Exploring Remote Sensing Techniques: Satellite Image Processing for Diverse Study Targets Using Various Learning Paradigms

Sai Bhargav Kasetty
Department of Analytics – SCOPE, V.I.T, Vellore, Tamilnadu, India
Email Id: kasettisai.bhargav2023@vitstudent.ac.in

Dr. Rajakumar K
Department of Analytics – SCOPE, V.I.T, Vellore, Tamilnadu, India
Email Id: rajakumar.krishnan@vit.ac.in

Abstract: *Remote sensing technology is indispensable for comprehending and monitoring the Earth's surface through the acquisition of data from satellite imagery. This literature review delves into the realm of satellite image processing across various study objectives, employing diverse learning paradigms. The scope of study encompasses a broad array of applications, including land cover classification, change detection, object detection, segmentation, image fusion, and retrieval systems. The methodologies explored in extracting meaningful insights from satellite data span supervised, unsupervised, semi-supervised, and self-supervised learning techniques. Supervised learning entails training models with labeled data to categorize and identify specific features, while unsupervised learning facilitates pattern and structure extraction from unlabeled data. Bridging the gap between supervised and unsupervised methods, semi-supervised learning amalgamates labeled and unlabeled data. In contrast, self-supervised learning exploits inherent data properties for representation learning without manual labeling. By scrutinizing the application of these learning paradigms across various study objectives in remote sensing, this literature review offers valuable insights into the progress and challenges in satellite image processing for comprehending Earth's surface dynamics.*

Keywords: *Remote sensing, semi-supervised learning,Unsupervised learning, self-supervised learning, Satellite Image Processing, supervised learning*

Introduction

Remote sensing (Rs) is a powerful tool that has revolutionized the field of Earth observation and has become an integral part of many scientific disciplines [1]. It involves the acquisition of information about the Earth's surface by using sensors mounted on satellites, aircraft, or drones. This technology has greatly expanded our ability to study and monitor our planet, providing valuable insights into various environmental processes and changes [2]. One of the key components of remote sensing is satellite image processing, which involves the analysis and manipulation of data collected by these sensors to extract meaningful information. This process encompasses a wide range of techniques, including preprocessing, enhancement, classification, change detection, and semantic segmentation. These techniques are used to identify and interpret features and patterns within the images, providing a better understanding of the Earth's surface and its changes over time [3].

Classification is one of the most widely used techniques in satellite image processing, which involves grouping pixels into different categories based on their spectral characteristics. This allows for the mapping of land cover types or study areas, such as water bodies, urban areas, and forests, and their identification [4]. Change detection, on the other hand, is used to detect and monitor changes in land cover over time, providing valuable information for environmental monitoring and management [5]. Semantic segmentation takes this a step further by not only identifying land cover types but also distinguishing different objects within the same class, such as different types of buildings/vegetation [6].

In recent years, the use of deep learning techniques in satellite image processing has gained significant attention. These techniques, such as supervised, semi-supervised, self-supervised learning, and unsupervised have shown great potential in improving the accuracy and efficiency of image processing tasks[7]. Supervised learning involves using labeled data to train algorithms to recognize patterns and features within the images, while unsupervised learning relies on clustering algorithms to identify patterns without prior knowledge. Semi-supervised learning combines elements of both supervised and unsupervised learning, while self-supervised learning involves training algorithms to learn from the data itself, without the need for labeled data [8].

Remote sensing and satellite image processing have become indispensable tools for studying the Earth's surface and its changes. With the continuous advancements in technology and the integration of deep learning techniques, the potential for these tools to provide valuable insights and support for various applications, such as environmental monitoring, land use planning, disaster management, and many others, is constantly growing [9-12]. This literature study aims to provide a comprehensive overview of the different techniques and applications of remote sensing and satellite image processing, highlighting their importance and potential for future research and development.

Literature Review

Using the IEL (IEEE & IET) online databases, a systematic literature search was conducted to find the most recent relevant articles for this comprehensive review within the past year. After several attempts, a title/keyword search was performed in IEL using the following query: "satellite image processing", "deep learning-based satellite image processing", "classification/object detection/segmentation/change detection of remote sensing images using deep learning models", "Satellite Image Retrieval". The search was also limited to include papers that utilized data from the most commonly used remote sensing platforms. This resulted in a total of 262 papers, which were used as the basis for further analysis.

Out of the initial 262 studies, 150 were from peer-reviewed journals, with the remaining papers being conference proceedings that were not included in this review. After a detailed examination of the 150 journal papers and an eligibility assessment, 71 were found to be unrelated to this review and were subsequently excluded.

Literature Review from the recent Journal Articles gathered are used to answer the following research questions mentioned as follows:

RQ1. What are all the types of learning paradigms and deep learning models that are commonly used in satellite image processing?

RQ2. What are all the study targets and study areas identified using the different types of learning algorithms?

RQ3. Which technique is considered the frequently used learning paradigm for the different study targets?

RQ4. What are the future directions for satellite image processing using the different learning paradigms?

Remote sensing techniques have become increasingly popular in the field of Earth and environmental studies due to their ability to gather data from large and inaccessible areas. These techniques utilize satellite images to capture and analyze information about the Earth's surface and its environment. With the advancements in technology, researchers have been able to use various learning paradigms to process and interpret these satellite images for diverse study targets. This literature study aims to explore the different remote sensing techniques and learning paradigms that have been utilized in satellite image processing for anextensive range of study targets on the ground of Earth and environmental studies.

Semantic Segmentation

Segmentation in satellite image processing is the process of dividing an image into smaller, meaningful parts, allowing for easier analysis and interpretation of the data. It helps identify different features and objects in satellite imagery, such as land cover, buildings, and roads. Table 1 drawn as a case study from the selected papers illustrates the most commonly used learning paradigms in the selected journal articles for semantic segmentation along with their findings and limitations.

Object Detection

Object detection in satellite image processing is the process of identifying and locating specific objects or features within satellite images, using deep learning [1]. This enables the extraction of valuable information and insights from the vast amount of data captured by satellites, making it a crucial tool in various industries such as agriculture, urban planning, and disaster management [2]. Table 2 illustrates the most commonly used learning paradigms in the selected journal articles for object detection along with their findings and limitations.

Change Detection

Change detection, on the other hand, is utilized to monitor and detect changes in land cover over time, providing valuable information for environmental monitoring and management. Table 3 illustrates the most commonly used learning paradigms in the selected journal articles for change detection along with their findings and limitations.

Classification

Classification is one of the most widely used techniques in satellite image processing, which involves grouping pixels into different categories based on their spectral characteristics. This allows for the identification and mapping of land cover types such as water bodies, forests, and urban areas. Table 4 illustrates the most commonly used learning paradigms in the selected journal articles for change detection along with their findings and limitations.

