**W1**

**Abstract**

Remote sensing involves acquiring information about Earth's surface through the measurement and analysis of electromagnetic radiation emitted or reflected from the surface without direct contact. Central to this process is the electromagnetic spectrum, encompassing wavelengths from ultraviolet, visible, and infrared to microwave, each interacting differently with atmospheric constituents and terrestrial surfaces. Upon encountering Earth’s atmosphere, electromagnetic radiation undergoes scattering processes such as Rayleigh, Mie, and non-selective scattering, affecting both data quality and interpretation. Understanding these scattering mechanisms is critical for effective atmospheric correction and accurate surface interpretation.

Once radiation reaches Earth's surface, it interacts through reflection, absorption, and transmission. These interactions produce unique spectral signatures that enable identification of various land-cover types such as vegetation, soil, water bodies, and urban features. To effectively capture and utilize these interactions, remote sensing sensors possess four critical types of resolutions: spectral, spatial, temporal, and radiometric. Spectral resolution allows differentiation between wavelengths, aiding in distinguishing materials based on their spectral signatures. Spatial resolution determines the detail level or smallest discernible feature size. Temporal resolution defines the revisit frequency, crucial for monitoring dynamic changes, while radiometric resolution refers to the sensor’s sensitivity in detecting small differences in emitted or reflected radiation, influencing image detail and precision.

Platforms like Landsat and Sentinel satellites provide global datasets balancing these resolutions, supporting extensive research in environmental monitoring, agriculture, forestry, and urban planning. Landsat, offering moderate-resolution imagery, facilitates long-term environmental studies, while Sentinel missions provide higher spatial and temporal resolution data, significantly improving precision in detailed land-use applications. Sentinel data are accessed primarily through the Copernicus Browser, a user-friendly platform offering efficient data retrieval and analysis, enhancing global data accessibility for diverse research needs.

**Application**

Landsat and Sentinel datasets have significantly impacted environmental monitoring through practical applications in agriculture, forestry, and urban studies. For example, Landsat imagery has been extensively utilized for monitoring deforestation, urban expansion, and agricultural dynamics. Hansen et al. (2013) employed Landsat data globally to analyze forest loss and gain, leveraging Landsat’s moderate spatial and temporal resolutions to map changes consistently over three decades. By loading Landsat imagery and calculating spectral indices such as NDVI and NBR, researchers effectively monitored forest cover dynamics, supporting policy decisions on sustainable forestry management and biodiversity conservation.

Sentinel data accessed via the Copernicus Browser also support targeted, high-resolution applications. For instance, Sentinel-2's high spatial (10-20 m) and temporal (5-day revisit) resolution imagery has proven particularly effective in precision agriculture. A study by Jin et al. (2022) demonstrated using Sentinel-2 data to estimate within-field wheat grain yield. Their approach involved acquiring Sentinel-2 imagery through Copernicus, computing vegetation indices (NDVI, EVI), and integrating these indices into regression models to predict grain yields accurately. This precise yield estimation facilitated optimized management strategies for farmers, enhancing agricultural productivity and sustainability.

Similarly, Sentinel-1 radar data from Copernicus have supported forestry research. Schwartz et al. (2022) utilized Sentinel-1 radar backscatter data in conjunction with optical Sentinel-2 imagery to produce high-resolution forest canopy height maps using advanced deep learning techniques. This integration provided robust estimates of biomass and forest structural metrics crucial for carbon accounting and sustainable forest management practices. Thus, practical applications of Landsat and Sentinel datasets demonstrate substantial potential in addressing environmental challenges and informing decision-making across diverse sectors.

**Reflection**

As an urban and rural planning student, engaging with remote sensing has been both intriguing and transformative for my academic perspective. Initially, I approached remote sensing as an entirely new discipline, with little exposure to concepts such as electromagnetic waves, atmospheric scattering processes, or sensor resolutions. However, learning about how electromagnetic radiation interacts uniquely with Earth's surfaces, creating distinctive spectral signatures, opened my eyes to the incredible potential of remote sensing technologies. Understanding these interactions, including scattering phenomena like Rayleigh and Mie scattering, has significantly improved my ability to interpret and analyze remotely sensed imagery accurately.

The exploration of Landsat and Sentinel datasets particularly fascinated me, as these satellites provide comprehensive global imagery vital for detailed environmental analyses and effective spatial planning. The practical process of accessing Sentinel data through the user-friendly Copernicus Browser inspired me, making me appreciate the power and accessibility of modern satellite data. Nonetheless, mastering these platforms required overcoming technical challenges such as understanding sensor characteristics, handling complex atmospheric corrections, and conducting rigorous accuracy assessments.

