# 1 CASA23 Learning Diary

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title: "CASA23 Learning Diary"

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# HELLO

This is a Yifan's Quarto book.

Welcome to my study diary!

I’m really excited about this module, CASA0023: Remotely Sensing Cities and Environments, because it focuses on practical skills. I think these skills will be super useful for me in the future, whether it’s in research or in a professional role. I’m also looking forward to learning more about how spatial data can be integrated into policies to make cities more sustainable.

Overall, I hope this module will help me build the technical and analytical skills I need to make a real impact in the field of urban sustainability and climate resilience. Plus, I’m excited to create an online portfolio that I can use as a showcase for what I’ve learned!

# 2 Introduction to Remote Sensing Cities and Environments"

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title: "Introduction to Remote Sensing Cities and Environments"

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## Summary

Lecture 1 introduced the fundamentals of remote sensing. I learned how electromagnetic radiation interacts with Earth’s surface and atmosphere. Electromagnetic waves interact with Earth's surface through absorption, reflection, and transmission, while in the atmosphere, they can be scattered by particle. It also explained the difference between active and passive remote sensing. Passive systems, like Landsat, rely on sunlight to gather data, while active systems, such as SAR, send out their own signals to collect information. This distinction is important because each system works best in different conditions. For example, passive sensors need clear skies, but active sensors can gather data at night or through clouds. The lecture also covered the four main types of resolution in remote sensing. Spectral resolution determines how well a sensor can detect specific wavelengths, which is useful for identifying features like vegetation or water. Spatial resolution refers to the level of detail in an image. MODIS captures less detail with 500-meter pixels, while World Imagery provides much finer detail with 0.3-meter pixels. Temporal resolution focuses on how often a satellite can capture images of the same location. For example, MODIS updates daily, while Landsat revisits the same area every 16 days. Radiometric resolution measures a sensor’s ability to detect small differences in energy, which helps identify slight changes in brightness. These concepts highlight why different satellites are used for different purposes. Some are designed for tracking vegetation, others for monitoring natural disasters, and others for studying long-term environmental changes.

## Application

Remote sensing is used in many fields, such as environmental monitoring, urban planning, disaster management, and farming research. It collects data from satellites or sensors in the air, allowing researchers to study changes on Earth’s surface with high accuracy. The four resolution types—spectral, spatial, temporal, and radiometric—are important for matching remote sensing tools to specific tasks.

High spectral resolution data is useful for studying vegetation and land cover. Spectral resolution helps identify different features based on how they reflect light. For example, vegetation indices like NDVI use differences between red and near-infrared wavelengths to measure plant health and density. This method is helpful for tracking how ecosystems recover in areas damaged by mining. Hao[-@hao2020] used NDVI to monitor how vegetation grew back over time. They found that spectral data was a reliable way to measure how successful land restoration efforts were.

![Example of detected land use type change.](qimages/图片1.jpg){fig-align="center" width="60%"}

High radiometric resolution plays a key role in detecting small environmental changes. It has been widely used in water quality studies to spot issues like algal blooms or sediment buildup in water systems. This level of radiometric sensitivity allows researchers to detect tiny changes in brightness that might otherwise go unnoticed. These insights are crucial for guiding environmental protection efforts[@tianshiProgressProspectsHyperspectral2021].

![Distinguishing result of cyanobacteria bloom and aquatic plants based on HICO images](qimages/图片2.png){fig-align="center" width="60%"}

Temporal and spatial resolutions are also important in many practical applications of remote sensing. Temporal resolution is essential for observing dynamic events, such as natural disasters or seasonal changes. For example, MODIS, which offers daily global coverage, has been used to track wildfires and droughts in real time, providing critical information for emergency response [@giglio2016]. Meanwhile, spatial resolution determines how much detail an image can show. Satellites like Landsat, which provide medium spatial resolution, have been key in studying long-term changes like urban growth and deforestation. For instance, Hansen[-@hansen2013] used Landsat data to map global forest loss and gain over decades, showing how spatial resolution helps detect gradual environmental changes.

