A Systematic Review of Satellite Image Classification

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***Abstract*—With the rapid development of remote sensing technology, high-resolution satellite images play an essential role in fields such as environmental monitoring, urban planning, agricultural assessment, and disaster management. As one of the core tasks of satellite data processing, the accuracy and efficiency of satellite image classification directly affect the reliability of subsequent applications. This paper reviews the main methods of satellite image classification, including traditional machine learning methods (e.g., Support Vector Machine, Random Forest) and deep learning methods (e.g., Convolutional Neural Networks, Transformer). Firstly, this paper analyzes which classification tasks are the main focus of current research and then examines the advantages and disadvantages of different methods. In addition, this paper explores the application of techniques such as multi-source data fusion, few-shot learning and semantic segmentation in improving classification performance. The experimental results demonstrate that deep learning-based classification methods perform well in complex scenarios but still face challenges such as high sample labelling costs and insufficient model generalization capability. Finally, this paper suggests that future research could combine self-supervised learning, lightweight networks, and 3D satellite information mining to further enhance classification accuracy and practical applicability.**

***Keywords*—classification method, classification types, classification role**

I. Introduction

IN recent years, with the rapid development of remote sensing technology, high-resolution satellites, unmanned aerial vehicles (UAVs), and aerial remote sensing platforms acquired massive, multi-temporal, multi-spectral, and even hyperspectral remote sensing image data. These data have a wide range of application value in fields such as land resources survey, environmental monitoring, precision agriculture, disaster assessment, and smart cities. However, how to efficiently and accurately extract effective information from huge remote sensing images has become one of the key issues in remote sensing data processing. Satellite image classification, as the core technology of remote sensing information extraction, aims to classify each pixel or area in the image to a specific feature class (e.g., water bodies, vegetation, buildings, roads, etc.), and its classification accuracy and automation level directly affect the reliability of subsequent applications.

Traditional satellite image classification methods mainly rely on manually designed features (e.g., texture, spectrum, shape, etc.) combined with machine learning algorithms (e.g., Support Vector Machines (SVMs), Random Forests (RFs), and Maximum Likelihood Classification (MLCs)) for classification. Although these methods perform well under certain conditions, the classification accuracy is often limited when faced with complex scenes, high-resolution images, or high similarity between categories. In recent years, deep learning methods (e.g., Convolutional Neural Network (CNN), U-Net, Transformer, etc.) have made breakthroughs in satellite image classification tasks by virtue of their powerful feature extraction and end-to-end learning capabilities. In particular, deep learning methods based on semantic segmentation (e.g., DeepLab, PSPNet, etc.) are able to realize pixel-level classification, which significantly improves classification accuracy.

However, satellite image classification still faces many challenges. The first is the high cost of sample labelling high-quality labelled data requires professional knowledge and a lot of manpower, while small-sample learning and weakly supervised learning have become a research hotspot; the second is the problem of multi-source data fusion, how to effectively combine different modal data such as multispectral, hyperspectral, LiDAR and SAR to improve the classification performance; then there is insufficient model generalization ability, when the distribution of training data and test data is inconsistent (such as cross-region, cross-temporal phase classification), the model performance may drop significantly; finally, about the computational efficiency and real-time, the processing of high-resolution large images requires high computational resources, and lightweight networks (e.g., MobileNet, EfficientNet) and edge computing become the optimization direction.

In the preliminary literature review, we focused on the existing satellite image classification methods. By compiling search index terms related to satellite image classification and subsequent searches in popular search engines, we identified 150 potentially relevant papers. After refining the scope, we selected 100 papers directly related to the topic of this survey. The selected works are analyzed, categorized, and discussed in detail in this manuscript. In this paper, we systematically sort out the current research status of satellite image classification, compare and analyze the advantages and disadvantages of traditional machine learning and deep learning methods, and discuss the role of cutting-edge technologies such as multi-scale feature fusion, self-supervised pre-training, and three- dimensional remote sensing information mining in improving the classification performance. Finally, this paper looks forward to future research directions, including the potential of self-supervised learning, knowledge distillation, and remote sensing macromodel for future applications in satellite image classification.

The research in this paper, we aim to provide reference for the development of satellite image classification technology and promote its practical application in the fields of smart earth, precision agriculture, and disaster emergency response.

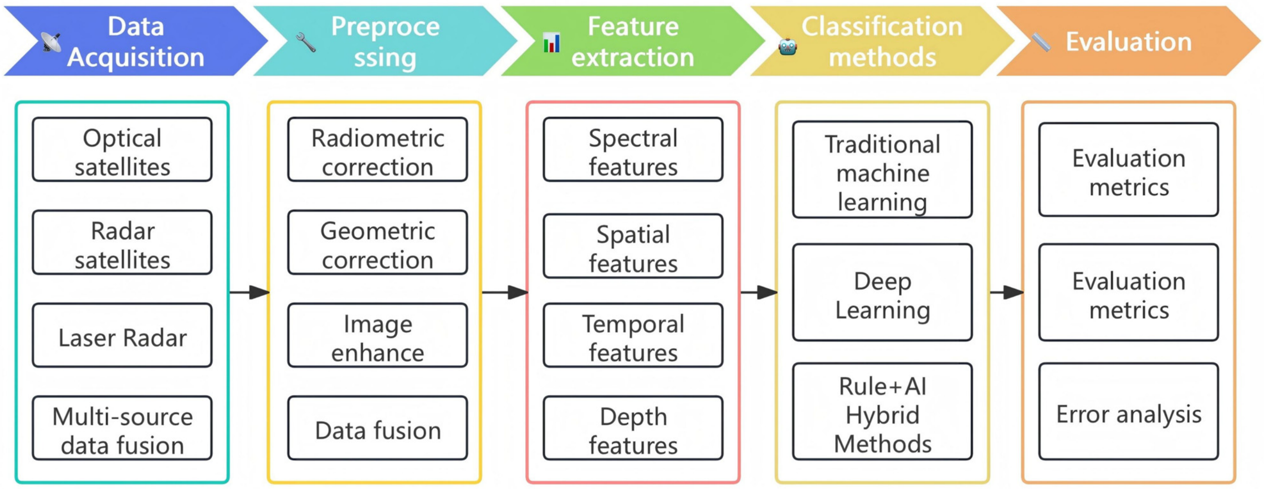

Fig. 1. Satellite remote sensing image classification.