Moving forward, my interest in urban and regional development aligns perfectly with the capabilities provided by Sentinel and Landsat imagery. My future research might focus on monitoring urban sprawl, evaluating land-use changes, and assessing ecological impacts in rapidly urbanizing areas, integrating remote sensing techniques with urban spatial models. I envision using Sentinel's high-resolution imagery accessed via Copernicus for precision planning, sustainable land management, and optimizing urban green infrastructure design.

Overall, this course has profoundly shaped my analytical and technical skills, equipping me to tackle real-world urban planning challenges with innovative, data-driven methods. I am excited about the opportunities that remote sensing will offer my future research, and I'm committed to deepening my expertise in these technologies to support sustainable urban and regional development effectively.

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**W3**

**Abstract**

Remote sensing imagery often requires comprehensive preprocessing to ensure accurate interpretation and reliable application. This preprocessing typically includes geometric correction, atmospheric correction, empirical line correction, orthorectification, and radiometric correction, which collectively ensure high-quality remote sensing data for precise analysis. Geometric correction addresses spatial distortions arising from sensor orientation and Earth's curvature, aligning satellite imagery accurately with real-world geographic coordinates. Orthorectification specifically corrects imagery by considering terrain elevation variations, essential for accurate spatial alignment and mapping.

Atmospheric correction removes distortions caused by atmospheric particles and gases, ensuring that the spectral reflectance recorded represents true surface characteristics. Methods such as empirical line correction provide practical atmospheric correction approaches, calibrating remotely sensed images using known reflectance targets within the imagery, offering simplicity and efficiency, particularly for imagery lacking detailed atmospheric data.

Radiometric correction adjusts sensor-measured radiance into physically meaningful surface reflectance values, correcting for sensor variations and illumination differences between images. The Landsat Analysis Ready Data (ARD) products exemplify rigorous radiometric correction by providing standardized surface reflectance datasets, significantly simplifying analytical workflows and promoting consistency across temporal and spatial scales.

Furthermore, image enhancement techniques, including histogram equalization, contrast stretching, and spatial filtering, improve visual interpretability of remotely sensed imagery, aiding subsequent classification, change detection, and other image-based analyses. Data joining methods facilitate combining imagery datasets across different dates, sensors, or ancillary data sources, enriching analytical contexts and enhancing interpretability, especially in multi-temporal or multi-sensor remote sensing analyses. Together, these preprocessing techniques create robust, high-quality data foundational for accurate environmental assessment, spatial analysis, and informed decision-making.

**Application**

In practical remote sensing applications, preprocessing techniques such as geometric correction, atmospheric correction, and radiometric calibration significantly enhance data reliability. For example, geometric and orthorectification corrections have been critical in precise land-cover mapping. Roy et al. (2014) illustrated how Landsat ARD products—characterized by standardized geometric and radiometric corrections—enabled consistent global mapping of surface reflectance. These ARD products, preprocessed to correct sensor biases and atmospheric effects, allow researchers and planners to focus directly on analysis without intensive preprocessing efforts.

In agricultural monitoring, empirical line correction has proven effective, particularly when atmospheric conditions are uncertain or variable. Studies by Smith and Milton (1999) demonstrated that using empirical line correction with known ground targets effectively removed atmospheric distortions from hyperspectral data, significantly improving vegetation indices' accuracy for crop health assessments.

Image enhancement and data joining have proven essential in environmental change analyses. For instance, applying image enhancement techniques such as histogram stretching and edge detection in combination with temporal data joining facilitates detecting subtle environmental changes over time. Kennedy et al. (2010) employed data joining of multi-temporal Landsat imagery combined with enhanced visualization techniques to successfully track forest disturbances and regrowth patterns, offering valuable insights into forest management and conservation strategies.

These comprehensive preprocessing approaches collectively enhance the usability and accuracy of remote sensing data, fostering effective applications in agriculture, forestry, urban planning, and environmental monitoring, thus directly supporting informed decision-making processes.

**Reflection**

Exploring remote sensing preprocessing techniques—geometric, atmospheric, empirical line corrections, orthorectification, and radiometric adjustments—has fundamentally reshaped how I approach spatial data analysis. Before this experience, I took satellite imagery at face value, assuming that what I saw was a direct representation of reality. Learning the intricacies behind geometric and radiometric corrections, particularly the rigor of Landsat ARD products, opened my eyes to how essential precise data preparation is for accurate interpretation and effective planning.

Initially, concepts like empirical line correction and atmospheric adjustment felt abstract, challenging my ability to grasp their practical importance. Yet, as I engaged more deeply, I began appreciating how these techniques directly affect the reliability of analyses in urban and regional planning. Specifically, understanding orthorectification clarified why previous attempts at overlaying satellite images with vector maps often failed due to subtle terrain-related distortions. Now, I am far more confident in performing spatially accurate analyses critical for precise urban infrastructure planning or ecological assessments.