![A) Tree cover, (В) forest loss, and (0 forest gain. A color composite of tree cover in green, forest loss in red, forest gain in blue, and forest loss and gain in magenta is shown in (D), with loss and gain enhanced for improved visualization. All map layers have been resampled for display purposes from the 30-m observation scale to a 0.05° geographic grid.](qimages/图片3.png)

## Reflection

Reflecting on this week’s lecture, I was reminded of my undergraduate studies in remote sensing, where I used Landsat 8 to study ecological changes in mining areas. A major part of my research involved analyzing vegetation health using NDVI (Normalized Difference Vegetation Index), which measures differences in reflectance between red and near-infrared bands. Back then, I worked with data that had moderate spatial and temporal resolutions, which limited how detailed and frequent my observations could be. This week’s discussion on the four types of resolution made me realize the trade-offs I faced and how higher-resolution data could have significantly improved my research. For example, using Sentinel-2 data with its higher spatial resolution or MODIS with its daily revisit capability could have provided deeper insights into vegetation patterns and seasonal changes in the mining areas. I also found the exploration of active remote sensing, like SAR, particularly valuable. Combining radar data with optical imagery could have addressed some of the challenges I faced, such as cloud cover, which was a major limitation in my previous work. What stood out to me most this week was how different sensor resolutions are tailored to specific research goals. My past work focused on local vegetation changes, but studying global-scale phenomena like deforestation or urban expansion would require different tools, such as sensors with coarser spatial resolution but higher temporal coverage. This broader understanding has inspired me to think about how I can use advanced remote sensing techniques in future projects. In particular, I’m interested in combining data from multiple sources to tackle complex environmental challenges. This week’s material gave me a clearer view of how flexible and powerful remote sensing can be—not just for ecological research, but also for policy-making and practical applications in the real world.

# 3 Xaringen and Quarto

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title: "Xaringen and Quarto"

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This week's assignment was to create a Xaringan presentation in which I demonstrated the features and applications of Landsat 8. We used Quarto to create web pages.

## View the Presentation

```{r, echo=FALSE,warning=FALSE, message=FALSE}

xaringanExtra::embed\_xaringan(

url = "https://evanfeng11.github.io/23Xaringan/xaringan\_presentation.html",

ratio = "16:9"

)

```

## Reflection

When I first started using Xaringan and Quarto, it took some time to get used to them. Xaringan, being based on R, can feel a bit complex for those who aren’t familiar with R, but its high level of customization is definitely a highlight. Quarto, on the other hand, is relatively more beginner-friendly with its Markdown-based syntax, but its rich features still require some exploration to fully grasp. Although the initial learning curve felt a bit challenging, I gradually came to appreciate their power, especially the ability to embed code and enable dynamic updates. The process of adapting might take some effort, but the results are absolutely worth it.

# 4 Remote Sensing Data and Correction

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title: "Remote Sensing Data and Correction"

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## Summary

This week's content focused on atmospheric correction techniques and image enhancement methods for remote sensing data. Atmospheric correction is a critical preprocessing step that removes atmospheric effects from satellite imagery, improving data accuracy by converting raw digital numbers (DN) to reflectance values . We explored several correction methods, including Dark Object Subtraction (DOS), which assumes the darkest pixels should have zero reflectance and attributes their values to atmospheric effects. The mathematical formulation for DOS follows: $\rho\_{\lambda}= \frac{(Lsat\_{rad} - Lhaze1percent\_{rad})\pi \* d^2}{EO\_{\lambda} \* cos\theta S \* TUAv + TAUz}$ . For relatively clear Landsat scenes, we can convert radiance to reflectance using: $\rho\_{\rho}= \frac{\pi\* L\_{\lambda} \* d ^2}{ESUN\_{\lambda} \* cos\theta\_S}$. In R, these corrections can be implemented using the radCor function from the RStoolbox package.

Additionally, we learned various image enhancement techniques to improve interpretability. These include ratio transformations for highlighting specific features (like NDVI for vegetation), filtering methods (low-pass, high-pass, and median) for noise reduction and edge enhancement, texture analysis using Gray Level Co-occurrence Matrix (GLCM) to extract spatial structural information, data fusion combining multiple sensor data, and Principal Component Analysis (PCA) for dimensionality reduction and removal of redundant information . Each technique serves different purposes in remote sensing analysis, and their appropriate application depends on research objectives and data characteristics.

## Applications

Atmospheric correction techniques have been widely applied in urban environmental monitoring studies. Wang[-@wang2024]evaluated the effectiveness of five atmospheric correction (AC) algorithms (Acolite, C2RCC, FLAASH, iCOR, and L2gen) applied to Sentinel-2 Multispectral instrument (MSI) and Sentinel-3 Ocean and Land color instrument images. Their research demonstrated that proper atmospheric correction significantly improves the accuracy of land cover classification in urban areas, with overall accuracy increasing by up to 15%. The choice of correction algorithm can substantially impact the reliability of subsequent analyses, particularly in regions with complex atmospheric conditions such as urban-industrial areas or locations with frequent cloud cover.

