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Remote sensing imagery segmentation in object-based analysis: A review of methods, optimization, and quality evaluation over the past 20 years

Badia Ez-zahouani [a,*], Ana Teodoro [b], Omar El Kharki [a], Liu Jianhua [c], Ioannis Kotaridis [d], Xiaohui Yuan [e], Lei Ma [f]

[a] Geomatics, Remote Sensing and Cartography Unit, FSTT, Abdelmalek Essaadi University, Tetouan, Morocco
[b] Department of Geosciences, Environment and Spatial Planning and ICT (Institute of Earth Sciences) – Porto Pole, Faculty of Sciences, University of Porto, Porto, Portugal
[c] Key Laboratory for Urban Geomatics of National Administration of Surveying, Mapping and Geoinformation, School of Geomatics and Urban Spatial Information, Beijing University of Civil Engineering and Architecture, Beijing, 100044, China
[d] Aristotle University of Thessaloniki, Faculty of Engineering, School of Civil Engineering, Lab. of Photogrammetry - Remote Sensing, 54124, Thessaloniki, Greece
[e] University of North Texas, Denton, TX, 76203, USA
[f] School of Geography and Ocean Science, Nanjing University, Nanjing, 210023, China

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ABSTRACT

Object-based image analysis (OBIA) has become a key research topic for decades and represents an attractive paradigm leading to accurate features classification and recognition. It is based on a key fundamental technical support, named segmentation, which produces physically and semantically image objects with homogeneous pixels, and it can be used in whole or in part for research related to object-oriented analysis. This paper reviews all the steps comprising segmentation and the methods for each step by reviewing literature published in relevant remote sensing journals between 2000 and 2022. In addition, segmentation methods are discussed, compared, and categorized into general and detailed categories. The SOTA researches focusing on the most advanced methods at all steps are also presented while highlighting future research opportunities and needs. The novelty of the review is the adoption of a new classification of segmentation methods by time scale, which reveal the evolution history and trend based on their internal relations. Particularly, this work covers all the approaches and methods that make up the segmentation steps, with analyses, comparisons, and future research perspectives. Finally, conclusions about the SOTA methods, critical conclusions about open challenges, and directions and recommendations for future research are presented.

1. Introduction

Remote sensing (RS) has evolved by developing satellite image processing methods for extracting spatial information. Initially, classification was pixel-based and qualified by conventional classification algorithms (Costa et al., 2018). However, several limitations appeared in the pixel paradigm, which was criticized in the late 1990s (Blaschke et al., 2014). Indeed, the approach is based on low and medium-resolution images, where the objects of interest are small or the same size as the corresponding pixels, and a pixel

* Corresponding author.
E-mail address: badia.ezzahouani@etu.uae.ac.ma (B. Ez-zahouani).

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can have one or more objects of interest, depending on the spatial resolution of the image. However, with the advent of very high-resolution (VHR) images such as IKONOS, Quickbird, WorldView-1, RapidEye, GeoEye-1, WorldView-2 and WorldView-4, GaoFen, GeoEye-2 and SPOT6 and 7, the spatial resolution has become much finer (1.5 m), and objects of interest often contain multiple (Blaschke et al., 2014)- (Zhang et al., 2020a). Consequently, the pixel-based approach for VHR images, unmanned aerial vehicle (UAV), light detection and ranging (LiDAR), or even sonar data has become limitative. There is a growing awareness of object-based image analysis (OBIA) methods. OBIA has made significant progress in spatially explicit information extraction workflows for spatial planning, monitoring, mapping, and management programs (Blaschke, 2010; Ruiz et al., 2021), (Teodoro and Araújo, 2016). It has become the rising paradigm in RS and geographic information systems (GIS) (Blaschke et al., 2014), (Blaschke, 2010). OBIA was supported by the release of commercial software for object-based analysis, "eCognition", in 2000 to meet the growing demand for fast and accurate classification results (Blaschke et al., 2014).

OBIA bridges between the raster RS images and vector data of Geographic Information System (GIS) (Hay and Castilla, 2008), by using both data types to extract and classify information from RS images. This raster and vector data integration enables a more comprehensive and accurate RS data analysis. It allows for integrating RS data with other types of spatial data (e.g., digital elevation model, vector data etc.). A growing number of OBIA-related publications and applications have emerged to support geographic intelligence, i.e., relevant information in a geographic context (Kucharczyk et al., 2020). The trends behind the significant and rapid growth in publications in the field of OBIA are mainly related to the arrival of VHR satellite image data and the advent of eCognition software, which supports OBIA. It is used by more than 50% of papers for this purpose, and its success has spurred the development of other software (Blaschke, 2010). However, it is a proprietary software.

OBIA comprises two main steps: (1) segmentation of the image into homogeneous and (2) mutually exclusive regions or meaningful objects of interest (Gonçalves et al., 2019), where image objects are the basic spatial units of analysis (Costa et al., 2018). Objects are defined as a set of connected pixels with homogeneous features (Ming et al., 2015). Image segmentation is not an end; it plays a crucial role in OBIA workflows and thus represents a step in the processing chain to obtain "meaningful objects." In contrast, OBIA depends primarily on the appropriate choice of a segmentation technique.

Segmentation is a crucial step in OBIA approach, in which the quality of the segmented objects determines the quality of the final result. OBIA included the segmentation covers multiple fields such as damaged buildings (Yan et al., 2019), crop inventories (Duarte et al., 2018), geological and environmental research (Mikes et al., 2015), urban planning, GIS map dressing and updating (Grinias et al., 2016), roads and buildings (Grinias et al., 2016), change detection (Wang et al., 2018a), snow seasonality studies (Thompson and Lees, 2014), landslide inventories (Martha et al., 2012), invasive exotic plant detection (Gonçalves et al., 2019), imperviousness detection and different land cover classes (Verbeeck et al., 2012), and many other applications (Teodoro et al., 2011).

Hot research areas and subtopics of the OBIA approach are the specific concepts of OBIA hierarchy and scale (Ming et al., 2015), (Wang et al., 2019)- (Shen et al., 2019), OBIA segmentation (Kucharczyk et al., 2020), (Yan et al., 2019), (Hossain and Chen, 2019)- (Yang et al., 2017b) OBIA change detection (Cheng and Han, 2016) OBIA accuracy evaluation (Costa et al., 2018), (Clinton et al., 2010)- (Costa et al., 2015), segmentation combined with classification (Troya-Galvis et al., 2017), (Zanotta et al., 2018), (Na et al., 2021a) and Deep Learning (DL) combined with OBIA (Kucharczyk et al., 2020), (Tong et al., 2018)- (Zhao et al., 2017), fully sematic segmentation with DL Indeed (Pastorino et al., 2022), generally OBIA studies shifted toward deep learning applications and developing specific models for segmentation problems (Zhang et al., 2018). The combination of OBIA and change detection analysis methods is a significant area of research in RS. It allows for detecting and monitoring changes in land use and land cover at the object level over time, providing a more detailed and nuanced understanding of environmental change (Punitha and Sutha, 2019)- (Persello and Bruzzone, 2012). Furthermore, dynamic research fields in the segmentation stage comprise improvement and standardization of segmentation steps, feature extraction and space reduction, and accuracy evaluation (Kucharczyk et al., 2020).

It must be mentioned that segmentation has received and will continue to receive significant attention in the RS community; for this, Hay and Castilla (2008) and Louw and van Niekerk (Louw and Van Niekerk, 2018) labeled segmentation as a "poorly posed problem or unstructured problem," leading to a statement about the advanced techniques focused on the development of methods applicable to any setting deemed necessary and strongly recommended.

Several literature reviews have focused on the segmentation topic. Mikeš et al. (Mikes et al., 2015) benchmarked and comparatively evaluated segmentation techniques and methods of great interest in RS. Ming et al. (2015) conducted an interesting literature review on scaling parameter selection based on spatial statistics. Liu et al. (2017) conducted a literature review on scaling through multi-scale segmentation techniques. Ez-zahouani et al. (Ez-zahouani et al., 2023) performed a recent review on the determination of segmentation parameters for OBIA from conventional to recent approaches. Ma et al. (2017) performed an exhaustive meta-analysis of general issues considered in OBIA studies. They reviewed 173 scientific articles and derived multiple endpoints from different studies to test correlations between the extracted endpoints for further evaluation. Moreover, El-naggar (El-naggar, 2018) conducted a review dedicated to the optimization of segmentation parameters. Costa et al. (2018) researched supervised methods for evaluating segmentation accuracy. Chen et al. (2018) examined emerging trends and future opportunities for OBIA. Hossain and Chen (2019). provided a comprehensive review of OBIA techniques and discussed different segmentation techniques and algorithms. Kucharczyk et al. (2020) published a review introducing and detailing the future directions of geographic object-based image analysis. Sun et al. (2021) reviewed road segmentation for Synthetic Aperture Radar (SAR) images. Neupane et al. (2021) performed a meta-analysis on DL semantic segmentation of urban features in RS images. However, Yuan et al. (2021), Ma et al. (2019), and Zhu et al. (2019) reviewed DL methods for semantic segmentation of RS images in literature reviews. More recently, Kotaridis and Lazaridou (2021) performed a meta-analysis on the advances and progress of RS image segmentation. The reviews already cited are of great importance for the advancement of knowledge as they are references in the field of segmentation and OBIA. Furthermore, our review is characterized by focusing on segmentation while covering all steps through description, analysis, criticism and future needs.

Based on the information mentioned before, there are several reviews in OBIA, especially in the domain of RS image segmentation. Nevertheless, these reviews considered one or two segmentation steps, for instance, the determination and selection of optimal parameters of segmentation (Ming et al., 2015) (Liu et al., 2017) (El-naggar, 2018) (Ez-zahouani et al., 2023), or segmentation methods and algorithms (Mikes et al., 2015) (Hossain and Chen, 2019) (Ma et al., 2017) (Neupane et al., 2021), evaluation of segmentation quality (Costa et al., 2018) (Jozdani and Chen, 2020), etc. In contrast, this study reviews all steps of OBIA as shown in Fig. 1, including (1) determination and selection of optimal segmentation parameters, (2) segmentation methods and tools, (3) optimization of segmentation parameters, (4) feature extraction and reduction, (5) evaluation of segmentation quality. In this context, this paper provides a focused and encompassing view of the RS image segmentation steps and all its sub-steps, specifying future directions and perspectives of each step.

This review covers all steps of the segmentation procedure (Fig. 1) and is divided into several parts.

This work is motivated by several reasons, as already mentioned. In general, the growing importance of RS imagery, the popularity of the OBIA approach for RS image analysis, and the rapid technological progress that this field has experienced, especially with deep learning algorithms. In particular, it is expected to overcome the lack of comprehensive, in-depth studies; Although several works are available on RS image segmentation in object-based analysis, comprehensive studies need to summarize the different methods, optimization techniques, and quality assessment measures commonly used. Overall, this review article's expected results can help consolidate the existing knowledge, identify research gaps, provide a comprehensive and up-to-date summary of the current state-of-the-art, and identify future research directions that can further advance this field.

2. Methodology

To carry out this literature review, we collected and analyzed data on remote sensing imagery segmentation for object-based image analysis: optimization, methods, and quality evaluation. The systematic search on this topic was performed using the SCOPUS bibliographic database, which covers most international remote sensing journals and also MDPI database.

It was used two queries to retrieve the appropriate data. The keywords used to perform the queries are related to segmentation and remote sensing, namely "Remote sensing" AND ″Segmentation" OR ″OBIA″, and "Remote sensing" AND ″Segmentation" AND ″OBIA″, for the first and second queries, dated from 2000 to 2022, 11 942 and 320 publications were returned, respectively. We used the database retrieved from the second query; 126 publications were retained for detailed analysis after filtering and manual analysis of titles, abstracts, and conclusions. The following rules were formulated to purge the literature and case studies related to segmentation manually.

- Studies that apply the OBIA technique include the segmentation and segmentation step.
- Studies specifically dealing with segmentation.
- Applied research studies devoted to a single segmentation step, such as determining segmentation parameters or segmentation algorithms.
- A literature review on the topic.
- Studies that briefly mentioned segmentation methods without providing detailed information were not included.

For this literature review, a specific and concise database was developed to provide a basis for comparison. Additionally, the database includes all literature identification fields, such as title and author. The latter also includes information fields for segmentation, namely:

- The segmentation parameters to be determined and the segmentation methods and criteria used to determine the parameters.
- The optimization methods used to determine the segmentation parameters.
- Segmentation algorithms.
- Tools used.
- Methods for feature selection, extraction, and reduction.