Rather than focusing solely on how preprocessing aids data accuracy, I found myself fascinated by how these methods enhance the storytelling aspect of spatial analysis. Image enhancement, for example, is more than technical procedure—it transforms complex data into visually engaging narratives, vital when communicating findings to policymakers or communities. This realization inspired me to consider innovative research directions, such as exploring how advanced visualization methods combined with properly corrected remote sensing data can strengthen public participation in urban planning processes.

Ultimately, learning about remote sensing corrections has shifted my perspective from being merely a passive data user to an active analyst capable of critically assessing data quality and effectively communicating its significance. This new insight will undoubtedly influence my future work, guiding me toward creating more accurate, transparent, and engaging spatial analyses that meaningfully contribute to sustainable planning and policy development.

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**W4**

**Abstract**

Jakarta, Indonesia’s capital city, is increasingly vulnerable to severe flooding due to factors such as heavy rainfall, rapid urbanization, land subsidence, climate change, and inadequate drainage infrastructure. Frequent flooding events have exacerbated environmental degradation, particularly affecting mangrove wetlands that serve as critical natural barriers protecting urban areas. Mangrove degradation not only reduces biodiversity but also weakens the city’s resilience against future flooding events. Flood-driven land degradation, combined with ongoing land-use transformations and climatic variability, creates urgent environmental policy challenges. Effective management and restoration of mangrove ecosystems thus become essential components of sustainable urban strategies. Addressing these interconnected issues requires comprehensive monitoring approaches to inform targeted interventions, policy-making, and strategic urban development.

Jakarta, as a member of the C40 Cities Climate Leadership Group, has implemented various policies to address its chronic flooding issues. These policies include the Jakarta Coastal Defence Strategy and Flood Mapping initiative, which aims to minimize land subsidence by limiting groundwater extraction, providing alternative water supplies, and developing water retention basins. Additionally, the city launched the Socially Inclusive Climate Adaptation for Urban Revitalization Project, focusing on relocating residents from flood-prone areas and revitalizing reservoirs to enhance water storage capacity. Jakarta has also committed to increasing green open spaces from 10% to 30% by 2030, constructing parks to reduce flood duration and improve quality of life.

**Application**

Remote sensing technologies can robustly support Jakarta’s flood management policies, specifically targeting mangrove wetland degradation resulting from flooding. Following methodologies exemplified in recent studies, such as Adhikari et al. (2022), effective monitoring and restoration strategies can be implemented using advanced remote sensing analysis.

Firstly, high-resolution multispectral imagery from Sentinel-2 and Landsat-8, available through Copernicus and USGS respectively, provides an ideal dataset for classifying and monitoring mangrove wetlands. Using the Random Forest (RF) algorithm, classification models can be trained by selecting representative mangrove and other wetland vegetation samples within Jakarta. Studies recommend using 15-20 training samples per class for accuracy (Adhikari et al., 2022). Model optimization parameters—including unlimited decision-tree depth, selecting two variables per split, and building up to 300 trees—ensure robust classification performance.

Post-classification techniques, such as NDVI thresholding, effectively isolate vegetation areas, improving accuracy by separating mangroves from terrestrial vegetation. Visual interpretation is then utilized to correct misclassification issues. Subsequently, assessing mangrove degradation involves calculating the dynamic change rate using the land-use dynamic degree formula, along with developing a land-use transition matrix to visualize conversions of mangrove areas into other land-use types. The Landscape Intrusion Index (LII) further quantifies the encroachment of urbanization into mangrove zones, indicating priority areas for intervention.

For identifying mangrove restoration priority areas, maximum wetland extents can be extracted efficiently by combining spectral indices (NDVI, NDBI, MNDWI, SMMI). OTSU thresholding and decision-tree methods help exclude urban areas, isolating relevant wetland habitats. Deep learning approaches, particularly APSMnet, employing ResConv modules and Transformer architecture, further enhance mangrove classification precision by capturing both local features and long-distance spatial dependencies. Finally, prioritization of restoration areas integrates mangrove degradation (LII and AWLII indices), transition matrices, and existing urban policies, delineating high, medium, and low-priority restoration zones. These technical methods collectively empower policymakers in Jakarta to make informed, effective decisions on environmental resilience and mangrove restoration.

**Reflection**

Through examining Jakarta’s environmental and urban development policies, I have gained a deeper appreciation of the intricate relationship between urban expansion, environmental degradation, and climate resilience. Flooding in Jakarta is symptomatic of broader environmental governance issues: rapid urban growth without adequate preservation of natural buffers such as mangroves highlights a reactive rather than proactive approach to environmental management. The comprehensive methodologies detailed in recent literature reinforce the need for an evidence-driven, scientifically rigorous policy response to urban environmental challenges.