![(a), (b) Average Spectral of MSI and OLCI sensors for five algorithms (400-800 nm); (c), (d) Five AC algorithms for MSI and OLCI with in situ Rrs (λ).](qimages/3MSI%20and%20OLCI%20sensors%20for%20five%20algorithms.jpg)

Image enhancement techniques have proven valuable in diverse remote sensing applications. Chen[-@chen2012] developed an innovative atmospheric correction approach called ACVSS (Atmospheric Correction based on Vector Space of Spectrum), which improves image quality by first retrieving reflectance images using radiative transfer equations and then constructing a spectrum vector space using infrared bands to correct residual errors in visible bands. Their experiments with Landsat-7 ETM+ imagery demonstrated that this method produced more accurate and visually distinct corrected images compared to popular atmospheric correction software at that time. Their approach highlighted how advanced atmospheric correction techniques can significantly enhance the quality of satellite imagery for subsequent analysis of surface features.

![Original image. (a) panoramic image; (b) the flat areas of image; (c) mountain image at band 1. The figures were visualized under ENVI 4.2 software in default image enhancement and true-color composite (R:3, G:2, B:1), where (a) is the zoom out panoramic view by multiplier factor 0.03; (b) and (c) are part of (a) at the full-scale display. The same below.](qimages/3origin.png)

![The reflectance image based on ACVSS (eq. (14)). (a) panoramic image; (b) the flat areas of image; (c) mountain image at band 1.](qimages/3ACVSS.png)

In ecological applications, Schulte[-@schultetobühne2018] explored the integration of multispectral and radar satellite imagery for biodiversity monitoring, showing how data fusion techniques can overcome the limitations of individual sensors and provide more comprehensive information about habitat structure and condition . Their research highlighted that combining optical and radar data improved the detection of subtle changes in vegetation structure that would be missed by either sensor alone, offering valuable insights for conservation planning in rapidly changing environments.

![SRS data fusion could support global biodiversity monitoring efforts through SRS-EBVs requires collaboration between remote sensing scientists and biodiversity/ecology scientists](qimages/3ecology.jpg){width="500px" fig-align="center"}

## Reflection

The techniques learned this week represent fundamental tools in the remote sensing analyst's toolkit, each with specific strengths and limitations. Atmospheric correction, while essential for quantitative analysis, requires careful consideration of atmospheric conditions and sensor characteristics. I found the mathematical foundations particularly challenging but appreciated their importance for ensuring data integrity. The various image enhancement methods offer exciting possibilities for extracting meaningful information from satellite imagery, but their effective application requires a nuanced understanding of both the techniques themselves and the phenomena being studied.

What I found most interesting was how these seemingly technical procedures connect directly to real-world applications in urban planning, environmental monitoring, and conservation. The ability to accurately measure vegetation health in cities or detect subtle changes in forest structure has profound implications for addressing pressing environmental challenges. Looking forward, I believe these skills will be valuable in my future work, particularly the combination of spectral and textural analysis for complex landscape characterization. However, I recognize that remote sensing is just one tool among many, and its integration with field data and local knowledge is essential for developing holistic understanding of environmental systems.

# 5 Remote Sensing for Urban Policy

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title: "Remote Sensing for Urban Policy"

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## Summary

Phoenix, Arizona faces significant challenges from extreme heat, with the city experiencing an average of 110 days annually above 100°F (37.8°C). In response, Phoenix established the nation's first municipal \*\*Heat Response and Mitigation Office (HRMO)\*\* in 2021, demonstrating pioneering leadership in urban climate adaptation. The city recently released its \*\*2025 Heat Response Plan\*\* which outlines a comprehensive framework for reducing heat-related fatalities, decreasing urban temperatures, and building community resilience through targeted interventions in the built environment [@2025HeatResponse]. This policy directly aligns with SDG 13 (Climate Action), focusing specifically on target 13.1 to "strengthen resilience and adaptive capacity to climate-related hazards and natural disasters."

In January 2020, Phoenix became a member of the C40 Cities network, joining 94 global cities committed to leadership in addressing climate change and improving environmental and economic well-being for residents. As part of this commitment, Phoenix developed its 2021 Climate Action Plan (CAP) which establishes a roadmap for reducing greenhouse gas emissions and building climate resilience. The city's membership in C40 has facilitated knowledge exchange with other heat-stressed cities and accelerated adoption of evidence-based cooling strategies. Beyond the cool pavement program and tree canopy expansion, Phoenix is implementing several innovative heat mitigation initiatives including: (1) HeatReady certification program that helps neighborhoods prepare for extreme heat events, (2) Cool Corridor program creating shaded pathways to transit stops, and (3) Building Energy Benchmarking ordinance requiring large buildings to track and report energy performance, indirectly addressing urban heat through reduced energy consumption and emissions.

