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Change detection of multisource remote sensing images: a review

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ABSTRACT
Change detection (CD) is essential in remote sensing (RS) for natural resource monitoring, territorial planning, and disaster assessment. With the abundance of data collected by satellite, aircraft, and unmanned aerial vehicles, the utilization of multisource RS image CD (RSICD) enables the efficient acquisition of ground object change information and timely updates to existing databases. Although CD techniques have been developed and successfully applied for approximately six decades, a systematic and comprehensive review that addresses emerging trends, including multisource, data-driven, and large-scale artificial intelligence (AI) models, is lacking. Therefore, first, the development process of RSICD was reviewed. Second, the characteristics of multisource RS images were analyzed, and all publicly available RSICD data that we could gather were collected and organized. Third, RSICD methods were systematically classified and summarized on the basis of the detection framework, detection granularity, and data sources. Fourth, the suitability of specific data and CD methods for diverse applications and tasks was assessed. Finally, challenges, opportunities, and future directions for RSICD were discussed within the context of high-resolution imagery, multisource data, and large-scale AI models. This review can help researchers better understand this field, shed light on this topic, and inspire further RSICD research efforts.

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Change detection; remote sensing; multisource images; image processing; review

1. Introduction

Remote sensing (RS) is an emerging reconnaissance technique with the unique advantage of rapidly acquiring detailed information on surface objects across extensive areas (Goetz, Rock, and Rowan 1983; Mello et al. 2023; Wu et al. 2022). The utilization of multitemporal RS images for change detection (CD) provides crucial insight into surface changes and facilitates a precise understanding of land surface dynamics. RS image CD (RSICD) refers to the use of multiple temporal RS images and other auxiliary data covering the same area to identify and analyze land surface changes (Ban and Yousif 2016; Singh 1989), such as land cover types, spatial distributions, and characteristics of objects (Deren 2003). Currently, RSICD has been widely applied in various

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fields, including land resource utilization (Lv, Liu et al. 2022; Park and Song 2023; Song, Hua, and Li 2023; Zhang, Yue, Tapete, Shangguan et al. 2020), ecological resource monitoring (Cardama, Heras, and Argüello 2023; Silveira et al. 2019; Wang et al. 2018), natural disaster mapping (Huang and Jin 2020; Jarrett and Hölbling 2023; Lv, Wang et al. 2022; Tupas et al. 2023; L. Wang et al. 2023), agricultural crop monitoring and yield assessment (Kaur et al. 2023; Mazzanti et al. 2021; Silva-Perez et al. 2021; Wang et al. 2018), urban development research (Li et al. 2019; Xiao et al. 2023; Zhou et al. 2023), and multitemporal military target detection (Kahar, Hu, and Xu 2022; Zhang et al. 2020).

With the continuous development of RS technology, a substantial volume of multitemporal, multisensor, and multiresolution RS images have become available, thereby expanding the potential of CD. In tandem, the utilization of artificial intelligence and big data methodologies has propelled the rapid advancement in CD technology. Several scholars have extensively reviewed CD, covering methodologies (Cheng et al. 2024; Hussain et al. 2013; Khelifi and Mignotte 2020; Zhu et al. 2024), processing workflows (Zhu 2017), applications (Gu and Zeng 2024), and data sources, including optical (Adeli et al. 2020; Lv, Liu et al. 2022), synthetic aperture radar (SAR) (Sun et al. 2021), and 3D point clouds (Stilla and Xu 2023; Xiao et al. 2023). These reviews have provided valuable insights and served as reference points for subsequent related research. Nevertheless, prevailing research reviews have predominantly concentrated on individual data sources. The integration of multisensor, multiplatform, and multiangle RS data has the potential to significantly improve temporal resolution for monitoring object changes and overcome the limitations of individual RS technologies (Sun, Lei, Guan, Li et al. 2022; Sun et al. 2022). For example, optical RS images can supply abundant color and texture information, whereas SAR technology can capture surface details under diverse weather and lighting conditions. Integrating these various data types enables the exploitation of their strengths to achieve more precise and reliable CD (Sun, Lei, Guan, Kuang et al. 2022; Sun, Lei, Tan et al. 2022; Tan et al. 2022). Additionally, data-driven CD has emerged as a predominant approach. However, literature reviews have yet to encompass a comprehensive catalog of publicly available CD data or a thorough analysis of the applicability of diverse CD data and methods across specific tasks and scenarios.

Therefore, to further explore the capabilities of multisource RSICD, a comprehensive review of its development history was conducted herein, followed by a summary of existing methodologies. Moreover, this study offers insights into the challenges and opportunities for multisource RSICD, with the primary contributions outlined as follows:

- A comprehensive review of the historical evolution of RSICD is presented, although this topic has received relatively little attention in existing literature review studies. This review can help scholars build a comprehensive knowledge framework for RSICD and provide valuable insights into current trends.
- The characteristics of multisource RS images are analyzed, and available RSICD data are collected and organized for the training of large-scale AI models, thereby offering benchmark data for assessing the model performance.
- A detailed analysis is conducted to evaluate the strengths and weaknesses of RSICD methods. In addition, mainstream RSICD methods are introduced on the basis of the detection framework, detection granularity, and data sources. Furthermore, the suitability of specific data and CD methods for diverse applications and task characteristics is assessed.
- In response to emerging trends such as high-resolution imagery, multisource data, and large-scale artificial intelligence models, the challenges in RSICD are discussed, along with potential strategies to address them.

The remainder of this paper is organized as follows: the development history of RSICD is described in Section 2. The data, methods, processes, evaluation metrics, and applications of RSICD are introduced in Sections 3.1, 3.2, 3.3, 3.4, and 3.5, respectively. A discussion and conclusion are provided in Sections 4 and 5, respectively.

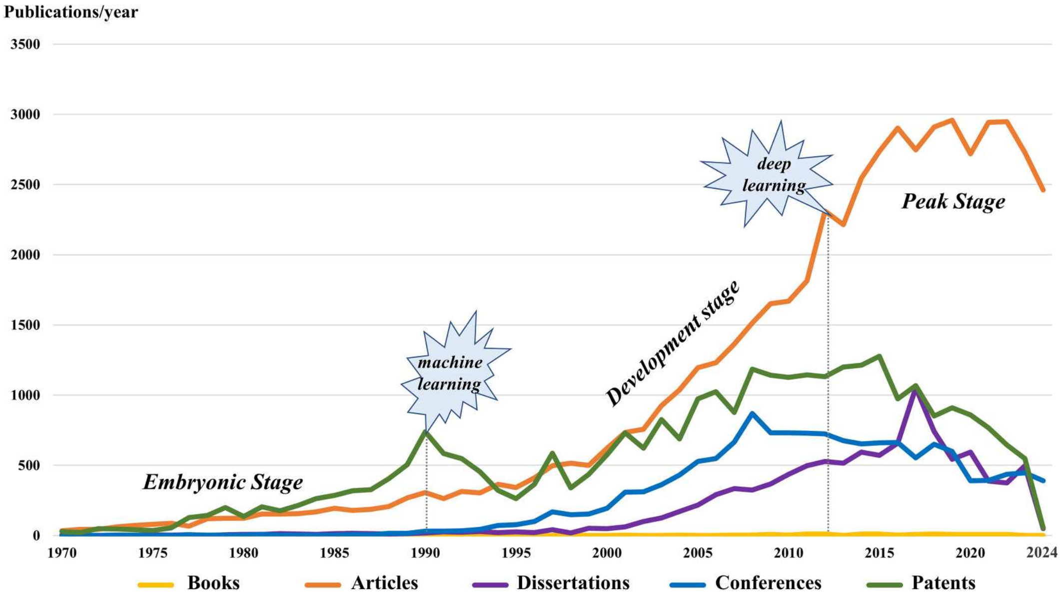


Figure 1. Publication statistics of CD methods (Data updated through June 2024).

2. Development history of RSICD

This paper presents a comprehensive analysis of the CD-related literature, and three key stages are identified in the history of CD research: the embryonic, development, and peak stages. These stages are characterized by two significant advances in machine learning and deep learning techniques, which serve as the time boundaries. The specific stages are shown in Figure 1. Moreover, this section provides an overview of the evolution of CD methods over time, summarizing the methods and task characteristics of each stage, as shown in Figure 2.

2.1. Embryonic stage

In the 1960s, advancements in RS technology contributed to attempts to use satellite data for analyzing changes at the surface. Rosenfeld (1961) defined early CD issues while automating reconnaissance data analysis. Kawamura (1971) pioneered the use of aerial imagery for detecting and identifying urban development changes. Lillestrand (1972) delineated the procedures for

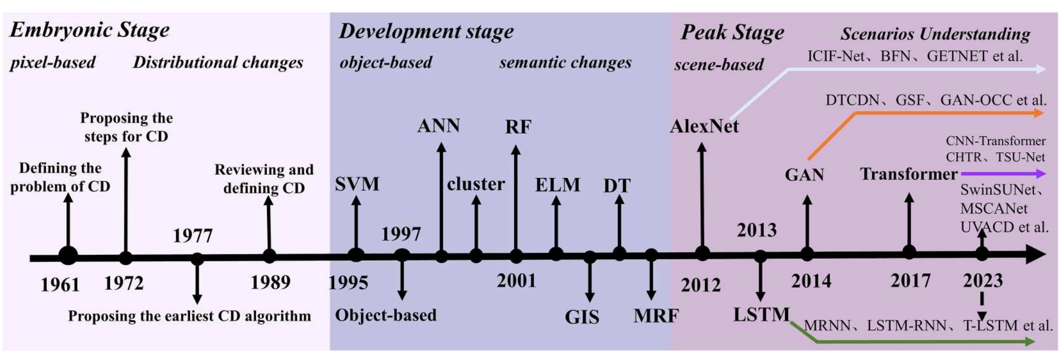


Figure 2. Evolution of CD methods.

