruction . Source : Ballinger (2024)

For me, the performance of open-source data in outperforming VHR satellite data is a significant finding. Although it should be validated in different climatic regions, as Ollie mentioned in the paper, it presents promising potential to be explored. The utilization of open-source data will encourage faster knowledge development, as people from diverse backgrounds can explore and find the 'rabbit hole.' In budget-based institutions, if the goal can be easily achieved with open-source data, it will make spending more effective. However, we must admit that commercial data might have more strengths, but let's save our energy here.

9.3 Reflection

If SAR is this good at penetrating objects and imaging at night, what kind of weaknesses does it have? I was thinking when backscattering signals bounce off back by so many things (many speckles- term for noise in radar), it must be challenging to analyze. Moreover, the appearance of SAR images as grayscale is also less intuitive. Apparently, this question has been explored by Wang and Patel (n.d.), they address the grayscale and speckle issues by applying convolutional neural nets (CNNs). I am not sure if I can fully understand what it means, but the intuition is to make SAR images appear more like the visible images by despeckled and colorized image.

In the future, I would really like to use SAR to assess landslide risk**.** In my hometown, hill areas are famous with its scenic view and forest-like nuance however it is really prone to land slide. Even when I drive pas through the road, there are lots of sign "Beware of potential Land Slide". With a high density of vegetation in such settings, using SAR in Sentinel 1 will be perfect to assess this condition. However, I must admit the journey to really use SAR and interpret the data will be very challenging for me.

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