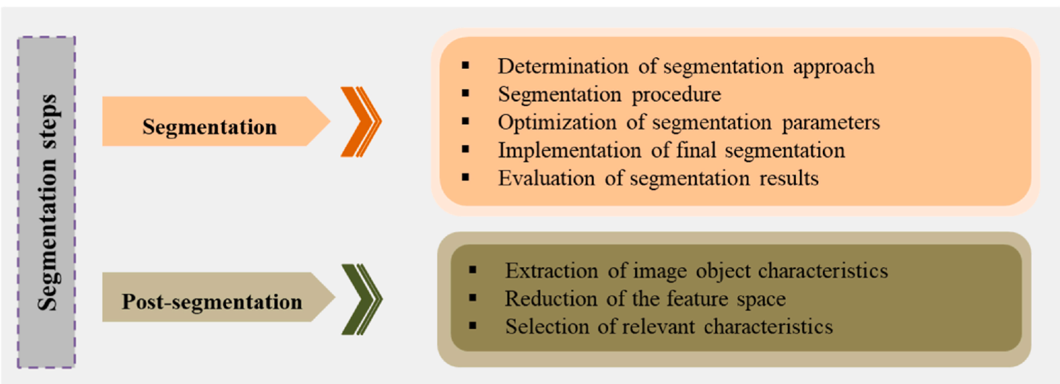

Fig. 1. The segmentation steps.

- Methods and metrics for assessing segmentation quality.

3. Determination and selection of optimal segmentation parameters

The quality of the segmentation results is directly related to the optimal selection of the segmentation parameters, which require adequate parameterization. These parameters supervise the segmented objects' size, shape, and boundaries. However, parameters change from one segmentation method to another, but the most well-known and used are the compactness, shape, and scale of considering the multi-resolution algorithms (El-naggar, 2018), (Gibril et al., 2018). Scale is the most important of these parameters for many techniques (Ming et al., 2015). Generally, scale relates to the range of study, resolution ratio, heterogeneity, cartographic scale and semantic granularity. Scale takes a different name depending on the segmentation algorithm, e.g., absolute and relative scales (Blaschke, 2010); scales in the form of windows or functions (Blaschke, 2010); pixel-based, object-based, and pattern-based scales (Ming et al., 2011); and the so-called spatial or spectral scale (Liu et al., 2017).

3.1. Methods for determining optimal segmentation parameters

To determine optimal segmentation parameters, a distinction must be made between manual methods based on a trial-and-error and semi-automatic or automatic methods approaches (Johnson and Jozdani, 2018), (Drăguţ et al., 2014). Automatic approaches are divided into supervised and unsupervised methods (Wang et al., 2019), (Clinton et al., 2010), (Liu et al., 2012)- (Grybas et al., 2017).

Supervised methods measure the arithmetic or geometric similarity or overlap between segmented and reference objects. Methods used include Euclidean distance (ED2 and ED3) (Witharana and Civco, 2014), adjustment equation (Ma et al., 2015), and fuzzy logic (Yan et al., 2019) to compute segmentation metrics. In addition, the under-segmentation and over-segmentation metrics were used (Bialas et al., 2019) to determine the optimal segmentation parameters. These methods are subjective and produce results that vary by interpreter but are widely used (Liu et al., 2017).

Unsupervised methods rely on statistical and mathematical measures to determine the quality of segmentation results (Wang et al., 2019). These measures maximize intra-segment homogeneity and inter-segment heterogeneity by satisfying predetermined conditions (Johnson and Jozdani, 2018). Table 1 below summarizes the methods used in this category.

It is essential to note that most of the methods for determining the optimal scale or scale range for segmentation are based on local variance, ROCLV, local variance ratio (LVR), average local variance (AVL), variograms, and semi-variograms. Furthermore, only one scale can be used for segmentation (Zhang et al., 2009), (Hamedianfar and Gibril, 2019), especially for homogeneous areas, and in most cases, multi-scale image segmentation is performed.

Other interesting remarks are that the methods for determining the segmentation parameters are based on a posteriori evaluation of the multi-scale segmentation rather than the pre-estimation of optimal scale parameters. To this end, Ming et al. (2015) applied spectral and geospatial statistical methods to cluster-based pattern recognition using spatial and spectral bandwidths and fusion thresholds, relying on ALV. Liu et al. (2017) used ALV and ROCLV for posterior methods. Meanwhile, Louw and van Niekerk (Louw and Van Niekerk, 2018). extended ALV to object boundary local variance (OBLV) to measure topographic changes and decide whether object boundaries intersect morphological discontinuities and LVR, assuming that topographical differences throughout morphological boundaries will be more pronounced than changes within landform components. In addition, Qiu et al. (2016) proposed a method combining adaptive pre-estimation of scale parameters based on spatial statistics and mean shift segmentation. Ming et al. (2016) used an adaptive pre-estimation method of optimal scaling parameters based on spatial statistics for cropland extraction, and the results confirmed the method's effectiveness. More recently, Xu et al. (2019) extracted cropland from remotely sensed images using stratified pre-estimation of segmentation parameters.

Table 1
Different unsupervised methods used for determining optimal segmentation parameters.

Methods	References
Local variance (LV).	(Hay et al., 2001) (Kim et al., 2008; Drăguţ et al., 2009, 2010; Karl and Maurer, 2010), (Drăguţ et al., 2014)
Global score (GS).	(Johnson and Xie, 2011), (Böck et al., 2017)
Overall goodness (OG).	Johnson et al. (2015)
Global objective function based on the spatial autocorrelation of the Moran index and variance.	Espindola et al. (2006)
Estimation Scale Parameters (ESP) tool and ESP2	(Drăguţ et al., 2010), (Drăguţ et al., 2014)
Estimation of optimal segmentation parameters in two stages of global and local evaluation, using Moran's weighted variance and Moran's I-index, respectively, and local heterogeneity statistics.	Johnson and Xie (2011)
Weighted sum of intra-segment homogeneity and inter-segment heterogeneity.	Zhang et al. (2012)
Classical semi-variogram method.	Ming et al. (2012)
Modified rates of change of local variance (ROCLV) method.	Zhao et al. (2012)
Local-scale parameter (SP) optimization procedure by substituting Moran's I-index with Geary's index.	Cánovas-García and Alonso-Sarría (2015)
Energy function method to improve the intra-segment homogeneity, calculated using the average spectral angle in a segment.	Yang et al. (2015a)
Unsupervised scale parameter optimization method and tool (USPO) by measuring intra-segment homogeneity using area-weighted variance (WV) and inter-segment heterogeneity employing overall Moran's I.	Johnson et al. (2015)
The robust Taguchi statistical process combined with the objective function proposed by Espindola et al. (Espindola et al., 2006).	(Hamedianfar and Gibril, 2019), (Tonbul and kavzoglu, 2020)

Regarding the criteria used, the existing literature mainly uses homogeneity measures, marginalizing the contribution of heterogeneity measures (Wang et al., 2019). Some criteria for homogeneity and heterogeneity measurements are a spectrum, color, shape, size, texture, context, and spectral angle (Shen et al., 2019; Louw and Van Niekerk, 2018; Dey et al., 2010). In contrast, several researchers use both homogeneity and heterogeneity measures, such as Espindola et al. (2006), Tian and Chen (Tian. and Chen, 2007), Kim et al. (2008), He et al. (2009), Corcoran et al. (2010), Johnson and Xie (2011), Ming et al. (2015), Chen et al. (Wang et al., 2019), and Zhang et al. (2020b).

3.2. Advances/Novel methods for optimal segmentation parameters selection

Trends in determining scaling parameters are local approaches, such as adaptive scaling and scaling by geographic objects (Hu et al., 2017; Su, 2019). The idea for object-specific optimization started with Felzenszwalb and Huttenlocher in 2004 (Felzenszwalb and Huttenlocher, 2004), followed by Akçay and Aksoy (2008) with unsatisfactory results. Moreover, Yi et al. (2012) also studied scale synthesis methods. As Zhang and Du (2016). they mentioned two methods; the first is based on local adjustment called structure-specific local optimization strategy (Yang et al., 2015a), (Su, 2019), (Zhou et al., 2017)- (Xiao et al., 2018), and the second is to segment the image into different regions and then use a global evaluation metric to find the optimal segmentation scale for every region (Zhang et al., 2020b), (Kavzoglu et al., 2017)- (Georganos et al., 2018). Shen et al. (2019) showed that scaling parameters must be adapted for different areas or land covers. Zhang et al. (2020b) conducted a study to find the optimal segmentation scale for each geographic object by exploiting the variation in the homogeneity of each segment between neighboring segmentation scales; the result is a set of minimum and maximum segmentation scales, which improves the segmentation quality by considering coarse and fine objects. In addition, Wang et al. (2019) used an unsupervised approach to select segmentation parameters using within-segment homogeneity (WSH), between-segment heterogeneity (BSH), and F-measure; and implying common boundaries between each segment and its neighbors; this approach could not determine the optimal scale. More recently, Wang et al. (2022) used variational scaling segmentation based on spectral indices and local spatial statistics to determine the optimal scales and represent different geographical objects. They also developed a watershed transformation based on a scalable evolutionary watershed method. Moreover, several research papers have used adaptive scaling parameter calculation (Liu et al., 2017), (Yang et al., 2014)- (Chini et al., 2014). More specifically, they use physical image parcels (PIPs), whose scale parameters gradually change and whose spectral homogeneity decreases until they become similar to semantic image objects (SIOs) by adapting to real-world objects in the image. Liu et al. (2018) pointed out that solutions are needed to adaptively compute appropriate scaling parameters to describe heterogeneous and homogeneous ranges of adjacent pixels in spatial and spectral space for simultaneous segmentation.

In addition to these two approaches, a general approach for estimating appropriate scaling parameters is often employed. Johnson and Jozdani (2018). were performed a meta-analysis and mathematical modeling via a nonlinear regression tree (RT) to determine the segmentation parameters, especially scale. This approach yielded beneficial results for all land cover classes except the “water” class.

However, we concluded that some studies perform **segmentation without directly performing parameterization** and intensive computations (Witharana and Lynch, 2016), (Martha et al., 2010)- (Jozdani et al., 2018), and often **segmentation is combined with classification** (Son et al., 2014), (Troya-Galvis et al., 2017)- (Zanotta et al., 2018), (Chini et al., 2014).

4. Segmentation methods and tools

Segmentation divides an image into uniform segments or regions, named segments, objects, or regions (El-naggar, 2018). Segmentation approaches, methods, techniques, and algorithms have been classified into various groups in previous studies, namely, color-or spectrum-based and texture-based algorithms (Guo et al., 2005). Segmentation methods are classified into different categories: first, there are four most common ones, namely (i) edge-based algorithms, (ii) point/pixel-based algorithms, (iii) region-based algorithms, and (iv) hybrid approaches (Dey et al., 2010). In another perception, bottom-up approaches combine pixels or groups of pixels into objects, while top-down approaches divide the whole image into objects based on heterogeneity criteria (Dey et al., 2010), (Benz et al., 2004). Furthermore, the three conventional segmentation approaches in previous work are (i) pixel-based, (ii) edge-based, and (iii) region-based segmentation methods (Blaschke et al., 2014). Spectrum-based (Fig. 3) and region-based methods include several other methods or sub-methods (Tilton et al., 2015). There are further categorizations into supervised and unsupervised methods (Ma et al., 2017), and unsupervised methods can be divided into edge-based, region-based algorithms, and hybrid approaches (Hossain and Chen, 2019). These unsupervised methods can be divided into spectral, regional, hybrid, and semantic approaches (Kotaridis and Lazaridou, 2021). Furthermore, segmentation is based on the properties of the satellite image, i.e., texture, color or brightness, context, and geometry (Sun et al., 2021). According to Wang et al. (2022), these properties allow segmentation methods to fall into four categories: thresholds or feature groups, edge detection, region growth or extraction, and iterative pixel classification. Alternatively, image segmentation algorithms can belong to two or more categories.

The choice of the segmentation method depends on several criteria, such as image type, tools used, research objectives, and overcoming some challenges related to own study. Fig. 2 presents our categorization scheme of the methods. For simplicity, the conceptual details of these techniques are clarified, and mathematical details are evaded.

4.1. Spectrum-based methods

Spectrum-based methods serve as effective segmentation techniques. Leveraging the spectral information present in the data, these methods enable the partitioning of the image into distinct regions.