Table 1. Typical CD methods during the embryonic stage.

Methods	Typical	Characteristics	Advantages	Disadvantages
Algebra	Image differencing	Corresponding pixel subtraction.	Simple, intuitive, and explainable.	Susceptible to noise.
	Image ratioing	Corresponding pixel division.	Eliminate multiplicative errors.	Challenges in threshold setting and sensitivity to noise.
	Image regression	Regress image moment to another, make a difference.	Eliminating environmental influence.	Difficult to establish regression relationship.
Transformation	PCA	Compute covariance matrix for K-L transform.	Eliminate redundant information.	Rely on geometric texture information.
	K-T	Fixed conversion factor on PAC.	Separation of soil and vegetation.	Conversion factor dependent sensor.
	CCA	Studying correlations between typical variable pairs.	Eliminate spectral-temporal correlations and highlight temporal differences.	Susceptible to noise, lacks concentrated change information.
Classification	Post-classification	Classify images, then compare each pixel to derive the changes.	Obtain change types and eliminate atmospheric interference.	Accuracy depends on classification.
	Direct classification	Treat CD as image classification, directly classify change regions.	Intuitive and easy to understand.	Unable to obtain change types.

implementing automated CD, incorporating correlation coefficients to assess the image registration quality. Five years later, Weismiller et al. (1977) introduced the earliest CD algorithm, namely, image differencing, in which Landsat multispectral scanner data were used to monitor coastal environments. Eghbali (1979) introduced a K-S test method aimed at rectifying and detecting changes in temporal image pairs. Subsequently, various digital CD methods have been developed for monitoring land use changes (Estes, Jensen, and Simonett 1980; Gordon 1980) and urban development (Howarth and Boasson 1983; Jensen 1981). Singh (1989) conducted the first comprehensive review of CD, defining it as the process of identifying differences in the state of an object or phenomenon over different time intervals. This widely cited definition marked the start of CD as an independent field.

At the embryonic stage, CD research methods were mainly based on pixel-by-pixel comparisons. Change information was extracted by analyzing the spectral differences of RS images pixel by pixel. These methods can be roughly divided into algebraic methods (Angelici, Bryant, and Friedman 1977), image transformation methods (Byrne, Crapper, and Mayo 1980), and classification comparison methods (Jensen et al. 1987), each with unique strengths and weaknesses as outlined in Table 1. During this period, CD focused mainly on urbanization and land use changes due to the acceleration in urbanization, with the research data relying primarily on low-resolution RS data from the same sensor.

2.2. Development stage

In the 1990s, machine learning methods, represented by statistical methods and support vector machines (SVM), provided significant developments and breakthroughs (Burges 1998; Chapelle, Haffner, and Vapnik 1999; Vapnik 1999). Various machine learning methods, such as SVM (Cao et al. 2014; Habib et al. 2009; Nemmour and Chibani 2006), Markov random field (MRF) (Bruzzone and Prieto 2000; Touati, Mignotte, and Dahmane 2019), random forest (RF) (Liu et al. 2008), decision tree (DT) (Im and Jensen 2005), clustering (Carlotto 2005; Chen and Gopalakrishnan 1998), including k-means clustering, hierarchical clustering, expectation-maximization clustering, and extreme learning machine (ELM) (Jia et al. 2016) methods, have been applied in the field of RSICD.

Table 2. Typical CD methods in the developmental stage.

Methods	Characteristics	Advantages	Disadvantages
SVM	Optimally classify in feature space.	Theoretically sound for nonlinearity, robust to noise.	Not suitable for large datasets, difficult parameter selection.
ANN	Using neural layers for feature extraction.	No manual feature design needed	Poor interpretability and high data requirements
MRF	Modeling land cover changes using graph models.	Contextual and spatial considerations, highly scalable.	Difficult parameters, high complexity, not for non-stationary scenes.
DT	Using a decision tree based on input feature values.	Eliminate redundant information Interpretability, robustness, and multi-data type compatibility.	No global optimization, unsuitable for continuous changes.
ELM	Generate hidden layer nodes, calculate output weights, classify land cover changes.	Fast computation, strong generalization, suitable for large-scale data.	Significantly influenced by parameters, weights, and noise.
Clustering	Studying correlations between typical variable pairs.	Eliminate spectral-temporal correlations, emphasize temporal disparities.	Segment feature data to mine patterns and features of change.
GIS	Integrate RSI with other data as prior knowledge and conduct overlay analysis.	Handle multisource data, be interpretable, and incorporate prior knowledge.	Inability to accurately recognize complex semantic changes.
Object-oriented	Segmentation of RSI for continuous semantic and spatial inter-object point variations.	Consider context and spatial relationships; minimize noise impacts.	Detection accuracy affected by segmentation and weak generalization.

In addition to machine learning methods, the most notable approaches at this stage were geographic information systems (GIS) (Jia et al. 2016; Xiuwan 2002) and object-oriented (Im, Jensen, and Tullis 2008; Lu et al. 2011; Tang, Zhang, and Huang 2011; Walter 2004) CD methods, as indicated in Table 2. GIS technology offers a significant advantage in CD by utilizing various data sources as prior knowledge (Su, Zhang, and Chen 2005). For instance, GIS can symbolically represent the interpreted terrain data, such as topographic maps, thematic maps, road networks, and land use data, serving as a knowledge base for CD. It can also be used to directly overlay RS images for spatial analysis to identify changed objects and their types, presenting the information visually. Object-oriented methods aim to segment RS images into objects with semantic and spatial continuity, utilizing object-level attributes and relationships to detect changes across different periods. In contrast to pixel-based CD methods, object-oriented approaches effectively incorporate the contextual information and spatial relationships of objects, enhancing the precision and dependability of CD analysis. Notably, GIS-based and object-oriented methods have often been combined with machine learning for CD applications (Guo and Du 2017; Hussain et al. 2013; Walter 2004).

At the developmental stage, there were significant advancements in data, methods, and applications. High-resolution datasets like QuickBird, IKONOS, and ALOS became more readily available and reached the meter-level resolutions. This achievement facilitated the development of the object-oriented concept and increased the amount of GIS-assisted data employed in CD. Consequently, there was a shift from pixel-based analysis to object-based analysis. In combination with GIS-based and object-oriented methods, machine learning has emerged as the mainstream approach because of its notable comprehension capabilities. Owing to advances in methods, researchers have focused not only on identifying changes and their distribution but also on achieving a greater semantic understanding and predicting changes more accurately. Furthermore, CD applications have expanded beyond urban development and land use changes to encompass diverse areas, such as environmental (Cardama, Heras, and Argüello 2023; Silveira et al. 2019; Wang et al. 2018), agriculture (Kaur et al. 2023; Mazzanti et al. 2021; Silva-Perez et al. 2021; Wang et al. 2018), and disaster monitoring (Huang and Jin 2020; Jarrett and Hölbling 2023; Lv, Wang et al. 2022; Tupas et al. 2023; L. Wang et al. 2023).

2.3. Peak stage

The ReLU activation function was introduced in 2012 in AlexNet (Krizhevsky, Sutskever, and Hinton 2017) during the ImageNet competition. It addresses the issue of vanishing gradients and has exhibited a remarkable accuracy compared with that of algorithms of the same era. With its notable feature extraction capability, deep learning has since been rapidly introduced into the field of RSICD, becoming the mainstream method for CD (Tian et al. 2023; Wang, Zhu et al. 2024; Wang, Yan et al. 2023; Yang et al. 2023; Ye et al. 2023). On the basis of the feature extraction frameworks used, these methods can be divided into convolutional neural network (CNN)-based CD methods (Song et al. 2022; Yang et al. 2023), recurrent neural network (RNN)-based CD methods (Chen et al. 2019; Sawant et al. 2022), generative adversarial networks (GAN)-based CD methods (Gong et al. 2023; He et al. 2022; Ren et al. 2020), auto-encoder (AE)-based CD methods (Li et al. 2018; Su et al. 2022; Xu et al. 2013), and transformer-based CD methods (Li et al. 2022; Song, Hua, and Li 2023; G. Wang et al. 2022). Their respective advantages and disadvantages are shown in Table 3. The CNN model can be employed for feature extraction from images via convolution and pooling operations, whose representative methods include LeNet, AlexNet, VGG, GoogLeNet, and ResNet. Classic CNN methods applied in CD include the ICIF-Net (Feng et al. 2022), 3DSE-CNN-2DLSTM (Wang and Yin 2024), GETNET (Wang et al. 2019), Siamese-CNN (Kou et al. 2023),and Twin-CNN (Padilla et al. 2023) methods. The RNN model aims to process sequential data through recurrent connections, in which the most representative method is the Long Short-Term Memory (LSTM). Classic RNN methods used in CD include the MRNN (Chen et al. 2019), LSTM-RNN (Y. Peng et al. 2020), T-LSTM (Jing et al. 2020), dual-LSTM (Shi and Chehade 2021), Unsupervised-LSTM (Saha, Bovolo, and Bruzzone 2022) methods. The GAN model is based on adversarial training between the generator and discriminator, enabling the generator to produce realistic data samples, whose representative methods include the Pix2Pix, CycleGAN, and Style-GAN. Classic GAN methods used in CD include Translation-GAN (Li et al. 2021), Siamese-GAN (Fang et al. 2020), GAN-OCC (Jian, Chen, and Cheng 2021), Semisupervised-GAN (F.

Table 3. Typical CD methods during the peak phase.