However, integrating these advanced remote sensing methodologies into actual policy frameworks demands not just technical proficiency but also institutional commitment and governance innovation. Policies targeting mangrove restoration must align closely with broader urban and regional planning objectives to be effective. Furthermore, mangrove degradation, while exacerbated by flooding, also reflects underlying economic and social pressures. Restoration strategies should, therefore, incorporate community engagement, incentives for sustainable land use, and stronger regulatory frameworks to ensure lasting impacts.

Reflecting on this, I recognize that examining Jakarta's environmental policies reveals the complexities of urban environmental management. While initiatives like limiting groundwater extraction and increasing green spaces are commendable, their effectiveness depends on enforcement and community engagement. The challenge lies in balancing urban development with environmental sustainability, requiring integrated planning and collaboration across sectors. Jakarta's participation in global networks like C40 provides opportunities to share knowledge and resources, but local adaptation of these strategies is crucial. The focus on mangrove restoration highlights the importance of natural barriers in urban resilience, emphasizing the need for data-driven approaches to monitor and protect these ecosystems. Ultimately, the success of these policies hinges on the commitment of all stakeholders to prioritize environmental health alongside economic growth.

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**W5**

**Abstract**

Google Earth Engine (GEE) is a cloud-based platform widely used for processing large-scale geospatial datasets efficiently. Its robust infrastructure allows users to access, analyze, and visualize extensive satellite imagery collections without requiring local computational resources. The initial setup of GEE is straightforward, involving account registration, accessing the code editor, and familiarizing oneself with JavaScript or Python interfaces for scripting. GEE's key strength lies in its diverse built-in functions and tools, including loading image collections, reducing images across specified spatial or temporal domains, performing regression analyses, and utilizing data joining and filtering techniques.

Image collections in GEE, such as Landsat, Sentinel, or MODIS data, are efficiently accessed using ee.ImageCollection(). Reducing image collections using functions like ee.Reducer.mean() allows users to generate representative images by computing statistical summaries (mean, median, sum) across multiple images, useful for time-series analysis or regional studies. Regression analysis functions in GEE (ee.Reducer.linearFit()) facilitate modeling environmental trends, predicting continuous spatial variables, or evaluating relationships between imagery-derived indices and ground data. Additionally, the ability to filter and join datasets based on attributes (dates, sensor types, or spatial coverage) provides users with flexible, powerful means for selecting relevant subsets of large datasets.

Accuracy assessment and validation of GEE-derived results can involve spatial cross-validation and statistical measures (e.g., Kappa statistics, Overall Accuracy), ensuring the reliability and robustness of analytical outcomes. Despite its numerous advantages, users may initially face learning curves regarding scripting proficiency and understanding the cloud-based execution paradigm.

**Application**

Google Earth Engine’s capabilities have been extensively applied in environmental research, agriculture monitoring, urban planning, and disaster management. For instance, image collections from Sentinel-2 or Landsat satellites have been efficiently used to analyze vegetation health, monitor deforestation, or assess urban growth dynamics. Loading these collections in GEE involves simple scripting, enabling rapid data access and processing. Reducing these collections spatially or temporally helps extract meaningful insights, such as monthly vegetation indices or annual urban expansion rates. For example, Gorelick et al. (2017) illustrated GEE's effectiveness in global forest loss monitoring, demonstrating the platform's capacity to reduce and summarize extensive global imagery datasets rapidly.

Regression techniques in GEE have also been utilized for predicting crop yields by establishing relationships between spectral indices (NDVI, EVI) derived from satellite imagery and ground-based agricultural data. Filtering and joining tools in GEE allow combining remote sensing imagery with ancillary data sources (meteorological data, topographic variables), providing comprehensive analysis frameworks that significantly improve predictive accuracy.

Further, GEE's straightforward setup and cloud-based infrastructure have made sophisticated analytical workflows accessible to researchers worldwide, democratizing geospatial analytics. The platform’s intuitive interface facilitates quick iterations, visualization of results, and sharing of scripts, thus fostering collaboration and accelerating research across diverse disciplines.

**Reflection**

While Google Earth Engine has transformed geospatial analysis through powerful computational capabilities and extensive data access, some challenges and limitations persist. Initial setup and scripting in GEE require users to possess programming proficiency, particularly in JavaScript or Python, potentially creating barriers for non-specialists. Additionally, although powerful, the complexity of certain functions (e.g., advanced reducers, regression methods) demands considerable expertise to achieve optimal outcomes and accurate interpretations.