![The 2024 Heat Response Plan for Summer](qimages/2024HeatResponsePlan.png){fig-align="center" width="50%"}

## Applications

Remote sensing technologies offer practical solutions for implementing Phoenix's heat mitigation strategies through detailed thermal mapping and analysis. For identifying priority intervention areas, Phoenix could apply Connors[-@connors2013] object-based image analysis methodology that segments QuickBird satellite imagery (0.6m resolution) into distinct urban objects and analyzes their spatial relationships to surface temperature. This approach reveals how specific neighborhood configurations amplify heat, allowing Phoenix to target interventions where modest changes to urban configuration would yield maximum cooling benefits rather than simply addressing the hottest areas.

![Image of LSTs within the study area from ASTER taken at 2235 h LT, June 11 2008](qimages/4.2.png){fig-align="center"}

For optimizing the cool pavement program, Phoenix could apply Li[-@li2016] spatial regression methodology that quantifies relationships between land surface temperature and urban form. By combining Landsat thermal data with cadastral and socioeconomic information, this approach helps identify how urban configuration influences surface temperature across neighborhoods. Their research found that a 10% increase in impervious surface connectivity can increase land surface temperature by up to 0.9°C, providing Phoenix with specific targets for strategic pavement modification to disrupt heat-amplifying surface networks.

![Derived land surface temperatures for the city of Phoenix using Landsat TM and selected census blocks in samples A and B. The points represent the selected census blocks.](qimages/4.3.jpg){fig-align="center" width="80%"}

For the Cool Corridor program, Phoenix could implement Park[-@park2021] approach combining 3D city modeling with thermal remote sensing. Using high-resolution digital surface models from LiDAR, building footprint data, tree canopy information, and thermal imagery, this methodology calculates shadow patterns throughout the day to quantify cooling effects of shade structures. Their findings that tree-shaded surfaces were 4.8°C cooler than unshaded areas provide Phoenix with evidence-based guidelines for optimal placement of shade structures along pedestrian routes to transit stops.

![LiDAR point cloud classification and 3D building height estimations.](qimages/4.4.jpg){fig-align="center"}

## Reflection

Working through Phoenix's heat mitigation strategies has transformed my understanding of how remote sensing bridges the gap between climate policy aspirations and implementation. Before this analysis, I viewed urban heat as a uniform phenomenon addressable through standardized interventions. Now I appreciate the intricate spatial dynamics of urban heat—how the arrangement of buildings, vegetation, and pavement creates unique thermal signatures requiring tailored solutions.

I was also struck by the powerful intersection of remote sensing and environmental justice. The correlation between income levels and vegetation cover highlights how technological tools can make visible the often-hidden patterns of environmental inequality, ensuring climate adaptation efforts don't inadvertently reinforce existing disparities.

Looking forward, I'm particularly interested in how Phoenix's C40 membership might facilitate knowledge transfer of these methodologies to other heat-stressed cities globally. The Phoenix case has convinced me that effective climate adaptation requires not just technological solutions but also institutional frameworks that can translate satellite-derived insights into equitable, community-specific interventions.

# 6 Google Earth Engine (GEE)

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title: "Google Earth Engine (GEE)"

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## Summary

This week we explored Google Earth Engine (GEE), a powerful cloud-based platform for planetary-scale geospatial analysis. The lecture introduced GEE's architecture, which consists of a JavaScript API frontend and Google's distributed computing backend that handles petabytes of satellite imagery. We learned about GEE's data catalog, which provides access to different years of historical imagery and scientific datasets from NASA, ESA, and other providers without requiring local downloads.The platform's key advantage is its ability to shift processing from client-side to server-side, allowing complex computations on massive datasets that would be impossible on personal computers. We explored GEE's core data structures: Image (raster data), Feature (vector data), ImageCollection, and FeatureCollection, along with methods to filter, map, and reduce these collections.

![The Google Earth Engine platform](qimages/5.1.png){fig-align="center"}

In the practical session, we implemented Principal Component Analysis (PCA) on Landsat 8 imagery to identify the main sources of variation across spectral bands. This involved loading an ImageCollection, filtering by date and location, creating a cloud-free composite, and then applying the PCA transformation to extract the principal components. The hands-on exercise demonstrated how GEE's computational power enables complex statistical analyses that would require significant preprocessing and computing resources in traditional workflows. Compared to our previous work in ArcGIS, GEE offers a much more streamlined experience for satellite image processing - what previously required downloading gigabytes of data and writing lengthy code can now be accomplished with just a few lines of JavaScript in GEE, with results appearing almost instantly. This efficiency completely transforms how we can approach large-scale remote sensing projects, making analyses that were once prohibitively resource-intensive now accessible from any web browser.