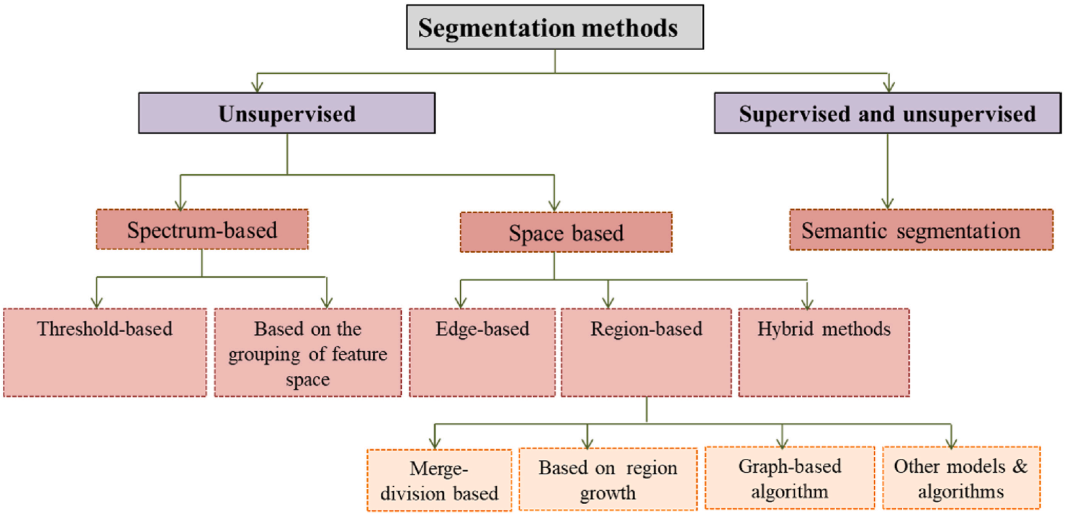

Fig. 2. Classification/categorization of segmentation methods adopted in this literature review.

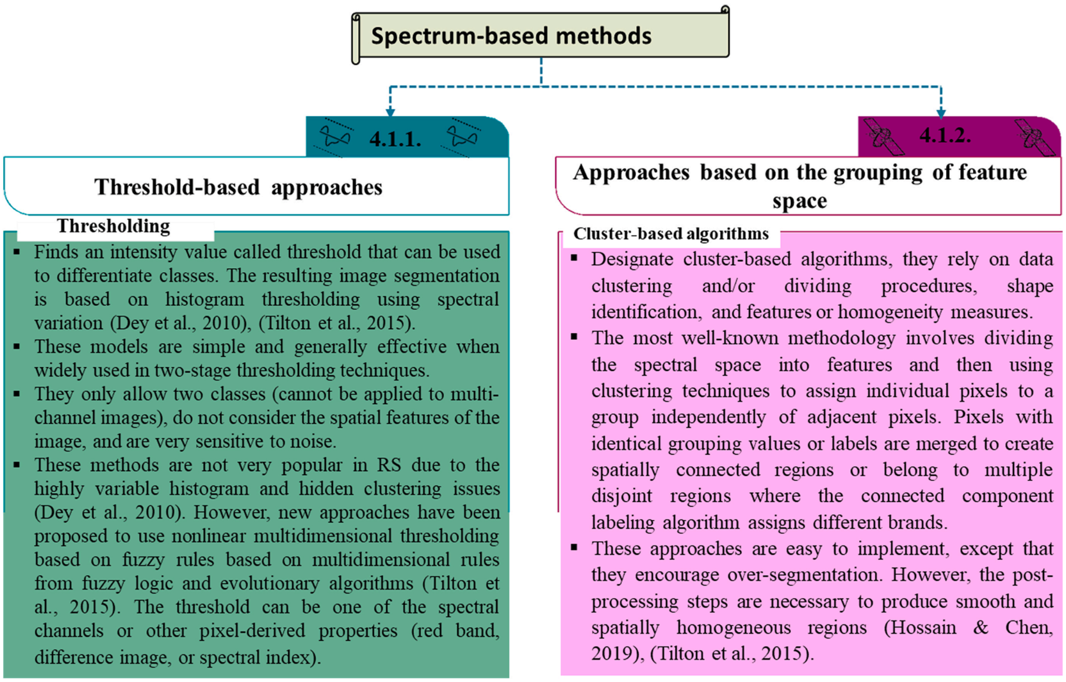

Fig. 3. Spectrum-based methods representative scheme.

4.2. *Space based methods*

Space-based segmentation methods rely on the assumption that neighboring pixels or regions that are spatially close to each other are more likely to belong to the same object or class. These methods (Figs. 4 and 5) typically use some measure of spatial similarity or distance between pixels or regions as a criterion for grouping them. Overall, space-based segmentation methods leverage spatial relationships between pixels or regions to guide the segmentation process and are widely used in remote sensing and other image analysis applications.

4.2.1. *Edge-based approach*

Edge-based approaches have emerged as a promising technique to enhance segmentation accuracy and efficiency. By focusing on detecting and utilizing edge information within an image, these methods enable the identification of object boundaries and finer details, contributing to a more precise and contextually aware segmentation process

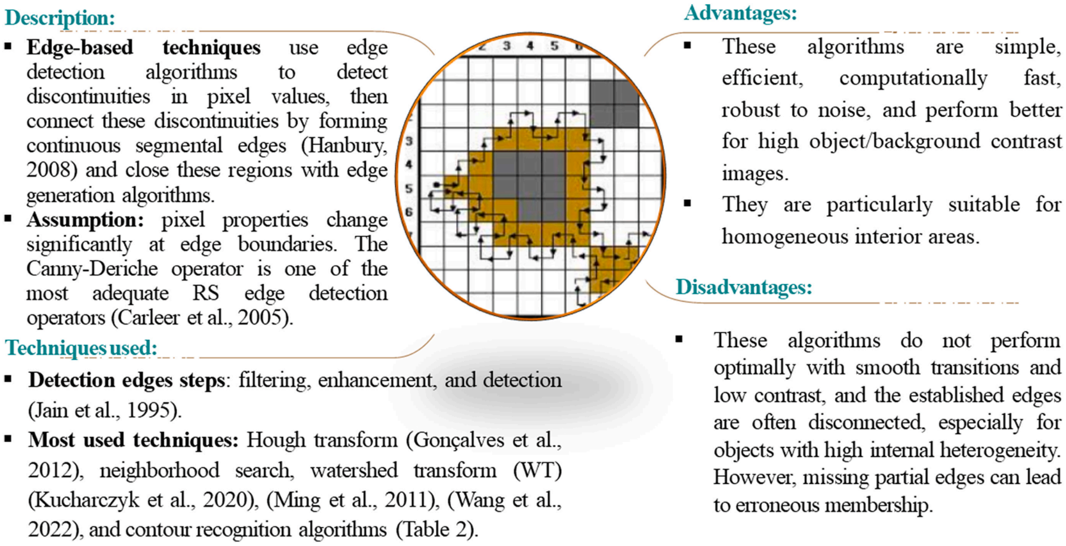

Fig. 4. Edge-based methods representative scheme (Carleer et al., 2005; Gonçalves et al., 2012).

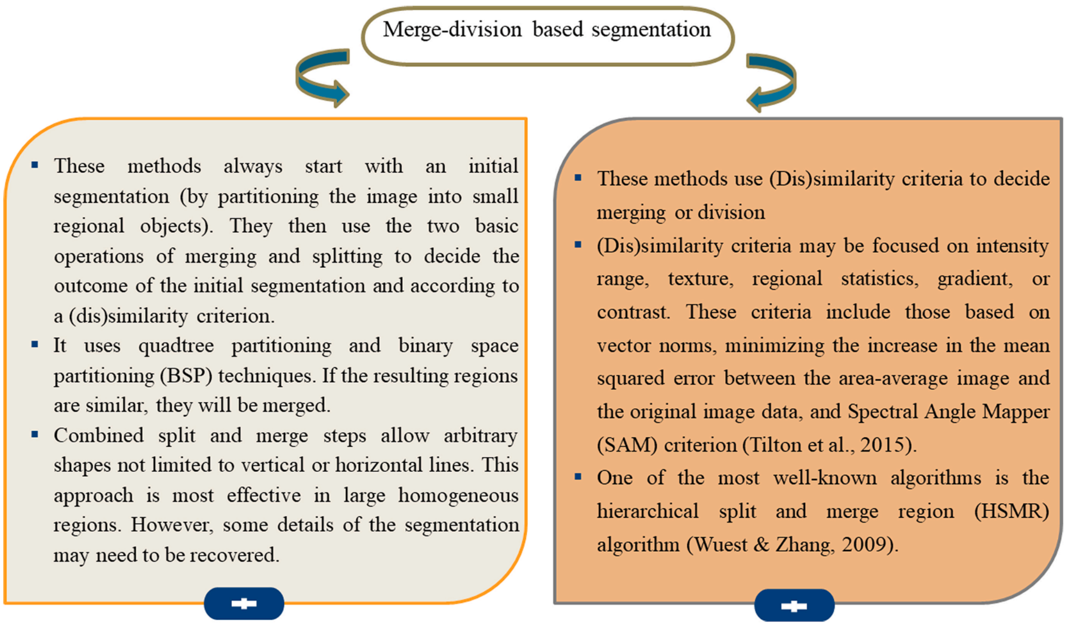

Fig. 5. Merge-division based segmentation methods representative scheme.

4.2.2. Region-based approaches

4.2.2.1. Merge-division based segmentation. Merge-division based segmentation is used to partition an image into coherent regions or objects. This technique combines merging and dividing regions iteratively to achieve a more refined segmentation result.

4.2.2.2. Segmentation based on region growth. Regarding to Fig. 6 and to overcome the problems encountered with region growth, multiresolution segmentation (MRS) emerged (Baatz et al., 2000a, 2000b). It is based on the Fractal Net Evolution Approach (FNEA) (Table 2), a hierarchical region fusion segmentation. It is a bottom-up approach, starting with a unique pixel. It also includes a hierarchical relationship between various levels; each coarser level receives entry from the finer level; when an object is determined as the coarser level, it repeats its representativeness at each finer level, which is considered similitude (Ming et al., 2015), (Hossain and Chen, 2019), (El-naggar, 2018). SRM groups data in pairs using local homogeneity criteria (Louw and Van Niekerk, 2018).

Furthermore, multi-scale segmentation strategies remain popular in inter-object heterogeneity, with large-scale segmentations suitable for distinguishing large objects, while small scales are for small objects (Benz et al., 2004). This approach is most employed to produce multi-scale segmentation by setting different thresholds (Zhang et al., 2020b). The MRS approach is complex but can yield promising results if implemented correctly, especially when dealing with large-scale difficulties (Dey et al., 2010). Also, the multi-scale concept can be combined with any other segmentation approach or method. Xi et al. (2019) proposed an effective spatio-

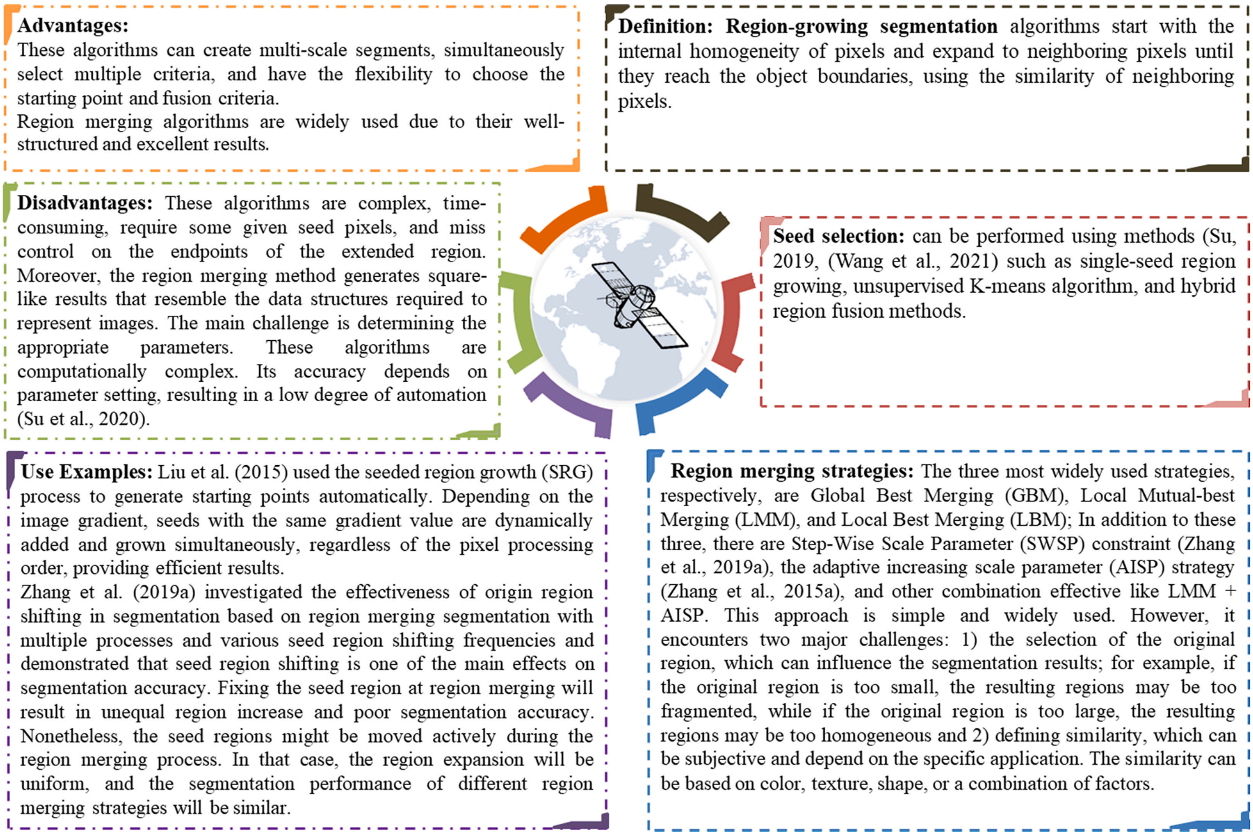

Fig. 6. Region growth segmentation methods representative scheme.