II. Classification Methods

The process of satellite image classification follows a systematic and well-structured pipeline designed to convert raw satellite imagery into meaningful land cover and land use information. Initially, satellite data is acquired across multiple spectral bands and temporal snapshots, capturing essential spatial and spectral characteristics of the Earth's surface. Subsequently, this raw imagery undergoes preprocessing to enhance its quality. This includes radiometric correction to account for sensor inconsistencies and geometric correction to align images with a standard coordinate system. Once preprocessed, relevant features are extracted, encompassing spectral indices, spatial texture metrics, and temporal patterns. These features serve as inputs to classification models, ranging from traditional machine learning approaches such as Support Vector Machines (SVM) to advanced deep learning architectures like Convolutional Neural Networks (CNN). The classification results are subsequently validated using statistical performance metrics, such as Overall Accuracy (OA), the Kappa coefficient, and the F1-score, ensuring robustness and reliability in remote sensing applications.

Mathematically, let I(x, y, λ, t) represent the raw satellite image, where (x, y) denotes spatial coordinates, λ corresponds to the spectral wavelength, and t represents the temporal dimension. The preprocessing stage refines this data by applying radiometric correction.

$$I' = \frac{I - I_{\text{dark}}}{I_{\text{white}} - I_{\text{dark}}}, \tag{1}$$

and geometric transformation via a mapping function H is

$$(x', y') = H(x, y). \tag{2}$$

Feature extraction follows, deriving spectral characteristics such as the Normalized Difference Vegetation Index (NDVI):

$$\text{NDVI} = \frac{I_{\text{NIR}} - I_{\text{Red}}}{I_{\text{NIR}} + I_{\text{Red}}}, \tag{3}$$

and spatial texture measures such as entropy from the Gray- Level Co-occurrence Matrix (GLCM) is

$$H = -\sum_{i,j} P(i,j) \log P(i,j). \tag{4}$$

These extracted features form a feature vector $\mathbf{F} \in R^d$, which serves as input to a classifier f(**F**). For instance, in an SVM-based classification approach:

$$\mathrm{f}(\mathbf{x}) = \mathrm{sign}(\mathbf{w}^{\mathrm{T}}\mathbf{x} + \mathrm{b}), \tag{5}$$

where **w** is the weight vector and b is the bias term. The classification accuracy is subsequently assessed through OA.

$$OA = \frac{TP + TN}{TP + TN + FP + FN}, \tag{6}$$

where TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively. This structured and mathematically rigorous framework ensures a reliable and interpretable transformation of satellite imagery into classified outputs with quantifiable accuracy.

A. Traditional Methods

1) Classification based on spectral features

In satellite image classification, the method of combining spectral and texture features significantly improves the accuracy and robustness of feature classification by making full use of the complementarity of different information sources. The core principle lies in the fact that spectral features reflect the material composition and reflective properties of features, while texture features portray the spatial structure and distribution pattern of feature surfaces, and the combination of the two can describe the essential attributes of features more comprehensively. For example, when distinguishing vegetation types, spectral features can identify differences in chlorophyll content, while textural features can capture the roughness or arrangement of tree crowns, thus avoiding light or shadow interference caused by relying solely on spectral information. Pan *et al.* [1] introduced a method that surpassed both Random Forest and object-based image analysis. Showcasing its practicality and effectiveness in mapping individual buildings in densely populated urban villages highlights its potential for accurately characterizing unplanned urban settlements at the building level. However, Maryam *et al.* [2] contribution is twofold: first, they introduced FloodNet, a high-resolution UAV imagery dataset for post-disaster damage assessment; second, they evaluated various classification, semantic segmentation, and visual question answering (VQA) methods on this dataset. To the best of our knowledge, this is the first VQA study focused on UAV imagery for disaster damage assessment.

In satellite image classification, the method of combining spectral, textural, and geometric features significantly improves the accuracy and robustness of feature classification by means of multi-level and multi-angle feature characterization. The core principle of this approach is to make full use of the complementary advantages of different feature types: spectral features reflect the material composition and reflective properties of features, textural features describe the spatial structure and distribution pattern of feature surfaces, and geometric features portray the shape, size and spatial arrangement of features. The synergistic effect of the three features can describe the essential attributes of features more comprehensively, thus overcoming the limitations of a single feature type. For example, in urban feature classification, spectral features can distinguish between vegetation and water bodies, textural features help to identify different types of building roofs, and geometric features can effectively identify targets with specific shapes and spatial layouts, such as roads and squares.

Ensemble learning (EL) methods combine multiple classifiers to improve predictive performance compared to a single classifier. Jafarzadeh [3]evaluated various ensemble learning (EL) algorithms, such as AdaBoost, GBM, XGBoost, Light-GBM, and Random Forest (RF), for classifying remote sensing (RS) data, including high-resolution multispectral, hyperspectral, and PolSAR data. Compared to the base Decision Tree (DT) classifier, RF and XGBoost excelled with multispectral data, LightGBM and XGBoost with hyperspectral data, and XGBoost and RF with PolSAR data. The results highlight XGBoost's strong performance across diverse RS data types. Boulila *et al.* [4] introduced a novel CNN-LSTM hybrid model to predict urban expansion across multiple regions in Saudi Arabia.

2) Object-based classification

About the use of satellite image classification to process dynamic analysis, Lu *et al.* [5] provided a global-scale analysis of sandy shoreline dynamics from 1984 to 2016 using automated satellite image processing. Sandy beaches were identified through *spectrally guided supervised* classification of a 2016 global composite image validated at 50 global locations. Shoreline changes were detected using over 1.9 million Landsat images, with rates calculated at 500m intervals along coastlines. The method was quantitatively validated across diverse environments, offering a comprehensive assessment of shoreline changes in meters per year.

Tamouk *et al.* [6] compared the accuracy of parallelepiped, minimum distance, and chain classification methods. They found that the chain method outperformed the others in terms of overall accuracy, surpassing the minimum distance and parallelepiped methods. The study also identified optimal band combinations for land-cover detection, highlighting band 4 of Landsat 5TM as the key to improving accuracy. A table summarizing suitable band combinations for detecting land- cover objects was developed based on band features and prior research.

Cheng *et al.* [7] introduce a novel urban environment classification method, leveraging easily accessible Google Earth data, to analyze formality and informality by examining buildings and their surroundings. It offers a scalable solution for real-time urban socio-environmental monitoring, forecasting, and computational modeling, thus enhancing the policy- making process with timely and informative insights.

3) Classification based on feature transformation

Abburu *et al.* [8] have proposed the suggestion that satellite image classification involves grouping pixel values into meaningful categories and can be categorized into automatic, manual and hybrid methods, each with its pros and cons. Most methods fall under the automatic category, and selecting the appropriate approach depends on specific requirements.

B. Deep Learning Methods

1) Convolutional neural network

Using CNNs for remote sensing image recognition is challenging because of complex backgrounds and small objects. To solve this problem, Zhao *et al.* [3] designed an Enhanced Attention Module (EAM) to improve feature extraction and generalization, and their method achieved an accuracy of 94.29% on the NWPU- RESISC 45 dataset. Ding *et al.* [9] introduced a cross-view matching approach based on location classification (referred to as LCM), which evaluates the similarity between UAV and satellite views. This method was implemented and tested using the latest UAV-based geo-localization dataset.