Methods	Characteristics	Advantages	Disadvantages	Representation
CNN	Extract image features with CNN and compare two feature differences to detect changes.	Highly capable of image feature extraction.	Requires large training samples.	ICIF-Net (Feng et al. 2022), 3DSE-CNN-2DLSTM (Wang and Yin 2024), GETNET (Wang et al. 2019), Siamese-CNN (Kou et al. 2023), Twin-CNN (Padilla et al. 2023), etc.
RNN	Use RNN for sequence data, capture temporal relationships.	Handles time series data effectively.	Higher complexity and long training inference time	MRNN (Chen et al. 2019), LSTM-RNN (Y. Peng et al. 2020), T-LSTM (Jing et al. 2020), dual-LSTM (Shi and Chehade 2021), Unsupervised-LSTM (Saha, Bovolo, and Bruzzone 2022), etc.
GAN	Generator generates change image, discriminator distinguishes between original and changed images.	Generates highly realistic data.	Instability in the training process	Translation-GAN (Li et al. 2021), Siamese-GAN (Fang et al. 2020), GAN-OCC (Jian, Chen, and Cheng 2021), Semisupervised-GAN (F. Jiang et al. 2020), etc.
AE	Compress input data to low-dimension feature, then decoder reconstructs data.	Processing unlabeled data, suitable for anomaly detection.	Sensitive to noise and anomalies.	EM-SDAE (Lu et al. 2020), VGAE (Su et al. 2022), CAGSL (K. Xiao et al. 2023), CAE (Paul, Ghamisi, and Gloaguen 2023), etc.
Transformer	Using self-attention for spatial and contextual modeling.	Improved global information capture.	Large model size, limited local information capture	CNN-Transformer (M. Liu et al. 2022), SwinSUNet (Zhang, Wang et al. 2022), TransUNetCD (Li et al. 2022), SMBCNet (J. Feng et al. 2023), etc.

Jiang et al. 2020) methods. The AE algorithm is an unsupervised learning neural network that maps input data to a low-dimensional space for feature extraction via an encoder and then maps it back to the original data space using a decoder. Representative methods for AE include sparse autoencoder, denoising autoencoder, and variational autoencoder. Classic AE methods applied in CD include the EM-SDAE (Lu et al. 2020), VGAE (Su et al. 2022), CAGSL (K. Xiao et al. 2023), and CAE models (Paul, Ghamisi, and Gloaguen 2023). Transformer utilizes attention mechanisms to achieve enhanced sequence modeling through parallel computation and global information interaction. This approach has gained significant popularity, with notable implementations including BERT, GPT, and Lent. With respect to the problem of CD, several classic transformer methods have been employed, such as CNN-Transformer (M. Liu et al. 2022), SwinSUNet (Zhang, Wang et al. 2022), TransUNetCD (Li et al. 2022), and SMBCNet (J. Feng et al. 2023).

At the peak stage, there was a significant increase in the availability of data from multiple platforms and sensors, resulting in a substantial volume of information suitable for CD. Multisource RSICD has become a new research hotspot, achieving submeter data resolutions. Data-driven approaches, such as deep learning, have demonstrated a notable potential in extracting semantic features and bridging differences across various sensors. CD now focuses on providing a scene-based understanding, spatial relationships and not just facilitating object-based analysis. Additionally, CD has been extensively applied to monitor climate change, encompassing phenomena such as glacier retreat and ocean temperature fluctuations, while also providing valuable support for emergency responses during disasters.

3. RSICD method

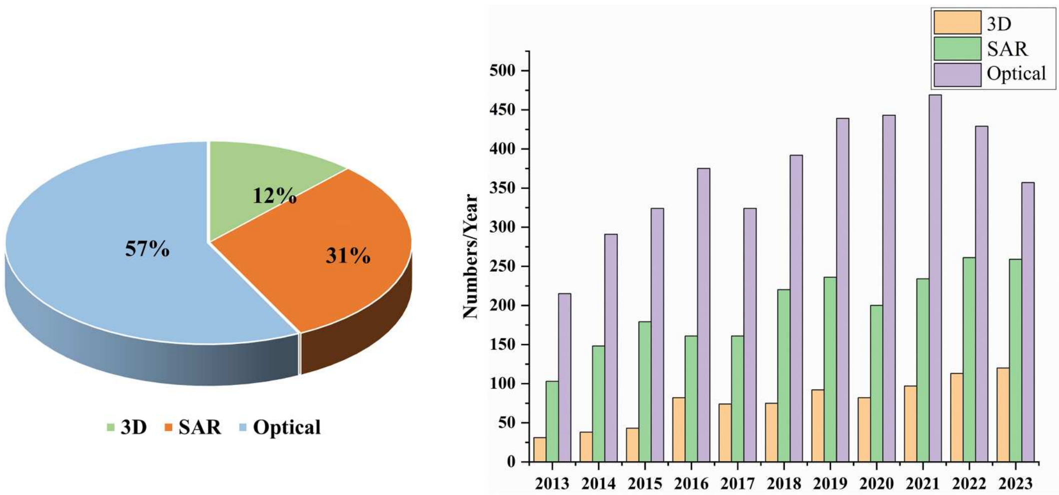
This section focuses on two key trends in this field: multisource RS and data-driven approaches. Specifically, the existing system of RSICD is comprehensively summarized from five perspectives, namely, data, methods, experimental processes, evaluation criteria, and applications, aiming to offer a concise and comprehensive understanding of the current state of CD.

3.1. Benchmark datasets

Currently, CD data has transitioned from relying solely on single imaging mechanisms, such as visible light and hyperspectral images, to encompassing multiple imaging mechanisms, including optical, infrared, synthetic aperture radar (SAR), and point clouds, acquired via various platforms, such as drones and satellites. In this paper, the advantages and disadvantages of commonly employed CD data sources are summarized in Table 4. Moreover, Figure 3 shows a comprehensive overview of the

Table 4. Advantages and disadvantages of multisource data.

Data sources	Advantages	Disadvantages
SAR	1. Weather-independent (clouds, rain, snow have no impact);	1. Data interpretation difficulty;
	2. Penetrates through clouds and vegetation;	2. Susceptible to geometric deformation and electromagnetic interference;
	3. Detects object scattering and surface deformation.	3. Highly affected by coherent spot noise.
MSI	1. High spatial resolution;	1. Limited by weather;
	2. Acquire spectral.	2. Limited by spectral resolution.
HSIs	1. Capable of distinguishing objects with similar spectral features;	1. Large amount of data;
	2. Rich spectral information.	2. Processing and storage relatively complex;
		3. Cost expensive.
3D point cloud	1. Provides terrain elevation and topographic information;	1. Uneven data density, greatly affected by noise;
	2. Assists in 3D modeling, spatial analysis, etc.	2. Data acquisition is difficult and high cost.



(a) Proportion of each data source **(b) Statistics on publications from CD data sources**

Figure 3. Statistical analysis of publication volume (CD) from various data sources.

research results of different data sources over the past decade. Furthermore, we compiled and provided information on publicly available datasets for CD, along with links for accessing benchmark datasets, to facilitate researchers in their utilization and promote further advancements in CD methodologies driven by large-scale AI.

3.1.1. Optical CD dataset

Optical imagery has become the most commonly used data source for CD because of its notable interpretability, high resolution, and rich spectral information. Its intuitive nature allows straightforward assessment of ground cover changes through the observation of visual features such as brightness and color in images. Moreover, optical imagery typically offers high spatial resolution, enabling the provision of detailed information on ground features. Significantly, optical imagery can provide data across multiple spectral bands, including visible light and infrared bands, which supplies a wealth of information on ground features and are beneficial for CD tasks. To provide a greater understanding of the optical imagery used for CD, typical hyperspectral and multispectral images are described in this paper.

(1) Multispectral CD dataset: Multispectral RS images capture a broad spectrum of data across multiple spectral bands, from visible light to near-infrared and shortwave infrared wavelengths. This spectral richness is instrumental in detecting surface changes. The use of multispectral images in CD is also advantageous because of the extensive data accumulation over time. Satellites such as Landsat and SPOT have been operational since the 1970s and 1980s, respectively, thus providing a substantial archive for analyzing long-term change trends. Despite the high spatial resolution provided by many multispectral RS satellites, the application of multispectral images in CD exhibits certain challenges. Multispectral images, with more spectral bands than RGB images, nonetheless, offer a lower spectral resolution than do hyperspectral images, which complicates the identification of subtle spectral features and the differentiation of components within mixed pixels. The notable multispectral images used in CD include Landsat (Kamarudin et al. 2018), Sentinel-2 (Pomente, Picchiani, and Del Frate 2018), QuickBird (Pomente, Picchiani, and Del Frate 2018), SPOT (Chang et al. 2010), high-resolution satellite series (Fan, Lin, and Han 2019), and Worldview (Tarantino et al. 2016).

(2) Hyperspectral CD dataset: Compared with RGB and multispectral images, hyperspectral images provide dozens to hundreds of narrow bands that can capture the spectral characteristics

of the Earth's surface in detail, greatly enhancing the classification accuracy and the ability to recognize ground objects. As a result, materials with similar spectral properties can be identified and differentiated from hyperspectral images, offering unique advantages in detecting changes such as vegetation health, soil type, and pollutant dispersion changes. Despite these benefits, the large volume of hyperspectral data demands considerable computational resources and storage for processing and analysis, which results in challenges in CD. Moreover, hyperspectral images are generally characterized by a lower spatial resolution and a more limited coverage than those of multispectral images. Common sensors for acquiring hyperspectral imagery include the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (Padrón-Hidalgo et al. 2019), Hyperion (Dahiya et al. 2023; Wu, Du, and Zhang 2018), and Moderate-Resolution Imaging Spectroradiometer (Huang and Friedl 2014; Lu et al. 2016), among others.

To facilitate a more comprehensive understanding of the datasets used for optical CD, this paper provides a comprehensive compilation of data on commonly used public optical CD datasets, as detailed in Table 5. It includes information on their sources, spatial resolutions, image dimensions, and the total number of images. Moreover, it describes their primary applications in various fields, such as land-use and land-cover change (LUCC), building change detection (BCD), urban development and transformation (UDT), disaster damage assessment (DDA), and the monitoring of natural resources (MNR), changes in street scenes(CSS).