temporal multiresolution segmentation (ST-MRS) method that uses a new spatiotemporal model (ST) as a new spatiotemporal unit. This way, existing single-time MRS methods can be extended to the spatiotemporal domain to partition satellite image time series (SITS) into relatively uniform ST-cubes. Zhang et al. (2020b) used segmentation based on multi-scale hierarchical region fusion and developed coarse and fine fusion strategies to generate the final optimized segmentation. Yan et al. (2019) used a multifunctional composite segmentation method based on enhanced fast scan algorithm merging (FSAM), spectral, shape, and local and global texture heterogeneity computation with promising results.

Region merging can be performed by MRS and other popular algorithms, such as mean shift (MS). It is a robust and adaptive non-parametric density estimation clustering algorithm, where image segmentation is done by clustering the spatially and spectrally closest pixels. It is designed to analyze complex spaces (Lourenço et al., 2021), with the advantages of specific scaling parameters and hierarchical relationships between segmentation levels. Also, hierarchical stepwise optimization (HSWO) is a clustering method that initiates with a single data point and decreases clusters number by fusing. In contrast, the recursive hierarchical segmentation method (RHseg) represents an improvement result of HSWO.

Regarding to methods, MRS, Mean Shift, and Simple Linear Iterative Clustering (SLIC) are popular segmentation methods in remote sensing, each offering distinct characteristics and performance attributes. MRS is widely used and stands out for its adaptability and ability to handle complex landscapes, adjusting adaptively the segmentation scale to produce homogeneous regions and ensuring spatial coherence in segmented objects, it is known also for its ability to handle images with varying spatial resolutions and complex landscapes (Baatz et al., 2000a, 2000b). On the other hand, Mean Shift (Ming et al., 2012), (Karl and Maurer, 2010) is a non-parametric clustering algorithm, that excels in identifying spatially cohesive regions with irregular shapes and varying densities, making it suitable for object extraction in cluttered scenes, it also offers robustness against noise. However, its computational cost and parameter tuning requirements should be considered, especially for large datasets (Lourenço et al., 2021). SLIC, a superpixel-based method, strikes a balance between accuracy and efficiency, generating regular and compact superpixels of uniform size; it combines the advantages of both superpixel and clustering techniques (Zhang et al., 2019a, b, c). This makes SLIC beneficial for region-level analysis and processing of large datasets. Ultimately, the choice among these segmentation methods should be driven by the specific requirements of the remote sensing application, dataset characteristics, and the desired trade-offs between accuracy, computational efficiency, and adaptability (Csillik, 2017).

4.2.2.3. Graph-based algorithms. The process is viewed as a graph dividing issue, where nodes illustrate single pixels or regions, and edges join spatially neighboring vertices. Edges weights represent the (dis)similarity between adjacent pixels/regions connected using edges (Dezsős et al., 2012). Then, the main concept is to identify subgraphs correlating to the image scene regions

Table 2
Different categories of image segmentation methods, their sub-methods, and algorithms.

Methods	Sub-methods	Algorithms	References
Space-based	Edge-based	Watershed Transform.	(Li and Xiao, 2007), (Yang et al., 2017a)
		Morphological profiles based.	Lv et al. (2014)
		Edge-constrained.	Susan et al. (2012)
		Marker.	Gaetano et al. (2015)
		Edge-embedded.	Li et al. (2010)
		Grey Level Co-occurrence Matrix (GLCM).	Na et al. (2021b)
		Optimal edge detector.	Ma and Manjunath (2000)
		Hierarchical.	Guimarães et al. (2012)
		Hierarchical Watershed (HW).	Zhao and Popescu (2007)
	Graph-based	Seeded.	(Jain Preetha et al., 2012), (Jain et al., 1995)
		Mean shift (MS).	(Ming et al., 2012), (Karl and Maurer, 2010)
		Region Adjacency Graph (RAG).	(Zhang et al., 2015a), (Zhang et al., 2017b)
		Statistical sorting.	Hossain and Chen (2019)
		Multiple features.	Liu et al. (2021)
		Structural constraints.	Wang et al. (2017)
		Scale-space filtering.	Tzotsos et al. (2011)
	Region merging	Spectral variance difference.	Chen et al. (2015)
		Hierarchical Multiple Markov Chain.	Scarpa et al. (2009)
		Hierarchical Split Merge Refinement.	Wuest and Zhang (2009)
		Tree-Structured Markov Random Field (TS-MRF).	D'Elia et al. (2003)
		Texture Fragmentation and Reconstruction (TFR).	Gaetano et al. (2009)
		Recursive-TFR (R-TFR).	Scarpa et al. (2012)
Hybrid segmentation		Region Based, Watershed Algorithms.	Hanbury (2008)
		Quatree, Merging region growing algorithm spectral.	Ventura et al. (2022)
		Spectral Angle (SA), Watershed Transformation (WT), and RAG.	Zhang et al. (2019b)
		WT, Average constrat maximization.	Ciecholewski (2017)
		WT, threshold-based region merging.	Yang et al. (2017b)
		FNEA, WT.	(Liu, 2018), (Baatz, 2000)
		WT, heterogeneity-change-based merging.	Chen et al. (2014)
		Gravitational field-based segmentation, hierarchical region merging.	Zhang et al. (2017c)
		Edison operator, FNEA, ant colony optimization.	Chen et al. (2022)
		R-tree, RAG.	Hu et al. (2016)
		Quadtree, RAG.	Fu et al. (2013)
		Canny edge detector, boundary adjustment, MRS.	Zhang et al. (2008b)
		Morphological information, region merging.	Liu et al. (2015)
		Gradient, WT, and region merging.	Castilla et al. (2008)
		Region merging, region splitting.	Jain Preetha et al. (2016)
		WT, RAG, NNG, and objective heterogeneity and relative homogeneity (OHRH) for region merging.	Tzotsos et al. (2018)
		WT, objective heterogeneity (OH) for region merging.	Yang et al. (2017b)
		WT, Full Lambda-Schedule algorithm (FLSA).	Tzotsos et al. (2018)
		Random Forest (RF), region merging.	Su et al. (2020)
		Hierarchical split and merge rule (HSMR), fuzzy logic.	Wuest and Zhang (2009)
		Statistical region fusion (SRM), minimum heterogeneity rule (MHR) for object fusion.	Zhang et al. (2017c)
		Dynamic hierarchical classifier (DHC) combine TS-MRF and R-TFR.	Mikes et al. (2015)
Semantic segmentation	Machine Learning	RF, SVM, k-NN, K-means, CRF, DT, AdaBoost BN …	(Su et al., 2020), (Bialas et al., 2019), (Du et al., 2015), (Huang and Zhang, 2013)
	DL: Convolutional Neural Network (CNN)	AlexNet, ImageNet, VGGNet and their versions, GoogLeNet, ResNet, DenseNet, ShuffleNet, StixelNET, DeconvNet, MAP, R–CCN, ResNet, ZFNet …	(Zhao et al., 2017), (Punitha and Sutha, 2019), (Neupane et al., 2021), (Yuan et al., 2021), (Ma et al., 2019), (Zhu et al., 2019), (Paisitkriangkrai et al., 2015), (Borba et al., 2021), (Zang et al., 2021), (Zhang et al., 2018), (He et al., 2017), (Kemker et al., 2018), (Zhao et al., 2017)

(continued on next page)

Table 2 (*continued*)

Methods	Sub-methods	Algorithms	References
	DL:Fully Convolutional Network (FCN)	U-Net, SegNet, DeepLab and their versions, FCN and their versions, VGG and their versions, Fast-FCN …	(Zhang et al., 2020a), (Neupane et al., 2021), (Yuan et al., 2021), (Ma et al., 2019), (Zhu et al., 2019), (Borba et al., 2021), (Zang et al., 2021), (Pastorino et al., 2022), (Deng, 2019)

in this graph. Two algorithms were successfully applied to RS applications: (1) optimal forests and (2) normalized cuts. The growing interest in image segmentation using graph-based algorithms makes it a powerful tool (Wang et al., 2018b). Graph-based algorithms encounter first-order dependencies when pixels have the same distinction as adjacent regions and second-order dependencies when pixels have the same measure of variation in multiple regions. Well-performing algorithms include effective graph-based Felsenzwalb image segmentation, optimal forest coverage, and normalized cuts (Felzenszwalb and Huttenlocher, 2004). These algorithms raise the amount of data to be treated (several edges per pixel). Nevertheless, they are still useful tools, popular for their ability to visualize global features. In addition to being computationally complex, this limits their implementation in practical applications.

4.2.3. Other space-based models/algorithms

In addition to the space-based models and techniques already discussed above, Markov Random Field and the Fuzzy Model are also worth mentioning:

- **The Markov Random Field (MRF**) model is an unsupervised segmentation approach that considers spatial context, texture, and prior knowledge of interest for image modeling. See Li's book (Li, 2009) for details. Previous studies have used MRF as a segmentation model with promising results (Grinias et al., 2016), (Sarkar et al., 2002)- (Zhang et al., 2017b) (Jung et al., 2005). Nevertheless, mathematical formulas and high computing intricacy are the main disadvantages.
- **The Fuzzy Model** adds fuzzy boundaries to objects. It is derived from fuzzy clustering and fuzzy thresholding methods (Lizarazo, 2012). It is possible and easy to associate fuzzy models with most existing models, such as fuzzy MRF and fuzzy neural models or histogram thresholding (Dey et al., 2010). The decision to incorporate fuzzy models depends on the obtainable degree of segmentation complexity, and its advantage is ambiguity resolution.

4.3. Hybrid methods

Hybrid segmentation (HS) has been the subject of several works (Table 2), including using two or three segmentation methods (Su et al., 2020). It considers boundary and region information (Tzotsos et al., 2018). HS combines initial segmentation and subsequent region merging has recently received increasing (Hossain and Chen, 2019; Hanbury, 2008). Among other segmentation algorithms, the MRS algorithm is the most requested for HS (Johnson and Jozdani, 2018). It stems from several practical needs. First, consider that edge-based methods can accurately identify segment edges but often have difficulty closing them; region-based methods create closed segments but often find it challenging to delineate segment boundaries accurately (Hossain and Chen, 2019). However, HS methods overcome these limitations by combining these forces to find segment edges by employing edge-based methods and growing closed segments by region-based methods (Wang et al., 2018a; Yang et al., 2017b). For the HS approach, Chen et al. (2014) and Johnson and Xie (2011) suggested using local parameters and equally considering intra-segment homogeneity and inter-segment heterogeneity criteria. However, existing HS algorithms face some limitations, such as they usually employ a unique global parameter to supervise the region merging procedure, which limits the excellent quality of adjustment between segments and geo-objects, as homogeneous and heterogeneous segments are considered in the same way (Yang et al., 2017b) challenging to implement. HS provides better results than other approaches, uses local and global homogeneity criteria, eliminates noise effects, and has efficient seed selection.