Kiani [10] has found a novel image-smoothing method for satellite imagery, focusing on global gradient minimization across the image. By discretizing the continuous problem and using finite difference differentiation, a 5×5-pixel template is created. Convolving this template with multi-band images effectively distinguishes image elements, offering a fast and precise solution. A case study in northern Iran, including the Caspian Sea, demonstrates its superiority over traditional Laplacian methods in identifying image phenomena.

Zhang *et al.* [11] investigated land use/cover classification and change detection in urban regions by applying deep learning to high-resolution remote sensing images. A Fully Atrous Convolutional Neural Network is introduced for robust feature extraction and land cover classification. Change detection is performed by comparing current classification maps with legacy GIS maps, evaluating both pixel- and object-based methods. Tested on data from Wuhan, China (8000 km^2), including 0.5m aerial images (2014) and 1m satellite images (2017), FACNN outperformed other CNNs in classification accuracy. Object-based change detection proved superior to pixel-based methods, providing precise change maps for urban land cover updates. Moreover, Ji *et al.* [12] proposed a GAN-based domain adaptation method for land cover classification, addressing scenarios where target remote sensing images differ significantly from labelled source images. The approach aligns source and target images in image, feature, and output spaces through adversarial learning in two stages. Source images are stylized to match target images, training a Fully Convolutional Network (FCN) for semantic segmentation. This end-to-end framework integrates domain adaptation and segmentation for accurate land cover classification.

Janne *et al.* [13] focused on boreal forest ecosystems and demonstrated the use of deep learning methods, specifically 3D-CNN, for the first time on a large hyperspectral dataset. Their study targets three major tree species—Scots pine, -way spruce, and birch—as well as European aspen, a keystone species in boreal forests. The research aims to compare the performance of 3D-CNN with SVM, RF, GBM, and ANN in tree species classification and to assess the accuracy of recognizing four common boreal tree species from hyperspectral data at the tree level. Moreover, Yuri *et al.* [14] evaluated the effectiveness of different CNN architectures for classifying cloud, shade, and land cover types in PlanetScope and Sentinel-2 images at the scene level and investigated whether combining CNN models with varied architectures enhances performance.

Hamouda *et al.* [15] identified three treatment scenarios: multi-dimensional analysis, band-by-band information extraction, and feature reduction, which simplifies data into a single 2D image and reduces computation time. Reduction methods in CNNs are categorized into two types: selective methods, which partially reduce spectral information and maintain 3D efficiency for classification, and total reduction methods, which output a 2D image to minimize computation time.

$$y_n = \mathrm{softmax}(H_n) \tag{7}$$

Land-cover classification involves labelling pixels in remote-sensing images with corresponding land-cover categories. They propose a hybrid algorithm combining patch-wise classification and hierarchical segmentation using majority voting.

2) Time-series remote sensing classification

The problem of model degradation in deep learning exists. Xia *et al.* [16] proposed a dilated multi-scale cascade forest method for classifying satellite cloud images. The method enhances feature extraction by increasing diversity through multi-scale scanning and expanding the receptive field with a dilated structure, improving efficiency without losing texture and spatial correlation. Additionally, the number of network layers is determined automatically based on system performance.

Xu *et al.* [17] proposed an enhanced land classification method integrating Recurrent Neural Networks (RNN) and Random Forest (RF) using publicly available satellite imagery. By exploiting multi-temporal spectral signatures and phenological patterns from satellite time series, this hybrid approach performs concurrent pixel- and object-based classification, achieving 87% accuracy and surpassing conventional remote sensing techniques.

3) Multi-source data fusion methods

The key steps first involve the pre-processing and alignment of multi-source data to ensure that the images of different modalities are spatially and radiometrically aligned, e.g., by removing sensor differences through geometric correction and radiometric normalization. Subsequently, the network architecture design becomes the core aspect, which usually employs sub-networks with shared weights or independent branches to extract the features of each modality separately. In the feature extraction phase, a CNN or a vision transformer (ViT) captures spectral-spatial features via local receptive fields or self-attention mechanisms, while a recurrent neural network (RNN) or a 3D convolution may be introduced for temporal data to handle the time dimension. Feature fusion strategies can be categorized into early, intermediate, and late fusion, depending on the stage of fusion. Early fusion directly splices the raw input data and is suitable for highly correlated modalities; intermediate fusion performs feature interaction at the intermediate network layer, e.g., by dynamically weighting the contributions of different modalities through channel attention (e.g., SE module) or spatial attention; and late fusion integrates the classification results of each modality at the decision-making layer, e.g., through weighted voting or probabilistic averaging. In addition, advanced fusion methods introduce cross-modal comparative learning or adversarial training to enhance feature consistency and reduce inter-modal distributional differences. Ultimately, the fused higher-order features output feature class probabilities via fully connected layers or classifiers and are combined with post-processing (e.g., conditional random fields) to optimize spatial continuity. The optimization of the whole process relies on an end-to-end loss function, which may incorporate cross-entropy loss, feature reconstruction loss, or multi-task learning objectives to ensure that the fused features are both discriminative and maintain semantic alignment between modalities. This approach significantly outperforms single-modal classification models in typical applications such as urban land use classification, crop monitoring, or disaster assessment and especially exhibits greater robustness in occlusion, illumination changes, or missing data scenarios.

Tong *et al.* [18] proposed a scheme for training transferable deep models to achieve land-cover classification using unlabeled multi-source high-resolution remote sensing (HRRS) images. This scheme introduces a hybrid classification method that can simultaneously extract accurate category and boundary information. Experiments on datasets including Gaofen-2, Sentinel-2A, and Google Earth demonstrate the scheme's effectiveness. Additionally, the authors present GID, the largest well-annotated HRRS land-cover dataset, comprising 150 Gaofen-2 images covering over 50,000 km² in China, offering a high-quality resource for advancing HRRS-based land-cover classification.

The core principle of the deep learning-based multi-source data feature fusion method in satellite image classification is to make full use of the complementary information of different sensors or data modalities and to automatically adaptively extract and coherently integrate the multi-level feature representation through deep neural networks to improve the classification accuracy and the ability to parse complex feature scenes. Satellite remote sensing data usually contain multiple sources such as multispectral, hyperspectral, SAR, and LiDAR, and each data modality has unique physical properties and information advantages. For example, optical imagery provides rich spectral information but is sensitive to cloud occlusion, while SAR data can penetrate clouds and capture surface structural features but is weak in material discrimination. Deep learning multi-source fusion methods adaptively mine the intrinsic correlations between these modalities through end-to-end training to construct a more discriminative joint feature space.