Table 1: Several learning paradigms in segmentation

Ref. No.	Study Target (Study Area)	Learning Paradigm	Findings	Limitations
[1]	Land use &Land cover mapping (LULC – Forest & Mountain)	Supervised	The paper presents an innovative dual-branch deep learning framework designed to efficiently utilize multisensor and multitemporal Rs data, resulting in enhanced land-cover classification performance compared to existing methods.	The proposed deep learning model in the paper tends to misclassify minority classes due to the presence of relatively few labeled samples in the training set, leading to overfitting.
[2]	Change detection (CD) (Urban)	Supervised	The study found that the proposed Adaptive Fusion NestedUNet model outperformed other models in CD tasks on optical remote sensing images, showcasing improved feature representation, and accurate identification of changed regions.	The lack of contrast with other models, thereby limits a thorough assessment of the proposed model's performance.

[3]	Sea ice extraction (Snow)	Supervised	The proposed lightweight network, U-Net, demonstrated superior performance in Sea Ice lead extraction from non-pre-processed synthetic aperture radar images, providing higher accuracy, and efficiency compared to traditional semantic segmentation methods.	As highlighted in the paper, a notable limitation of this study is the omission of polarization features from consideration.
[4]	Snow segmentation (Snow)	Unsupervised	The study presents a novel unsupervised algorithm that effectively differentiates between wet& dry snow using Dual-Polarized synthetic aperture radar data.	The study does not quite address the potential impact of varying atmospheric conditions on the performance of the proposed algorithm.
[5]	Impervious Surface Extraction (Urban)	Supervised	The CroFuseNet model effectively improves urban impervious surface extraction accuracy.	Atmospheric conditions are likely to affect the model's performance.
[6]	Segmentation (Agriculture)	Supervised	The multiscale pyramid sieve module improves segmentation accuracy in Rs images.	The paper does not provide specific resolution details for the satellite multispectral images used.
[7]	Plant organ segmentation (Trees)	Supervised	The study successfully used deep learning models to segment sorghum plant organs and measured phenotypic traits from LiDAR 3D point cloud data.	The research was conducted under controlled conditions, limiting its applicability to real field environments.
[8]	Segmentation of seafloor (Water)	Supervised	The multi-look sequence processing net based on RNN and U-Netoutperforms other algorithms in weakly labeled seabed image segmentation.	Finding accurately categorized imagery for SAS image segmentation is challenging and time-consuming, as it requires coordination with divers and oceanographers to manually survey an area.
[9]	Land cover segmentation (Urban)	Supervised	The study centers on crafting a proficient and resilient DPPNet tailored for land cover segmentation derived from high-resolution satellite images.	The computational efficiency of the DPPNet is not compared with other existing methods, which is an important aspect considering the goal of reducing computational complexity.
[10]	3D point cloud Segmentation (Urban & Trees)	Supervised	The paper surveys and compares multiple state-of-art DL models for point cloud semantic segmentation. The target of this study is to deliver a summary of existing methods but doesnot appear to provide a new DL model.	This study primarily focuses on categorizing and discussing existing 3D point cloud segmentation methods but does not propose a novel model or address real-time processing efficiency.

[11]	Flood mapping (Water)	Supervised	The study finds that lightweight versions of the U-Net model maintain accuracy and run much faster than the baseline model for flood mapping, making them excellent options for routine flood monitoring applications.	The study's synthesized flood images might not perfectly capture the complexity and diversity of real-world flood events.
[12]	Segmentation (Urban)	Supervised	This paper presentsthe segmentation into hyperspectral image understanding for the initial time and proposes the spectral-spatial feature pyramid network to advance the presentation of HSI segmentation	The method put forward struggles with intricate image nuances and accomplishes precise instance segmentation in remote sensing images.
[13]	Image Matching (Mountain and Trees)	Supervised	The paper introduces multi-scale attention gated residual U-Net, which demonstrates superior matching accuracy and precision in SAR-optical image matching.	Difficulties in handling heavily warped images and inability to effectively deal with rotation and scale differences
[14]	Semantic Labeling (Urban)	Supervised	The paper presents EfficientUNetTransformer, a new model that improves the semantic segmentation of high-resolution images.	The paper does not provide clarity on the computational efficiency or runtime of the proposed model.
[15]	Segmentation (Urban & Forest)	Semi-Supervised	The proposed semi-supervised deep learning method significantly improved image segmentation accuracy with fewer labeled samples.	The paper uses datasets not specifically designed for semi-supervised remote sensing semantic segmentation, limiting the potential applicability of the findings.
[16]	Semantic segmentation (Urban)	Supervised	The paper proposed a strategy combining deep learning and principal component analysis for UAV Rs image SS, enhancing performance.	Images in the visible spectrum are limited to capturing information within the RGB bands, which may lead to confusion regarding the spectral characteristics of objects.
[17]	Semantic segmentation (SS) (Urban)	Self-Supervised	The paper proposes MemoryAdaptNet (MA-Net), a network for Unsupervised Domain adaptation SS of HRS imagery, which outperformed baseline and existing models.	The paper did not provide a comprehensive comparison with all existing methods or discuss the model's computational efficiency.

Source: Primary data

Table 2: Several learning paradigms in Object Detection

Ref. No.	Study Target (Study Area)	Learning Paradigms	Findings	Limitations
[18]	Ship detection (Water)	Self-Supervised	The findings highlight the potential of training a highly transferable global SAR feature extractor without labels and its applicability and extendability in downstream few-shot learning tasks.	The limitation of this paper is that the model developed is prone to robustness issues if the dataset used is changed.
[19]	Ship detection (Water)	Supervised	This method is well-suited for detecting ships in SAR images with sparse targets and can efficiently differentiate between noise and ship targets in SAR images.	Loss of valuable information in the back end and middle of the Nnet due to min-pooling
[20]	Ship detection (Water)	Supervised	The developed model in this paper efficiently detects the ships and extends the idea of feature improvement and feature combination to increase the performance	Performance decline in detecting extreme-size targets when moving from optical models to SAR images.
[21]	Ship detection (Water)	Supervised	The model developed in this paper generates semi-soft labels to leverage complete information and dark knowledge without mismatched annotations and is used for ship detection.	Label assignment impacts SAR ship detection performance. Feature fusion can result in loss of information from original feature map.
[22]	Building displacement (Urban)	Supervised	This approach surpasses traditional methods in detecting various types of building displacements and proves to be efficient in identifying potentially anomalous buildings in Rome through the utilization of LSTM.	This model doesn't fit for identifying the building displacements in other cities and towns leading to robustness issue.
[23]	Flood detection (Water)	Supervised	The proposed flood mapping framework surpasses other methods in accuracy and performance.	Flood mapping only provides information on affected areas, not flooded state at different times. Parameter adjustment may be complex and require tuning. The proposed model may not capture significant changes in permanent objects.
[24]	Object detection (Water)	Supervised	The article suggests a feature aggregation module called CSn that can capture long-range dependencies in CNNs by incorporating higher-order spatial and channel interactions, similar to the Transformer model.	Poor performance in detecting small objects in remote sensing, as these targets are often of various sizes and take up only a few pixels.