4.4. Semantic segmentation

It is a supervised learning approach that consists in assigning each pixel a class label of its encompassing image object, assigned by ML using a set of algorithms, namely: MRF, Bayesian Network (BN), Neural Networks (NN), Nearest Neighbors (k-NN), Support Vector Machine (SVM), Active Support Vector Machine (aSVM), Decision Tree (DT), and Random Forest (RF). Deep learning improves segmentation performance, a promising approach for unsupervised image segmentation due to its ability to integrate neighborhood relationships (Neupane et al., 2021), (Wahbi et al., 2023). Especially convolutional neural networks (CNNs) (Wang et al., 2015) and fully connected networks (FCNs) have achieved remarkable results in multiple domains, as have conditional random fields (CRFs) for smooth region labeling (Paisitkriangkrai et al., 2015). Also, multiscale semantic segmentation has been implemented to address cropping issues in VHR images. However, it has some limitations, such as DL models usually require setting many parameters, which may lead to non-essential details in some image objects, provide results on low spatial resolution, and to a large extent, it is necessary to split the image into several fractions to analyze it. Moreover, blurring class boundaries and reducing object details are complex tasks. Besides FCN and CNN approaches and their derivatives, the “Segment Anything Model” (SAM) is a deep learning image segmentation model in planetary data that outperforms previous approaches. SAM was trained in 2023 in a high-quality dataset of millions of images and billions of masks, significantly larger than previous databases. It is a shape detector that focuses on circular/elliptical shapes; SAM has enormous potential as a crater detection algorithm (CDAs) and as a planetary tool for pattern recognition in general and craters in particular. For other uses and terrestrial observations, transfer learning can be successfully applied to exploit the strength of SAM (Giannakis et al., 2023). For further information on semantic methods, see reviews by Yuan et al. (2021), Ma et al. (2019).

4.5. Tools

Compared to segmentation tools, based on analysis by Kotaridis and Lazaridou (2021) in 65% of cases studies, the most used software was eCognition; this is consistent with the findings of Ma et al. (2017); among the 254 cases studied, eCognition was also used in about 81% of cases, ENVI was used in about 4%, and the other software was mainly SPRING and ERDAS. OTB/Monteverdi and ArcGIS with MSS segmentation algorithm proved good software. Lourenço et al. (2021) showed that open source software could be used to analyze VHR images like proprietary software, such as open source software OTB/Monteverdi is an excellent and cheap classification option. The emergence of a new R package named SegOptim combines various segmentation algorithms, including open source and proprietary software (GRASS GIS, Orfeo Toolbox, RSGISLib, SAGA GIS, TerraLib, ESRI ArcGIS) (Gonçalves et al., 2019). Table 3 lists some segmentation software, algorithm types, and availability.

5. Optimization, extraction and reduction feature of segmentation parameters

5.1. Optimization of segmentation parameters

This step could be attached to the deterministic part of the segmentation parameters or as the continuation of the method part since it precedes the final segmentation. It aims to 1) improve the accuracy of the results and 2) determine the optimal and appropriate parameters for segmentation. Several works have optimized segmentation parameters; Table 4 below lists the methods.

Furthermore, different combination strategies lead to different parameter optimization results. Several consulted papers prove that no single combination strategy is the best for getting suitable segmentation parameters in all cases. Therefore, the study of new combination strategies and appropriate selection methods in a specific application is also desired and a vital topic for the future (Wang et al., 2019). In this regard, future work should focus on improving object-specific optimization measures from two considerations: (1) design optimization measures to eliminate scale range limitations; (2) design class-specific optimization measures to optimize segmentation for every land use category (Zhang et al., 2020b); (3) and design a computational approach in an application or software, and general scope that optimizes the segmentation results of multiple algorithms.

5.2. Feature extraction

Image features are bridges connecting objects to semantic categories (Du et al., 2015) and are employed in training classification algorithms, with features serving as explicative variables (Kucharczyk et al., 2020). There are different features: global and local or visual and size, i.e., texture, spectrum, shape, size, context, and geometry (Grinias et al., 2016), (Dey et al., 2010). Furthermore, the characteristics of geographic objects for SITS analysis are spatiotemporal heterogeneity, spatiotemporal correlation, and scale charac-

Table 3
Different methods of segmentation and their availability in the most used software.

Tools/Software	Algorithms types	Availability	References
OTB/Monteverdi (ORFEO)	Region and edge base, pixel based.	Open sources	Toolbox (2014)
SCRM	Based on regions and edges.		Castilla et al. (2008)
InterIMAGE			Costa et al. (2010)
SAGA GIS			Böhner et al. (2006)
GRASS GIS			GRASS (2014)
SPRING			Spring-DPI (2019)
TerraLib	Region based.		Gonçalves et al. (2019)
RSGISLib			RSGISLib (2021)
eCognition	Region and edge base, pixel based.	Commercial	eCognition (2013)
ENVI	Edge based.		ENVI (2022)
IDRISSI			Gonçalves et al. (2019)
ERDAS Imagine			Li and Xiao (2007)
PCI	Region based.		PCI Geomatica (2022)
ArcGIS			Pro (2021)
InterSeg			Happ et al. (2016)
BerkeleyImgseg	Region-growing, region-merging		Imageseg. (2022) (2022)
SEGEN	Region-growing, region-based		Gofman (2006)
RHSeg	Region-growing, spectral clustering	Open sources and commercial implemented in package	Gonçalves et al. (2019)
NumPy, SciPy, Scikit-Image, Open CV, Pillow/PIL, SimpleITK, Matplotlib, Pgmagick.	Machine Learning algorithms	Open sources and commercial	Sosa-Rey et al. (2022)
Torch/PyTorch, Caffe2, CNNDroid, TensorFlow, Keras, MXNet, Microsoft Cognitive Toolkit, Theano, ONNX, DL4J, CoreML, Snapdragon, DeepLearningKit	Deep Learning architecture		(Mohammad et al., 2022), (Deng, 2019)

Table 4
Different methods used for the optimization of segmentation parameters.

Methods of optimization	References
Discrete Markov Random Field (MRF) optimization	Grinias et al. (2016)
Genetic algorithms	(Gonçalves et al., 2019), (Nikfar et al., 2012)
Fuzzy logic	Wuest and Zhang (2009)
Iterative optimization	Wang et al. (2021)
Combination of optimization techniques based on statistical Taguchi technique and F-score segmentation quality metric	Hamedianfar and Gibril (2019)
Object-specific optimization method for multi-scale hierarchical segmentation based on the binary partition tree (BPT) model	Zhang et al. (2020b)
Espindola et al. method	Espindola et al. (2006)
Optimization approach based on region fusion image segmentation error detection and correction approach, using iterative optimization model, fusion criteria, and region ownership conflict (ROC)	Wang et al. (2021)
Adaptive parameter optimization for multi-scale segmentation	Shen et al. (2019)
An unsupervised multiscale optimization method is based on an optimization indicator of local peak (LP) and global segmentation results, while local sub-segmentation regions are refined after isolation	Xiao et al. (2018)
Multi-resolution segmentation (MRS) with statistical region fusion and minimum heterogeneity rule (MHR)	Li et al. (2008)
Graph-based segmentation with MRS	Gu et al. (2018)
Novel energy function	Yang et al. (2015b)
Mean shift with spectral and spatial statistics for scale selection	Yang et al. (2014)
Regression tree model with generalizable scale parameters and SRM	Jozdani et al. (2018)
Spatial autocorrelation for scale selection and SRM	Johnson and Xie (2011)
Classification driven approach for scale selection	Dronova et al. (2012)
An adaptive approach for scale selection	Zhang et al. (2017b)
Hybrid metaheuristics approach for parameter tunnig	Quirita et al. (2016)

teristics (Xi et al., 2019). In general, features are attributes in the GIS language that can be computed from various images. There are other composite features such as Histogram of Oriented Gradients (HOG) features and their extensions, Bag of Words (BoW) features, Sparse Representation (SR) based features, and Haar-type features (Cheng and Han, 2016).

Features are used in a complementary way. Shape and size measurements are often used, referring to a multi-scale/multi-resolution image segmentation approach to delineating complex objects well (Dey et al., 2010). Moreover, it is often used in joining with spectral and texture measurements, not to mention the spatial context that defines a pixel's relationship to its neighborhood. However, few methods use context-based segmentation; otherwise, context-based segmentation and classification usually go through Markov random field. Besides, it is essential to note that geometric and texture features are more important for classification than spectral features (Du et al., 2015).

Feature extraction can be performed using filters, such as the Gabor filter (Sirmaçek and Ünsalan, 2010), which allows the extraction of local feature points. After extraction, facultative processes may be conducted to enhance the feature's performance and appearance, first fusion, then reduction, and in some cases, selection (Cheng and Han, 2016). Linear vector concatenation is a simple and largely used feature fusion technique. Some nonlinear feature fusion techniques have also been used, like heterogeneous feature machines (HFM) and the sparse multimodal learning (SMML) approach (Cheng and Han, 2016). Also, normalization is necessary to overcome bias due to scale differences.

5.3. Feature reduction

Considering the generated object's characteristics leads to process complexity, long processing time, and increased computation. Additionally, redundant features make noise, reducing classification accuracy (Lu and Weng, 2007). All these hinder the transferability of OBIA rulesets to diverse study areas and fields and require feature selection and reduction methods.

Reducing the feature space represents a way to identify and localize the most influential and essential features instead of the whole (Pedergnana et al., 2013). The reduction techniques maximize separating distances between classes by minimizing the number of input features. Supervised, semi-supervised and unsupervised methods are used for feature selection (Table 5).

Regarding metaheuristic FS techniques, Schiezaro and Pedrini (2013) mentioned that feature selection using artificial bee colony (FS ABC) performed higher than particle swarm optimization, ant colony optimization, and genetic algorithm. Furthermore, Hamedianfar et al. (Hamedianfar and Gibril, 2019) found that the same technique outperformed Chi-Square, SVM-REF, VSURF, Boruta, genetic algorithm, and Correlation-based feature selection.

Comparing these methods, the most commonly used are feature space optimization (FSO), Jeffreys-Matusita distance, CTA, RF, CART, CFS, DT distance, and Wrapper (Ma et al., 2017). Nevertheless, it is possible to use manually identified features and their combinations for further classification. So, ML methods have become famous for feature space reduction, and some researchers are reducing features using the most advantageous non-parametric ML solutions. Despite so many methods, Ma et al. (2017) observed that just 22% of research studies used space reduction, and eCognition's FSO is one of the most widely used methods. Chen et al. (2018) recorded that no consensus exists in the GEOBIA community on reducing feature space. Also, it recorded that feature space reduction can be built into a classifier. Finally, feature reduction involves selecting the most relevant features. In contrast, selection allows features or feature combinations to be ordered by importance.

Table 5
Most used methods for reduction features of segmented objects.

Approaches	Methods	References
Unsupervised feature selection	Principal component analysis (PCA)	Chen et al. (2015)
	Minimum noise fraction (MNF)	Chen et al. (2015)
	Particle swarm optimization (PSO) [a]	Alizadeh Naeini et al. (2018)
Supervised feature selection	RF	Duro et al. (2012)
	Classification and regression trees (CART)	Shahi et al. (2017)
	Classification tree analysis (CTA)	Shahi et al. (2017)
	Chi-square	Shahi et al. (2017)
	Correlation-based feature selection (CFS)	Ma et al. (2015)
	SVM with recursive feature removal (SVM-RFE)	Huang and Zhang (2013)
	Boruta	Li et al. (2017)
	Variable selection using RF (VSURF)	Georganos et al. (2018)
	Genetic algorithm (GA)	Shi et al. (2018)
	Partial least squares	Kembhavi et al. (2011)
	Linear Discriminant Analysis (LDA)	Hariharan et al. (2012)
	Ficher Discriminant Analysis	Sugiyama (2007)
	Feature space optimization (FSO)	Ma et al. (2017)
	Jeffreys-Matusita distance (JM)	Ma et al. (2017)
	Winnowing and minimum relevance maximum redundancy (mRMR)	Ma et al. (2017)
Unsupervised/Supervised feature selection	Artificial bee colony (ABC) optimization technique[a]	Belgiu and Drăguţ (2016)
	DT distance	Ma et al. (2017)
	Wrapper	Ma et al. (2017)
Semi-supervised feature selection	Ant colony optimization (ACO)[a]	Al-Ruzouq et al. (2018)

[a] Metaheuristic FS techniques.

