--- title: "Week 1 Learning Diary" author: "Luo Huangchen" format: html ---

**🌍 Week1**

**Summary**

This week's course introduces the basic concepts and methods of remote sensing (Remote Sensing). Remote sensing refers to the technology of obtaining information about the Earth from a distance, usually with the help of sensors on platforms such as satellites, aircraft or drones [@campbell2011]. We discussed in depth the difference between active and passive remote sensing: active remote sensing uses signals emitted by itself (e.g. radar, lidar, etc.) and receives reflected information, while passive remote sensing relies on information reflected from sunlight hitting the surface, such as the Landsat and Sentinel satellites [@jensen2009].

Remote sensing data usually have four types of resolution: spatial resolution (pixel size), spectral resolution (number of detected bands), temporal resolution (revisit period) and radiometric resolution (sensitivity of detected spectra). These resolutions determine the application range and accuracy of remote sensing data. At the same time, the electromagnetic spectral signature (Spectral Signature) of the Earth's surface enables remote sensing technology to effectively differentiate between different feature types, such as vegetation, water bodies, and soils. In addition, we discussed that the acquisition of remote sensing data may be affected by atmospheric conditions such as clouds and haze, which makes it necessary to ensure the quality and validity of data through atmospheric correction and other means [@schowengerdt2007].

**Applications**

Remote sensing technology has in fact long permeated every aspect of our lives, especially in the matter of responding to natural disasters, where its role is becoming increasingly important. For example, the synthetic aperture radar (SAR) in active remote sensing, which we mentioned in class, is particularly powerful in flood detection. Traditional optical satellites are easily blocked by clouds, but SAR is different, it can ‘penetrate’ the clouds to monitor the ground conditions around the clock, so it is particularly useful in emergency situations such as floods [@amitrano2024]. A recent reading also highlights that with climate change and increased urbanisation, flooding is becoming more frequent, making it vital to be able to identify and monitor flooded areas quickly and effectively, a need that SAR data meets, and one that can help governments to respond quickly and allocate resources for disaster relief[@twele2016].

Fig. 1 Three types of scattering of radar signals

*Source:* [*Amitrano et al. (2024)*](https://doi.org/10.3390/rs16040656)

In addition to flood monitoring, passive remote sensing data are also widely used, such as the Landsat and Sentinel-2 satellites that we often hear about, and their applications in agriculture and the ecological environment are particularly numerous. As an example, satellite data can be used to calculate the vegetation index (NDVI), which helps the agricultural sector to more accurately assess the growth of crops and predict yields, and can even monitor changes in the ecological environment in real time. Moreover, using cloud computing platforms such as Google Earth Engine, people can easily analyse large-scale land cover changes and even monitor global ecological trends [@gorelick2017; @zhu2014].

Figure 2 Schematic of the Google Earth Engine

*Source:* [*Gorelick et al. (2017)*](https://doi.org/10.1016/j.rse.2017.06.031)

However, remote sensing is not a panacea, especially in cities and areas with vegetation cover, where SAR data can still be difficult to analyse. This is because buildings and vegetation in cities can cause complex signal reflections, making accurate identification of flooded areas tricky at times. Overall, however, the convenience and comprehensiveness provided by remote sensing data gives us more initiative in disaster response and environmental management, and the future development prospects are still worth looking forward to.

**Reflection**

The first week of remote sensing class made me realise right away that this technology is not just an abstract theory in the academic field, but a real tool that can make a difference in people's lives. Of interest to me was the fact that active remote sensing (SAR), which we mentioned in class, has particularly prominent applications in natural disaster, especially flood monitoring. My previous understanding of remote sensing may have been limited to the simple application of satellite imagery, but I had no idea that it also has such great potential to address the risks associated with urbanisation and to protect people's lives and property.

At the same time, I also noticed that although SAR can overcome the shortcomings of traditional optical images (such as the influence of cloud cover), there are still some challenges in its practical application. For example, the processing of SAR data in complex environments such as cities is still difficult, which reminds me that there are still quite a few practical problems to overcome between the development of the technology and the landing of the application. In addition, I am particularly interested in cloud platforms such as Google Earth Engine, which greatly reduces the threshold of remote sensing data analysis and allows us to quickly carry out large-scale environmental monitoring on a global scale, which is very attractive for both academic research and practical work.

One of the deepest feelings I got from this class is that remote sensing technology has really brought people closer to the Earth's environment. Although there are still a lot of technical details that I need to learn in depth, I am already looking forward to what I can learn next and the role this knowledge can play in my future studies and career.