3.1.2. SAR CD dataset

SAR imagery offers advantages for all-weather and continuous monitoring, effectively mitigating the limitations associated with relying solely on optical methods. First, SAR maintains its ability for efficient observation and data collection under conditions where optical image sensors are rendered inoperable, such as under dense cloud cover or at night, thus ensuring continuous and accurate monitoring information. Second, SAR primarily capitalizes on the reflection intensity and backscatter coefficient of ground features in response to microwave signals, thereby minimizing the impacts of surface materials and color differences on CD. Therefore, SAR can eliminate the influences of surface materials and color differences on CD. In contrast to optical imagery, which is often impeded by vegetation cover, SAR imagery provides the exceptional ability to penetrate vegetated regions and rugged terrain, enabling the capture of subsurface information. Consequently, the use of SAR imagery for CD offers significant advantages under specific scenarios.

However, owing to its imaging mechanism, SAR images are difficult to directly interpret via visual inspection. Moreover, SAR images are generally more expensive than optical CD datasets. Thus, there is a relative scarcity of publicly available SAR CD datasets, as detailed in Table 6.

3.1.3. 3D and heterogeneous CD dataset

Currently, most publicly available CD datasets primarily consist of optical data sources, while there is still a relative scarcity of CD datasets using 3D point clouds and heterogeneous data, as indicated in Table 7. 3D point clouds offer abundant geographic information and precise data on spatial structures, and they are not constrained by lighting conditions or occlusion. Hence, such data are more suitable for CD in complex environments such as densely populated urban areas and heavily forested regions.

The utilization of multisource heterogeneous data for CD provides numerous advantages in emergency responses to catastrophic events. First, this approach significantly improves the temporal resolution, meeting the urgent response requirements. Second, it enhances the richness of change information by expanding the spectral coverage through multiple sensors, enabling the extraction of additional object attributes. Third, it compensates for the limitations of employing a single sensor. For example, optical sensors may fail to capture clear images under adverse weather conditions or under dense cloud cover, whereas radar sensors can penetrate clouds and retrieve surface information. Therefore, heterogeneous CD has become a prominent research focus at the current stage.

Table 5. Public Optical Dataset for CD.

Type	Dataset	Sensor	Resolution	Image size	Amount	Contents	Download
MSI	S2MTCP (Leenstra et al. 2021)	Sentinel-2	10 m	600 × 600	1520	UDT	https://zenodo.org/record/4280482/
	Hi-UCD (Tian et al. 2020)	/	0.1 m	1024 × 1024	1293	UDT	https://drive.google.com/drive/folders/1fzAn4Bez_S6KX83iYABjAIASCzzhRJPQ
	LEVIR-CD (Chen and Shi 2020)	Google Earth	0.5 m	1024 × 1024	637	LUCC	http://chenhao.in/LEVIR/
	SECOND (Yang et al. 2021)	Sentinel-2	/	512 × 512	4662	LUCC	http://www.captain-whu.com/PROJECT/SCD/
	Google (D. Peng et al. 2020)	Google Earth	0.55 m	1006 × 1168–4936 × 5224	20	LUCC	https://github.com/daifeng2016/Change-Detection-Dataset-for-High-Resolution-Satellite-Imagery
	LEVIR-CD+	/	0.5 m	1024 × 1024	985	LUCC	https://github.com/S2Looking/Dataset
	MtS-WH (Wu, Zhang, and Zhang 2016)	IKONOS	1 m	7200 × 6000	1	LUCC	http://sigma.whu.edu.cn/newspage.php?q=2019_03_26
	HRSCD (Daudt et al. 2019)	/	0.5 m	10000 × 10000	291	UDT	https://ieee-dataport.org/open-access/hrscd-high-resolution-semantic-change-detection-dataset#
	S2Looking (Shen et al. 2021)	/	0.5 ∼ 0.8 m	1024 × 1024	5000	BCD	https://github.com/S2Looking/Dataset
	WHU Building (Ji, Wei, and Lu 2018)	/	0.2 m	15354 × 32507	1	BCD	https://study.rsgis.whu.edu.cn/pages/download/building_dataset.html
	DSIFN (Zhang, Yue, Tapete, Jiang et al. 2020)	Google Earth	/	512 × 512	3940	BCDC	https://drive.google.com/drive/folders/1yutLU4WI7eeeGbuxilsq2OtGQr9EHDLy?usp=sharing
	OSCD (Daudt et al. 2018)	Sentinel-2	10,20,60 m	/	24	UDT	https://ieee-dataport.org/open-access/oscd-onera-satellite-change-detection#files
	AICD (Bourdis, Marraud, and Sahbi 2011)	synthesize	0.5 m	800 × 600	1000	/	https://computervisiononline.com/dataset/1105138664
	SZTAKI (Benedek and Szirányi 2008, 2009)	/	1.5 m	952 × 640	13	LUCC	http://web.eee.sztaki.hu/remotesensing/airchange_benchmark.html
	CCD (Lebedev et al. 2018)	Google Earth	0.03–1 m	256 × 256	16000	LUCC	https://pan.baidu.com/s/1×u0kIpThW2koLcyfcJEEfA
	ABCD (Fujita et al. 2017)	/	0.4 m	128 × 128	8506	DDA	https://github.com/gistairc/ABCDdataset
	SpaceNet7 (Van Etten et al. 2021)	Planet	4 m	1024 × 1024	24	UDT	https://spacenet.ai/sn7-challenge/
	SYSU-CD (Shi et al. 2021)	/	0.5 m	256 × 256	20,000	UDT	https://github.com/liumency/SYSU-CD
	X-View2 (Weber and Kané 2020)	Worldview	0.3 m	/	/	DDA	https://×view2.org/
	CLCD (M. Liu et al. 2022)	GaoFen2	0.5–2 m	512 × 512	600	MNR	https://zenodo.org/record/4280482/https://github.com/liumency/CropLand-CD
HSIs	Santa Barbara	AVIRIS	20 m	984 × 740	1	LUCC	https://citius.usc.es/investigacion/datasets/hyperspectral-change-detection-dataset/
	Bay Area	AVIRIS	20 m	600 × 500	1	LUCC	https://citius.usc.es/investigacion/datasets/hyperspectral-change-detection-dataset/
	Hermiston	HYPERION	30 m	390 × 200	1	MNR	https://citius.usc.es/investigacion/datasets/hyperspectral-change-detection-dataset/
	Farmland	HYPERION	30 m	450 × 140	1	LUCC	https://rslab.ut.ac.ir/data
	River (Wang et al. 2019)	HYPERION	30 m	463 × 241	1	MNR	https://share.weiyun.com/5×dge4R

Table 6. Public SAR dataset for CD.

Dataset	Sensor	Resolution	Image size	Amount	Contents	Download
COSMOSkyMed	COSMO-SkyMed	15 m	/	3	MNR	http://poles.tpdc.ac.cn/zh-hans/data/449c91bc-bf6b-4246-845b-ea26b39d0f61/
Bern	ERS-2	/	301 × 301	1	UDT	https://github.com/yolalala/RS-source
San Francisco dataset	ERS-2	/	256 × 256	1	LUCC	https://github.com/yolalala/RS-source
Farmland	Radarsat-2		7666 × 7692	2	MNR	https://share.weiyun.com/5M2gyVd
Mexico	Landsat ETM+	/	512 × 512	/	LUCC	/

3.2. RSICD techniques

With the improved RS resolution, diverse scenes, and availability of annotated data, RSICD methods have become increasingly varied. These methods can be categorized into different systems on the basis of different classification criteria, such as the temporal phase, feature extraction approach, utilization of prior information, data source, detection granularity, detection framework, and spatial dimension, as shown in Figure 4. To comprehensively describe the existing RSICD methods, mainstream RSICD methods are introduced based on the data source, detection granularity, and detection framework.

3.2.1. Classification based on the data type

RSICD methods can be classified into two categories on the basis of the data type: homogeneous and heterogeneous CD methods. The most commonly used homogeneous CD methods are the optical RSICD (Kou et al. 2023; Marsocci et al. 2023; Zhang, Feng et al. 2022) and SAR RSICD (Sun et al. 2020; Zhang et al. 2022). Optical RS CD methods are prone to influence by various factors, including imaging conditions, image acquisition timing, and noise. In contrast, SAR imaging is resistant to the effects of daylight irradiation, cloud cover, and weather conditions, enabling the capture of high-resolution two-dimensional images. However, the acquired SAR images often suffer from significant coherent speckle noise. Therefore, the development of high-quality difference maps and the design of effective classification methods are critical issues in SAR CD research. The quality of the difference map significantly impacts the CD accuracy. Several methods have been proposed for generating difference maps, including ratio or subtraction-(Gong, Zhou, and Ma 2011), difference maps (Zheng et al. 2013), and wavelet fusion (Ma, Gong, and Zhou 2012).

In recent years, heterogeneous RSICD has emerged as a new research area of interest (Du et al. 2024; Han et al. 2024; Sun et al. 2024), as shown in Figure 5(a). Heterogeneous CD generally refers to the variations between different sensor types and imaging modes within the same sensor type. Such variations include differences between images captured at different times by various sensors, such as historical maps and digital elevation model (DEM) (James et al. 2012; Li 2003), lidar data and images (Qin and Gruen 2014; Zhou et al. 2020), optical and SAR (Du et al. 2024; X. Jiang et al. 2020), optical imagery and open street maps (Chen et al. 2024), etc. Additionally, it covers variations within the same sensor type due to different imaging modes, such as spectral channels in optical sensors or microwave frequencies/polarizations in radar equipment. Examples of heterogeneous images include multispectral image pairs from Landsat-5 and Landsat-8, as well as SAR images from TerraSAR-X and COSMO-SkyMed.

Heterogeneous CD involves data from different sensors with notably distinct properties, storage methods, and presentation formats, as illustrated in Figure 6. Compared to homogeneous change detection, heterogeneous CD poses several challenges. First, the challenges arising from the different imaging mechanisms of heterogeneous sensors. The assimilation of images from different sources into a common space is hampered by differences in imaging mechanisms and characteristics, highlighting the need for effective assimilation mapping methods (D. Wang et al. 2022).