6. Evaluation of the segmentation quality

Generally, the segmentation results will encounter over-segmentation (OS) and under-segmentation (US) anomalies. OS occurs when the image is divided into segments whose area is smaller than the segmented object, while the US is the opposite (El-naggar, 2018).

In addition to time-consuming, subjective visual interpretation with reproducible results (Van Coillie et al., 2014) and application-based indirect evaluation (Li and Xiao, 2007), qualitative evaluation of segmentation results is done by supervised and unsupervised (Fig. 7, Table 6) and geometric and non-geometric approaches (Costa et al., 2018).

Recently, the research on metrics has taken a new and more intensified dimension. Costa et al., [2018] (Costa et al., 2018) evaluated image segmentation accuracy and quality in coverage mapping applications and reviewed supervised methods and 66 metrics. Jozdani and Chen (2020). compared 21 metrics for evaluating the segmentation of buildings of different shapes.

To clarify the supervised approach, reviews from Clinton et al. (2010), Räsänen et al. (2013), Whiteside et al. (2014), (Montaghi et al., 2013), Costa et al. (2018), and Jozdani and Chen (2020) compared dozens of metrics. These reviews are beneficial for exploring image segmentation accuracy aspects and quality evaluation. On this basis, the following lessons were learned:

- There are no tested metrics to track the changes a segment undergoes across various segmentation processes. These metrics only assess the quality of the final segmentation, presenting errors or inaccuracies in the outcomes. It is highly recommended to establish metrics that store segments' information and integrate this into the computational process (Jozdani and Chen, 2020).

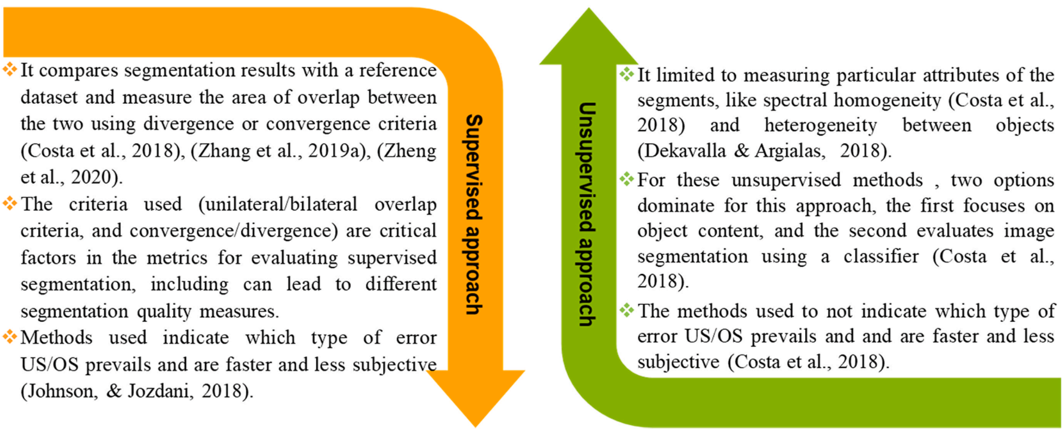

Fig. 7. Difference between supervised and unsupervised approaches for evaluating segmentation quality (Dekavalla and Argialas, 2018; Zheng et al., 2020).

Table 6
Most used metrics for evaluating segmentation quality.

Approaches	Metrics used	References
Unsupervised methods	Fuzzy classifiers.	Yang et al. (2017a)
	ESP tool.	Drăguţ et al. (2014)
	GS.	Cheng and Han (2016)
Supervised methods	Purity Index (PI).	Van Coillie et al. (2014)
	Segmentation Evaluation Index (SEI).	Yang et al. (2015b)
	Potential Segmentation Error (PSE).	(Liu et al., 2012), (Yang et al., 2015b)
	Number of Segments Ratio (NSR).	(Liu et al., 2012), (Yang et al., 2015b)
	Bilateral Overlap Index.	(Zhang et al., 2017a),
	OS.	(Costa et al., 2018), (Clinton et al., 2010), (Johnson and Jozdani, 2018), (Su and Zhang, 2017)
	US.	(Costa et al., 2018), (Clinton et al., 2010), (Johnson and Jozdani, 2018), (Su and Zhang, 2017)
	Fitness Function (F).	(Tian. and Chen, 2007), (Costa et al., 2008)
	ED2 and ED2.	(Liu et al., 2012), (Yang et al., 2015b)
	D-metric.	(Clinton et al., 2010), (Zhang et al., 2015a)
	F-measure (F-score).	(Zhang et al., 2015b), (Zhang et al., 2020b), (Johnson et al., 2015)
	Precision-recall curves.	(Zhang et al., 2015b), (Zhang et al., 2018)
	Precision and recall to measure US and OS.	(Johnson et al., 2015), (Tian. and Chen, 2007), (Zhang et al., 2020b)
	Geometric-thematic evaluation method	Costa et al. (2015)
	Area Fit Index (AFI)	(Kavzoglu and Tonbul, 2018), (Mohan Vamsee et al., 2017), (Kavzoglu and Tonbul, 2017)
	Quality Rate (Qr)	(Kavzoglu and Tonbul, 2018), (Mohan Vamsee et al., 2017), (Kavzoglu and Tonbul, 2017)

- Efficient use of ML methods is vigorously desired, especially since ML can share the robustness of supervised and unsupervised evaluation techniques and determine the most accurate segmentation method (Zhang et al., 2008a). These techniques already exist but are immature and need to be researched. For this, focusing on more general and intelligent metrics is essential. On this issue, Jozdani et al. (2018) attempted to (1) create and develop metrics that could account for the variation of unique segments crossing a reference polygon at different points; and (2) exploit the ability of machine learning algorithms to evolve more flexible, reliable, and general solutions.
- There are a large variety of metrics that capture US/OS errors, and they are not reliable. However, they can be used to understand the type of error encountered and to parameterize an algorithm. In some cases, the choice of metrics must best suit the specifics of the study. For instance, evading the US is higher precedence in some situations since previous research has proven that OS is not as harmful as the US (Wang et al., 2019), (Johnson and Jozdani, 2018).
- Combining geometric-type evaluation measures based on area and surface and those based on a position can significantly improve segmentation quality evaluation (Möller et al., 2013). Generally, these methods depend on comparing object geometry, and reference polygons are the most used (Costa et al., 2018). In this sense, many supervised methods frequently concentrate on the geometry of the evaluated objects, ignoring that a supervised but non-geometric approach can be applied (Wang et al., 2004).
- Increase the segmentation evaluation results without assigning equal weights to all sub-segmented regions/classes. This means that US error methods based on weighted classes can help assess the quality of the segmentation results. Metrics used to evaluate the segmentation results may not provide a complete picture of the segmentation performance, especially when dealing with complex scenes or multi-class segmentation. One issue with these metrics is that they treat all sub-segmented regions or classes equally, which may not accurately reflect the importance or relevance of each class or region in the application context. For instance, in a land cover classification task, some classes, such as urban areas or water bodies, maybe more critical than other classes, like grassland or forest. Therefore, giving equal weights to all sub-segmented regions/classes may not accurately reflect the overall segmentation performance. To address this issue, it is crucial to consider the relative importance of each class or region and assign weights accordingly.
- Most existing evaluation strategies concentrate exclusively on overall performance evaluation. Nevertheless, these methods could be more efficient when two segmentation outcomes with a similar global performance show various local error distributions. Recently, more studies have been turning to local evaluation or validation, focusing on evaluating each areal entity individually (Costa et al., 2018). Furthermore, quantifying the segmentation error locally and globally is the most optimistic. The method is relevant and robust, comparing many segmentation algorithms with similar overall performances (Su and Zhang, 2017).
- Although many supervised and unsupervised methods measure segmentation quality, many still consider classification results the best measure of segmentation quality (Liu and Xia, 2010). However, accurate classification accuracy does not automatically mention excellent segmentation quality (Wang et al., 2019).

In RS applications, evaluating the accuracy of image segmentation is in a relatively early stage of maturation. Information on assessments against the widespread use of visual interpretation-based qualitative assessments is generally unavailable (Kotaridis and Lazaridou, 2021). In this sense, Ye et al. (2018) reviewed various works and found that about 16% of them incorporate a method for evaluating segmentation accuracy; supervised methods are the most used for segmentation quality assessment, with 38.2% of the cases examined by Zhang et al. (2014) study. Aside from a few suggestions, no one approach dominates. The choice of an appropriate method could be more explicit. It is a complex decision requiring consideration of the advantages and disadvantages of possible methods, like facility use and bias. However, it is essential to note that there is usually no right or incorrect method. The pertinence of methods depends on their compatibility with the application in question. Moreover, there currently needs to be a standard approach to relating reference polygons to OBIA polygons; no consensus exists on which segmentation accuracy measures to apply.

7. Discussion and prospects for future research

For determining optimal segmentation parameters, unsupervised methods are objective and repeatable processes (Böck et al., 2017), efficient and fast (Wang et al., 2019) but still computationally intensive (Johnson and Jozdani, 2018). The most commonly used methods are VL, weighted variance, ALV, OBLV, spectral angle, and ESP2 tool. Otherwise, all these methods rely on a posteriori evaluation, while pre-estimating the parameters provides reliable results. Intra-segment homogeneity measures are the most used in evaluation criteria, while a balance between them and inter-segment heterogeneity measures is vigorously sought. The current trends for determining optimal segmentation parameters, especially scale, are towards adaptive scaling and scaling by a geographic object or object-specific optimization using SISs and SIOs. However, a general approach is sought, ombining classification with segmentation.

Despite all the methods and techniques discussed, determining optimal values of segmentation parameters remains a challenge, especially since segmentation is always a highly interactive process involving subjective trial and error. According to Kotaridis and Lazaridou (2021), 50% of analysts use qualitative methods to obtain optimal values for segmentation parameters for their research, which generates problems later on. In addition, there is no ideal spatial scale for feature analysis and identification. Moreover, all existing segmentation algorithms treat scale differently. We expect that advances in segmentation-scale processing to generate meaningful image objects will progress rapidly.

It should be noted that it is difficult to portray the heterogeneity of many diverse image objects in complex scenes with a unique local or global parameter value. Otherwise, future segmentation optimization methods based on individual image objects rather than larger scales can improve segmentation techniques and results. Recommendations for parameter determination have been reworded as follows:

- Comparison of future trending methods (object-level optimization) to local and global scale approaches;
- Multi-level hierarchical segmentation for capturing image objects of different sizes and classes is desirable;

Moreover, there is interest in transfer learning (Tuia et al., 2016) and active learning (Persello and Bruzzone, 2012), recognized as potential methods. Kemker et al. (2018) and Ma et al. (2019) pointed out that further exploration should be made to improve semantic segmentation networks in the future (Zhang et al., 2018), (Zhu et al., 2018). Finally, it is observed that despite the variety of methods existent, there needs to be more universality of methods or algorithms in various applications (Liu et al., 2017). Although different robust segmentation algorithms are emerging, producing wanted segments that correspond to real-world objects is still challenging. This issue is mainly due to the variation in image features that limits the transferability of segmentation parameters (Johnson and Jozdani, 2018).

Optimization is a step related to determining of segmentation parameters and segmentation methods. The optimization suggestions are as follows:

- The use of statistical or application-based approaches at the software level to optimize the segmentation parameters is recommended;
- Future work on improving the object-specific optimization metrics should focus on two key components: (1) designing optimization metrics to remove the scale range constraints and; (2) developing class-specific optimization metrics to optimize segmentations for each land cover class;
- Researchers list the limitation of comparison between software-integrated segmentation optimization and new object-scale approaches (Zhang et al., 2020a).

For the evaluation of segmentation quality, there are various methods. For making an appropriate, suitable, and optimal choice, it is necessary to establish some criteria, namely: (1) the research study purpose; (2) the relative significance of the US and OS error; and (3) the advantages and disadvantages of potentials methods (Costa et al., 2018). In addition, several works of literature and comparisons have focused on all evaluation methods, including simple and compound methods. From all reviewed studies, D-measure, F-measure, and ED2 were found to describe over/under-segmentation errors and provide reliable results for assessing segmentation quality. However, some studies have reported that various methods can show very different segmentation results as optimal (Jozdani and Chen, 2020; Räsänen et al., 2013).

Moreover, the lessons learned are well articulated in the evaluation section (Section 6). Finally, it should be mentioned that the estimated bias in the assessment of image segmentation accuracy is not only due to an inappropriate choice of methods or their potential shortcomings but also due to the protocol used for implementation, including the baseline data to be acquired, the use of probabilistic sample design, the type of sample (Olofsson et al., 2014), (Costa et al., 2018). These methods are at an early stage of maturity, so research and comparisons are needed in this direction.