--- title: "Week 3 Learning Diary" author: "Luo Huangchen" format: html ---

**📢 Week 3: Learning Corrections**

**Summary**

This week's course took us on an in-depth exploration of important data correction methods and technical background in remote sensing data processing. First, we reviewed the history of the famous **Landsat** series of satellite data, with a special focus on the key contributions of technician Virginia Norwood, whose design of the digital multispectral scanner (*Multispectral Scanner* (MSS)) replaced the traditional analogue camera technique and drove a major change in remote sensing technology. Today, Norwood's *Whisk broom* scanning technique is at the heart of remote sensing data acquisition.

In terms of data processing, we specifically learnt about three key methods, namely geometric correction, atmospheric correction and orthometric correction. Geometric correction addresses the spatial error between the satellite image and the actual geographic location by calibrating the image position through Ground Control Points (GCPs). Atmospheric correction deals with the data bias caused by the atmosphere, including relative correction (e.g. dark object subtraction, pseudo-invariant feature method) and absolute correction (e.g. FLAASH model) to ensure that the acquired data reflect the surface conditions more realistically. Orthometric corrections are used to correct image distortions caused by the angle of observation of the satellite, using mathematical models and surface elevation data to produce an accurate image as if viewed from directly above.

**Summary of Remote Sensing Data Corrections**

|  |  |  |
| --- | --- | --- |
| **Correction Method** | **Main Purpose** | **Common Techniques** |
| **Geometric Correction** | Ensures spatial accuracy of images | Ground Control Points (GCP) |
| **Atmospheric Correction** | Removes atmospheric interference (clouds, haze, etc.) | - Relative Correction: Dark Object Subtraction, Pseudo-Invariant Feature Method <br>- Absolute Correction: FLAASH Model |
| **Orthorectification** | Eliminates distortions caused by satellite viewing angles | Mathematical models, DEM-based corrections |

Through this week's study, I have gained a deep understanding of the complexity behind the process of remote sensing data processing, the seemingly tedious but very important steps that ensure the efficiency and accuracy of the data in scientific research and practical applications, and enable us to use remote sensing data more confidently in analyses and decision-making.

**Application**

After studying the remote sensing data correction techniques during the week, I purposely reviewed some examples of remote sensing correction applications in practical research, which helped me better understand the practical value of these methods. For example, in crop estimation studies, atmospheric correction techniques have a significant impact on the accuracy of vegetation indices. The accuracy of NDVI data can be significantly improved by accurate atmospheric correction, which can better monitor the true health of crops and thus help farmers to increase yields and reduce losses (@song2001). In addition, some studies have also clearly pointed out that remote sensing data without correct geometric correction may lead to significant overestimation or underestimation of forest fire area (@roy2016). Therefore, the importance of accurate geometric correction in the field of disaster management cannot be overstated.

The application of orthometric correction, on the other hand, reminds me of practical examples in urban planning. For example, in urban expansion studies, image distortion caused by satellite image tilting can seriously affect the accurate measurement of urban area, which can be effectively avoided after accurate ortho-correction, helping decision makers to grasp urban expansion trends more accurately (@lefebvre2016). This study used Sentinel-2 data to update the Copernicus High Resolution Impermeable Layer (HRL IMD), which improves the accuracy of urban change monitoring through remote sensing data fusion, as exemplified in the figure below which detects the changes in the city of Rennes for the years 2012-2015. This shows that orthorectification is not only applicable to traditional geographic studies, but also plays a crucial role in modern large-scale urban monitoring missions.

**Urban Change Detection in Rennes (2012-2015)** *Source:* [*Lefebvre, Sannier and Corpetti (2016)*](https://doi.org/10.3390/rs8070606)

Through these application cases, I also began to think that although the methods we learnt in class are very mature, in practice, we still need to flexibly adjust the calibration strategy according to specific research scenarios. After all, disturbances in real environments are often more complex. This also inspired me to pay more attention to the flexibility and applicability of remote sensing methods in my future study and research.

**Reflection**

Through this week's study, I deeply feel that remote sensing data processing is not simply a matter of ‘taking a picture’, but requires a lot of rigorous and detailed technical processing and correction steps behind it. In the past, I always thought that satellite images were just taken and used directly, but now I realise that this is just the beginning of the data processing journey. From data acquisition to real application, every step in between - be it geometric, atmospheric or orthometric correction - must be rigorously executed to ensure the accuracy and usability of the final data.

I was struck by the fact that these seemingly complex and trivial steps all lead to a common goal: to ensure that we make the right decisions when facing environmental problems. For example, through accurate atmospheric corrections, we can obtain more accurate data on vegetation cover and thus plan for ecological protection more effectively. In addition, thinking about current technological developments, such as the increasing maturity of cloud computing platforms and automated processing technologies, I am also confident that in the future these data processing processes will become more streamlined and efficient, and our research and decision-making processes will become more reliable and timely. This anticipation of the future makes me even more enthusiastic and motivated for the subsequent courses and exploration of remote sensing technology.