Table 7. 3D and heterogeneous CD dataset.

Data	Dataset	Sensor	Resolution	Image size	Amount	Content	Download
Point clouds	SHREC (Ku et al. 2021)	CycloMedia	/	/	78	CSS	https://kutao207.github.io/
	Change3D (Nagy, Kovács, and Benedek 2021)	Velodyne HDL-64	/	1024 × 384	2000	CSS	http://mplab.sztaki.hu/geocomp/Change3D.html
	City-scale Scene (Yew and Lee 2021)	/	/	2464 × 2056	30	CSS	https://yewzijian.github.io/ChangeDet
	URB3DCD	/	/	/	/	CSS	https://ieee-dataport.org/open-access/
	Lidar-SCU (Zováthi, Nagy, and Benedek 2022)	MLS	/	/	/	CSS	https://github.com/sztaki-geocomp/Lidar-SCU
Hetero-geneous	HTCD (Shao et al. 2021)	Google Earth; UAV	0.5 m 0.07 m	11 K × 15 K 1.3 M×1.0 M	1; 15	UDT	https://github.com/ShaoRuizhe/SUNet-change_detection
	California (Luppino et al. 2019)	Landsat 8; Sentinel-1A	15 m	2000 × 3500	/	LUCC	https://sites.google.com/view/luppino/data
	Italy (Touati, Mignotte, and Dahmane 2019)	Landsat 5; optics	30 m	412 × 300	/	MNR	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	UK1 (Luppino et al. 2019)	TerraSAR; QuickBird 2	0.65 m	2325 × 4135	/	DDA	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	France1 (Luppino et al. 2019)	TerraSAR; Pleiades	2 m	4404 × 2604	/	BCD	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	France2 (Touati, Mignotte, and Dahmane 2019)	TerraSAR; WorldView 2	0.52 m	2000 × 2000	/	BCD	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	UK2 (You, Cao, and Zhou 2020)	SPOT; NDVI	25 m	554 × 990	/	DDA	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	Shuguang (Liu et al. 2018)	Radarsat-2; Google Earth	8 m	921 × 593	/	BCD	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	Island Town (You, Cao, and Zhou 2020)	Radarsat-2; Google Earth	8 m	415 × 403	/	UDT	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	Hubei Campus (You, Cao, and Zhou 2020)	OuickBird; IKONOS	2.44 m	240 × 240	/	BCD	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	Wuhan University (You, Cao, and Zhou 2020)	OuickBird; IKONOS	3.28 m	400 × 400	/	BCD	https://www.iro.umontreal.ca/ mignotte/ResearchMaterial/index.html
	River (Sun et al. 2022)	Radarsat-2; Optical	8 m	291 × 343	/	DDA	https://github.com/yulisun/INLPG/tree/master
	Forest fire in Texas (Volpi, Camps-Valls, and Tuia 2015)	Landsat 5; EO-1 ALI	30 m	1534 × 808	/	MNR	https://zenodo.org/records/8046719

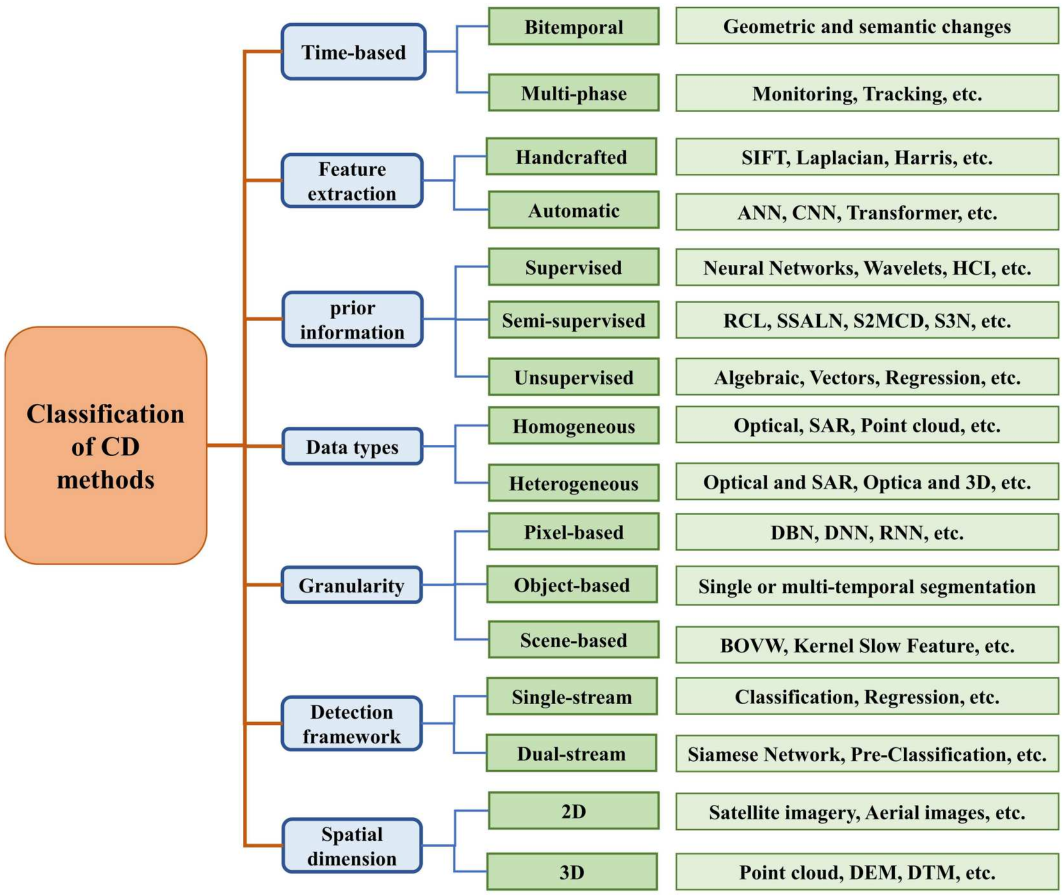
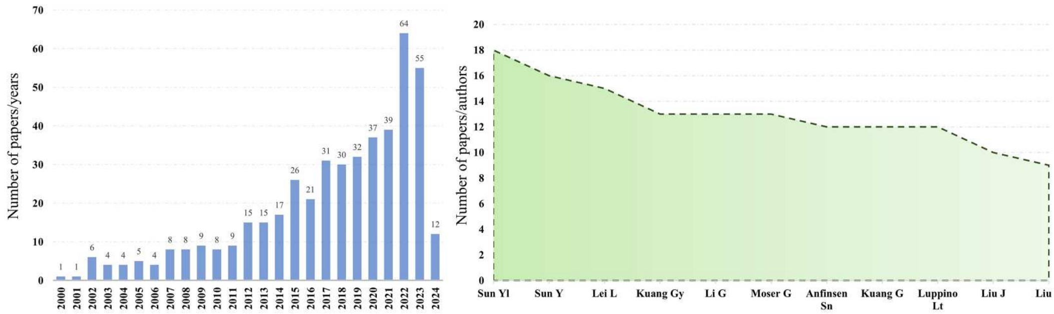


Figure 4. Classification of RSICD methods.

Second, challenges stemming from varied conditions for satellite imaging. Significant differences exist among imaging scenarios, imaging angles, and resolutions (Y. Feng et al. 2023), necessitating adaptable and robust algorithms. Third, high-resolution images increase the complexity of CD tasks because of the increased heterogeneity, differences in the object size, and issues such as scattering variations and speckle noise. Consequently, specialized algorithms for high-resolution imagery are essential. Moreover, inherent image noise, particularly speckle noise in SAR images, complicates the extraction process. Finally, the scarcity of publicly available datasets for heterogeneous CD, attributed to annotation challenges and high manual costs, necessitates the development of unsupervised algorithms or the utilization of transfer learning methods to maximize the use of existing dataset resources (Sun et al. 2024).

Many scholars have studied and proposed numerous methods for addressing the above issues (Z.-G. Liu et al. 2022; Lv, Huang et al. 2022; Sun, Lei, Guan, Li et al. 2022; Sun, Lei, and Kuang 2023; Sun, Lei, Li et al. 2021), as shown in Figure 5(b). It is essential for these methods to transform the data into a comparable metric space for direct comparison during heterogeneous RSICD. Based on the transformation methods, these approaches can be broadly categorized into two categories: feature transformation and image regression. Feature transformation methods entail converting two images into the same feature domain and subsequently comparing the transformed features. Common feature transformation methods include deep neural network



(a) Statistics on the literature heterogeneous RSICD

(b) Top ten authors ranked by literature volume in heterogeneous RSICD studies

Figure 5. Statistics of the Literature on Heterogeneous RSICD.The statistical data were retrieved from the Web of Science using the keywords ‘remote sensing’, ‘change detection’, and ‘heterogeneous’.

approaches (D. Wang et al. 2022; Wang, Cheng et al. 2023), similarity measurement methods (Alberga 2009; Touati, Mignotte, and Dahmane 2018; Wan, Zhang, and You 2018), and methods involving comparisons after classification (Slwritz 1987; Wu et al. 2020). Image regression methods aim to transform two images into another image domain before undertaking a comparison (Luppino et al. 2018; Xiao, Sun, and Lei 2022). In addition to difference and change maps, the image regression method introduces an additional regression image, which can aid in visual analysis for determining change information and identifying change categories. However, the image regression method is more susceptible to noise and domain shifts, and involves pixelwise computations, resulting in a higher computational load. In contrast, feature transformation methods appear to be more robust and adaptable. Most feature transformation methods rely on supervised learning techniques and often require large-scale and high-quality sample data. At present, heterogeneous RSICD is instrumental across various domains, including urban management (Gao et al. 2024; Xiao et al. 2023), natural resource monitoring (Gao et al. 2024; Lv, Huang et al. 2023; Lv, Zhong et al. 2023), environmental monitoring (Han et al. 2024), and disaster response (Hong and Shi 2023; Lv, Huang et al. 2023; C. Wang et al. 2023; Z. Wang et al. 2023) owing to its easy acquisition, high temporal resolution, and notable variety of data characteristics.