To address these challenges, continued development of user-friendly interfaces, such as graphical modeling tools or integration of visual programming languages, could significantly lower entry barriers. The integration of machine learning and AI-assisted scripting could also streamline processes, simplifying parameter optimization and improving analytical efficiency. Furthermore, enhanced visualization features, such as real-time feedback on parameter adjustments, could facilitate users’ understanding and improve confidence in results.

Technological innovations, including improved integration with open-source machine learning libraries (e.g., TensorFlow, PyTorch) or enhanced API capabilities, would allow GEE users to undertake increasingly complex spatial modeling tasks directly within the platform. Additionally, reinforcing accuracy assessment protocols, such as built-in spatial cross-validation modules or standardized error metrics (Kappa, Overall Accuracy), would strengthen the rigor and reliability of results produced by the platform. Ultimately, addressing these issues through technological and interface innovations will further expand GEE’s applicability in environmental management, policy decision-making, and scientific research.

**Useful Links and Videos:**

* **GEE Official Documentation (Getting Started)**:  
  https://developers.google.com/earth-engine/guides/getstarted
* **Reducing Image Collections**:  
  https://developers.google.com/earth-engine/guides/ic\_reducing
* **Filtering Data in GEE**:  
  https://developers.google.com/earth-engine/guides/ic\_filtering
* **Regression Analysis in GEE**:  
  https://developers.google.com/earth-engine/tutorials/tutorial\_api\_06
* **YouTube Tutorial – Google Earth Engine for Beginners**:  
  <https://www.youtube.com/watch?v=JFvxudueT_k>
* **YouTube Tutorial – GEE Image Processing and Analysis**:  
  <https://www.youtube.com/watch?v=ZxSJNY0fL1Q>

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**W6**

**Abstract**

Classification of remote sensing imagery has greatly evolved with advancements in machine learning techniques, significantly improving the extraction of land-cover information from complex datasets. Supervised classification approaches rely on labeled training data to guide model learning, typically delivering higher classification accuracy in clearly defined scenarios. Conversely, unsupervised methods do not require labeled datasets; instead, they cluster imagery based solely on intrinsic spectral and spatial properties, providing initial insights and assisting in discovering unknown land-cover categories. Although unsupervised classification efficiently handles exploratory tasks, it may produce ambiguous classifications and lacks interpretability. Supervised approaches, though accurate, heavily depend on extensive, high-quality training samples that may be challenging to collect in practical scenarios.

Within the realm of supervised classification, regression trees and random forests are particularly effective techniques widely adopted due to their robustness, interpretability, and predictive power. Regression trees operate by recursively partitioning data into homogeneous subsets based on straightforward decision rules, making them highly interpretable yet prone to overfitting. To overcome this limitation, random forests employ an ensemble approach, constructing multiple regression trees trained on random subsets of data (bootstrapping) and random subsets of variables. By aggregating predictions from numerous trees, random forests significantly reduce model variance and mitigate overfitting, leading to improved generalization performance.

Support Vector Machines (SVM) represent another powerful supervised classification method, particularly suitable for remote sensing data characterized by high-dimensional feature spaces. SVM identifies an optimal decision boundary (hyperplane) that maximizes the margin between distinct classes, providing high accuracy even with limited labeled training data. However, the successful application of SVM strongly depends on appropriate kernel selection and parameter optimization, potentially requiring extensive computational resources and expertise.

The complementary strengths of these supervised techniques, supported by initial unsupervised exploratory analyses, contribute significantly to improved accuracy, interpretability, and reliability in remote sensing image classification. Effective classification accuracy assessment is usually carried out using error matrices and derived metrics such as Producer’s Accuracy (PA), User’s Accuracy (UA), Overall Accuracy (OA), and Kappa statistics, which collectively provide quantitative measures of classification reliability. This part will be introduced next week.

**Application**

In practical remote sensing image classification, regression trees and random forests have seen extensive application in diverse fields such as forestry, agriculture, and urban studies. For instance, Belgiu and Drăguţ (2016) effectively employed random forests in mapping agricultural landscapes, demonstrating superior accuracy compared to traditional classifiers due to random forests' robustness against noise and reduced tendency toward overfitting. Their workflow involved carefully selecting predictor variables, training multiple regression trees with bootstrapped samples, and aggregating results through majority voting, significantly enhancing classification accuracy.

Similarly, Pal (2005) illustrated the effective use of Support Vector Machines (SVM) for urban land-cover classification, highlighting SVM's ability to handle complex, high-dimensional spectral data effectively. By systematically selecting kernel functions and optimizing parameters using cross-validation, the study demonstrated SVM's superior classification accuracy and generalization capabilities compared to conventional approaches.