[25]	Ship detection (Water)	Supervised	The proposed method integrates convolution and transformers for SAR ship detection. - The RetinaNet architecture is employed for both regression &classifying tasks.	Traditional convolutional models have limitations in Global-Modeling capability. The computational cost of the transformer grows exponentially with large input feature size.
[26]	Ocean front detection (Water)	Supervised	The paper demonstrates that the Holistically-Nested Edge Detection model and the small Convolutional Encoder-Decoder Network are the most efficient and accurate deep learning models for ocean front detection using uncorrected satellite imagery.	The human-annotated ground-truth data used for training was imperfect, and the created models were found to be less effective in detecting chlorophyll ocean fronts than sea surface temperature fronts.
[27]	Object detection (Urban)	Supervised	The proposed Hierarchical Information Enhancing Detector effectively addressed the size-unfitting proposal problem in remote sensing object detection	one potential limitation could be the generalizability of the detector to datasets or object detection tasks outside of the ones tested.
[28]	Ship detection (Water)	Supervised	The paper proposes the hybrid representation learning enhancement based on CNN for detection of ship from SAR	The developed model is prone to generalizability and computational efficiency issues when it is evaluated on diverse datasets.
[29]	Ship detection (Water)	Supervised	This paper presents a CNN-based lightweight SAR detection network for multi-class detection, incorporating the adaptive scale distribution attention method.	The generalizability of the proposed model is lost when it is evaluated on the other real time datasets.
[30]	Ship detection (Water)	Supervised	The paper devised a multitask learning framework, MLDet, successfully enhancing Synthetic Aperture Radar ship detection accuracy and robustness in complex environments.	Small targets against vegetation background are harder to detect. Strong speckle noise in SAR Images
[31]	Crop field detection (Agriculture)	Supervised	The paper proposed a deep learning-based approach for detecting and delineating productive crop fields.	Poor quality training data associated with significant mistakes. Time consuming task due to many convolutional layers.
[32]	Weeds detection (Agriculture)	Supervised	This paper proposed a graph weed network for weeds detection and classification.	Deep neural network-based methods require large dataset for training. GPU- based systems are required due to high computational cost.
[33]	Ship detection (Water)	Supervised	The paper developed a SAR target detection method called SAR NAS which utilizes NAS to optimize the network structure.	Difficulties in model design for SAR target detection.

[34]	Ship detection (Water)	Supervised	Ship detectors based on the faster RCNN able to to detect all automatic ship	Lower accuracies achieved in the datasets when compared to the initial dataset.
[35]	Ship detection (Water)	Supervised	This paper introduces a novel R-CNN-based ship detection model that leverages the capabilities of deep learning and SAR images to achieve precise ship target detection.	Less features available for small targets.
[36]	Object detection (Urban)	Supervised	This paper introduces a novel method for object detection called the Single-State Rotate Object Detector, which utilizes dense prediction and false positive suppression techniques.	The evaluation of this method is primarily focused on aerial datasets of images and datasets of scene texts, which may limit the generalizability of the results to other domains or datasets.

Source: Primary data

Table 3: Several learning paradigms in Change Detection

Ref. No.	Study Target (Study Area)	Learning paradigm	Findings	Limitations
[37]	Land cover change detection (LccD) (Urban)	Supervised	The paper found that the deep enhance module into adjacent layers of the ResNet (DESNet) model significantly improves semantic CD accuracy in Rs images.	Not sensitive enough to the edge of changed objects. Difficulty capturing tiny discontinuous changes in localized objects.
[38]	Land cover change detection (Forest)	Supervised	This paper demonstrates that its proposed data augmentation method significantly improves the accuracy of deforestation detection in complex scenarios.	Suitable only for thin cloud-covered or haze areas. Detection errors in thick cloud-covered regions due to the invisibility of ground objects.
[39]	Land cover change detection (Urban)	Supervised	The proposed Triple-Stream Network significantly improves accuracy in HRS Rs image CD, outperforming nine mainstream methods.	Bitemporal (images taken at several intervals) images with large differences pose a challenge. No proper research on multiclass ground object types.
[40]	Land cover change detection (Agriculture)	Supervised	The proposed method, AMCAN, demonstrated superior hyperspectral change detection performance compared to other methods on multiple datasets, especially for subtle changes detection.	Cumulative errors of classification affects change detection result. Low spatial resolution of hyperspectral sensors.
[41]	Land cover change detection (Urban)	Supervised	The paper presents AERNet, an edge refinement net for spotting building changes in Rs images, demonstrating strong performance and generalization.	Scarcity of the labeled multispectral images.

[42]	Land cover change detection (Urban)	Supervised	The paper introduces the Asymmetric Cross-Attention Hierarchical Network, a new approach for change detection in bitemporal remote sensing images. This method combines CNN and transformers more efficiently, resulting in reduced computational complexity.	The paper effectively reduces computational complexity, but acknowledges challenges with varying definitions of 'change'.
[43]	LccD (Forest & Urban)	Supervised	The proposed Change Guiding Network demonstrated superior performance in Rs image CD tasks across multiple datasets.	The paper does not discuss the limitations of the proposed Change Guiding Network specifically.
[44]	Land cover change detection (Forest)	Supervised	The Dual-Attention cross-fusion context net effectively detects Rs changes, outperforming other methods in comparative experiments.	The method struggles to detect subtle object changes on datasets with low spatial resolution.
[45]	Land cover change detection (Agriculture)	Semi-Supervised	The paper introduces an effective hyperspectral CD method using Semi-supervised graph neural nets and Convex deep learning (DL).	Scarcity of hyperspectral image data. Need for mathematically sophisticated regularizers.
[46]	Land cover change detection (Forest)	Supervised	Iterative training sample augmentation improves change detection in land cover accuracy with Deep learning techniques.	Lacks sensitivity towards the edges of altered objects.
[47]	Land cover change detection (Forest)	Supervised	The integration of the multiscale information module, position channel attention module (PCAM), and change gradient guide module (CGGM) within the CNN architecture significantly improved the detection performance.	Scarcity of the labeled multispectral image data.
[48]	Time series analysis and change detection (TSCC) (Water & Urban)	Supervised	The paper presents a deep learning-based framework SAR-TSCC for detecting and analyzing long-time series SAR image changes with high accuracy.	The lack of real training data is mentioned as a limitation, but no further information is provided on how this limitation was addressed. It doesn't discuss the generalizability of the proposed framework to different geographic areas of SAR data.
[49]	LccD (Urban and Forest)	Self- supervised	The paper developed an effective CD method for Rs images, enhancing accuracy by utilizing Self-supervised learning and Variational information Bottleneck theory.	The paper does not thoroughly discuss potential limitations, such as the method's performance in different types of environmental settings or scalability issues.
[50]	Time series analysis (Forest)	Supervised	Using temporal data from VIIRS images, the proposed transformer network outperformed existing models in detecting active fires effectively.	The paper does not discuss potential limitations such as the impact of cloud cover on detection accuracy.