3.2.2. Classification based on the granularity

On the basis of granularity, CD methods can be broadly divided into three categories: pixel-based (Gamba, Dell’Acqua, and Lisini 2006; İlsever and Ünsalan 2012), object-based (Chen et al. 2012; Hussain et al. 2013), and scene-based CD (Fang, Guo, Lin et al. 2023; Fang, Guo, Wang et al. 2023).

(1) Pixel-based CD method: This method analyzes registered RS images at the pixel level to determine whether each pixel has changed (Shu et al. 2021). Early pixel-based methods involved simple algebraic operations and threshold selection, while advanced techniques such as principal component analysis and morphological transformation have been developed. Pixel-based methods are easy to implement, computationally efficient, and facilitate the identification of small changes at high resolutions. However, they are sensitive to noise and environmental conditions (Han et al. 2020).

(2) Object-based CD method: In the object-based CD method, objects are treated as processing units, and attributes such as shape, texture, spectral, and positional information are considered (Jing et al. 2020). The image is divided into objects with similar attributes, and attribute differences between matched objects at different time are compared for CD. Object-based methods reduce misclassifications caused by noise, improve accuracy, and require suitable object segmentation thresholds (Chen et al. 2022). However, determining these thresholds is challenging, and the quality of object segmentation affects the results.

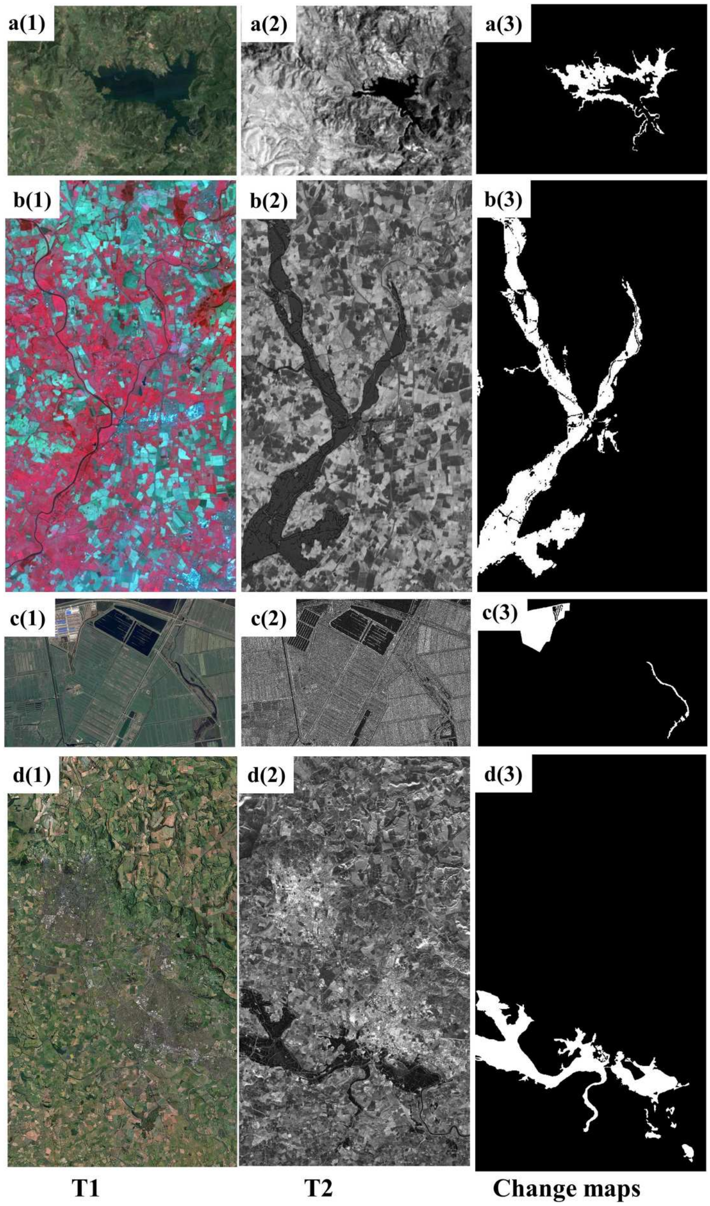


Figure 6. Heterogeneous Remote Sensing Image Change Detection (RSICD) with Different Multimodal Cases. (a) and (b) are acquired by different sensors of the same type, while (c) and (d) are acquired by sensors of different types. a(1), b(1), c(1), and d(1) represent images at T1, a(2), b(2), c(2), and d(2) represent images at T2, and a(3), b(3), c(3), and d(3) represent the change detection label images.

(3) Scene-based CD method: Scene-based CD focuses on changes in the entire scene, rather than just individual objects within it (Wu, Zhang, and Zhang 2016). For example, changes such as the addition of a building on campus, new roads in an industrial park, or increased green areas in a residential area, do not alter the nature or function of the scene. Even if there are changes in specific buildings or objects within the scene, as shown in Figure 7, the overall scene remains the same, and these changes may not be detected by scene-based CD methods. Similarly, changes in vehicles on a road or boats on a river may occur, but as long as the main function is retained, such changes may not be detected either. The superiority of scene-based CD methods lies in their ability to distinguish

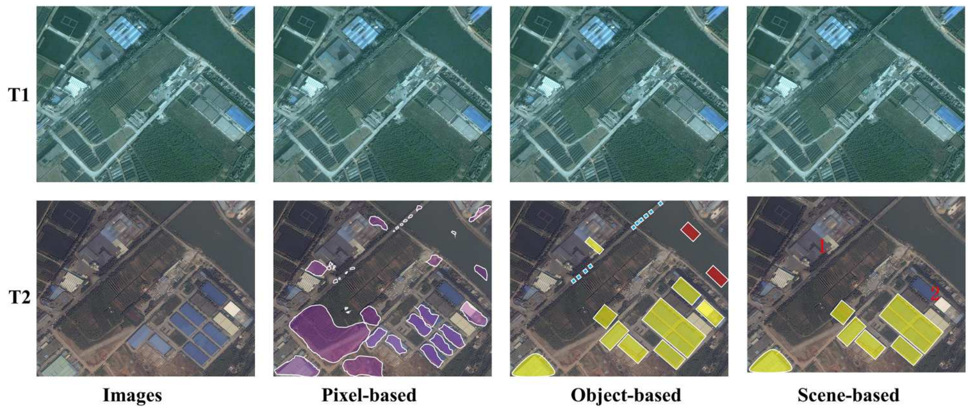


Figure 7. CD methods based on pixel, object and scene.

object types within images and selectively extract relevant changes (Zhang, Du, and Zhang 2015). This imposes a greater demand for semantic analysis of the images. Furthermore, scene-based CD methods provide both improved accuracy and interpretability. Nevertheless, this approach necessitates the construction of distinct models or rules, exhibiting formidable obstacles under complex scenarios.

3.2.3. Classification based on the detection framework

According to the detection framework, CD methods can be categorized into single- and dual-stream frameworks (Afaq and Manocha 2021; Seydi et al. 2024). The single-stream framework involves a unified processing pipeline where multitemporal RS images are directly input into a single module for change information extraction, utilizing structures such as direct classification (Liu et al. 2016; Lv et al. 2018) (Figure 8a1) and image regression (Figure 8a2) (Ma et al. 2019; Zhang et al. 2016). Early fusion is typically employed in the single-stream framework, facilitating the direct integration of multitemporal image data before feature extraction. This allows the model to leverage combined data representations from the outset, enhancing the ability to effectively learn differential features, particularly at the initial stages of network processing (Shi et al. 2020). In contrast, the dual-stream framework bifurcates data input into parallel branches of a network, facilitating the independent extraction of multitemporal image features through structures such as siamese networks (Figure 8b1) (Li et al. 2024; Yang et al. 2024; Zhu et al. 2022) and post-classification approaches (Figure 8b2) (Tan et al. 2023; Q. Wang et al. 2024). Late fusion strategies are prevalent in the dual-stream framework, where features or decisions from each branch are integrated after individual feature extraction stages. This approach more effectively accommodates variations in input image characteristics, optimizing the utilization of distinct data sources. Network frameworks can be comprehensively designed on the basis of data characteristics and task requirements.

3.3. RSICD architecture

The general CD workflow involves dataset construction, data preprocessing, CD implementation, and accuracy assessment, as shown in Figure 9. Dataset construction entails acquiring relevant data and labeling samples. Data preprocessing involves geometric registration and radiometric correction of images to ensure accurate CD. CD algorithms aim to identify changes, their locations, land cover types before and after changes, and temporal and spatial distribution patterns. Accuracy assessment aims to qualitatively and quantitatively evaluate the results.