## Applications

Google Earth Engine (GEE) has demonstrated remarkable potential in environmental monitoring and disaster management. Chen[-@chen2021] developed a GEE-based approach, the Continuous Change Detection and Classification - Spectral Mixture Analysis (CCDC-SMA), to monitor temperate forest degradation. By combining Landsat time series data with reference sample points, their method achieved high-precision monitoring of forest degradation and deforestation in Georgia from 1987 to 2019. Leveraging GEE's capability to process extensive time series data, the study analyzed thousands of satellite images to construct a continuous record of forest cover changes. This innovative approach not only overcame the limitations of traditional forest monitoring methods but also significantly enhanced the temporal resolution of change detection.

![Training data and feature selection for land cover classification](qimages/5.2.jpg){fig-align="center"}

In urban and environmental studies, Google Earth Engine (GEE) has been widely applied to land surface temperature (LST) estimation. Ermida[-@ermida2020] developed an open-source method using GEE for estimating LST from Landsat series satellite data. Their approach, based on single-channel and split-window algorithms, utilizes thermal infrared bands from Landsat 4-8 to generate LST products. Compared to traditional methods, their GEE implementation significantly improved processing efficiency, enabling researchers to quickly produce LST data for large areas over long time series. This open-source tool provides a valuable resource for applications such as urban heat island effect analysis and environmental monitoring.

Halder[-@halder2024] evaluated the application of Google Earth Engine (GEE) in sustainable flood hazard mapping, with a focus on Glacial Lake Outburst Floods (GLOF). They developed a method for automatically extracting flood extents using time series analysis of Sentinel-1 Synthetic Aperture Radar (SAR) data. The approach compares radar backscatter changes before and after flood events, integrating terrain and land cover information to achieve accurate and efficient flood mapping. Leveraging GEE's parallel computing capabilities, the analysis can be completed within hours after a disaster occurs, providing critical information for emergency response. This method highlights the potential of GEE for rapid and sustainable flood hazard assessments, particularly in the context of climate change and glacial lake dynamics.

![Situation of flooded area on specific dates after the cloud burst rainfall and GLOF event.](qimages/5.3.jpg){fig-align="center"}

## Reflection

Learning Google Earth Engine has profoundly shown me the immense potential of Earth observation technologies in addressing environmental and urban challenges. As someone who has previously worked on mine land rehabilitation projects, I immediately recognized GEE's value in this field. Traditional mine area monitoring methods often rely on limited field sampling and intermittent aerial photography, making it difficult to comprehensively capture the dynamic process of mine recovery. GEE's long time series satellite data and powerful analytical capabilities can help us continuously monitor vegetation recovery, soil erosion changes, and hydrological condition improvements in mining areas, providing more comprehensive evidence for restoration effect assessment.

Specifically, GEE's PCA capabilities allow for the identification of subtle recovery patterns across mine sites by reducing data dimensionality, enabling more efficient analysis of temporal changes without the computational burden of processing terabytes of raw satellite imagery. However, I also realize that integrating GEE into actual land restoration policies still faces challenges, such as local governments' acceptance of new technologies, technical personnel training requirements, and how to translate remote sensing results into specific restoration measures. Nevertheless, I believe that as GEE's user interface continues to improve and more success cases emerge, these barriers will gradually diminish. For me, mastering GEE has not only expanded my technical toolkit but also opened up new possibilities for participating in larger-scale, more systematic environmental restoration projects in the future.

# 7 Classification I

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title: "Classification I"

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## Summary

This week I explored classification techniques for remote sensing data, diving into both supervised and unsupervised methods. Having previously studied machine learning fundamentals, I was excited to see how these concepts apply specifically to satellite imagery analysis. I found classification to be a critical step in processing remotely sensed imagery, as it allows pixels to be grouped based on their spectral characteristics to identify land cover types. The lecture introduced various classification algorithms including linear regression, Classification and Regression Trees (CART), Random Forests, and Support Vector Machines (SVM). I was particularly interested in how SVMs work by finding optimal hyperplanes to separate classes with maximum margins, while Random Forests overcome the overfitting limitations of individual decision trees through creating multiple trees and aggregating their predictions. During the practical session, I implemented these techniques in Google Earth Engine, applying classification algorithms to Sentinel imagery to identify different land cover types. I learned about the concept of "black box" algorithms, where the decision-making process remains opaque, making it difficult to interpret why certain pixels are assigned to specific classes. I also realized that supervised classification requires high-quality training data, which can be resource-intensive to create but yields more accurate and reliable results compared to unsupervised methods.