Zhu *et al.* [19]aimed to enhance crop-type classification by fusing Landsat and MODIS imagery, using data from the Arlington Agricultural Research Station, Wisconsin (2010–2014) as a test case. They selected 87 combinations of one or two cloud-free Landsat images per year and applied the STARFM algorithm to generate Landsat-like predictions for MODIS dates. These predictions were evaluated against original Landsat images, and classification accuracy was assessed under three scenarios: using only Landsat images, are combining Landsat with all STARFM predictions. The results were analyzed in terms of band wavelengths, base pair numbers, and dates to quantify the improvements in classification accuracy. Kanji *et al.* [20] explored the evolution of optical satellite capabilities and their impact on vessel detection research.

It reviews methods and accuracies for vessel detection and classification using optical imagery, as well as opportunities for fusing optical data with other sources. Key factors affecting accuracy include weather conditions, cloud cover, haze, solar angle, and sensor characteristics, which complicate method selection and present ongoing challenges. To enhance relevance, future algorithms should accommodate diverse targets, meteorological conditions, and optical satellite sensors.

The core of the spatiotemporal feature fusion method in satellite image classification lies in mining the spatial distribution law and temporal evolution characteristics of the feature targets at the same time and breaking through the limitations of static analysis through the synergistic characterization of multi-dimensional features. The theoretical basis of this approach lies in the fact that surface coverage types often have both spatial correlation and temporal dynamics; for example, crop growth follows seasonal patterns, urban expansion shows directional trends, and the extent of water bodies changes periodically with precipitation. Traditional single-time-phase classification methods lose these dynamics, while spatiotemporal fusion is able to capture more essential discriminative features of features by organically combining multi-temporal observation sequences with spatial structural features.

4) Self-supervised/unsupervised deep learning

Kim *et al.* [21] developed the KIOST-OpenSARShip dataset, derived from OpenSARShip, for ship classification. By comparing pixel brightness across different polarizations and aligning ship headings, they enhanced image similarity within ship types. This improved dataset achieved up to 19.34% greater accuracy using VV- and VH-polarized composite images compared to single-polarization images. Future work will focus on refining classification by incorporating additional ship characteristics. Ba *et al.* [22] introduce USTC SmokeRS, a large-scale benchmark for smoke detection using MODIS satellite imagery, comprising 6,225 images across six classes from diverse global regions. To establish a baseline, they assess cutting-edge deep-learning models for image classification.

Li *et al.* [23] designed a method to extract supervision information from geographical knowledge and created a robust representation learning framework to mitigate noise from label discrepancies between remote sensing images and geographical data. Additionally, they built the Levir-KR pre-training dataset, comprising 1,431,950 Gaofen satellite images of varying resolutions, to effectively support network pre-training.

A highly effective bi-directional feature fusion module is incorporated into the YOLO framework to improve multi-scale ship detection in high-resolution SAR images. This module fuses multi-resolution features and improves information interaction while maintaining computational efficiency. Sun *et al.* [24] propose an arbitrary-oriented ship detector based on YOLO with bi-directional feature fusion and angular classification. Moreover, Zhang *et al.* [25] employed MobileNet V2 as the base network, incorporating dilated convolution and channel attention to enhance feature discrimination. Additionally, a multi-dilation pooling module is introduced to capture multi-scale features, further boosting CNN's performance.

III. Classification Types

A. Classified according to Electromagnetic Bands

The significance of classifying remote sensing images by electromagnetic bands lies in revealing the differences in ground object features through spectral information from different bands, thereby enhancing the accuracy and application scope of remote sensing interpretation. The electromagnetic spectrum, ranging from visible light to microwave, captures the reflection, radiation, or scattering characteristics of ground objects at various wavelengths. The comprehensive utilization of multi-band data enables more precise and reliable classification of ground objects. Tooke *et al.* [26] proposed an opinion that quantitatively analyzed DeepLabV3 Plus' ability to classify complex marsh vegetation, examining classification accuracy across different remote sensing datasets with varying spatial resolutions.

Schedl *et al.* [27] provided an opinion that adaptive path planning aims to quickly and reliably locate people, which is crucial in time-critical applications like SAR. The drone facilitates SAR operations in remote areas with unstable network coverage by transmitting only detection results to the rescue team. These results can be interpreted on remote mobile devices, even with minimal-bandwidth connections, such as satellites. Loschky *et al.* [28] found that a comparison of the fundamental similarities and differences in the rapid categorization of aerial and terrestrial views helps identify basic information sources and processes.

B. Categorized according to the Purpose of Application

1) land use

Land use and land data are critical for urban planning, resource inventory, global environmental modelling, and monitoring greenhouse gas emissions from deforestation and degradation. While most LULC mapping in Brazil is based on optical remote sensing data, its application is limited in tropical regions due to persistent cloud cover. To address this, Camargo *et al.* [29] proposed using Synthetic Aperture Radar (SAR) data from active systems operating in the microwave spectrum. SAR images are highly sensitive to soil moisture, surface roughness, and vegetation structure, complementing optical imagery.

Yu *et al.* [30] proposed that classifying land use and land cover (LULC) using satellite imagery is an essential approach for tracking changes on Earth. Supervised classification methods are commonly used, with the assumption of feature independence, though this is rarely tested. The default approach for LULC classification involves using all bands as input features to models. Sicre *et al.* [31] sought to assess the role of multispectral satellite imagery (both optical and radar) in land use and land cover classification, which is crucial for monitoring crops and surface types to support efficient resource and environmental management.

Mehmet *et al.* [32] aim to map crops by classifying satellite image time series. It develops a crop classification method that incorporates expert knowledge through a three-level hierarchical label structure, improving the mapping of rare crop types. The label hierarchy is represented in a convolutional recurrent neural network to predict three labels with different levels of detail for each pixel.

A method based on road data block decomposition and a semi-transfer deep neural network model was developed for urban land use mapping using high spatial resolution multi-spectral remote sensing images. Despite progress in previous studies, challenges remain, including large data requirements for training neural networks, complex convolutional neural network (CNN) structures, slow training speeds, and difficulties in processing multispectral and hyperspectral images with traditional CNN models. These challenges affect the capability of CNNs to effectively and precisely extract and map land cover data across extensive areas. To address these, Hu *et al.* [33] proposed an innovative framework that combines cross-band spectral information fusion layers and global average pooling layers for extracting land cover from multispectral and hyperspectral satellite imagery. They developed a DCNN model capable of automatically constructing training datasets and applied it to land cover extraction in Qinhuangdao, Hebei Province, comparing the results with traditional methods.

2) Disaster monitoring

Applications in flood prevention and control, Aqil *et al.* [34] believe that the 2014 Indus River flood in Pakistan was analyzed using the HEC-RAS model combined with GIS and Landsat-8 satellite imagery. The model helps estimate the flood's spatial extent and evaluates the damage by examining changes in LULC types within the river basin.