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title: "Week 4 Learning Diary"

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Week 4 Policy

Summary

Guangzhou, a core city in southern China, has experienced rapid urbanisation over the past decades. Studies show that between 1986 and 2018, Guangzhou's built-up land increased by 439.34%, while vegetation cover decreased by 19.99% [@guo2021]. While this expansion has been accompanied by economic take-off, it has also brought about problems such as the intensification of the urban heat island effect, fragmentation of green space, and rising ecological pressure. In response, the Guangzhou Municipal Government issued the ‘Guangzhou Territorial Spatial Master Plan (2020–2035)’, which clearly defines the red line of ecological protection and the urban growth boundary in order to achieve a “compact, green and orderly” urban spatial vision [@zhang2024].

Remote sensing technology has played a central role in this policy transition. From Landsat, Sentinel to domestically produced high-frequency high-fraction satellites, remote sensing provides Guangzhou with high-frequency, comparable data on land use, thermal environment and green space cover. This enables a closed-loop assessment mechanism of “quantifiable”, “monitorable” and “adjustable” policy objectives [@zhao2024]. At the same time, remote sensing provides a tool platform for urban village identification and boundary delineation, greening actions for heat island mitigation, and urban growth modelling.

The case of Guangzhou reveals how remote sensing can be transformed from an auxiliary tool to an “operating system” for urban policy realisation.

Applications

Land use/cover change (LUCC) monitoring and assessment

@guo2021 used Landsat and Sentinel multi-source remote sensing imagery, combined with a random forest classifier, to analyse land use change in Guangzhou from 1986–2018. The results showed that the average annual growth of construction land was 41.11 km², which significantly compressed the vegetation cover.

Remote sensing enables the positive correlation between urban expansion and GDP growth (R² = 0.98) and the negative effect of vegetation reduction (R² = 0.97) to be quantitatively verified, which directly supports the design of urban growth boundary (UGB) management and ecological compensation mechanisms.

Spatial diagnosis and mitigation guidance of urban heat island effect (UHI)

Based on surface temperature data from Landsat-8 TIRS inversion, @zhao2024 found that the heat island effect in Guangzhou is concentrated in the high-density built-up area in the southwest, while the green space–rich area in the north shows a significant cooling effect.

This information encourages planners to increase green space and tree canopy cover along tropical areas in the form of “green cooling corridors”, to achieve targeted cooling strategies.

Fig. 1 Annual average surface temperature distribution in Guangzhou (2018–2023)Source: Zhao (2024)

Identification and spatial governance of urban villages

Urban villages in Guangzhou are typical “spatial informal” structures, and @tu2024 developed an identification system that integrates remote sensing imagery, points of interest (POIs), and census data, and carried out urban-scale fine identification in Guangzhou, with an accuracy of 91.82%.

The results were used to support the policy assessment of SDG 11.1.1 and to guide the integration of informal settlements into mainstream urban regeneration programmes.

Fig. 2 The geographic distribution of POI data and their use in urban village identification in the Greater Bay AreaSource: Tu et al. (2024)

Urban growth boundary projections and planning simulations

@zhang2024 used an artificial neural network–cellular automata (ANN-CA) model to simulate the urban expansion trend of Guangzhou up to 2030, and identified Panyu and Nansha as key growth areas. The results were used by the Guangzhou Municipal Natural Resources Bureau to optimise the “eastward and southward expansion” urban development strategy, and to lay out the infrastructure and green space system in advance.

Reflection

The case of Guangzhou demonstrates how remote sensing can help a city to maintain a scientific and forward-looking approach to environmental management in the face of rapid development. Remote sensing not only provides a macro view of geographic facts, but also transforms abstract policy goals into visible, measurable and controllable objects.

However, there are still technical bottlenecks and social equity issues in this process. On the one hand, the acquisition and processing of high-resolution remote sensing images requires high technical and financial resources, and it may be difficult for small and medium-sized cities or developing regions to replicate Guangzhou's practice. On the other hand, although remote sensing can accurately identify “where it is hot” and “where there is a lack of greenery”, it is difficult to measure the actual feelings and participation of residents, and it is easy to ignore the “humanistic temperature” of urban governance.

For me personally, the remote sensing practice in Guangzhou has strengthened my understanding of “data-supported urban governance”. I realise that it is difficult to achieve sustainable urban development by remote sensing technology alone, and that it must be used in conjunction with GIS, ground surveys, and public collaborative mechanisms in order to achieve people-centred smart governance.