[51]	Land cover change detection (Water & Agriculture)	Supervised	The novel CNN-based triplet transformer framework outperforms other models in hyperspectral image change detection with competitive computational efficiency.	The complexity of the method affects practicability. Difficulty in exploring middle and long-range dependencies in hyperspectral images.
[52]	Change detection (Water & Forest)	Supervised	The paper contributes to the field of PolSAR change detection by proposing a novel method and evaluating its performance against existing methods and distance measures.	The paper doesn't address the limitations of reusing labeled samples and the model's effectiveness and generalization.

Source: Author

Table 4: Several Learning Paradigms in Classification

Ref. No.	(Study Area) Study Target	Learning Paradigm	Findings	Limitations
[53]	(Urban) OBIA	Semi-Supervised	The paper proposes a CNN model for the scene classification of unlabelled multispectral images using multilevel pseudo labels.	The model struggles with distinguishing between similar classes and fails to accurately represent differences in local details.
[54]	(Urban) LULC	Semi-Supervised	The paper introduces a semi-supervised long-tail CNN model that incorporates spatial neighborhood information for hyperspectral image classification. This approach efficiently extracts and integrates features from unbalanced hyperspectral data.	Pseudo-labels determined by neural networks may not ensure satisfactory accuracy.
[55]	(Urban & Forest) LULC	Supervised	The paper suggests a new model, AGCNN, for Rs image classification that solves the problem of fixed CNN and time-consuming training.	Granules with equal roughness and maximum overlying of granules can lead to mis-classification.
[56]	(Urban) LULC	Supervised	The paper introduces an adaptive migration collaborative network (AMC-Net) designed for multimodal Rs image classification. This network employs an attribute migration strategy (AMS) to mitigate the representation gap between multispectral (MS) and panchromatic (PAN) images, thereby enhancing the quality and similarity between the two modalities.	The proposed model demonstrates promising results in terms of accuracy, while ensuring accuracy its timeliness is relatively low. This suggests that the method may be computationally intensive or slow, which could be a limitation for real-time applications.

[57]	(Urban) LULC	Unsupervised	This paper offers a new class-wise domain adaption method for land cover classification, solving the overlapping classes issue in existing methods. The deep Siamese network-based solution proved effective on benchmark datasets.	The datasets used in the paper limit the generalizability of the results to other regions apart from India, sri lanka, and Bangladesh.
[58]	(Urban) LULC	Supervised	The paper highlights the potential of HS data in identifying ground objects and addresses the limitations of existing methods in preserving the integrity of ground objects under the cloud using a general multimodal transformer framework, which assigns unique labels to each pixel on its ground cover.	The computational requirements and efficiency of the framework may need to be evaluated in larger-scale applications.
[59]	(Agriculture & Urban) LULC	Unsupervised	Unsupervised information is used to help prevent overfitting in a classification model for hyperspectral images, which can occur due to limited data.	The paper focuses on hyperspectral image classification with few training samples, but it does not address the issue of class imbalance, which is common in HS data and can affect the performance of classification algorithms.
[60]	(Urban) Scene classification	Supervised	A new module called Inductive Shifted Window Multihead Self-Attention (SW-MSA) is proposed, which combines CNN to improve its inductive bias.	A large amount of training data is required for worthy results. Two stream structures with insufficient information interaction. Too many parameters in the method.
[61]	(Urban & Forest) LULC	Supervised	The paper highlights the limitations of existing explanations in some cases, such as being limited to specific channels and not investigating the impact of important information from other channels	The paper mentions that SHAP is a computationally expensive explainable AI technique, but it does not elaborate on any specific limitations or challenges associated with its use.
[62]	(Urban & Forest) LULC	Supervised	The paper presents a method that combines pseudo labeling and spectral indexing techniques to refine labels in multimodal data, specifically images from different dates. This approach enhances the performance of the fine-grained dual network by addressing the challenge of coarse segmentation in deep learning models.	The limitation of this paper is that the pseudo-labels determined by CNN may not ensure the required accuracy.
[63]	(Urban, Forest, Water) LULC	Supervised	The paper proposes a small-scale segmentation method for post-processing to improve the fragmentation of classification results. This method helps in combining labels across class boundaries.	The proposed approach has limitations for practical application.

[64]	(Urban & Forest) LULC	Supervised	Proposed scheme for land cover classification using interactive segmentation combining CNN-based method with user-guided segmentation, aiming for improved accuracy and reduced manual effort.	The datasets used in this paper lack more complex scenarios, which may limit the generalizability of the proposed method. Many land cover datasets are annotated with multiple categories on the same image, which can lead to an imbalance between categories and potentially affect the performance of the model.
[65]	(Urban) LULC	Semi-supervised	The paper introduces a Method for classifying SAR data using superpixels and a graph-based model to account for statistical complexities.	One drawback of the proposed method is its dependency on superpixels, as inaccurate superpixels can result in incorrect classification boundaries.
[66]	(Forest & Agriculture) LULC	Unsupervised	M3SPADA is a new framework that uses CNNs to adapt remote sensing data collected at different times for land cover mapping, despite varying weather or climate conditions.	The paper doesn't explore domain adaptation involving different sensors or geographical areas, focusing solely on domain adaptation across periods.
[67]	(Water) OBIA	Semi-supervised	This paper proposes a Multitask-generative adversarial Net model for oil spill detection, which optimizes oil spill classification and segmentation simultaneously despite limited training samples.	The model's effectiveness may be limited due to the lack of abundant and diverse oil spill datasets for training.
[68]	(Urban) LULC	Supervised	This paper introduces NNCNet, a method that improves hyperspectral and LiDAR data classification through the utilization of nearest neighbor-based contrastive learning and a bilinear attention fusion module. This approach effectively tackles the issue of limited labeled data.	The limitations of the paper include dependence on large datasets for achieving improved performance and the scalability of contrastive learning with varying sizes of training sets.
[69]	(Urban) LULC	Supervised	The paper presents a CNN-based novel approach to improving land-cover classification in hyperspectral remote-sensing images. While it outperformed other methods, it could be labor-intensive due to the sample generation process.	Despite increasing classification accuracy, the novel approach proposed in the paper demands more time due to its iterative nature, making it less time-efficient for practical applications.
[70]	(Urban) LULC	Supervised	The paper presents Pseudolabel-Based Unreliable Sample Learning for hyperspectral image classification, leveraging unreliable unlabeled samples via contrastive learning while maintaining the limitation of pseudolabel quality.	The paper does not fully discuss how optimal data enhancement methods for contrastive learning can be designed, which may avoid potential image distortions and improve model training.