Excessive accumulation of optically significant water components near the surface can hinder light penetration, impacting benthic organisms and ecosystem productivity. Fluvial sediment load is essential for preserving geomorphic features like river deltas and mangrove platforms. These features, influenced by sediment dynamics, rising sea levels, and disturbances, support blue carbon storage and act as defenses against storm surges and tidal floods. Monitoring sediment flux is critical for the sustainable management of coastal and inland ecosystems, as highlighted by Balasubramanian *et al.* [35].

3) Emerging areas of application

Satellite images are essential for research in areas such as sustainable development, agriculture, forestry, urban planning, and climate change. However, developing an efficient and precise semantic segmentation model remains a challenge. To address this, Wu *et al.* [36] proposed the Attention Dilation-LinkNet (AD-LinkNet) neural network, which utilizes an encoder-decoder structure, serial-parallel dilated convolutions, and a channel-wise attention mechanism.

McGlinchy *et al.* [37] noted that high-resolution satellite imagery (with a pixel size of less than 5 meters) allows for the identification of urban features like roads, sidewalks, paved surfaces, and rooftops, which are often blended with other materials in lower-resolution imagery, such as that from Landsat (30 m per pixel).

The objective of Ruben *et al.* [38] was to treat interference classification using spectrograms from GNSS receiver IF samples as a black-and-white image classification problem. They proposed efficient SVM and CNN classifiers with an accuracy of 90% or higher, as well as an open-access database providing clean and interfered GNSS signal spectrograms under various C/N0 and JSR conditions.

Sea ice detection is crucial for marine disaster management. While optical data provides rich spectral information, it struggles with differentiating similar land features, and SAR data, though rich in texture, is limited by being from a single source. Han *et al.* [39] proposed a deep learning-based sea ice classification method that integrates SAR and optical images using CNN for deep feature extraction and heterogeneous data fusion, improving classification accuracy. Moreover, Illarionova *et al.* [40] suggested that multi-spectral satellite imaging enables global-scale monitoring and assessment of properties or objects, with machine learning and computer vision techniques emerging as promising tools for automating satellite image analysis.

Fan *et al.* [41] highlighted the importance of crop type classification using satellite imagery for crop production management and food security. With satellite data available at spatial resolutions of 10 m to 30 m, such as optical sensors from China's GaoFen (GF) series, the Multispectral Instrument (MSI) on Europe's Sentinel 2 (S2), and the Operational Land Imager (OLI) on the USA's Landsat 8 (L8), its application has significantly expanded. These data sources are widely accessible and free of charge due to open data policies, providing numerous options for crop classification.

C. Classified according to the WORK Platform

LULC change describes human impacts on the Earth's surface and is vital for environmental change studies. Liu *et al.* [42] classified LULC change driver analysis methods into qualitative and quantitative approaches. Qualitative methods can show trends but are limited in quantifying factor impacts, while quantitative methods like correlation analysis, regression, principal component, and logistic regression models can better explain the relationships between driving factors and LULC changes. Urban LULC extraction from remote sensing images is challenging, especially for large cities. Medium-resolution images (e.g., Landsat TM) lack detailed LULC info, and very high-resolution images (e.g., IKONOS, QuickBird) often fail to provide comprehensive data. Research on large-area urban LULC extraction remains limited due to satellite data limitations and high computational costs. Cai *et al.* [43] addressed this issue by using Chinese GF-1 and GF-2 data, combining geometric and texture features through multi-resolution image segmentation and OBIA, to classify urban LULC into homogeneous types like water or vegetation.

Ienco *et al.* [44] proposed a suggestion that modern Earth observation (EO) missions like ESA's Copernicus program provide high-resolution radar and optical imagery (Sentinel-1 & Sentinel-2) with high temporal frequency, enabling the collection of satellite image time series (SITS). To effectively combine complementary information from S1 and S2, they propose a deep learning architecture called TWINNS (TWIn Neural Network Sentinel data), which discovers spatial and temporal dependencies for land cover classification.

James *et al.* [45] focused on ground-based remote sensing in the Riverina region of New South Wales, Australia. The area relies on irrigation from the Murrumbidgee River for crops, which include annuals (e.g., cotton, rice, wheat, and barley) and perennials (e.g., citrus, grapes, and almonds). Farmers rotate crops or leave fields fallow.

Satellite remote sensing is a valuable tool for flood mapping, with the availability of free satellite data enabling low-cost flood mapping globally. Davide *et al.* [46] proposed a semi-automatic method using free satellite images and open-source software intended for flood disaster management communities. Case studies in Spain and Italy were used with MODIS, Proba- V, Landsat, Sentinel-2, and Sentinel-1 SAR data to detect floods. Flood detection performance was computed based on water depth models and ground truth data, with results showing the importance of considering different factors when selecting the optimal flood map.

Emergency response is increasingly challenging in developing countries due to more frequent disasters and limited resources. High-quality disaster impact data is vital. Tinka *et al.* [47] highlight the growing interest in using remote sensing for automated damage assessment, which offers faster, more accurate, cheaper, and safer evaluations than manual methods. Remote sensing data from satellites and UAVs is especially effective in identifying building damage, which is easier to detect than economic losses, and has been used in social, economic, and environmental analysis. Satellite data offers wide coverage and automatic collection, while UAVs provide high-resolution data without cloud interference.

Ma *et al.* [48] highlighted the advantages of SAR images for marine monitoring, especially with the Gaofen-3 (GF- 3) satellite. Traditional methods struggle to extract effective features for target classification in SAR images. Taking advantage of this feature, they proposed a marine target classification and detection method using CNN. This approach included annotating eight different types of marine targets in the GF-3 SAR images, and a CNN model with six convolutional and pooling layers was designed for image patch classification. Additionally, a multi-resolution input single-shot multi-box detector (MR-SSD) was introduced for better feature extraction. A complete workflow was proposed, including land-sea segmentation, cropping, detection, and coordinate mapping, with experimental results demonstrating the method's effectiveness. The formula is as follows:

$$x(i,j) = \begin{cases} 1 & if\, 0(i,j) > T \\ \dfrac{0(i,j)}{T} & if\, 0(i,j) \le T \end{cases} \tag{8}$$

Satellite remote sensing has been used to assess areas with limited access, although mapping small land-based oil spills remains challenging due to pixel size. The availability of freely available Sentinel images was evaluated for mapping oil spills using machine learning. Low *et al.* [49] showed that Sentinel-1 and Sentinel-2 data could map oil spills with 90% classification accuracy in South Sudan. The accuracy improved (95%) when temporal and spatial variables quantifying proximity to oil infrastructure were added. Using Sentinel satellite images to monitor oil spills could be an effective and accurate method for regular monitoring.