In the future, I hope to promote the two-way empowerment between remote sensing and urban policy, both in academic research and in practice. --- title: "Week 6 Learning Diary" author: "Luo Huangchen" format: html ---

**Week6**

**Summary: Classification in Remote Sensing**

In this week's course, we learnt about Google Earth Engine (GEE), a widely used cloud computing platform in remote sensing, which is a geospatial analysis platform based on cloud computing technology launched by Google. The most important feature of GEE is that it can process large-scale remote sensing data online in real time, helping researchers to easily analyse and visualise complex geospatial data without being limited to the performance constraints of local computers [@gorelick2017].

The course highlights the difference between two key concepts of GEE data processing: client-side and server-side. Client-side processing relies on the performance of the user's own computer and is suitable for simple tasks, whereas server-side processing takes advantage of the powerful computing capabilities of the Google Cloud and can efficiently parallelise complex tasks. This means that we should use server-side functions whenever possible when using GEE to improve processing efficiency [@mutanga2019].

In practice, we learnt the data filtering methods of GEE, such as filterDate() (time range filtering) and filterBounds() (spatial range filtering). Proper use of these filtering methods can significantly reduce the amount of computation and avoid unnecessary data downloads and memory errors [@gorelick2017]. In addition, the data visualisation function of GEE is powerful; by adjusting the appropriate spatial resolution and band combination, we can quickly view the features of satellite images, such as vegetation, water bodies or urban areas.

Data reduction and statistical analysis is also one of the important functions of GEE. We specifically learnt about zonal statistics and image reduction. Zonal statistics, such as the reduceRegion() function, can easily calculate the Normalized Difference Vegetation Index (NDVI) or rainfall for a specific region, which is widely used in agricultural monitoring and ecological research [@amani2020]. Image downscaling can use methods such as median() or mean() to efficiently handle large amounts of data, thus reducing the computational resources required for analysis.

Taken together, this week's course demonstrates how the combination of cloud computing and remote sensing technology has significantly lowered the technical barrier to remote sensing analysis and increased the availability and efficiency of data analysis.

**Application**

Google Earth Engine (GEE) has been widely used in many fields, such as environmental monitoring, agricultural production management, climate change analysis and disaster response, due to its powerful cloud computing capability and rich data resources.

One of the application cases that impresses me is the long-term monitoring of land cover changes using the GEE platform. In this week's reading, I learnt about a study on high-resolution analysis of global forest change based on GEE. The study took full advantage of GEE's cloud computing and processed more than 650,000 Landsat satellite images, resulting in fine-grained monitoring of forest change on a global scale.

In the past, this type of global-scale big data processing was often extremely time-consuming, but with the capability of GEE, the efficiency and accuracy of the study can be greatly improved [@hansen2013].

**Fig. 1** Regional examples of forest cover change from 2000 to 2012  
*Source:* [*Hansen et al. (2013)*](https://doi.org/10.1126/science.1244693)

Not only forest monitoring, GEE has important applications in disaster response. For example, flood monitoring, in the past, when floods occurred, it has been a challenge to obtain timely information about the affected area. Maps of flood-affected areas can be quickly generated by GEE, which significantly improves the efficiency of disaster response operations [@devries2017]. Specifically, Sentinel-1 radar imagery can be rapidly analysed on the GEE platform, which is able to ‘cut through’ clouds and bad weather, providing accurate and timely data to support relief operations even under adverse weather conditions.

**Fig. 2** Flowchart of the SWF estimation algorithm demonstrated in this study  
*Source:* [*DeVries et al. (2017)*](https://doi.org/10.3390/rs9080807)

In addition, I am particularly interested in the application of GEE in agriculture. We can use the GEE platform to monitor the production of corn in the Midwest region of the U.S. in real time, and by calculating the vegetation indices (e.g., NDVI) in satellite images, we have established a crop yield prediction model [@azzari2017]. This method is more timely and accurate than traditional ground observation, and can help the agricultural sector make decisions in advance and optimise resource allocation.

**Fig. 3** Samples of the different cover types as seen in Google Earth high-resolution images:  
(a) rainfed crops (RFC),  
(b) irrigated crops (IRC),  
(c) urban areas (URB),  
(d) swamp natural vegetation (SWN),  
(e) open-canopy natural vegetation (OCN),  
(f) close-canopy natural vegetation (CCN).  
*Source:* [*Azzari and Lobell (2017)*](https://doi.org/10.1016/j.rse.2017.05.025)

In my opinion, the emergence of GEE is not only a technological advancement, but also a change in the way of thinking. In the past, remote sensing analyses were often limited by local computing resources, and researchers had to consider how to compress the data or reduce the precision of the analyses. Now, with GEE's cloud computing capabilities, we can be bolder in designing research programmes and attempting more complex and comprehensive data analysis. This shift means that remote sensing technology will play an even more critical role in solving major global problems.