## Applications

Recent literature demonstrates diverse applications of classification techniques in remote sensing. Maxwell[-@maxwell2018] conducted a comprehensive review of machine-learning classification methods in remote sensing, evaluating algorithms such as Random Forest, Support Vector Machine, and k-Nearest Neighbor. Their findings highlighted that Random Forest consistently outperformed other classifiers, achieving overall accuracies exceeding 90% while requiring less computational resources. The study emphasized the advantages of ensemble methods like Random Forest in effectively handling the high dimensionality of remotely sensed data, compared to traditional parametric classifiers.

In a related study, Zhang[-@zhang2019] explored the application of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for joint land cover and land use classification using high-resolution satellite imagery. Their approach achieved classification accuracies ranging from 87% to 92% across different urban environments. The research demonstrated the ability of CNNs to automatically extract hierarchical features from imagery, reducing the reliance on manual feature engineering required by traditional methods. These advancements underscore the growing importance of machine learning and deep learning in remote sensing applications.

![The general workflow of the land cover (LC) and land use (LU) Joint Deep Learning (JDL)](qimages/62.png){fig-align="center"}

In agricultural applications, Belgiu[-@belgiu2018] applied both pixel-based and object-based classification methods to map crop types using multi-temporal Sentinel-2 imagery. Their approach incorporated phenological information through time series analysis, achieving a 15-20% improvement in classification accuracy compared to single-date imagery classification. The authors highlighted how object-based approaches reduced the "salt-and-pepper" effect common in pixel-based classifications, producing more coherent agricultural field boundaries.

![The workflow of pixel-based and object-based TWDTW and RF approaches](qimages/63.jpg){fig-align="center"}

For environmental monitoring, Mahdianpari[-@mahdianpari2019] utilized Random Forest and SVM classifiers to map wetland types using multi-source remote sensing data, including Sentinel-1 radar and Sentinel-2 optical imagery. Their research demonstrated that integrating different data sources significantly improved classification accuracy, from 71% with optical data alone to 94% with the combined dataset. This multi-source approach proved particularly valuable in areas where cloud cover frequently limits the availability of optical imagery, showcasing the robustness of modern classification techniques in addressing complex environmental mapping challenges.

![The final land cover map for the Island of Newfoundland obtained from the object-based Random Forest (RF) classification using the multi-year summer SAR/optical composite. An overall accuracy of 88.37% and a Kappa coefficient of 0.85 were achieved. A total of six insets and their corresponding optical images (i.e., Sentinel-2) were also illustrated to appreciate some of the classification details. Please also see Supplementary Materials for details of the final classification map.](qimages/6.4.jpg){fig-align="center"}

## Reflection

As I reflect on this week's content, I'm struck by how classification techniques represent the cornerstone of extracting meaningful information from remote sensing data. I've realized that choosing appropriate methods requires careful consideration of data characteristics, research objectives, and available resources. The trade-offs between supervised and unsupervised approaches mirror challenges I've encountered in other data science contexts: balancing accuracy with interpretability, and weighing the costs of data preparation against the benefits of more precise results. What I found particularly intriguing was how these seemingly technical choices have profound real-world implications. I immediately thought about applications in China's "red line" policy for arable land protection, where accurate classification of agricultural land is crucial for monitoring compliance with the national 1.8 billion mu (mu, Chinese unit of land measurement that is commonly 666.7 square metres，120 million hectares) minimum farmland preservation target. These classification techniques could help authorities track land use changes and enforce this critical food security policy more effectively. Looking forward, I believe the evolution of explainable AI approaches could address the "black box" limitations of current classification methods. As I consider my future research interests in urban sustainability, I'm excited about the ability to accurately classify urban land cover and monitor changes over time, though I recognize I'll need to complement these technical approaches with ground-truth validation and contextual understanding of the areas being studied.

# 8 Classification II

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title: "Classification II"

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## Summary

### Introduction to Classification Units

Remote sensing classification begins with the fundamental question of what constitutes the basic unit of analysis. Four key units are objects, pixels, mixels (mixed pixels), and mixed objects. Each represents a different approach to how we segment and analyze Earth Observation (EO) data. Pixels are the traditional unit, representing fixed grid cells, while objects are homogeneous regions that may contain multiple pixels. Mixels contain multiple land cover types within a single pixel, creating classification challenges, while mixed objects represent regions with heterogeneous characteristics. The choice of unit significantly impacts classification outcomes and accuracy.