Zagajewski *et al.* [50] highlighted the use of Earth and Sentinel satellites for large-scale environmental monitoring and biodiversity conservation. These satellites can monitor various forest types and identify up to 12 tree species, reducing the cost of intensive fieldwork and sometimes serving as a good alternative to aerial imagery. Multi-temporal data helps distinguish species diversity during different phenological stages, enabling monitoring of plant conditions, including early detection of bark beetle outbreaks in trees, which is a significant challenge for European forests. Accurate forest-type mapping is essential for carbon sink estimation and ecological assessment. Traditional surveys are time-consuming, and high-resolution commercial satellite images are costly and not widely available. Spracklen *et al.* [51]employed Sentinel-2 imagery and supervised classification to analyze the spectra of broadleaf, coniferous, and mixed forests in the Carpathian Mountains of Ukraine, investigating the potential of machine learning for forest species identification. This study is the first to use Sentinel-2 data and decision tree classifiers to identify old-growth broadleaf forests. Their primary objectives were to identify tree species in temperate forests, assess the feasibility of using random forest classification to map old-growth forest areas and evaluate how spectral bands, multi-temporal imagery, and additional data influence map accuracy. Jiang *et al.* [52] introduced MLP neural networks for surface water extraction, conducting large-scale experiments to evaluate its performance. They compared the algorithm to previous methods using water quality index and support vector machines and analyzed its reliability in suppressing noise, including clouds, mountains, buildings, and snow/ice shadows. After optimizing the bands and analyzing preprocessing and training samples, their proposed algorithm shows promising capabilities for global surface water mapping and contributes to a deeper understanding of Earth's global change dynamics. The accuracy of the MLP for each study area is presented.

Hu *et al.* [53] proposed a spectral-temporal feature selection method based on crop phenology. Their approach demonstrates the significant potential of combining the PSTFS method with SVM classifiers for maize and other land use classifications, providing accurate crop type maps from satellite data.

In recent years, the study of Synthetic Aperture Radar (SAR) data has emerged as both a challenging and fascinating subject in remote sensing. SAR sensors are capable of imaging the Earth's surface regardless of weather conditions or time of day, and their ability to penetrate clouds provides spatial information on crop types. Nima *et al.* [54] aimed to leverage deep learning methods to reveal better the capability of SAR data for identifying various crops during key growing seasons. In Zhang *et al.* [55] study, land cover in the study area is classified, and the vegetation area is extracted, with urban vegetation categorized into forests and grasslands for evaluation. "True" biomass data of the study area, obtained from airborne LiDAR, comprehensively reflects vegetation structure changes and growth conditions. Using 10 years of high-resolution optical imagery, the performance of parametric and non-parametric models for predicting selected biomass attributes is compared. An urban vegetation biomass inversion model is constructed and validated to achieve biomass inversion and monitoring of urban vegetation.

IV. Classification Role

A. Classification for Accuracy

The accuracy assessment of satellite image classification is a fundamental component in extracting and applying remote sensing information. Its significance lies not only in verifying the reliability of classification results but also in directly influencing the scientific validity and practical effectiveness of subsequent decision-making. Against the backdrop of remote sensing technology's widespread use in resource surveys, environmental monitoring, and disaster assessment, the quantitative analysis of classification accuracy serves as a critical step in ensuring data quality.

Phiri *et al.* [56] proposed that advances in satellite remote sensing have revolutionized Earth's surface monitoring. The Copernicus program, by ESA and the EU, supports effective monitoring through Sentinel-2 multispectral products. Sentinel-2, launched in 2015, aims to provide high-resolution data for land cover/use, climate change, and disaster monitoring. Numerous studies have used Sentinel-2 for land cover classification, but no specific review on its land cover/use monitoring applications has been conducted.

Mohammed *et al.* [57] used the confusion matrix and Kappa coefficient methods for remote sensing image interpretation, providing reliable accuracy estimates and error analysis to improve classification accuracy. Moreover, Alzahem *et al.* [58] proposed a new satellite data augmentation method using GANs and Vision Transformers (ViT), improving classification accuracy from 76.9 percent with traditional methods to 98.7%. The method enhances performance by leveraging GANs to model the underlying statistical distribution of the original images.

Eihan *et al.* [59] proposed fuzzy classification as a new satellite image classification method, where each class is modelled as a fuzzy set. That allows for the handling of a pixel belonging to multiple classes or none at all. The main challenge is estimating the pixel's category using the membership function for each class. Furthermore, Jia *et al.* [60] proposed an adaptive mutation particle swarm optimization-based SVM to improve crop classification in remote sensing. Experiments in Harbin using Gaofen-1 satellite imagery and vegetation index time series showed that the optimized SVM outperformed traditional methods such as BP neural networks, decision trees, and non-optimized SVM. Additionally, Machado *et al.* [61] highlighted that high-resolution satellite images offer a new perspective for urban studies, especially in the context of transportation systems and sustainable urban development. They propose a method for identifying key urban features for transportation planning using object-based classification, focusing on areas with high concentrations of trip generators.

Applied in João Pessoa, Paraíba, Brazil, the method showed promising results.

Wei *et al.* [62] used eight OLI images from Sanjiangyuan National Park to create a 30 m × 30 m vegetation dataset. The SVM classifier effectively distinguished major land use types with high accuracy, but accuracy was lower for some alpine grassland types, particularly desert grassland and alpine meadow. That highlights the limitations of Landsat-8 multi-spectral imagery in high-resolution grassland classification. The method is also applicable to other multispectral satellites with matching bands. Wan *et al.* [63] classify crop categories in Jianan Plain, Taiwan, using a WorldView 2 image with SVM. GLCM texture information enhances accuracy, and GRA detects misclassified paddy rice regions.

Mitidieri *et al.* [64]emphasized the need for an objective and repeatable assessment method for large-scale river monitoring. Innovative techniques that enhance the understanding of river processes and enable consistent characterization are crucial for improved river management. Furthermore, Xia *et al.* [65] proposed an improved multidimensional residual deep network (ResMNet) for cloud and snow detection in satellite imagery. The method effectively extracts both image and spectral features, classifying satellite images into cloud-free, snow, cloudy, and mixed categories. Simulations showed that ResMNet outperforms other models, including SVM, random forests, and CNNs, with higher classification accuracy.

Regarding CNN methods, in terms of high-dimensional data advantages, CNNs can automatically extract hierarchical features from high-dimensional data such as images and videos through local sensory wilds, weight sharing, and pooling operations, which significantly outperforms traditional methods in image classification tasks (e.g., ImageNet). In end-to-end learning, joint optimisation of feature extraction and classification layers avoids the bias of manual feature design. In terms of big data dependency, a large amount of labelled data is required to achieve high accuracy, and it is prone to overfitting with small samples. Regarding SVM methods, in terms of small-sample performance, based on the principle of structural risk minimisation, it may outperform CNNs on small-sample datasets (e.g., hundreds to thousands of instances), particularly in low-dimensional feature spaces. In terms of relying on feature engineering, features need to be manually designed (e.g., SIFT, HOG, etc.), and classification accuracy is limited by feature quality. For example, on the MNIST dataset, SVM puls manual features can reach 99%, but CNN can reach more than 99.7% by automatic feature learning. In terms of kernel function selection, nonlinear kernels such as Gaussian kernels can handle complex boundaries, but the choice of kernel function and parameters has a large impact on the results. In summary, CNN accuracy is usually higher with large data; SVM may be better with small data or well-defined features. Traore [66] suggested enhancing cholera monitoring in underdeveloped countries with satellite data mining techniques.