**Reflection**

The biggest feeling I got from learning Google Earth Engine (GEE) this week is that technology is really changing the research possibilities. In the past, remote sensing data processing often faced the problem of insufficient computing resources, especially when we tried to process large-scale satellite image data, the local computer would soon ‘strike’, but now just open the GEE platform, many analyses that used to be inconceivable instantly become feasible. This convenience really makes me feel that my research is full of more possibilities and I have more confidence to try new research methods.

However, I also realised that although GEE looks wonderful, it is not entirely without difficulties in practice. For example, how to use some built-in functions or datasets efficiently still needs to be further explored; at the same time, once Google changes the platform functionality, our code may suddenly ‘fail’. This requires us to keep track of the analysis process, regularly check for code updates, and adapt to new changes in the platform in a timely manner.

Overall, this study not only helped me to master a powerful analysis tool, but also made me start to think about the relationship between technology and research. The tool is only an aid, and how to effectively integrate this tool into concrete research may be more worthwhile for me to think about in depth in the future. I am also looking forward to using GEE to try to solve some real environmental problems in my future courses or research, so that I can really apply what I have learnt to real scenarios.

--- title: "Week 7 Learning Diary" author: "Luo Huangchen" format: html ---

**Week 7: Classification Methods and Applications**

**Summary**

This week's course focuses on the key methods and principles of remote sensing **classification**, especially the difference between **Supervised Classification** and **Unsupervised Classification** and their application scenarios. In Supervised Classification, we mainly studied **Decision Tree** and **Random Forest** algorithms. The professor emphasised that Decision Tree has the advantage of being intuitive and easy to understand, but it is also prone to **overfitting**, i.e. the model may be too sensitive to the training data and difficult to generalise to new data. To solve this problem, we also learnt the **Random Forest** method, which not only improves classification accuracy but also effectively reduces the risk of overfitting by integrating the results of multiple decision trees.

Another highlight of the course was the introduction of **Regression Tree**. While most of the classification algorithms we have come across in the past are for prediction of discrete categories, Regression Tree is able to deal with **continuous variables**, such as the estimation of the proportion of vegetation in land cover. The professor mentioned that regression trees are similar in principle to decision trees, but use numerical variables rather than category labels in node splitting, making them ideal for more refined environmental monitoring tasks.

In terms of **unsupervised classification**, we instead focused on **K-means clustering** methods. Instead of pre-labelling the training samples, this method automatically groups pixels based on the **spectral features** of the data, which is particularly useful in scenarios where explicitly labelled data is lacking. However, the professor also pointed out that K-means requires **manual judgement of the optimal number of categories** in practical applications, which adds to the subjectivity in its use.

Through this week's study, I further realised the importance of the **choice of classification method**: supervised classification is suitable for situations with sufficient training data, while unsupervised classification is suitable for exploratory analysis or scenarios with limited data. Overall, this week has given me a better understanding of how to choose the most appropriate classification tool for my actual needs.

**Applications**

The supervised and unsupervised classification methods I learned in this week's course got me thinking about how I can apply them more effectively to real-world remote sensing research.

Firstly, for **supervised classification**, I think the **Random Forest** algorithm has great potential. Compared with traditional decision trees, it significantly improves classification accuracy through the voting mechanism of multiple trees and mitigates the risk of overfitting, which is especially suitable for complex remote sensing analysis of urban environments. After reviewing the relevant literature, I found that the Random Forest approach has been widely used in monitoring urban land use changes and has demonstrated extremely high accuracy. For example, one study used the Random Forest algorithm to analyse Sentinel-2 imagery and successfully identified different land use types in the process of urban expansion, which was significantly better than the classification results of a single decision tree [@belgiu2016].

**Fig. 1** Training and classification phases of Random Forest classifier  
*Source:* [*Belgiu and Drăguţ (2016)*](https://www.sciencedirect.com/science/article/abs/pii/S0924271616000265)

On the other hand, the introduction of **regression trees** also reminded me of their potential for analysing urban vegetation and environmental indicators. I found that regression trees are particularly suitable for estimating **continuous environmental variables**, such as the proportion of vegetation cover within a city or the distribution of urban surface temperature. In past studies, regression trees have been successfully used to quantitatively analyse **urban heat island intensity** from remote sensing imagery, helping urban planning authorities to accurately identify areas with temperature anomalies [@imhoff2010].

**Fig. 2** Urban Heat Island Intensity and Spatial Distribution Across Different Biomes in the USA  
*Source:* [*Imhoff et al. (2010)*](https://doi.org/10.1016/j.rse.2009.10.008)

In addition, for cases where the data lacks explicit labelling, I believe that **unsupervised classification methods** such as **K-means clustering** are equally valuable. K-means can automatically identify feature types based on spectral similarity without predefined categories. This is useful for initial exploration of new remote sensing datasets or in areas where detailed ground data are lacking. However, the number of categories for K-means needs to be determined by humans, which may introduce some subjectivity. I note that some studies have used K-means for initial classification in urban landscape analyses, which was subsequently combined with a small amount of supervised data for fine-grained corrections, resulting in more accurate classification results [@gao2016]. This strategy of combining **unsupervised and supervised classification** is worth trying in depth in my future.