[71]	(Urban) LULC	Supervised	This paper introduced supervised learning based on spectral masking for hyperspectral image classification, improving feature extraction and classification accuracy.	Factors such as computational complexity, sensitivity to hyperparameters, or applicability to other datasets are potentially areas of concern.
[72]	(Urban & Fog) LULC	Supervised	This paper proposes a robust network for Land Cover Classification in foggy conditions, significantly improving classification accuracy.	This paper's limitations include insufficient classification accuracy for building roofs in dense fog and relatively low efficiency in handling foggy conditions.
[73]	(Urban) LULC	Supervised	The paper introduces a single-source domain expansion network, a novel framework for cross-scenecross-hyperspectral image classification, which significantly improves classification accuracy despite domain shift.	The solution proposed in the paper heavily relies on hyperparameter tuning, which can be complex and time-consuming. Its performance in diverse real-world applications remains untested.
[74]	(Urban) LULC	Unsupervised	The paper addresses the inefficiency of previous hyperspectral image feature extraction methods to handle mixed objects/noise, by proposing a Superpixelwise unsupervised Linear discriminant analysis (S3-ULDA) model for more effective extraction and classification of features.	The paper lacks an automatic mechanism to decide the optimal number of superpixels for segmentation and sees the potential to enhance the performance of feature extraction.
[75]	(Water & Forest) LULC	Supervised	The paper introduces a Spectral-Spatial Generative Adversarial Network (GAN) for super-resolution land cover mapping, aiming to enhance accuracy in addressing mixed pixel challenges.	The model's performance can be impacted by image registration inaccuracies, variations in scale factor, and dealing with mixed pixels.
[76]	(Urban) LULC	Supervised	The paper introduces a novel open-set hyperspectral image classification framework that enhances feature space discriminability, improving classification accuracy and better managing unknown classes.	The paper does not adequately address how the choice of hyperparameters influences performance, and the method requires extensive computational resources.
[77]	(Agriculture) LULC	Semi-supervised	The paper introduces a new framework, Spatially Aligned Domain Adversarial Neural Network, for temporally adapting land-cover mapping models via adversarial and self-training learning, addressing challenges in data variability over time.	The method might struggle with significant changes in landscape and land-cover class imbalance in the source data.

[78]	(Urban) LULC	Supervised	The paper introduces ViT-CL, a new method that combines Vision Transformer with Supervised contrastive learning for efficient Rs image scene classification and demonstrates its efficacy through multiple experiments.	The paper does not discuss the computational cost or time efficiency of their proposed model, ViT-CL, which could be significant.
[79]	(Urban) LULC	Supervised	This paper presents a wavelet-inspired attention-based Cnn for land cover classification in multispectral images, leveraging wavelet transform and attention mechanisms to improve spectral feature modeling, particularly with limited training samples.	One potential limitation of the paper is its performance and generalizability if applied to different types of imagery datasets or data with different characteristics.

Source: Author

Results and Discussions

In this section, the answers to the research questions are provided with answers based on the case studies chosen from the selected papers.

Learning paradigms, deep learning models and their frequency

In satellite image processing, various learning paradigms are commonly used to address different tasks (RQ1). Based on the provided data in the all above tables, the following types of learning paradigms are commonly employed:

- Unsupervised learning
- Semi-supervised learning
- Self-supervised learning
- Supervised Learning

Each of these paradigms serves different purposes and is applied to tasks such as change detection, segmentation, object detection, and classification in satellite image processing as shown in below Figure 1 along with their frequency of occurrence in the selected papers (RQ3).

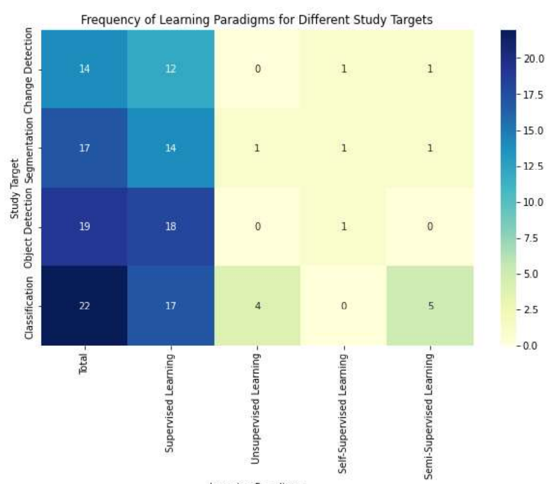

Figure 1: Frequency of Occurrence of the Learning Paradigms for Different Study Targets

Source: Author

Figure 2 shows that CNN is the predominant model utilized for analyzing remote sensing images, with Ensemble models, Unet models, and other models following closely behind.

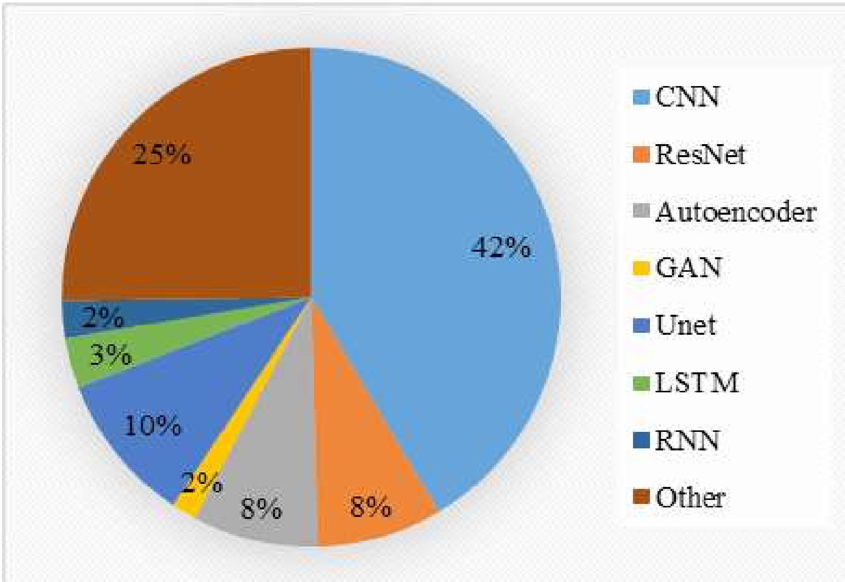

Figure 2: Frequency of Occurrence of the Deep Learning Algorithms for Different Study Targets

Source: Author

The Residual Network (ResNet) model, the Generative Adversarial Network (GAN) model, and the Autoencoder model also make appearances, while the triple stream net model and autoencoder model are less frequently used. CNN stands out as a model with distinct qualities that make it particularly suitable for handling multiband remote-sensing image data. The category of 'other' models encompasses MLP, YOLO, Triple stream Net, LDA, Fuzzy, Invertible NN, Point Net, and other black box models with optimization techniques.