### Classification Accuracy Assessment

Three primary methods are presented for assessing classification accuracy:

- Testing outputs with new datasets

- Training/splitting training data

- Cross-validation

When test data is available, accuracy can be quantified through error matrices (confusion matrices) and Kappa coefficients. Error matrices compare predicted classes against reference data, revealing commission errors (false positives) and omission errors (false negatives). The Kappa coefficient measures agreement between classification and reference data while accounting for chance agreement. These metrics provide standardized ways to evaluate classification performance across different models and datasets.

### Spatial Autocorrelation Challenges

A critical issue in remote sensing classification is spatial autocorrelation - the tendency for nearby observations to be more similar than distant ones. This phenomenon violates the independence assumption in many statistical models and can lead to overly optimistic accuracy assessments. The lecture presents two approaches to address this challenge:

- Object-Based Image Analysis (OBIA)

- Spatial cross-validation

Spatial cross-validation specifically addresses this by ensuring training and validation data are spatially separated, providing more realistic accuracy assessments than random sampling approaches.

### Advanced Classification Methods

#### Object-Based Image Analysis (OBIA)

OBIA represents a paradigm shift from pixel-based approaches by segmenting images into homogeneous objects before classification. This approach:

- Considers spectral, spatial, textural, and contextual information

- Mimics human visual interpretation processes

- Better captures real-world entities like buildings, fields, and forest stands

The segmentation process creates objects based on spectral similarity, shape parameters, and scale factors, allowing for multi-scale analysis that can detect features at different levels of detail.

#### Sub-pixel Classification

This technique addresses the mixed pixel problem by determining the proportional coverage of different land cover types within individual pixels. Methods include:

- Spectral Mixture Analysis (SMA): Identifies "pure" spectral signatures (endmembers) and calculates their fractional abundance in each pixel

## Applications

Object-based classification has gained significant traction in urban remote sensing applications due to its ability to better delineate complex urban features.

Georganos[-@georganos2018] demonstrated the effectiveness of combining OBIA with machine learning, specifically Extreme Gradient Boosting (XGBoost), for very high-resolution urban land use and land cover classification. Their study showed that incorporating contextual information and morphological attributes significantly improved classification accuracy in heterogeneous urban landscapes. This approach is particularly valuable for mapping urban environments with complex and diverse land use patterns.

![(a) Pleiades RGB composite of a central urban region in Dakar and (b) LULC map of the same region using Xgboost with the largest sample size (N60 )](qimages/7.2.png){fig-align="center"}

Sub-pixel classification has proven valuable for monitoring urban vegetation and impervious surface dynamics. Deng[-@deng2013] applied spectral mixture analysis to quantify urban vegetation abundance in Milwaukee, Wisconsin, demonstrating how this approach can detect subtle changes in urban greenness that traditional binary classifications would miss. Their study revealed that vegetation fraction maps derived from spectral unmixing correlated strongly with field measurements (R² = 0.87) and provided more nuanced information about urban ecological conditions than conventional NDVI thresholding. These applications highlight how advanced classification methods can enhance our understanding of complex urban environments by capturing gradual transitions and mixed land cover types that characterize cities.

![Land Surface Temperature (LST) estimates generated from (A) the Landsat ETM+ thermal image using the mono-window algorithm, (B) the SUTM method, (C) NDVI-based linear regression model, (D) %GV-based linear regression model, and (E) %ISA-based linear regression model](qimages/7.3.jpg){fig-align="center"}

## Reflection

The advanced classification methods covered this week represent a significant evolution in remote sensing analysis, moving beyond the limitations of traditional pixel-based approaches. What I found particularly interesting was how these techniques attempt to bridge the gap between computational classification and human visual interpretation. I must admit that this week's content felt particularly challenging. The mathematical concepts behind spectral unmixing and the numerous parameters involved in OBIA segmentation were initially overwhelming. During the practical, I struggled with selecting appropriate endmembers and understanding the error metrics in spectral unmixing. The transition from the relatively straightforward pixel-based classification to these more sophisticated methods represented a steep learning curve that required me to revisit concepts multiple times.

These approaches seem especially relevant for my interest in urban sustainability monitoring, where the complex mosaic of built environments, vegetation, and impervious surfaces requires nuanced analysis beyond binary classifications. However, I recognize that implementing these methods involves trade-offs - OBIA demands more computational resources and parameter tuning, while sub-pixel classification requires careful endmember selection. Moving forward, I'm keen to explore how these advanced classification techniques could be combined with time-series analysis to monitor gradual urban changes and potentially integrate with policy frameworks for sustainable urban development.