**Reflection**

This week's study on classification methods in remote sensing has made me further appreciate the *‘art of choice’* behind the analysis of remote sensing data. Faced with the two distinct paths of **supervised** and **unsupervised classification**, I realised that the choice of classification method depends not only on the data itself, but also on the research objectives and the availability of resources. In particular, tools such as **random forests** and **regression trees** showed me the balance between accuracy and efficiency, which may play a great role in urban research in the future.

In particular, the *‘majority voting’* mechanism of random forests gave me more confidence in the robustness and accuracy of the classification results. I started to think about how to use Random Forests to handle complex remote sensing data and capture the subtle differences in urban change in topics such as **urban heat island** and **land use change**. However, I also realised that the complexity of the Random Forest model itself makes the **interpretation of the results potentially difficult**, so in the future I will need to learn more about how to effectively interpret and communicate the results of classification models.

The presentation of **regression trees**, on the other hand, made me think further about the advantages of remote sensing in **quantitatively analysing continuous environmental variables**. This capability is particularly suited to the estimation of metrics such as **urban vegetation percentage** and **surface temperature**.

On the other hand, **unsupervised classification** methods such as **K-means clustering** enlightened me on how to be more flexible in preliminary data exploration, especially when the data are incomplete or under-labelled. However, I also noticed that determining the optimal number of classifications is still highly subjective, which also showed me how it is important to incorporate **supervised classification strategies based on unsupervised classification** in order to reduce subjective bias.

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**Week 8: Classification and Accuracy Assessment**

**Summary**

This week's course continues to explore classification methods while focusing on accuracy assessment of remotely sensed imagery.We started with several surface coverage products, such as **MODIS**, **GlobeLand30**, and the hipster-named **Dynamic World**, which was developed by Google and Microsoft and uses Convolutional Neural Networks (CNN) and Sentinel-2 data to provide *‘real-time’* and *‘global coverage’*.

It sounds pretty cool, but the professor immediately reminded us that although the data is new and fast, it also has a lot of problems, such as using **Top Atmospheric Reflectance (TOA)** to train the model, which may be mixed with atmospheric interference. In addition, its minimum mapping unit is **50×50 metres**, which makes the classified images look a bit blurry and unsuitable for fine urban studies after convolution processing.

We then learnt about two more ‘smart’ classification methods: **Object-Oriented Image Analysis (OBIA)** and **Sub-pixel analysis**.Instead of focusing on individual pixels, OBIA combines similar pixels into *“objects”*, which are analysed as a whole through spatial and spectral similarity — somewhat like a geographical version of clustering algorithms.Sub-pixel classification, on the other hand, tries to estimate the proportion of different features within a single pixel. This approach is especially suitable for complex urban scenes, where a pixel may simultaneously contain grass, concrete, and water.

The most enlightening part was the **accuracy assessment** section. We learnt about **producer accuracy**, **user accuracy**, **overall accuracy**, and the classic — but highly controversial — **Kappa coefficient**.The professor emphasised that you can't just look at a high value and assume that the model is good. Especially when the training and test data are too close, the classification accuracy is likely to be **overestimated**.This also made me realise that **accuracy assessment is not only a technical task, but also a logical and methodological process** — one that requires careful consideration of data quality, sampling strategy, and model robustness.

**Applications**

This week's study made me realise that the task of classifying urban remote sensing is often stuck between *“how to classify more accurately”* and *“how to know if the classification is accurate.”* Two methods are of particular interest to me: **Object-Oriented Image Analysis (OBIA)** and **Spectral Mixture Analysis (SMA)**. When processing high-resolution remote sensing imagery, I have found that traditional pixel-level classification often results in a *“pretzel effect,”* where the image appears to be sprinkled with noise. In contrast, the OBIA method better reflects the spatial continuity of real-world features by aggregating similar pixels into meaningful objects before classification. This approach not only improves the **readability** of the classified map but also reduces **classification errors** [@benz2004]. I think it is especially important in urban areas, where green spaces or water bodies tend to form coherent patches rather than being randomly scattered.

**Fig. 1** Example segmentation result in *eCognition*  
*Source:* [*Benz et al. (2004)*](https://doi.org/10.1016/j.isprsjprs.2003.10.002)

Another thing that struck me was the **SMA (Spectral Mixture Analysis)** method. In urban areas, a pixel often contains multiple features, such as roofs, grass, and pavement mixed together. Traditional classification forces a *“pick one”* approach, but SMA more reasonably assumes that each pixel is a combination of multiple features. By estimating the proportions of each component, we can obtain a more nuanced classification, which is particularly useful for assessing the proportion of urban green space cover or impervious surface [@small2003].