By integrating environmental and geographic factors, cholera-prone areas were identified. Combining satellite data with field data improves accuracy, helping to explain the environmental causes of disease evolution.

Mondini *et al.* [67] used a framework that analyzes SAR images' phase and amplitude to measure terrain characteristics and changes for landslide detection and mapping. Landslides are distinguished from stable terrain through expert classification, heuristic interpretation, or statistical modelling. Despite progress in the past 26 years, challenges remain in effectively using SAR images for landslide detection. They reviewed the theoretical and operational frameworks for this and discussed prospects with current and planned SAR satellite missions.

Dai *et al.* [68] proposed a coastline extraction method that improves water classification accuracy by leveraging increased repeat measurements from commercial satellites. They tested on 600 images and 12 samples; the method uses a superimposed water probability algorithm with multispectral images from QuickBird, WorldView-2, and WorldView-3, producing 2-meter resolution coastline, water probability, and repeat count maps.

Pastina *et al.* [69] explored using GNSS signals for ship radar imaging, a new application in GNSS remote sensing, including reflection measurement, passive radar, and synthetic aperture radar. GNSS-based passive radar can detect and locate ships in short-range surveillance. A processing chain designed to maximize the signal-to-noise ratio enables high-focus ship target imaging for non-cooperative target recognition.

Hao *et al.* [70] introduced the Siam-U-Net-Attn model, a deep learning approach with an attention mechanism, to evaluate building damage by analyzing satellite images taken before and after a disaster. When tested on the xView 2 dataset, the method effectively classified damage levels and performed building segmentation.

Ren *et al.* [71] applied fusion algorithms (PCA, Pansharp, Gram-Schmidt, and NNDiffuse) to GF-2 images, evaluated the fusion results qualitatively and quantitatively and classified the images using object-oriented learning algorithms. The study explored the effects of fusion methods and classification algorithms on the accuracy and adaptability of urban GF-2 satellite images.

B. Classification for Effect

The effectiveness of satellite image classification depends on multiple factors, such as data resolution and noise levels, the choice of machine learning models, feature extraction approaches, classifier robustness, and post-processing refinement.

1) Applications in agriculture

Agricultural applications require accurate land monitoring, especially for rice fields, to ensure timely food security actions. Traditional methods are expensive and slow. Nguyen *et al.* [72] aim to develop an autonomous system using satellite image data streams to differentiate crop and non-crop areas. However, this framework faces challenges, including crop seasonality, spectral complexity, and adverse conditions like clouds and solar radiation. Kpienbaareh *et al.* [73] highlighted that remote sensing has evolved into a cost-effective, near-real-time technology for large-scale operational mapping of agricultural landscapes. Over the past few decades, advancements in data storage and satellite technology have significantly enhanced the accuracy of crop type and land cover mapping. In numerous countries, crop inventory maps are derived from such satellite data. Hugo *et al.* [74] also suggested that hierarchical classification methods effectively handle large categories and achieve higher accuracy than classical methods. In agriculture, these methods assess farming practices and crop types independently of prior farmland masks.

The spatial distribution of land cover is key in land use classification. Li *et al.* [75] proposed methods using feature engineering, graph kernels, and GCN to compare graph-based and remote sensing-based land-use classification methods. Moreover, Hussain *et al.* [76] highlighted that rapid urbanization significantly impacts LULC, with increased vegetation in commercial and residential areas raising the land surface temperature (LST). LST data is essential for understanding environmental changes, urban climate, human activities, and ecological interactions. Wang *et al.* [77] found in a study on crop classification in the North China Plain, China, that the OA of a normal CNN was 85.2%, whereas an improved CNN model with the introduction of the attentional mechanism (CBAM) improved the OA to 91.5%, which was an increase of 6.3% points.

The role of multi-temporal observations in crop monitoring has become more important with the increasing frequency of satellite remote sensing image acquisition. Li *et al.* [78] proposed a crop classification method based on neural network transformers. They unified multi-band data from different sensors to obtain consistent time series and spatial features. The method uses a multi-layer encoding module to identify deep patterns in the multi-temporal sequence and employs a feedforward and softmax layer for crop classification, having a significant impact. Furthermore, José *et al.* [79] noted that remote sensing is a cost-effective technology for large-area agricultural monitoring. According to Lobell *et al.* [80], the average annual cost of using MODIS data for crop classification in crop monitoring in the Central Valley of California, USA, is about 0.02/ha, comparedtoupto8-12/ha for traditional ground surveys, a cost reduction of more than 99%. It is part of Earth observation, capturing crop and soil data via sensors on satellites, aircraft, or ground platforms. ARS technologies include camera and vehicle hardware design, real-time image data streaming, spectral/image preprocessing algorithms tools, computer vision, and machine learning, all used in agricultural decision support systems.

2) Applications in the field of disasters

Ji *et al.* [81] introduced a method to analyze wetland changes at various scales (metropolitan, watershed, sub-watershed) and improved urban wetland detection through fine-tuning classification results. They found that increased precipitation expanded wetlands, enhancing remote sensing coverage and trend interpretation. Moreover, Bai *et al.* [82] highlighted that satellite cloud images help identify weather phenomena and forecast conditions, with the challenge being the automatic classification and recognition of these images using deep learning.

Ahmad *et al.* [83] noted that natural disasters like floods, earthquakes, and storms can cause significant damage to life and infrastructure. Timely information is crucial for rescue operations, helping reduce losses. Understanding the extent of damage allows governments and NGOs to allocate resources effectively. In floods, information on road accessibility is vital for emergency response and resource allocation. Additionally, Chen *et al.* [84] utilized machine learning algorithms for time series classification and feature extraction with HMI/SHARP patches and GOES data to forecast solar flares. They employed LSTM models to categorize solar flares into B/C/M/X classes and distinguish between strong (M/X-class) and weak (B- class) flares before their peak, relying on SHARP parameters. Satellite image retrieval aids in areas like disaster management, military detection, meteorology, and urban design.

Content-based retrieval extracts relevant images from large databases. To enhance accuracy and reduce complexity, P.K. *et al.* [85] proposed a fuzzy multi-feature clustering technique. This method uses fuzzy sets representing query errors and clustering for unsupervised classification. Experiments show improved efficiency with high precision and recall.