1. Study targets and study areas

From the provided data in Figure 3 collected from the case studies, various study targets within the field of Rs and image analysis are evident (RQ2). LULC analysis stands out with a frequency of 24, indicating its importance in understanding landscape dynamics and human-environment interactions. Semantic segmentation with a frequency of 17 involves classifying each pixel in an Rs image into a precise group for detailed mapping. Object Detection, appearing 19 times, focuses on identifying and locating objects within an image, which is crucial for tasks such as infrastructure monitoring or disaster assessment. Land cover change detection, represented by a frequency of 13, involves comparing images of the same zone taken at dissimilar times to detect changes in land cover types, offering insights into environmental trends and urbanization patterns. Other targets include Object-Based Image Analysis (OBIA) and Temporal Analysis, each occurring twice, highlighting their roles in feature extraction and monitoring temporal changes, respectively. These study targets collectively contribute to the comprehensive analysis and understanding of the Earth's surface and its transformations over time.

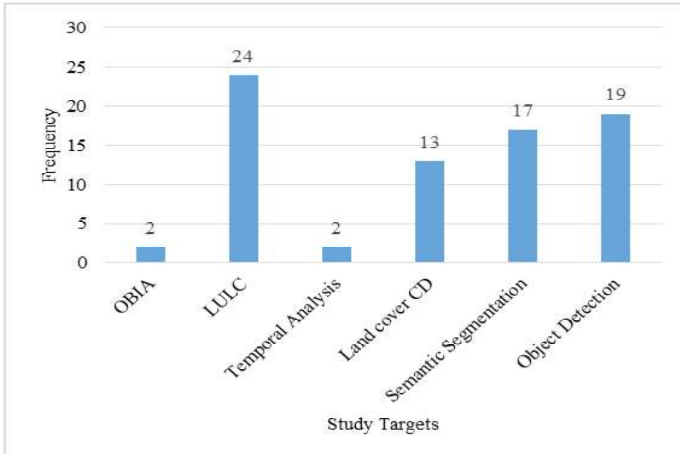

Figure 3: Frequency of Different Study Targets

Source: Author

The provided data in Figure 4 collected from the case studies reveals the distribution of study areas within the domain of remote sensing and geographic analysis. Urban areas emerge as the most frequently studied, with a frequency of 41, underscoring the significance of understanding urban dynamics, land use patterns, and the impact of human settlements on the environment. Forest areas, with a frequency of 17, represent another focal point, reflecting the importance of monitoring forest ecosystems, biodiversity conservation, and sustainable forestry practices. Agriculture, with a frequency of 8, indicates the attention given to agricultural landscapes, crop monitoring, and food security assessments. Water bodies, represented by a frequency of 22, are crucial study areas for water resource management, hydrological modeling, and aquatic ecosystem monitoring. The category "Other," encompassing features like fog, mountains, and trees, signifies a diverse range of study areas, each with its unique characteristics and ecological significance. Together, these study areas provide a comprehensive framework for analyzing and understanding the Earth's diverse landscapes and ecosystems.

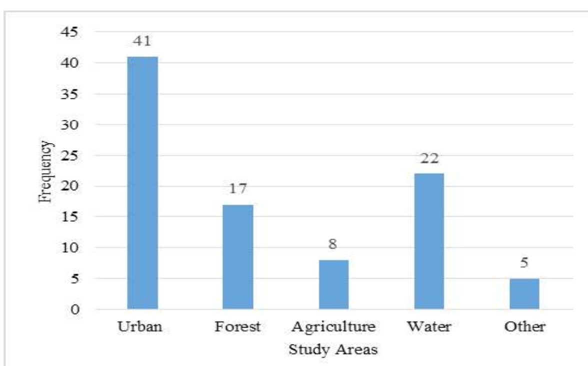

Figure 4: Frequency of the Study Areas

Source: Author

2. Future Direction

The collected data presents a comprehensive overview of the current landscape within remote sensing and image analysis, highlighting key study targets and areas of focus (RQ4). Moving forward, future research directions could involve integrating advanced machine learning techniques with high-resolution satellite imagery to enhance the accuracy and efficiency of land cover classification and object detection tasks. Additionally, there is a growing need to explore the applications of Remote sensing technologies in emerging targets such as precision agriculture, urban planning, and climate change monitoring. Furthermore, efforts can be directed towards developing innovative methodologies for multi-temporal analysis to better understand temporal changes in land cover dynamics and environmental processes. Collaboration across disciplines, including remote sensing, computer vision, and environmental science, will be crucial for addressing complex research questions and leveraging the full potential of remote sensing data for sustainable development and environmental management. Embracing open data initiatives and promoting data-sharing practices will also facilitate broader access to satellite imagery and encourage collaborative research efforts aimed at addressing global challenges related to land cover change, land use, and natural resource management.

3. Conclusion& Future Scope

In conclusion, remote sensing techniques have become an integral tool for studying diverse targets using various learning paradigms. Through the use of remote sensing images and advanced techniques for processing, researchers can gather valuable information and insights about the Earth's surface, atmosphere, and oceans. From monitoring environmental changes to mapping LULC, remote sensing has greatly enhanced our understanding of the world we live in. However, as technology continues to advance, there is still much to be explored and discovered in this field. By further developing and integrating different learning paradigms, we can continue to push the boundaries of Remote sensing and expose its full potential for a wide range of applications. Remote sensing will continue to be important for solving global problems and making decisions in the future. As such, researchers and practitioners need to stay updated on the latest advancements and collaborate to further advance this field of study. With continued efforts and advancements, remote sensing will continue to revolutionize our understanding of the Earth and help us make more informed and sustainable decisions for our planet.

Reference

1. Bergamasco, Luca, Francesca Bovolo, and Lorenzo Bruzzone. "A dual-branch deep learning architecture for multisensor and multitemporal remote sensing semantic segmentation." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2023): 2147-2162.

2. Li, Junwei, Shijie Li, and Feng Wang. "Adaptive Fusion NestedUNet for Change Detection Using Optical Remote Sensing Images." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

3. Liu, Shanwei, et al. "An Improved Lightweight U-Net for Sea Ice Lead Extraction from Multi-polarization SAR Images." IEEE Geoscience and Remote Sensing Letters (2023).

4. Liu, Chang, et al. "An Unsupervised Snow Segmentation Approach Based on Dual-Polarized Scattering Mechanism and Deep Neural Network." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-14.

5. Wu, Wenfu, et al. "CroFuseNet: A Semantic Segmentation Network for Urban Impervious Surface Extraction Based on Cross Fusion of Optical and SAR Images." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2023): 2573-2588.