**Fig. 2** False color composites and principal component representations of urban areas  
*Source:* [*Small (2003)*](https://doi.org/10.1016/j.rse.2003.04.008)

**Fig. 3** Example applications of spectral mixture analysis on urban IKONOS imagery  
*Source:* [*Small (2003)*](https://doi.org/10.1016/j.rse.2003.04.008)

These two figures in particular help me to understand the strengths of **Spectral Mixture Analysis (SMA)**: the consistency of SMA in revealing similar *“mixed structures”* such as high-albedo buildings, vegetation, and shaded areas — even in different cities — suggests that it has a good ability to **generalise**.

After the classification is done, the **accuracy assessment** is especially critical. In my opinion, high accuracy does not always mean that the model is good, especially if the training and validation samples are too close together spatially, and the model may *“leak”* [@foody2002]. I will be particularly concerned about the presence of **spatial autocorrelation** in future analyses.

After reviewing the literature, I found that these methods are also widely used in real urban studies, as the **SMA method** can be used to estimate vegetation cover in **Indianapolis**, and the **OBIA method** has been used to monitor changes in **urban tree canopy** and feature boundaries [@lu2004]. These ideas made me realise that what we are learning now is actually *“running”* in real projects.

**Reflection**

This week has made me realise that remote sensing classification is much more than just *‘labelling pixels’*. Not only do we need to know how to classify, but we also need to really understand if and how the results can be trusted.

In the course, the professor emphasised the issue of **spatial autocorrelation**, which made me rethink my previous superstitions about high accuracy. In the past, when I saw *‘95% accuracy’* in the literature, I thought it was a proof that the model was great, but now I know that the reason behind it is that the training and testing samples may be *‘too similar’* to each other. This detail reminds me that remote sensing is not only a technology, but also a place to practice **methodology and logic**.

I especially like the **OBIA** and **SMA** methods introduced this week, which both go beyond the simple assumption of *‘one pixel equals one feature’* and are closer to the complexity of the real world.

The idea of breaking down a pixel into its constituent parts, as in SMA, is not just a technical choice, but for me a **cognitive shift**: the objects we are analysing are not clearly distinguishable categories, but rather a **continuum**, a mixture of realities.

This started me thinking that in the future, if I were to engage in **urban carbon stock assessment**, **urban sprawl monitoring**, or **heat island analysis**, SMA or OBIA might provide more structured data support than traditional supervised classification.

In addition, I started to realise that **accuracy assessment is not just a ‘final step’**, but something that should be considered from the **very beginning** of designing a sampling strategy. For example:  
- How to divide the training/validation samples?  
- Is there any spatial overlap?  
- Are the evaluation metrics serving my actual goals?

These questions may not have been a concern before, but now they will become *“reminder bells”* in my project design.

In short, this week's content has helped me move from *‘using the tool’* to *‘understanding the tool’*, and given me more *‘confidence to question it’* when facing remote sensing data in the future. I think this is an **invaluable form of critical awareness**.

--- title: "Week 9 Learning Diary" author: "Luo Huangchen" format: html ---

**Week 9: Synthetic Aperture Radar (SAR) and Change Detection**

**Summary**

This week's lesson focuses on **Synthetic Aperture Radar (SAR)** and its application to **change detection**. This active remote sensing technique is very different from the optical remote sensing I've used before: SAR actively emits microwave signals and images by measuring the intensity of the backscatter, so it can penetrate clouds and work around the clock. This reminded me of the analogy my teacher used in class: *optical remote sensing is like our eyes, while SAR is more like ‘echolocation’ for bats*.

In the course, I learnt that the **echo intensity** in SAR images is strongly influenced by the **texture and structure** of the ground. For example, a flat water surface will produce **low echo values**, while regular vertical structures like urban buildings will produce **‘double reflections’** and show **higher echo intensity**. At the same time, the **polarisation** of the SAR, such as **VV** and **VH**, determines the echo performance of different features. For example, for the same water surface in calm and windy conditions, the VV polarisation will clearly reflect the change in water surface texture, while the VH will be almost unchanged, and the **C-band** will be used the most.

Of particular interest to me was the **Interferometric Synthetic Aperture Radar (InSAR)** technique, which can accurately capture **centimetre-level surface displacements** through *‘phase’* changes in wavelength. The instructor showed an interferogram of the **San Andreas Fault** in California, which clearly shows the smallest movements of the ground surface. This technique is not only used in seismic hazard studies, but also to create **terrain models** with high precision.