3) Applications in emerging areas

Yousef *et al.* [86] proposed a method for automatic mineral particle identification from satellite images using spectral abundance mapping and sparse principal component analysis (SPCA). The method employs endmember approximation and Kernel Extreme Learning Machine (Kernel-ELM) for supervised classification, with results showing dependence on the training spectrum. Wan *et al.* [87] pointed out that hyperspectral remote sensing has a good demonstration effect in the mining area. It is an important basis for improving and supplementing the original mineral geological maps and is an important field for subsequent work in mineral resources exploration.

Yan *et al.* [88] highlighted that the distribution gap between VHR datasets is mainly due to differences in data acquisition sensors and regions. VHR images from different sensors may vary in spectral bands, colour saturation, and GSD, while different regions can lead to differences in building styles and urban layouts. Domain Adaptation (DA) transfers knowledge from the source domain to the target domain, improving classifier performance in the target domain.

Aouragh *et al.* [89]identified groundwater potential areas by using topographic maps, thematic maps, field data, and satellite imagery to generate thematic layers (e.g., lithology, slope, karst degree, land cover, linear structures, and water system density). These layers were processed and integrated into GIS.

Fuzzy logic was applied to analyze fuzzy membership values, classifying them based on their contribution to groundwater and evaluating the thematic layers accordingly. Shetty *et al.* [90] found that SRS(Prop) favours major categories with good overall accuracy, while SRS(Eq) provides good per-category accuracy, even for minority categories. RF outperforms CART, SVM, and RVM with a confidence of 95%, with CART and SVM showing similar performance.

Chen *et al.* [91] proposed using high-quality multispectral images from the FY-4 satellite and advanced machine learning techniques to improve tropical cyclone (TC) intensity estimation. They introduced a tensor-based convolutional neural network (TCNN), which connects tensor decomposition and contraction operations. The TCNN uses a multi-task structure with a classification network for intensity and a regression network for wind speed.

Regarding the comparison of adaptability to complex scenarios, CNN's hierarchical modelling capability: capturing spatial locality, translational invariance and hierarchical structure through multi-layer convolution, suitable for processing data with spatial/temporal correlation such as images, videos, speech, etc. CNN's dynamic adaptability can be adapted to different complexity tasks by adjusting the depth of the network (e.g., ResNet, EfficientNet). CNN's computational cost is high, the number of parameters is large, and GPU-accelerated training is required. SVM, low-dimensional structured data: more suitable for tabular data or low-dimensional features (e.g., text TF-IDF vectors); unstructured data such as images need to be downscaled or feature extraction. SVM is more explanatory: support vectors clearly show the classification boundaries, which is suitable for scenarios that require model interpretation. In conclusion, CNN is more flexible in unstructured and complex data (e.g. natural scene images); SVM is more suitable for structured data or scenarios.

Sun *et al.* [92] proposed a method to allocate resources effectively in communities using street-level images and community profiles. The approach combines spatial data, such as satellites, thermal images, and Google Street View (GSV) images, with a deep learning model to classify street features. This scalable, indicator-based method supports sustainable development by identifying areas needing heat reduction and improving tree canopy coverage as a heat adaptation strategy, enhancing active travel and health outcomes. It also aids post-COVID urban planning.

Alejandro *et al.* [93] found that Sentinel-1's 6-day revisit time outperforms longer revisit times and that dual-polarization data gives better classification results than single-polarisation data. Combining coherence and backscatter improved accuracy by over 7 %, with an overall accuracy exceeding 86 %. That demonstrates the complementary nature of these features, and the combination of interferometric and radiometric radar data provides a reliable source of information for the application.

Patra *et al.* [94] employed remote sensing and GIS techniques to compute the normalized difference built-up index (NDBI). Using spatiotemporal satellite imagery and systematic observational data, they characterized urban expansion patterns. The study applied K-Means clustering for unsupervised land use/land cover (LULC) change detection, complemented by spatial interpolation techniques (e.g., Kriging) to analyze the distribution of rainfall, temperature, and groundwater levels. Finally, Kendall's Tau test quantified the relationships between these parameters and key hydrological components.

In application scenarios with high timeliness requirements, such as disaster monitoring, the ability to rapidly acquire and process remote sensing data directly affects the actual effect of classification methods. Although the current mainstream satellite image classification methods (e.g., deep learning models) have high accuracy, they still face many challenges in terms of timeliness. Firstly, the revisit cycle and transmission delay of high-resolution satellite data may lead to the lack of key data at the early stage of a disaster, while drones can respond flexibly but have limited coverage, making it difficult to meet the demand for rapid monitoring of large areas. Second, the traditional classification process usually relies on manual annotation and large-scale training data, but the dynamics and suddenness of disaster scenarios limit the generalisation ability of pre-trained models, e.g., rapid changes in the spread of mountain fires or flooded areas may lead to lagging or even failure of the model output. In addition, complex feature extraction and computation processes can further extend the processing time, making it difficult for classification results to provide real-time support for emergency decision-making. To address these issues, future research could explore the combination of lightweight models and edge computing to reduce the latency of data transmission and centralised processing by deploying adaptive classification algorithms at the UAV or near-Earth satellite end. At the same time, incremental learning and sample-less learning techniques are used to improve the model's ability to adapt to dynamic disaster scenarios, enabling it to quickly adjust its classification strategy based on a small number of newly acquired samples.

In summary, for different types of satellite images, selecting appropriate classification methods and choosing different classification approaches based on various application scenarios are key to improving classification accuracy and efficiency.

V. Conclusion

Satellite image classification is pivotal in various fields, including land use monitoring, urban planning, agriculture, disaster management, and environmental monitoring. With the rapid development of machine learning techniques, particularly deep learning, the accuracy and efficiency of satellite image classification have reached new heights. Methods such as CNNs, SVMs, and random forests have proven effective in analyzing complex spatial patterns and classifying pixels in satellite imagery.

However, challenges such as class imbalance, high-dimensional data, and the interference of cloud cover and atmospheric conditions continue to hinder the advancements in multi-source data integration. Combining optical, radar, and LiDAR images has shown promising results in mitigating these issues. The development of advanced preprocessing techniques and the continual evolution of algorithms further enhance the robustness and precision of classification systems.

As we look to the future, real-time processing capabilities and large-scale datasets from diverse satellite platforms will likely redefine the capabilities of satellite image classification. The continuous refinement of algorithms and the adoption of newer technologies will further push the boundaries of accuracy, opening new opportunities for a wide range of applications. The future of satellite image classification holds great potential for improving our understanding of the Earth's surface and enabling more effective decision-making across multiple domains.

Conflict of Interest

The author declares no conflict of interest.

Author Contributions

Zhiyan Liu searched, classified and wrote the paper; Haining Zhang analysed the direction and details of the paper; all authors approved the final version.

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