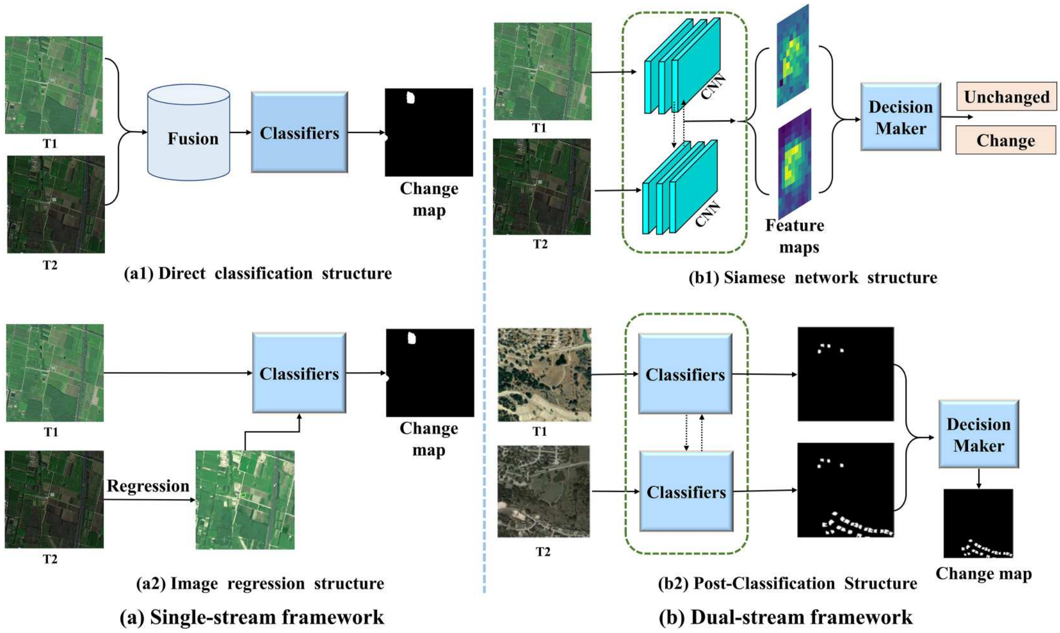


Figure 8. CD methods based on single and dual stream frameworks.

3.4. Performance evaluation

Evaluation metrics play a crucial role in assessing the performance of CD models. This section provides a brief introduction and analysis of common CD evaluation metrics, including precision (P), recall (R), overall accuracy (OA),intersection over union (IoU^c), F_1^c-*score*, and Kappa coefficient (K_a). P primarily focuses on the accuracy of the model, indicating the reliability of positive predictions. R focuses on the sensitivity and coverage of the model, representing its ability to capture true positive samples. The OA provides an evaluation of the model's overall performance, reflecting its classification ability across all categories. IoU^c is a metric used to evaluate the overlap between two

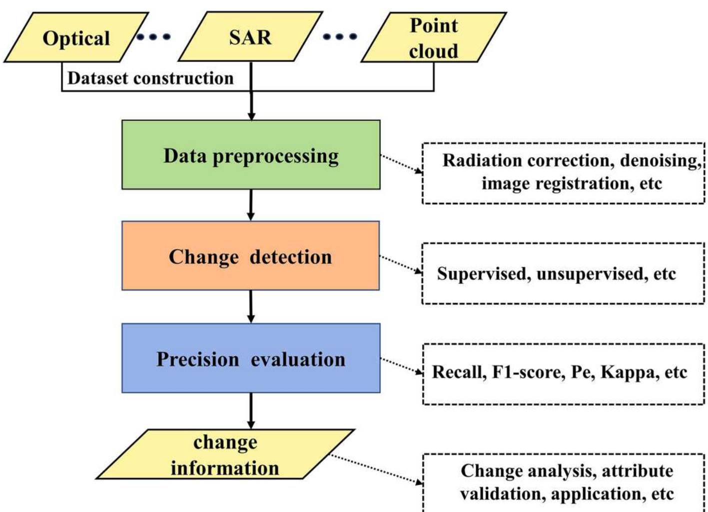


Figure 9. The process of RSICD.

bounding boxes or segmentation masks. It is calculated by dividing the area of intersection between the predicted and ground truth regions by the area of their union. The F_1^c-*score* balances the accuracy and coverage of the model, enabling a more comprehensive assessment of its performance. K_a is a measure of the consistency between the model and random classification, helping evaluate the extent of performance improvement relative to random classification.

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$P_e = \frac{(TP + FP) \times (TP + FN)}{(TP + TN + FP + FN)^2} \tag{4}$$

$$+ \frac{(FN + TN) \times (FP + TN)}{(TP + TN + FP + FN)^2} \tag{5}$$

$$K_a = \frac{OA - P_e}{1 - P_e} \tag{6}$$

$$IoU^c = \frac{TP}{TP + FP + FN} \tag{7}$$

$$F_1^c = \frac{2TP}{2TP + FP + FN} \tag{8}$$

where TP indicates true positives, TN is true negatives, FP represents false positives, and FN represents false negatives.

3.5. Applications of RSICD

With the advances in RS technology and image processing algorithms, CD exhibits important application value in monitoring vegetation cover (Silveira et al. 2019), land use (Lv et al. 2021, 2019), and urban development (Xu, Yu et al. 2024; Zhou et al. 2023), assessing military strikes, floods (Zhao, Sui, and Liu 2023), and geologic damage (Ghaderpour et al. 2024; L. Wang et al. 2023), and reconnaissance of military facilities, fortifications, and equipment deployments, as shown in Figure 10. In this section, these application types are categorized into three groups: dynamic monitoring, damage assessment, and target reconnaissance. Dynamic monitoring entails the use of multitemporal imagery to continuously observe long-term surface changes, including urban expansion, shifts in agricultural lands, and variations in vegetation cover. Damage assessment specifically aims to evaluate the extent of harm caused by significant events such as natural disasters–floods, earthquakes, and landslides–and military strikes. This process involves analyzing the conditions of the affected areas and emphasizing comparisons between pre- and post-event scenarios. Target reconnaissance focuses on observing the appearance and disappearance of critical targets, such as airplanes at airports and ships at ports.

Dynamic monitoring plays a crucial role in managing natural resources, particularly land use. It aims not only to detect regions and categories of changes but also to acquire the conversion relationships among various categories, such as farmland, forest and grassland, wetland, water area, and construction land. Object-oriented and semantic-based methods are commonly employed for this purpose, as they enable accurate classification of changes. In regard to data selection,

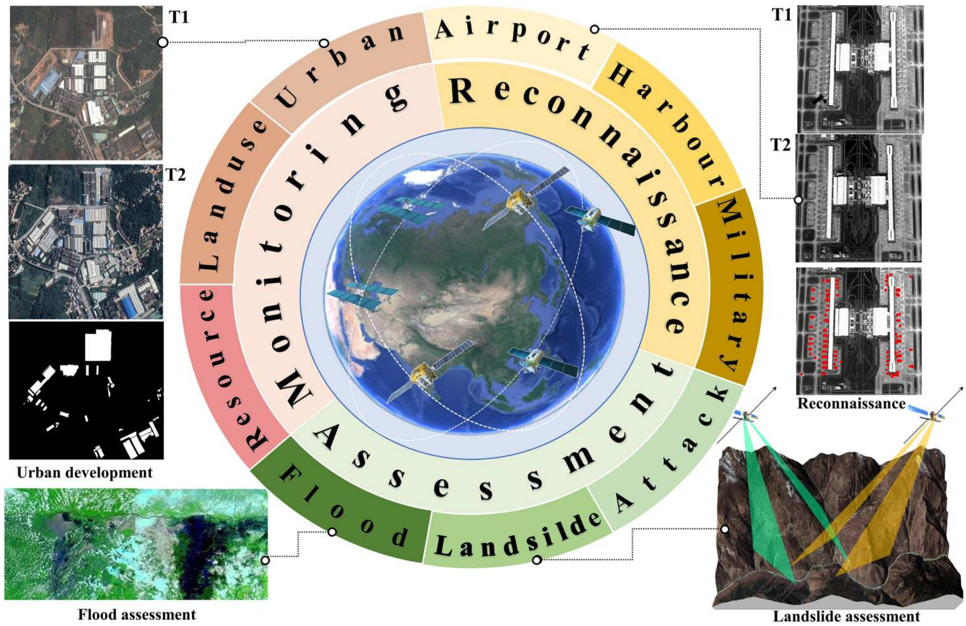


Figure 10. Applications of RSICD.

multiple time series images are commonly employed, primarily focusing on images of medium resolution. Satellites such as Landsat 8 OLI (30 m), Sentinel-2 (10 m), GF-1 (8 m), and ZY-3 (6 m) are commonly used for dynamic monitoring. Moreover, additional supplementary data may be chosen according to the specific tasks. For example, the NDVI can be used to monitor vegetation cover and changes in forests and grasslands, whereas the NDWI assists in water extraction within areas such as lakes and rivers. Furthermore, GIS technology can be employed to monitor farmland and urban development changes. Overall, dynamic monitoring not only helps in identifying past changes but also helps predict future trends, which serves as a crucial tool for effectively and sustainably managing natural resources.

Damage assessment is commonly employed in evaluating the damage caused by natural disasters and military strikes. This task necessitates the prompt acquisition of damage information to facilitate emergency response and military decision-making processes. Consequently, traditional object-oriented methods that require gradually setting thresholds are no longer applicable, and lightweight, transferable, and generalizable models have become the preferred choice. Within the context of flood CD, a prior categorization CD structure is often used, where a threshold is first set for categorization, followed by the extraction of change information. Generally, only the use of a single sensor faces the limitation of the temporal resolution. In contrast, the use of multiple sensors can greatly improve the temporal resolution and overcome the constraints of a single sensor. For example, optical RS images are susceptible to interference from weather, such as clouds, rain, and snow. Combining them with SAR imagery effectively compensates for this drawback.

In target reconnaissance, CD plays a critical role in identifying aircraft, ships, missile launch equipment, and nuclear waste. It is essential for obtaining timely battlefield intelligence data, comprehending enemy forces, and supporting commanders in strategic deployments. This task is mission oriented and focuses solely on the presence or absence of the target of interest. Additionally, reconnaissance targets often exhibit distinct scenarios, with changes occurring only at specific locations. For example, changes in aircraft at airports are typically confined to the apron and runway, whereas variations in military ships primarily occur at specific harbor locations. Consequently, multitask CD methods are commonly employed, enabling the identification and categorization of changes. Furthermore, leveraging prior knowledge from large fixed port and airport facilities can assist in identifying candidate areas for detected change targets. Considering the size of the interest target, submeter high-resolution satellite images are typically used, while the temporal resolution is flexibly chosen on the basis of the specific task.