One of the main challenges is that the current segmentation quality assessment which is often based on geometrically definable objects. While these features like buildings are important for certain applications, they represent only a small portion of the segmentation or classification problem. Therefore, relying solely on buildings as a metric for assessing segmentation quality may not capture the full complexity and variability of land cover patterns. Therefore, the segmentation quality assessment in OBIA requires significant improvement to enhance the accuracy and reliability of results. Shifting the focus from geometrically definable land use features to a broader consideration of land cover features is necessary to capture the complexity of the Earth's surface, including vegetation, water bodies, roads, agricultural fields, and natural landforms, the assessment can provide a more comprehensive evaluation of the segmentation quality and its ability to capture the spatial patterns of different land cover types (Jozdani and Chen, 2020). Additionally, the development of tools to analyze polygon similarities and the establishment of benchmark datasets contribute to advancing segmentation quality assessment; in fact, current metrics for analyzing polygon similarities often fail to capture the intricacies of polygon similarities comprehensively. Therefore, the field urgently needs refined metrics and tools that can assess the smoothness of object boundaries, the cohesion of objects within the same class, and the separation between different classes. This can foster advancements in segmentation techniques and promote the development of more accurate and reliable segmentation approaches. By addressing these challenges, the field can achieve more effective and informed analysis of remotely sensed data, facilitating applications in land cover mapping, change detection, and environmental monitoring (Ye et al., 2018).

Future research needs and perspectives on the overview are assigned in the following points:

- Determination and optimal selection of segmentation parameters are the pillars leading to good segmentation (Wang et al., 2019); current methods require to be compared with conventional methods, and improving the accuracies of these methods requires fruitful research in this direction;
- Segmentation methods must balance intra-segment homogeneity with inter-segment heterogeneity. However, studies comparing these segmentation optimization processes still need to be included. Therefore, future research in this direction is warranted.
- Future work should focus on finding better approaches without seeds or just methods for segmentation based on region growth, even when seeds are present.
- Edge-based approaches need to be improved in detecting textured objects; they should be based on local data and important larger-scale contextual information already lacking.
- Semantic segmentation represents a promising avenue, and other ML classifiers and fusion criteria need to be investigated to determine if they can enhance the segmentation performance. Furthermore, different images, including SAR or hyper-spectral data and images of diverse geocontents, should be tested with innovative and more advanced techniques (Su et al., 2020).
- The main research trend in OBIA in all these phases is toward deep learning; in this case, GEOCNNs, "Geographic Object convolutional neural networks," are a new form of GEOBIA (Liu et al., 2018), (Timilsina et al., 2019). This research will increasingly focus on stimulating innovation, proving and assessing multiple GEOCNN (multi-scale) approaches, and comparing them with conventional or deep learning OBIA methods such as CNN, FCN, and Mask R–CNN, considering thematic accuracy and segmentation accuracy. Also, transfer learning can handle massive training data required by DL methods (Pastorino et al., 2022) or by creating synthetic images from small training sets, data augmentation techniques, and using semi-supervised learning (Kemker et al., 2018).
- Some of the most promising current developments, e.g., Meta AI's Segment Anything, uses deep learning algorithms on the largest segmentation dataset (Giannakis et al., 2023).
- Achieving good accuracy using DL requires 1) multi-scale combination by using a multi-scale strategy such as MCCN, 2) fusion of data from different modalities by using multiple architectures or other data (MNE), 3) segmentation enhancement obtained by post-processing techniques (morphological smoothing, conditional random fields), and 4) the loss function to detect semantic boundaries (Yuan et al., 2021).
- Quantitative comparative studies of segmentation quality assessment methods should be conducted to comprehensively test and compare supervised methods employed in the RS community. Non-geometric methods should be inspected as they are ignored in quantitative studies.
- The relationship between segmentation and classification accuracy must be deeply investigated, as this relationship is often clear (Verbeeck et al., 2012), (Costa et al., 2017).
- Another fruitful research direction is to improve the description of contextual information from adjacent image objects. Proposals have been made for a geographic object-based image texture (GEOTEX), which treats each image object and its neighbors as a natural window/kernel to compute a new set of texture measures (Chen et al., 2018).
- The concept of OS/US error needs to be reevaluated, especially since original objects have more spectral than thematic meaning and impact the evaluation, and consider new approaches that can better account for contextual information, overcome the limitations of segmentation algorithms, and provide more nuanced evaluation metrics; even the selection of supervised or unsupervised evaluation approaches that frequently concentrate on thematic and primitive objects should receive more attention (Blaschke et al., 2014), (Ma et al., 2017).

The future of OBIA is indeed closely tied to the advancements in DL. DL models offer several advantages in various levels: 1) for segmentation, DL models can automatically learn and capture intricate patterns and relationships in the data (Neupane et al., 2021; Yuan et al., 2021), (Zhang et al., 2018). This can lead to more accurate and detailed object boundaries, resulting in improved segmentation results; 2) for dimensionality reduction, DL models can learn relevant features and perform automatic dimensionality reduction by extracting the most informative representations from the data (Zhao and Du, 2016). This can help to reduce computational complexity and to improve classification performance by focusing on the most discriminative features; 3) for classification: DL models can also be used for object classification in OBIA, the ability of DL models to capture complex and hierarchical relationships in the data can improve classification accuracy, especially when dealing with diverse and heterogeneous landscapes (Zhang et al., 2020a), (Wahbi et al., 2023). Furthermore, the integration of DL with OBIA can enable the incorporation of multi-scale and multi-sensor data, including high-resolution imagery, LiDAR data, and hyperspectral data. This integration allows for more comprehensive and accurate analysis by leveraging the complementary information from different sources. However, it's important to note that DL approaches for OBIA require large amounts of labeled training data, which can be a challenge in RS due to the cost and time required for data acquisition and annotation (Wang et al., 2015). Additionally, the interpretability of deep learning models is often lower compared to traditional OBIA approaches, which can make it difficult to understand the reasons behind their predictions (Borba et al., 2021), (Ma and Manjunath, 2000).

Finally, several recent studies combine the segmentation step simultaneously or iteratively under GE (CBS), which is important for OBIA workflows (Gonçalves et al., 2019), (Zanotta et al., 2018), (Chini et al., 2014). CBS allows optimizing both processes and exempts it from the choice of segmentation parameters with many other advantages. Some restrictions manifest as a specific combination of image segmentation and classification algorithms unsuitable for all tasks/targets (Gonçalves et al., 2019).

8. Conclusion

This paper was motivated by the popularity of OBIA in RS, and it reviews all segmentation steps, highlighting the advantages and shortcomings of all the methods used for each step and highlighting prospects and needs for future research. Meanwhile, a new classification of segmentation methods is proposed by time scale, which reveal the evolution history and trend based on their internal relations. Scholars have made many contributions, but it is still difficult to generate the physically desired segments corresponding to semantically real objects; furthermore, objects in high-resolution images consist of non-uniform regions, resulting in poor segmentation needing to be optimized urgently. Several recent approaches that are able to improve segmentation performance to a certain extent, such as collaborative classification segmentation, self-adaptive scaling segmentation methods, and hybrid approach, especially combining DL with OBIA under interpretability guidance of Geographical Law, and using object surfaces to guide the segmentation process, can be valuable.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

No data was used for the research described in the article.

Acknowledgment

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Appendix 1

Acronyms list

ABC	:	Artificial bee colony
ACO	:	Ant colony optimization
AISP	:	Adaptive increasing scale parameter
aSVM	:	Active Support Vector Machine
AVL	:	Average local variance
BN	:	Bayesian Network
BoW	:	Bag of Words
BPT	:	Binary partition tree
BSH	:	Between-segment heterogeneity
BSP	:	Binary space partitioning
CART	:	Classification and regression trees
CBS	:	Classification-based segmentation
CDAs	:	Crater detection algorithms
CFS	:	Correlation-based feature selection
CNNs	:	Convolutional neural networks
CRFs	:	Conditional random fields
CTA	:	Classification tree analysis
DHC	:	Dynamic hierarchical classifier
DL	:	Deep Learning
DT	:	Decision Tree
ED	:	Euclidean distance
ESP	:	Estimation Scale Parameters
F	:	Fitness Function

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ABC	:	Artificial bee colony
FCNs	:	Fully connected networks
FLSA	:	Full Lambda-Schedule algorithm
FNEA	:	Fractal Net Evolution Approach
FSAM	:	Fast scan algorithm merging
FSO	:	Feature space optimization
GA	:	Genetic algorithm
GBM	:	Global Best Merging
GEOCNNs	:	Geographic object-based convolutional neural networks
GEOTEX	:	Geographic object-based image texture
GIS	:	Geographic information system
GLCM	:	Grey Level Co-occurrence Matrix
GS	:	Global score
HFM	:	Heterogeneous feature machines
HOG	:	Histogram of Oriented Gradients
HS	:	Hybrid segmentation
HSMR	:	Hierarchical split and merge region
HSWO	:	Hierarchical stepwise optimization
HW	:	Hierarchical Watershed
K-NN	:	Nearest Neighbors
LBM	:	Local Best Merging
LDA	:	Linear Discriminant Analysis
LiDAR	:	Light detection and ranging
LMM	:	Local Mutual-best Merging
LV	:	Local variance
LVR	:	Local variance ratio
Mask R–CNN	:	Mask Region-CNN
MHR	:	Minimum heterogeneity rule
ML	:	Machine Learning
MNF	:	Minimum noise fraction
MRF	:	Markov Random Field
mRMR	:	Minimum relevance maximum redundancy
MS	:	Mean shift
NN	:	Neural Networks
NSR	:	Number of Segments Ratio
OBIA	:	Object-based image analysis
OBLV	:	Object boundary local variance
OG	:	Overall goodness
OH	:	Objective heterogeneity
OHRH	:	Objective heterogeneity and relative homogeneity
OS	:	Over-segmentation
PCA	:	Principal component analysis
PI	:	Purity Index
PIPs	:	Physical image parcels
PSE	:	Potential Segmentation Error
PSO	:	particle swarm optimization
RAG	:	Region Adjacency Graph
RF	:	Random Forest
RHseg	:	Recursive hierarchical segmentation
RISA	:	Region-based Image Segmentation Algorithm
ROC	:	Region ownership conflict
ROCLV	:	Rates of change of local variance
RS	:	Remote sensing
RT	:	Regression tree
R-TFR	:	Recursive-TFR
SA	:	Spectral Angle
SAM	:	Spectral Angle Mapper
SAM	:	Segment Anything Model
SAR	:	Synthetic aperture radar
SEI	:	Segmentation Evaluation Index
SIOs	:	Semantic image objects
SITS	:	Satellite image time series
SMML	:	Sparse multimodal learning
SOTA	:	State of the art
SP	:	Scale parameter
SR	:	Sparse Representation

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ABC	:	Artificial bee colony
SRG	:	Seeded region growth
SRM	:	Statistical region fusion
ST-MRS	:	Spatio-temporal multiresolution segmentation
SVM	:	Support Vector Machine
SWSP	:	Step-Wise Scale Parameter
TFR	:	Texture Fragmentation and Reconstruction
TS-MRF	:	Tree-Structured Markov Random Field
UAV	:	Unmanned aerial vehicle
US	:	Under-segmentation
USPO	:	Unsupervised scale parameter optimization
VHR	:	Very high-resolution
VSURF	:	Variable selection using RF
WSH	:	Within-segment homogeneity
WT	:	Watershed transform
WV	:	Weighted variance