Unsupervised methods, such as K-means clustering, often serve as preliminary analytical tools to explore data structure and identify natural groupings within remote sensing imagery. A two-step classification approach combining unsupervised and supervised methods can exploit each method’s strength. For instance, initial unsupervised clustering can reveal general land-cover categories, guiding the collection of training data for subsequent supervised methods such as random forests or SVM, thereby optimizing overall accuracy and resource efficiency (Lu & Weng, 2007).

These varied methodologies have collectively enhanced the precision and applicability of remote sensing data classification across diverse ecological, agricultural, and urban management scenarios.

**Reflection**

Despite significant advances in remote sensing classification methods, practical implementation remains challenging due to methodological and data-related constraints. Regression trees and random forests, while robust, require careful consideration of parameters, such as the number of trees and split criteria, to avoid overfitting or underfitting. Overfitting remains a critical issue, especially with regression trees, necessitating comprehensive validation strategies like spatial cross-validation or independent test datasets to ensure model reliability.

Support Vector Machines, although powerful, face challenges related to computational efficiency and parameter optimization. Selecting the most appropriate kernel and hyperparameters is often difficult without extensive experience or computational resources. Consequently, these barriers limit the accessibility of SVM methods for operational users and policymakers requiring quick and interpretable results.

Furthermore, supervised methods depend strongly on high-quality training datasets, which are costly, time-consuming, and sometimes impossible to obtain. This limitation highlights the importance of combining supervised methods with unsupervised approaches, which can guide training-data selection by identifying unknown land-cover categories and reducing reliance on expensive labeled datasets.

Emerging technological innovations such as deep learning models—particularly Convolutional Neural Networks (CNN)—could further address these limitations by automating feature extraction and reducing reliance on manual parameter tuning. Additionally, cloud computing and automated hyperparameter tuning methods offer promising avenues for streamlining classification workflows. These innovations, coupled with advancements in sensor technology, including hyperspectral and very high-resolution imagery, may substantially enhance the accuracy, interpretability, and practical application of remote sensing classification methods, thereby facilitating broader policy integration and operational decision-making.

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**W7**

**Abstract**

We will continue with the classification work this week. I will introduce sub-pixel based analysis, object-based analysis, and accuracy below.

Object-Based Image Analysis (OBIA) represents an innovative method for classifying remote sensing imagery, offering substantial improvements over traditional pixel-based techniques by analyzing imagery through segmented, meaningful geographic objects. This method integrates not only spectral data but also spatial context, shape, texture, and hierarchical information, thus significantly enhancing classification accuracy, particularly in complex and heterogeneous environments. Additionally, subpixel analysis complements OBIA effectively by addressing the mixed-pixel problem common in medium-to-coarse resolution imagery. Subpixel methods, such as spectral unmixing, enable the identification of land-cover components smaller than the sensor’s spatial resolution by quantifying fractional abundances of multiple land-cover classes within individual pixels. This integration of OBIA and subpixel analysis allows researchers to produce more detailed and accurate land-cover maps crucial for ecological monitoring and urban planning.

Assessing the accuracy of these advanced classification methods typically involves the error matrix (also known as a confusion matrix), a standard tool summarizing the agreement between reference data (ground truth) and classified outputs. From the error matrix, several critical accuracy metrics can be derived, including the Kappa coefficient, Producer’s Accuracy (PA), User’s Accuracy (UA), and Overall Accuracy (OA). The Kappa coefficient measures classification accuracy adjusted for chance agreement, providing a robust and commonly used metric. Producer’s Accuracy (PA) indicates the probability that a specific class is correctly identified in the classification relative to the ground reference data, reflecting omission errors. In contrast, User’s Accuracy (UA) measures the reliability of classified data from the user’s perspective, accounting for commission errors by indicating the likelihood that a classified pixel or object truly represents the referenced category. Overall Accuracy (OA) represents the proportion of correctly classified pixels or objects across all classes, offering an intuitive and widely accepted measure of general classification quality.

Further, spatial cross-validation methods provide rigorous accuracy evaluations by accounting for spatial autocorrelation within remote sensing datasets. By partitioning data into spatially independent subsets, spatial cross-validation ensures robust validation results, ultimately enhancing the reliability and generalizability of OBIA and subpixel analysis approaches in practical environmental monitoring scenarios.

**Application**

OBIA combined with subpixel analysis is extensively applied across various environmental and urban management scenarios. For example, OBIA has been effectively implemented in urban areas to extract impervious surfaces, vegetation, and water bodies, where spectral mixing within pixels is prevalent. Subpixel approaches, such as spectral mixture analysis (SMA), further refine OBIA classifications by quantifying fractional coverage of land-cover types within mixed pixels. Chen et al. (2018) successfully applied OBIA with SMA to improve urban impervious surface estimation, clearly demonstrating enhanced accuracy over traditional pixel-based approaches.