**Fig. 1** Example of InSAR surface displacement detection through interferogram generation  
*Source:* [*NASA-ISRO SAR Mission – Interferometry*](https://nisar.jpl.nasa.gov/mission/get-to-know-sar/interferometry/)

Finally, we explored the advantages of **SAR in change detection**. Compared with optical remote sensing, SAR has the characteristics of **stable imaging** and **less influence by light and weather**, so it can more accurately capture surface changes before and after disasters. The teacher cited the example of **building damage before and after the Ukrainian war**, which showed me the prospect of the wide application of SAR in the field of **urban management** and **post-disaster assessment**.

**Applications**

This week's study has given me a deeper understanding of the practical application scenarios of **Synthetic Aperture Radar (SAR)** and **InSAR** technology. I found that the advantage of SAR is that it is not disturbed by cloud cover and sunlight conditions, which makes it an important application prospect in the fields of **urban heat island monitoring** and **disaster assessment**.

In the field of **urban planning**, urban heat island has always been a key issue plaguing urban development. Monitoring based on traditional optical remote sensing is often affected by cloud cover and weather conditions, with more missing data, whereas SAR can steadily provide **all-weather data**, an advantage that leads me to believe that SAR data are more suitable for **long-term monitoring** of the urban heat island effect and its changing trends [@maclachlan2021]. I have further thought about how SAR can assist in analysing **historical urban problems**, for example, some areas affected by **historical inequitable planning** (e.g. redlining) tend to show more severe urban heat island phenomena, and **environmental health problems** are more prominent in these areas. It may be more informative for **urban policy making** in the future if the high timeliness of SAR can be combined with the long-term tracking of environmental changes in these areas [@wilson2020; @li2022].

Historical redlining categories across selected Texas cities

**Fig. 2** Historical redlining categories across selected Texas cities  
*Source:* [*Li et al. (2022)*](https://doi.org/10.1177/23998083211039854)

At the same time, I realise that **SAR data** has an important role to play in **identifying and managing urban ecosystems**. The **uneven distribution of green spaces and ecological services** in some regions is usually the result of historical policy influences, and this uneven distribution can further exacerbate **socio-economic inequities**. I believe that if SAR is used to continuously track **urban vegetation and greening**, it will help to adjust **urban greening policies** in a timely manner and improve the **ecological environment for residents** [@nowak2022]. Moreover, the **stability** and **high resolution** characteristics of SAR can ensure that the data are **highly reliable**.

**Fig. 3** Differences in percent tree cover between Class A and Class D neighbourhoods (Class D cover minus Class A cover) across U.S. cities  
*Source:* [*Nowak et al. (2022)*](https://www.fs.usda.gov/nrs/pubs/jrnl/2022/nrs_2022_nowak_001.pdf)

In terms of **disaster response**, I have found that **SAR is more suitable for quickly and accurately monitoring surface changes** after a disaster. Optical imagery is often difficult to provide post-disaster information quickly due to weather conditions, whereas SAR can quickly generate accurate data on surface changes after a disaster. I have learnt that SAR can provide **damage assessment** in a very short time after **earthquakes**, **floods**, and even **man-made disasters** (e.g. war damage). This not only helps directly in **post-disaster rescue operations** but also provides important **data support for post-disaster reconstruction** [@plank2014].

**Reflection**

This week's study of **SAR** and **InSAR** technologies has made me deeply aware of the **diversity of remote sensing tools** with unique advantages in practical applications. SAR technology is unaffected by clouds and weather and can provide data steadily around the clock, which is crucial in **urban planning**, **disaster response**, and **environmental monitoring**. The SAR echo characteristics mentioned in the class and the ability of InSAR technology to monitor surface changes with high accuracy have also inspired me to do a lot of future research.

Particularly interesting to me is the ability of **InSAR** to monitor **small surface displacements**, such as landslides, land subsidence, or earthquakes-induced surface micro-change. This ability to measure with **centimetre-level accuracy** is extremely valuable in **urban governance** and **disaster management**, making it clearer to me that if I want to study **urban geohazards** in the future, InSAR will be a powerful tool for me. I am also thinking further about how InSAR technology can be applied to **urban infrastructure monitoring**, such as long-term monitoring of **bridges**, **elevated roads**, or **underground pipelines** to detect structural risks in advance.

In addition, by reading the literature, I started to think deeply about the **integration of remote sensing technology with socio-economic issues**. Historical urban red line areas often face problems such as **heat island effect** and **unbalanced ecological services**, and SAR's **all-weather observation capability** can provide continuous spatial evidence of these **socio-economic phenomena**. I feel that this **interdisciplinary combination** of technology and social issues is very valuable and worthy of further exploration in my future research.

I am even considering how to **combine SAR and InSAR data with population health and economic development data** for joint analyses in future research designs to more comprehensively study **environmental justice** and **social inequality** issues.