6. Cao, Di, et al. “Deep Learning-Based Multiscale Pyramid Sieve and Analysis Module in Image Segmentation.” IEEE Access 11 (2023): 22307-22319.
7. Patel, Ajay Kumar, et al. “Deep Learning-Based Plant Organ Segmentation and Phenotyping of Sorghum Plants Using LiDAR Point Cloud.” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).
8. Gerg, Isaac D., and Vishal Monga. “Deep Multi-Look Sequence Processing for Synthetic Aperture Sonar Image Segmentation.” IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-15.
9. Sravya, N., et al. “DPPNet: An efficient and robust deep learning network for land cover segmentation from high-resolution satellite images.” IEEE Transactions on Emerging Topics in Computational Intelligence 7.1 (2022): 128-139.
10. Zhang, Ansi, et al. “Exploring Semantic Information Extraction from Different Data Forms in 3D Point Cloud Semantic Segmentation.” IEEE Access (2023).
11. Zortea, Maciel, et al. “Flood mapping using Sentinel-1 images and light-weight U-Nets trained on synthesized events.” IEEE Geoscience and Remote Sensing Letters (2023).
12. Fang, Leyuan, et al. “Hyperspectral image instance segmentation using spectral–spatial feature pyramid network.” IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-13.
13. Gazzea, Michele, Oscar Sommervold, and Reza Arghandeh. “MARU-Net: Multi-Scale Attention Gated Residual U-Net With Contrastive Loss for SAR-Optical Image Matching.” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).
14. AlMarzouqi, Hasan, and Lyes Saad Saoud. “Semantic Labeling of High Resolution Images Using EfficientUNets and Transformers.” IEEE Transactions on Geoscience and Remote Sensing (2023).
15. Zhang, Bin, et al. “Semi-supervised deep learning via transformation consistency regularization for remote sensing image semantic segmentation.” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2022).
16. Nuradili, Pakezhamu, et al. “UAV Remote Sensing Image Semantic Segmentation Strategy Based on Thermal Infrared and Multispectral Image Features.” IEEE Journal on Miniaturization for Air and Space Systems (2023).
17. Zhu, Jingru, et al. “Unsupervised domain adaptation semantic segmentation of high-resolution remote sensing imagery with invariant domain-level prototype memory.” IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-18.
18. Inkawhich, Nathan. “A Global Model Approach to Robust Few-Shot SAR Automatic Target Recognition.” IEEE Geoscience and Remote Sensing Letters (2023).
19. Li, Xiangwen, et al. “A Min-Pooling Detection Method for Ship Targets in Noisy SAR Images.” IEEE Access 11 (2023): 31902-31911.
20. Wang, Yao, et al. “A Prediction and Prior Information Guided SAR Ship Detection Method.” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).
21. Qin, Chuan, et al. “A Semi-Soft Label-Guided Network with Self-Distillation for SAR Inshore Ship Detection.” IEEE Transactions on Geoscience and Remote Sensing (2023).
22. Kuzu, Rýdvan Salih, et al. “Automatic Detection of Building Displacements Through Unsupervised Learning From InSAR

Data." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

23. Li, Congyu, et al. "Combining Time-Series Variation Modeling and Fuzzy Spatiotemporal Feature Fusion: A novel Approach for unsupervised Flood Mapping using Dual-polarized Sentinel-1 SAR Images." IEEE Transactions on Geoscience and Remote Sensing (2023).
24. Chen, Chengcheng, et al. "CS n Net: A Remote Sensing Detection Network Breaking the Second-Order Limitation of Transformers with Recursive Convolutions." IEEE Transactions on Geoscience and Remote Sensing (2023).
25. Wu, Haoyu, et al. "CTF-Net: A convolutional and transformer fusion network for SAR ship detection." IEEE Geoscience and Remote Sensing Letters (2023).
26. Felt, Violet, et al. "Fast Ocean Front Detection Using Deep Learning Edge Detection Models." IEEE Transactions on Geoscience and Remote Sensing (2023).
27. Zhang, Yuanlin, and Yuan Yuan. "Hierarchical information enhancing detector for remotely sensed object detection." IEEE Geoscience and Remote Sensing Letters 20 (2022): 1-5.
28. Zhou, Zheng, et al. "HRLE-SARDet: A Lightweight SAR Target Detection Algorithm Based on Hybrid Representation Learning Enhancement." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-22.
29. Chang, Hao, et al. "MLSDNet: Multi-class Lightweight SAR Detection Network Based on Adaptive scale distribution attention." IEEE Geoscience and Remote Sensing Letters (2023).
30. Zhao, Ming, Xin Zhang, and André Kaup. "Multitask Learning for SAR Ship Detection with Gaussian-Mask Joint Segmentation." IEEE Transactions on Geoscience and Remote Sensing (2023).
31. Nascimento, Eduardo, et al. "Productive Crop Field Detection: A New Dataset and Deep Learning Benchmark Results." arXiv preprint arXiv:2305.11990 (2023).
32. Naveed, Anum, et al. "Saliency-Based Semantic Weeds Detection and Classification Using UAV Multispectral Imaging." IEEE Access 11 (2023): 11991-12003.
33. Du, Wentian, et al. "SARNas: A hardware-aware SAR target detection algorithm via multiobjective neural architecture search." IEEE Transactions on Geoscience and Remote Sensing (2023).
34. Loran, Tamara, et al. "Ship detection based on faster R-CNN using range-compressed airborne radar data." IEEE Geoscience and Remote Sensing Letters 20 (2022): 1-5.
35. Gong, Yicheng, et al. "Small ship detection of SAR images based on optimized feature pyramid and sample augmentation." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).
36. Song, Beihang, et al. "SRDF: Single-Stage Rotate Object Detector via Dense Prediction and False positive Suppression." IEEE Transactions on Geoscience and Remote Sensing (2023).
37. Wang, Renfang, et al. "A Difference Enhanced Neural Network for Semantic Change Detection of Remote Sensing Images." IEEE Geoscience and Remote Sensing Letters (2023).
38. Wang, Zhipan, et al. "A New Remote Sensing Change Detection Data Augmentation Method based on Mosaic Simulation and Haze Image Simulation." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).
39. Zhao, Yu, et al. "A Triple-Stream Network With Cross-Stage Feature Fusion for High-Resolution Image Change Detection." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-17.

40. Dong, Wenqian, et al. "Abundance matrix correlation analysis network based on hierarchical multihead self-cross-hybrid attention for hyperspectral change detection." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-13.

41. Zhang, Jindou, et al. "AERNet: An attention-guided edge refinement network and a dataset for remote sensing building change detection." IEEE Transactions on Geoscience and Remote Sensing (2023).

42. Zhang, Xiaofeng, et al. "Asymmetric cross-attention hierarchical network based on CNN and transformer for bitemporal remote sensing images change detection." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-15.

43. Han, Chengxi, et al. "Change Guiding Network: Incorporating Change Prior to Guide Change Detection in Remote Sensing Imagery." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

44. Shangguan, Yu, Jinjiang Li, and Liang Chang. "Dual-Attention Cross Fusion Context Network for Remote Sensing Change Detection." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

45. Lin, Tzu-Hsuan, and Chia-Hsiang Lin. "Hyperspectral Change Detection Using Semi-Supervised Graph Neural Network and Convex Deep Learning." IEEE Transactions on Geoscience and Remote Sensing (2023).