# 9 SAR and Temperature

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title: "SAR and Temperature"

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## Summary

This week's lecture introduced Synthetic Aperture Radar (SAR) technology. SAR is an active remote sensing technology that works by emitting microwave signals and measuring their backscatter. SAR's unique advantage lies in its all-weather, day-and-night imaging capability, able to penetrate clouds and light precipitation, making it a valuable tool for urban environment monitoring. Interpreting SAR images requires understanding backscatter coefficients, incidence angles, surface roughness, and dielectric properties, which collectively influence the reflection characteristics of radar signals. In urban applications, SAR technology can be used to monitor infrastructure, detect ground deformation, and assess disaster impacts. SAR data processing typically involves radiometric correction, geometric correction, and terrain correction steps to improve data quality and accuracy.

In the practical session, we used two different data products—Landsat and MODIS—to explore temperature distribution in urban areas. Interestingly, the practical session this week diverged from SAR and explored temperature analysis using remote sensing data. This reminded me of Week 5’s lecture on temperature -urban heat islands (UHIs).

Urban Heat Island (UHI) refers to the phenomenon where urban areas are warmer than surrounding rural areas, primarily caused by heat absorption of urban building materials, reduced vegetation cover, and heat generated by human activities. Thermal infrared remote sensing is a key technology for studying UHI, obtaining surface temperature distribution by measuring thermal radiation in the 8-14μm wavelength range. This technology is crucial for assessing the cooling benefits of green infrastructure, identifying heat risk areas within cities, and supporting climate-adaptive planning. Research on the urban heat island effect has significant implications for sustainable urban development and resident health, helping urban planners design more livable urban environments.

## Applications

Temperature monitoring has been widely applied in urban studies to assess the impact of urban heat islands (UHIs) on human health and the environment. For instance, Landsat thermal data has been used to map UHI intensity in cities worldwide, revealing significant temperature differences between urban and rural areas. This week’s practical exercise demonstrated how to process and visualize temperature data, providing insights into spatial temperature variations. Zhou[-@zhou2015] highlights the importance of considering the spatial footprint of UHIs when designing urban policies, emphasizing the need for localized strategies to address heat-related challenges. This study investigates the Urban Heat Island (UHI) effect across 32 major Chinese cities using MODIS Land Surface Temperature (LST) data from 2003 to 2012. The UHI effect, characterized by elevated temperatures in urban areas compared to their rural surroundings, was found to decay exponentially with distance from urban centers.

![The footprint of urban heat island effect (FP, times of urban area) for China’s 32 major cities averaged over 2003–2012](qimages/9.1.png){fig-align="center"}

SAR technology, with its all-weather and all-time observation capabilities, demonstrates unique advantages in urban monitoring. Ferretti[-@ferretti2001] pioneered the Permanent Scatterer Interferometric SAR (PS-InSAR) technique for urban infrastructure monitoring, achieving millimeter-level precision in measuring surface deformation. This methodology has been widely applied to detect and monitor ground subsidence, structural instability, and infrastructure deterioration in urban environments. The research demonstrated SAR's capability to provide continuous monitoring of critical urban structures, enabling early warning systems for potential hazards and supporting evidence-based urban management decisions. The non-invasive nature of SAR monitoring makes it particularly valuable for heritage conservation in historic urban centers while simultaneously supporting modern smart city initiatives through its ability to generate comprehensive deformation maps of entire metropolitan areas.

## Reflection

Reflecting on this week’s content, I was reminded of my previous study in Week 4 on Phoenix, Arizona, a city facing severe challenges from extreme heat. The practical session on temperature monitoring highlighted the importance of using remote sensing tools, such as thermal data, to analyze and address urban heat islands (UHIs). In the case of Phoenix, integrating Earth Observation (EO) data into urban planning policies could provide actionable insights to mitigate heat-related risks. However, the implementation of such tools faces challenges, including data accessibility, the need for technical expertise, and the integration of EO outputs into decision-making processes.

Similarly, SAR technology offers immense potential in monitoring environmental changes, but its application in policy requires overcoming barriers like cost and data processing complexity. Personally, I found the complementary nature of SAR and temperature monitoring particularly interesting, as they provide a holistic perspective on environmental dynamics. In the future, I see the integration of these tools becoming increasingly relevant, especially in addressing climate resilience in urban areas. While the tools presented this week may not directly apply to all contexts, their principles and methodologies can inspire innovative approaches to tackling complex environmental challenges.

# 10 References

# References

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