Accuracy assessment using error matrices and Kappa coefficients is indispensable in OBIA studies. For instance, Myint et al. (2011) conducted comprehensive evaluations of OBIA-based urban land-use classifications utilizing confusion matrices and Kappa statistics, providing rigorous quantitative evidence of classification reliability. Additionally, spatial cross-validation has proven essential in studies involving spatial autocorrelation, ensuring independent training-validation partitions. Pohjankukka et al. (2017) demonstrated that spatial cross-validation significantly improved accuracy assessments compared to traditional random splits by accounting explicitly for spatial dependency.

Collectively, these methodological advancements enhance OBIA's practical utility in environmental monitoring, urban planning, and resource management. The combination of OBIA, subpixel analysis, and rigorous accuracy assessments provides reliable, detailed land-cover maps supporting policy decisions related to urban expansion, ecological conservation, and infrastructure development.

**Reflection**

Although OBIA, subpixel analysis, and spatial cross-validation significantly improve classification accuracy, several practical and methodological challenges remain. Firstly, OBIA’s segmentation accuracy highly depends on parameter settings such as scale, shape, and compactness, requiring considerable expertise for optimal calibration. Incorrect segmentation parameters can lead to suboptimal classification results, restricting OBIA’s straightforward application by non-expert users. Similarly, subpixel analysis depends on correctly identifying endmembers, which may vary spatially and temporally. Misidentification of spectral signatures can degrade classification results, potentially introducing bias or inaccuracies.

Moreover, accuracy metrics such as the Kappa coefficient, though widely utilized, have limitations, particularly sensitivity to prevalence effects and class imbalance. Recent critiques suggest using alternative metrics (e.g., producer’s/user’s accuracy or overall accuracy) for more stable assessments. Additionally, spatial cross-validation, despite its effectiveness, demands substantial computational resources and carefully designed spatial partitions. Poorly constructed validation subsets can inadvertently introduce biases, diminishing the evaluation reliability.

Future technological innovations could address these limitations. Integration of deep learning segmentation methods could automate optimal parameter selection in OBIA, substantially simplifying workflows. Advances in hyperspectral and super-resolution imagery might improve endmember identification, significantly enhancing subpixel accuracy. Additionally, adoption of robust statistical metrics and automated spatial partitioning algorithms powered by artificial intelligence could streamline accuracy assessments. Ultimately, these innovations would broaden the applicability of OBIA and subpixel analysis, promoting widespread adoption in environmental policy-making and practical resource management.

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**W8**

**Abstract：**

In this week's lecture, we will focus on the basics of SAR and how to see practical change detection with SAR

Synthetic Aperture Radar (SAR) technology has transformed remote sensing by providing reliable, all-weather, and day-night Earth observation capabilities. Unlike traditional optical sensors limited by atmospheric conditions, SAR utilizes active microwave signals capable of penetrating clouds and capturing high-resolution imagery consistently. Interferometric SAR (InSAR) further extends these advantages by leveraging phase differences between SAR images taken at different times to accurately measure subtle changes in Earth's surface elevation. This precise capability makes InSAR particularly valuable for monitoring natural hazards such as landslides, ground subsidence, volcanic activity, and earthquake-induced deformation. Differential InSAR (DInSAR) specifically measures surface displacement at millimeter-level accuracy by analyzing temporal changes, significantly enhancing disaster prediction and environmental management. However, these techniques face inherent limitations, including atmospheric disturbances, phase decorrelation, and difficulties in precise phase unwrapping, potentially reducing their accuracy and operational feasibility.

To quantitatively evaluate the accuracy and reliability of SAR and InSAR-derived classification and detection methods, Receiver Operating Characteristic (ROC) curves are increasingly utilized. ROC curves graphically depict the trade-off between detection sensitivity (true positive rate) and false alarm rates (false positives), enabling analysts to optimize classification thresholds and objectively assess algorithm performance. This ensures improved confidence in SAR-derived detection results, particularly in hazard identification and land-use classification scenarios.

Further advancements involve integrating SAR with optical remote sensing data, combining the unique advantages of both sensor types to overcome their individual limitations. Common fusion methods include Principal Component Analysis (PCA), Object-Based Image Analysis (OBIA), and Intensity Fusion. PCA reduces data redundancy by transforming multiple input bands from SAR and optical images into fewer informative principal components, improving image interpretability and classification accuracy. OBIA enhances accuracy by segmenting imagery into meaningful objects rather than individual pixels, effectively combining SAR’s structural detail with optical imagery’s rich spectral information. Intensity Fusion integrates SAR’s high spatial detail with the spectral fidelity of optical data, significantly improving land cover classification, urban planning, and agricultural monitoring applications. Despite these benefits, data fusion methods must carefully manage challenges related to spatial-temporal alignment, computational complexity, and varying sensor characteristics to maximize their practical value.