46. Lv, Zhiyong, et al. "Iterative Training Sample Augmentation for Enhancing Land Cover Change Detection Performance With Deep Learning Neural Network." IEEE Transactions on Neural Networks and Learning Systems (2023).

47. Lv, Zhiyong, et al. "Multi-scale Attention Network Guided with Change Gradient Image for Land Cover Change Detection Using Remote Sensing Images." IEEE Geoscience and Remote Sensing Letters (2023).

48. Li, Weisong, et al. "SAR-TSCC: A Novel Approach for Long Time Series SAR Image Change Detection and Pattern Analysis." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-16.

49. Wang, Congcong, et al. "Self-supervised Learning for High-resolution Remote Sensing Images Change Detection with Variational Information Bottleneck." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

50. Zhao, Yu, Yifang Ban, and Josephine Sullivan. "Tokenized Time-Series in Satellite Image Segmentation with Transformer Network for Active Fire Detection." IEEE Transactions on Geoscience and Remote Sensing (2023).

51. Wang, Xianghai, et al. "TriTF: A Triplet Transformer Framework Based on Parents and Brother Attention for Hyperspectral Image Change Detection." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-13.

52. Gui, Rong, et al. "Unsupervised PolSAR change detection based on polarimetric distance measurements and ConvLSTM Network." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

53. Liu, Qiang, et al. "A Multi-Level Label-Aware Semi-Supervised Framework for Remote Sensing Scene Classification." IEEE Transactions on Geoscience and Remote Sensing (2023).

54. Feng, Yining, et al. "A Novel Semi-Supervised Long-Tailed Learning Framework With Spatial Neighborhood Information for Hyperspectral Image Classification." IEEE Geoscience and Remote Sensing Letters 20 (2023): 1-5.

55. Pal, Sankar K., and Dasari Arun Kumar. "Adaptive Granulation-Based Convolutional Neural Networks With Single Pass Learning for Remote Sensing Image Classification." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2022): 57-70.

56. Ma, Wenping, et al. "An Adaptive Migration Collaborative Network for Multimodal Image Classification." IEEE Transactions on Neural Networks and Learning Systems (2023).

57. Kalita, Indrajit, and Moumita Roy. "Class-Wise Subspace Alignment-Based Unsupervised Adaptive Land Cover Classification in Scene-Level Using Deep Siamese Network." IEEE Transactions on Neural Networks and Learning Systems (2022).

58. Yao, Jing, et al. "Extended Vision Transformer (ExViT) for Land Use and Land Cover Classification: A Multimodal Deep Learning Framework." IEEE Transactions on Geoscience and Remote Sensing (2023).

59. Ji, Jian, et al. "Hyperspectral Image Classification Based on Unsupervised Regularization." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2023): 1871-1882.

60. Hao, Siyuan, Nan Li, and Yuanxin Ye. "Inductive Biased Swin-Transformer With Cyclic Regressor for Remote Sensing Scene Classification." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

61. Temenos, Anastasios, et al. "Interpretable deep learning framework for land use and land cover classification in remote sensing using SHAP." IEEE Geoscience and Remote Sensing Letters 20 (2023): 1-5.

62. Liu, Shang, et al. "Land Use and Land Cover Mapping in China Using Multi-modal Fine-grained Dual Network." IEEE Transactions on Geoscience and Remote Sensing (2023).

63. Ma, Yaobin, Xiaohua Deng, and Jingbo Wei. "Land Use Classification of High-Resolution Multispectral Satellite Images With Fine-Grained Multiscale Networks and Superpixel Postprocessing." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2023): 3264-3278.

64. Xu, Leilei, et al. "Land-Cover Classification With High-Resolution Remote Sensing Images Using Interactive Segmentation." IEEE Access 11 (2022): 6735-6747.

65. Ghanbari, Mohsen, Linlin Xu, and David A. Clausi. "Local and global spatial information for land cover semi-supervised classification of complex polarimetric SAR data." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2023).

66. Capliez, Emmanuel, et al. "Multi-Sensor Temporal Unsupervised Domain Adaptation for Land Cover Mapping with spatial pseudo labelling and adversarial learning." IEEE Transactions on Geoscience and Remote Sensing (2023).

67. Fan, Jianchao, and Chuan Liu. "Multitask GANs for Oil Spill Classification and Semantic Segmentation Based on SAR Images." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2023): 2532-2546.

68. Wang, Meng, et al. "Nearest Neighbor-Based Contrastive Learning for Hyperspectral and LiDAR Data Classification." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-16.

69. Lv, ZhiYong, et al. "Novel Land-Cover Classification Approach with Nonparametric Sample Augmentation for Hyperspectral Remote Sensing Images." IEEE Transactions on Geoscience and Remote Sensing (2023).

70. Yao, Huaxiong, et al. "Pseudo-Label-Based Unreliable Sample Learning for Semi-Supervised Hyperspectral Image Classification." IEEE Transactions on Geoscience and Remote Sensing (2023).

71. Liu, Weiwei, et al. "Self-Supervised Feature Learning Based on Spectral Masking for Hyperspectral Image Classification." IEEE Transactions on Geoscience and Remote Sensing (2023).

72. Shi, Weipeng, et al. "Semantic representation fusion based network for robust land cover classification in foggy conditions." IEEE Transactions on Geoscience and Remote Sensing (2023).

73. Zhang, Yuxiang, et al. "Single-source domain expansion network for cross-scene hyperspectral image classification." IEEE Transactions on Image Processing 32 (2023): 1498-1512.

74. Lu/, Pengyu, et al. "Spectral-spatial and Superpixelwise Unsupervised Linear Discriminant Analysis for Feature Extraction and Classification of Hyperspectral Images." IEEE Transactions on Geoscience and Remote Sensing (2023).

75. Shang, Cheng, et al. "Spectral–Spatial Generative Adversarial Network for Super-Resolution Land Cover Mapping With Multispectral Remotely Sensed Imagery." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2022): 522-537.

76. Li, Zhaokui, et al. "Supervised Contrastive Learning For Open-Set Hyperspectral Image Classification." IEEE Geoscience and Remote Sensing Letters (2023).

77. Capliez, Emmanuel, et al. "Temporal-Domain Adaptation for Satellite Image Time-Series Land-Cover Mapping With Adversarial Learning and Spatially Aware Self-Training." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2023): 3645-3675.

78. Bi, Meiqiao, et al. "Vision transformer with contrastive learning for remote sensing image scene classification." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2022): 738-749.

79 Singh, Abhishek, and Lorenzo Bruzzone. "WIANet: A Wavelet-Inspired Attention-Based Convolution Neural Network for Land Cover Classification." IEEE Geoscience and Remote Sensing Letters 20 (2022): 1-5.