4. Discussion

Through decades of rapid development, various RSICD methods have been developed and widely applied in different fields, producing enormous economic benefits and social value. Nevertheless, the growing availability of multisensor, multiplatform, and multiangle RS data, coupled with advancements in spatial and spectral resolutions, has posed both challenges and opportunities for RS image CD.

4.1. CD sample imbalance problem

In recent years, the diversity of CD methods has expanded, accompanied by a continuous increase in their accuracy (Parelius 2023). However, the persistent occurrence of class imbalance in CD has garnered limited attention. Left unaddressed, this imbalance poses a significant threat to the accuracy of CD methodologies (Zhang et al. 2023). The issue of CD sample imbalance is manifested in two main aspects. First, the proportion of change areas is considerably smaller than that of non-change areas (Weng et al. 2024). As a result, the model's weight parameters are more susceptible to non-change samples. Second, there is a risk of the target area of interest being overshadowed by a larger change area, particularly when the desired change target is relatively small. For instance, in the context of military target CD, the relatively small size of certain targets, such as vehicles, compared with larger land surface changes, frequently leads to the omission of the desired change target.

To address these challenges, potential enhancements can be pursued for both the data and algorithms. Various data augmentation methods have been used to improve the quality and quantity of the available data, including data augmentation methods such as scaling, rotating, and cropping change regions, as well as the use of GANs to generate synthetic samples (Oubara et al. 2024). Additionally, self-supervised learning has been implemented to create pseudo-labels in cases where there are limited samples for certain categories. Recently, the diffusion model has surpassed GAN in the image generation task to provide more diverse, realistic, and rich high-quality samples, which can be considered for generating CD samples (Wen et al. 2024). Conversely, if there is a large number of samples for particular classes, undersampling can be employed to select a batch of high-quality training samples. At the algorithmic level, the design of the loss function should consider the weighted balance between the change and non-change samples (Chen et al. 2021; Cheng et al. 2021; Ke and Zhang 2021), exemplified by techniques such as focal loss (Lin et al. 2017),dual focus loss (Zhang and Liu 2024), GHM (Gradient Harmonized Mechanism) Loss (Li, Liu, and Wang 2019), dice loss (Li et al. 2019), among others.

4.2. Pseudo-changes and complex scene problems

As the spatial resolution of images is improved, more details can be captured, which are prone to pseudo-changes caused by illumination, topography, and shadows. Therefore, eliminating pseudo-changes in high-resolution images caused by the imaging conditions has become a pressing issue in CD research (Hang et al. 2024; Huang et al. 2024; Zhou, Qian, and Ren 2024). Consideration of contextual information, multi-scale analysis (Xu, Ye et al. 2024), and combination of domain knowledge and auxiliary data, can be adopted in future research to better understand the change conditions in the scene and distinguish between real and pseudo-changes. In addition, specific methods tailored to the task characteristics can be adopted to eliminate pseudo-changes (Lv, Zhong et al. 2023). For instance, in agriculture and forestry CD, where most areas are continuous, the mean value method can be utilized to differentiate between color and pseudo-changes.

Simultaneously, with the increased resolution of RS images, it becomes increasingly challenging to recognize specific changes in complex scenes (Wen et al. 2024). It is important not only to identify the change objects but also to comprehend the semantic information of the scene to determine whether the observed changes are within the scope of the investigated changes. For example, distinguishing change objects becomes difficult in complex scenarios, such as construction in open spaces, soil resulting from seasonal crop rotation, and forest or grassland degradation. Therefore, it is essential to comprehend the semantic information both before and after a scene change to accurately determine its nature. Additionally, CD models trained based on specific datasets often struggle with generalization when applied to new scenarios. To address this issue, future research should focus on investigating techniques such as transfer learning (Habibollahi et al. 2022) and domain adaptation (Qu et al. 2024), which can help improve the generalizability of CD models. These methods allow the transfer of knowledge learned from the original domain to other domains, which improves the ability of models to adapt to new scenes and environments.

4.3. Alignment problems with multiple source heterogeneity

Multimodal data fusion, which involves using multiple data sources, has gained popularity in the era of big data (Ye, Zhang et al. 2024). This method enables a comprehensive utilization of RS data and has become a prominent research area (B. Liu et al. 2024; Wu, Geng, and Jiang 2024). Nevertheless, aligning various data sources is difficult due to differences in imaging mechanisms, geometric properties, and spatial scales (Wang, Xiong et al. 2024; Ye, Yang et al. 2024). Accurate alignment is essential for successful RSICD, as misalignment can impose a detrimental effect on the accuracy of CD (H. Zhang et al. 2024). The primary obstacle in aligning multiple data sources lies in effectively representing features and measuring similarity between images. Similarly, CD involves these same tasks. Due to differences in modalities, currently, many heterogeneous CD studies assume the transformation of multisource RS data into a common feature space for comparison, which can be categorized based on the transformation method into feature-based methods (Jiang et al. 2021; Liu et al. 2021) and image regression methods (X. Jiang et al. 2020; Luppino et al. 2024). Both registration and CD require extracting corresponding features and measuring the similarity between images, resulting in redundant computations. The extraction of corresponding features in change areas introduces registration errors, which subsequently impact the reliability of CD results. To address these issues, future studies are expected to incorporate registration and CD procedures. The accuracy of registration can be improved in the registration process by using unaltered data obtained through CD. Similarly, leveraging feature information extracted from image registration avoids repeated feature extraction and improves the computational efficiency in the CD process.

4.4. Challenges associated with big data, large-scale artificial intelligence, and cloud computing

The explosive growth in RS data, coupled with significant advancements in the computing power and the emergence of large-scale models, such as the GPT series (Brown et al. 2020), Claude series, LLaMa (Touvron et al. 2023), and Pan Gu (Bi et al. 2023), has resulted in unprecedented demands for advanced CD algorithms and data.

To meet the demands of data-driven approaches, it is crucial to establish a comprehensive CD dataset that encompasses multiple dimensions, temporal phases, and multi-tasks. Currently, mainstream datasets largely suffer from a lack of three-dimensional information. However, if the elevation within the study area changes, unpredictable influences on CD outcomes may occur (Deren 2003). Consequently, constructing datasets encompassing 3D point clouds or DEM proves instrumental in compensating for the absence of three-dimensional information and mitigating errors in CD (de Gélis, Corpetti, and Lefèvre 2024).

With respect to algorithms, large-scale models are increasingly being applied in the field of change detection (Li et al. 2024; Zheng et al. 2024), encompassing both supervised (Ding et al. 2024), and unsupervised learning methods (Tan et al. 2023). Researchers have utilized large models in RS to adapt to various tasks such as object detection, classification, and CD (Hong et al. 2024; W. Zhang et al. 2024), while others have directly applied these models specifically for CD tasks (Chen et al. 2023; Li, Cao, and Meng 2024). Owing to their training based on extensive datasets and their vast number of parameters, large-scale models hold significant potential for enhancing the effectiveness of CD. Additionally, large models enable intriguing research possibilities, such as employing GPT-like interactive methods between text and images to identify changes within images (C. Liu et al. 2024). In addition to applying large-scale models to CD, such as vision foundation models (VFMs) (Mishra, Karanjkar, and Rawat 2024; Zheng et al. 2024), Segment Anything Model (SAM) (Chen, Song, and Yokoya 2024; Ding et al. 2024; Mei et al. 2024), contrastive language–Image pre-training (CILP) (Dong et al. 2024; H. Zhang et al. 2024), it remains imperative to make the most of the prior knowledge and spatial-temporal-spectral characteristics of RS images. Spatially, there is significant correlation information present among different time-phase images in the same geographic region (H. Zhang et al. 2024), such as similar texture, spectral and shape features, conforming to a certain distribution pattern. However, in current CD methods, this correlation information and known scene information are rarely utilized. Therefore, an effective strategy to improve the CD accuracy is to utilize the spatial-temporal-spectral features of RS images and scene knowledge in future studies (Hu, Wu, and Zhang 2022; W. Wang et al. 2024; P. Zhang et al. 2024). In the temporal dimension, instead of solely extracting features from individual images, it is crucial to consider the correlation between features across different temporal phases. In the spatial dimension, two approaches can be adopted. First, anomaly detection methods can be utilized to identify abrupt changes that deviate from the overall distribution trend. Second, exploiting known scene information and prior knowledge can be beneficial. For example, when domain expertize is employed, regions where the target is susceptible to change can be extracted to constrain the spatial location of the target, thus reducing the number of false detections. Moreover, in the spectral dimension, there exists a significant correlation between the reflected intensity of the same object across various spectral bands.

5. Conclusion

RSICD, as one of the most pivotal techniques in Earth observation, permits more effective management and monitoring of natural resources and environmental changes. However, with advancements in RS and computer science, the availability of high-resolution, multisource heterogeneous RS images, data-driven methods represented by large-scale AI models, and platforms with notable computing capabilities have exhibited new opportunities and challenges for RSICD.

In this sense, this paper provides a comprehensive review, summary, and prospects of RSICD. First, the development process of RSICD is systematically organized, providing valuable insights into the latest trends. Second, currently available public CD datasets are compiled to fulfill the application requirements of data-driven methods. Three classification criteria–the detection framework, detection granularity, and data sources–are subsequently employed to elucidate RSICD methods and to explore the suitability of different CD data and methods for diverse application tasks and scenarios. Finally, the core challenges encountered and future developmental trends are described.

In future studies, the generation of large-scale, high-quality CD samples covering multiple sensors, time phases, and categories should be emphasized. By leveraging the spatial-temporal-spectral characteristics of RS images and incorporating relevant geoscientific knowledge, a coupled data-model-knowledge driven CD model can be constructed, which can facilitate a comprehensive understanding of complex scenes through the stages of change information extraction, change target identification, and change scene comprehension.

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Author Contributions

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Data availability statement

This is a review paper, no data has been used and the open data has been presented and referenced in the paper.

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