**Application:**

SAR technology has been proven to be valuable for general investigations of urban surface deformation. It can cover a large area of ground, allowing for comprehensive monitoring and analysis of ground movement, and has a wide range of applications. I will use research in two areas, landslide monitoring and urban infrastructure stability monitoring, as examples to introduce it.

First Application – Landslide Monitoring:

Li et al. (2020) utilized Synthetic Aperture Radar (SAR) imagery to effectively monitor and detect slow-moving landslides in mountainous terrain. Their workflow began by selecting multiple SAR images acquired from Sentinel-1 satellites, carefully preprocessing these data by applying radiometric calibration, geometric correction, and precise co-registration to align images spatially and temporally. Following this preprocessing, interferometric pairs were generated to capture the subtle ground movements indicative of landslide activity. The differential interferometric SAR (DInSAR) technique was then employed to generate displacement maps by calculating phase differences between paired SAR acquisitions over time. Crucially, advanced time-series InSAR analysis techniques were utilized, including persistent scatterer interferometry (PS-InSAR), to effectively mitigate atmospheric noise and decorrelation errors. The resulting displacement maps clearly delineated areas undergoing deformation, providing essential quantitative data for identifying active landslide zones. By integrating these SAR-derived deformation measurements into geographic information systems (GIS), the research enabled precise localization and temporal monitoring of landslides, significantly improving early-warning capabilities and disaster risk management strategies.

Second Application – Urban Infrastructure Stability Monitoring:

Li et al. (2023) applied SAR interferometry to monitor the stability of urban infrastructure. Their methodological framework started with acquiring high-resolution SAR images from spaceborne platforms such as TerraSAR-X and Sentinel-1, along with ground-based radar interferometry (GBRI). Preprocessing involved accurate georeferencing and stacking multiple SAR images to form a consistent time series. They then employed Persistent Scatterer Interferometry (PS-InSAR), a specialized interferometric method capable of identifying stable targets (such as buildings, roads, and bridges) within urban environments. This technique extracts coherent radar reflections from these persistent scatterers over extended periods, significantly enhancing detection accuracy and reducing noise caused by temporal decorrelation and atmospheric disturbances. Subsequently, phase unwrapping and atmospheric corrections were performed to translate radar phase measurements into precise displacement estimates. The final step involved creating detailed deformation maps highlighting millimeter-scale infrastructure movement, enabling the identification of critical structural instabilities. These results facilitated timely infrastructure assessments, effectively informing urban planners and policymakers in maintenance scheduling, risk assessment, and urban safety management.

**Reflection:**

Although Synthetic Aperture Radar (SAR), Interferometric SAR (InSAR), and SAR-optical data fusion technologies have shown significant potential in environmental monitoring, disaster prediction, and urban planning, practical implementation still faces notable challenges. Technical complexities in SAR data processing, including phase decorrelation, atmospheric delays, and difficulties in precise spatial-temporal alignment with optical datasets, present substantial hurdles. Furthermore, interpreting SAR results requires specialized expertise and extensive computational resources, limiting widespread adoption in policy-driven scenarios or operational applications.

Looking forward, innovative technical approaches could significantly enhance SAR/InSAR practical applicability. For instance, advanced machine learning (ML) and deep learning (DL) techniques could automate data interpretation and phase-unwrapping processes, drastically reducing computational costs and improving detection accuracy. Cloud-based SAR processing platforms leveraging artificial intelligence (AI) can streamline the processing workflow, democratizing data access and analysis. Additionally, integrating SAR data with Internet of Things (IoT) sensor networks, such as GPS or ground-based radar systems, offers real-time correction of atmospheric and surface-related inaccuracies, greatly enhancing monitoring reliability.

Recent advances in multi-sensor fusion techniques, such as advanced convolutional neural networks (CNNs) or Generative Adversarial Networks (GANs), could substantially optimize the fusion of SAR and optical data. These approaches have the potential to improve temporal and spatial consistency while maintaining high spectral accuracy, making fused data products more useful for decision-making processes. Further, developing robust automated accuracy assessment methods, including continuous integration of Receiver Operating Characteristic (ROC) curves, would provide critical performance metrics and support adaptive improvement of analytical models. Ultimately, these technological innovations could bridge the current gap between advanced SAR techniques and their effective integration into environmental policies and operational monitoring systems.

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