Appendix 2

Title	Authors	Paper Type	Publication Year	Journal
Optimal segmentation of high spatial resolution images for the classification of buildings using random forests	James Bialas, Thomas Oommen, Timothy C. Havens	Research paper	2019	Int J Appl Earth Obs Geoinformation
Geographic Object-Based Image Analysis – Towards a new paradigm	Thomas Blaschke, Geoffrey J. Hay, Maggi Kelly, Stefan Lang, Peter Hofmann, Elisabeth Addink, Raul Queiroz Feitosa, Freek van der Meer, Harald van der Werff, Frieke van Coillie, Dirk Tiede	Research paper	2014	ISPRS Journal of Photogrammetry and Remote Sensing
Optimal segmentation of a high resolution remote-sensing image guided by area and boundary	Jie Chen, Min Deng, Xiaoming Mei, Tieqiao Chen, Quanbin Shao & Liang Hong	Research paper	2014	International Journal of Remote Sensing
Geographic Object-based Image Analysis (GEOBIA): Emerging trends and future opportunities	Gang Chen, Qihao Weng, Geoffrey J. Hay & Yinan He	Research paper	2018	GIScience & Remote Sensing
A survey on object detection in optical remote sensing images	Gong Cheng, Junwei Han	Review paper	2016	ISPRS Journal of Photogrammetry and Remote Sensing
Supervised methods of image segmentation accuracy assessment in land cover mapping	Hugo Costa, Giles M. Foody, Doreen S. Boyd	Review paper	2018	Remote Sensing of Environment
Semantic classification of urban buildings combining VHR image and GIS data: An improved random forest approach	Shihong Du, Fangli Zhang, Xiuyuan Zhang	Research paper	2015	ISPRS Journal of Photogrammetry and Remote Sensing
Determination of optimum segmentation parameter values for extracting building from remote sensing images	Aly M. El-naggar	Review paper	2018	Alexandria Engineering Journal
Parameter selection for region-growing image segmentation algorithms using spatial autocorrelation	G. M. Espindola, G. Camara, I. A. Reis, L. S. Bins & A. M. Monteiro	Research paper	2006	International Journal of Remote Sensing
Large-scale urban mapping using integrated geographic object-based image analysis and artificial bee colony optimization from worldview-3 data	Alireza Hamedianfar & Mohamed Barakat A. Gibril	Research paper	2019	International Journal of Remote Sensing
Segmentation for Object-Based Image Analysis (OBIA): A Review paper of algorithms and challenges from remote sensing perspective	Mohammad D. Hossain, Dongmei Chen	Review paper	2019	ISPRS Journal of Photogrammetry and Remote Sensing
Unsupervised image segmentation evaluation and refinement using a multi-scale approach	Brian Johnson, Zhixiao Xie	Research paper	2011	ISPRS Journal of Photogrammetry and Remote Sensing
Image Segmentation Parameter Optimization Considering Within- and Between-Segment Heterogeneity at Multiple Scale Levels: Test Case for Mapping Residential Areas Using Landsat Imagery	Brian A. Johnson, Milben Bragais, Isao Endo, Damasa B. Magcale-Macandog and Paula Beatrice M. Macandog	Research paper	2015	ISPRS International Journal of Geo-Information
Identifying Generalizable Image Segmentation Parameters for Urban Land Cover Mapping through Meta-Analysis and Regression Tree Modeling	Brian A. Johnson, and Shahab E. Jozdani	Research paper	2018	remote sensing

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Title	Authors	Paper Type	Publication Year	Journal
On the versatility of popular and recently proposed supervised evaluation metrics for segmentation quality of remotely sensed images: An experimental case study of building extraction	Shahab Jozdani, Dongmei Chen	Research paper	2020	ISPRS Journal of Photogrammetry and Remote Sensing
Remote sensing image segmentation advances: A meta-analysis	Ioannis Kotaridis, Maria Lazaridou	Review paper	2021	ISPRS Journal of Photogrammetry and Remote Sensing
Geographic Object-Based Image Analysis: A Primer and Future Directions	Maja Kucharczyk, Geo rey J. Hay, Salar Gha arian and Chris H. Hugenholtz	Review paper	2020	remote sensing
Scale computation on high spatial resolution remotely sensed imagery multiscale segmentation	Jianhua Liu, Mingyi Du & Zhengyuan Mao	Research paper	2017	International Journal of Remote Sensing
An adaptive scale estimating method of multiscale image segmentation based on vector edge and spectral statistics information	Jianhua Liu, Heng Pu, Shiran Song & Mingyi Du	Research paper	2018	International Journal of Remote Sensing
Object-based land surface segmentation scale optimization: An ill-structured problem	Gerrit Louw, Adriaan van Niekerk	Research paper	2019	Geomorphology
A Review paper of supervised object-based land-cover image classification	Lei Ma, Manchun Li, Xiaoxue Mac, Liang Cheng, Peijun Du, Yongxue Liu	Review paper	2017	ISPRS Journal of Photogrammetry and Remote Sensing
Deep learning in remote sensing applications: A meta-analysis and Review paper	Lei Ma, Yu Liu, Xueliang Zhang, Yuanxin Ye, Gaofei Yin, Brian Alan Johnson	Review paper	2019	ISPRS Journal of Photogrammetry and Remote Sensing
Benchmarking of Remote Sensing Segmentation Methods	Stanislav Mikeš, Michal Haindl, Giuseppe Scarpa, and Raffaele Gaetano	Research paper	2015	IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING
Scale parameter selection by spatial statistics for GeOBIA: Using mean-shift based multi-scale segmentation as an example	Dongping Ming, Jonathan Li, Junyi Wang, Min Zhang	Research paper	2015	ISPRS Journal of Photogrammetry and Remote Sensing
Deep Learning-Based Semantic Segmentation of Urban Features in Satellite Images: A Review paper and Meta-Analysis	Bipul Neupane, Teerayut Horanont and Jagannath Aryal	Review paper	2021	remote sensing
Optimizing multiscale segmentation with local spectral heterogeneity measure for high resolution remote sensing images	Yu Shen, Jianyu Chen, Liang Xiao, Delu Pan	Research paper	2019	ISPRS Journal of Photogrammetry and Remote Sensing
Review paper of Road Segmentation for SAR Images	Zengguo Sun, Hui Geng, Zheng Lu, Rafał Scherer and Marcin Wo'zniak	Review paper	2021	remote sensing
Image segmentation algorithms for land categorization	James C. Tilton, Selim Aksoy and Yuliya Tarabalka	chapter	2015	Book: Remotely Sensed Data Characterization, Classification, and Accuracies
Unsupervised segmentation parameter selection using the local spatial statistics for remote sensing image segmentation	Yongji Wang, Qingwen Qi, Ying Liu, Lili Jiang, Jun Wang	Research paper	2019	Int J Appl Earth Obs Geoinformation
Variational-Scale Segmentation for Multispectral Remote-Sensing Images Using Spectral Indices	Ke Wang, Hainan Chen, Ligang Cheng and Jian Xiao	Research paper	2022	remote sensing
An Automated Method to Parameterize Segmentation Scale by Enhancing Intrasegment Homogeneity and Intersegment Heterogeneity	Jian Yang, Yuhong He, and Qihao Weng	Research paper	2015	IEEE Geoscience and Remote Sensing Letters
A Review paper of deep learning methods for semantic segmentation of remote sensing imagery	Xiaohui Yuan, Jianfang Shi, Lichuan Gu	Review paper	2021	Expert Systems With Applications
Land-Use Mapping for High-Spatial Resolution Remote Sensing Image Via Deep Learning: A Review paper	Ning Zang, Yun Cao, Yuebin Wang, Bo Huang, Liqiang Zhang, and P. Takis Mathiopoulos	Review paper	2021	IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING
An Unsupervised Evaluation Method for Remotely Sensed Imagery Segmentation	Xueliang Zhang, Pengfeng Xiao, and Xuezhi Feng	Research paper	2012	IEEE Geoscience and Remote Sensing Letters
A Review paper of Researches on Deep Learning in Remote Sensing Application	Ming Zhu, Yongning He, Qingyu He	Review paper	2019	International Journal of Geosciences
Object based image analysis for remote sensing	T. Blaschke	Review paper	2010	ISPRS Journal of Photogrammetry and Remote Sensing
On the Objectivity of the Objective Function—Problems with Unsupervised Segmentation Evaluation Based on Global Score and a Possible Remedy	Sebastian Böck, Markus Immitzer and Clement Atzberger	Letter	2017	remote sensing

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Title	Authors	Paper Type	Publication Year	Journal
SegOptim—A new R package for optimizing object-based image analyses of high-spatial resolution remotely-sensed data	João Gonçalves, Isabel Pôças, Bruno Marcos, C.A. Mücher, João P. Honrado	Research paper	2019	Int J Appl Earth Obs Geoinformation
Integrating User Needs on Misclassification Error Sensitivity into Image Segmentation Quality Assessment	Hugo Costa, Giles M. Foody, and Doreen S. Boyd	Research paper	2015	Photogrammetric Engineering and Remote Sensing
Automated parameterization for multi-scale image segmentation on multiple layers	L. Drăgut, O. Csillik, C. Eisank, D. Tiede	Research paper	2014	ISPRS Journal of Photogrammetry and Remote Sensing
Classifying a high resolution image of an urban area using super-object information	Brian Johnson, Zhixiao Xie	Research paper	2013	ISPRS Journal of Photogrammetry and Remote Sensing
Algorithms for semantic segmentation of multispectral remote sensing imagery using deep learning	Ronald Kemker, Carl Salvaggio, Christopher Kanan	Research paper	2018	ISPRS Journal of Photogrammetry and Remote Sensing
A systematic comparison of different object-based classificationtechniques using high spatial resolution imagery in agriculturalenvironments	Manchun Li, Lei Ma, Thomas Blaschke, Liang Cheng, Dirk Tiede	Research paper	2016	International Journal of Applied Earth Observation and Geoinformation
A new segmentation method for very high resolution imagery using spectral and morphological information	Jing Liu, Peijun Li, Xue Wang	Research paper	2015	ISPRS Journal of Photogrammetry and Remote Sensing
Quantitative land cover change analysis using fuzzy segmentation	Ivan Lizarazo	Research paper	2012	International Journal of Applied Earth Observation and Geoinformation
Assessing the performance of different OBIA software approaches for mapping invasive alien plants along roads with remote sensing data	P. Lourenço, A.C. Teodoro, J.A. Gonçalves, J.P. Honrado, M. Cunha, N. Sillero	Research paper	2021	International Journal of Applied Earth Observation and Geoinformation
Object-oriented analysis of multi-temporal panchromatic images for creation of historical landslide inventories	Tapas R. Martha, Norman Kerle, Cees J. van Westen, Victor Jetten, K. Vinod Kumar	Research paper	2012	ISPRS Journal of Photogrammetry and Remote Sensing
Optimization of multiresolution segmentation by using a genetic algorithm	Maryam Nikfar, Mohammad Javad Valadan Zoej, Ali Mohammadzadeh, Mehdi Mokhtarzade, Afshin Navabi	Research paper	2012	Journal of Applied Remote Sensing
Semantic Segmentation of Remote Sensing Images through Fully Convolutional Neural Networks and Hierarchical Probabilistic Graphical Models	Martina Pastorino, Gabriele Moser, Sebastiano B. Serpico, and Josiane Zerubia	Research paper	2022	IEEE Transactions on Geoscience and Remote Sensing
Direct, ECOC, ND and END Frameworks—Which One Is the Best? An Empirical Study of Sentinel-2A MSIL1C Image Classification for Arid-Land Vegetation Mapping in the Ili River Delta, Kazakhstan	Alim Samat, Naoto Yokoya, Peijun Du, Sicong Liu, Long Ma, Yongxiao Ge, Gulnura Issanova, Abdula Saparov, Jilili Abuduwaili and Cong Lin	Research paper	2019	remote sensing
Machine learning-assisted region merging for remote sensing image segmentation	Tengfei Su, Tingxi Liu, Shengwei Zhang, Zhongyi Qu, Ruiping Li	Research paper	2020	ISPRS Journal of Photogrammetry and Remote Sensing
Local and global evaluation for remote sensing image segmentation	Tengfei Su, Shengwei Zhang	Research paper	2017	ISPRS Journal of Photogrammetry and Remote Sensing
Geostatistical modelling of spatial dependence in area-class occurrences for improved object-based classifications of remote-sensing images	Yunwei Tang, Jingxiong Zhang, Linhai Jing, Han Gao	Research paper	2018	ISPRS Journal of Photogrammetry and Remote Sensing
Applying object-based segmentation in the temporal domain to characterise snow seasonality	Jeffery A. Thompson, Brian G. Lees	Research paper	2014	ISPRS Journal of Photogrammetry and Remote Sensing
A Spectral Band Based Comparison of Unsupervised Segmentation Evaluation Methods for Image Segmentation Parameter Optimization	Hasan TOMBUL, Taşkın KAVZOĞLU	Research paper	2020	International Journal of Environment and Geoinformatics (IJEGEO)
Gully mapping using geographic object-based image analysis: A case study at catchment scale in the Brazilian Cerrado	Alex Garcez Utsumi, Teresa Cristina Tarl'e Pissarra, David Luciano Rosalen, Marcílio Vieira Martins Filho, Luiz Henrique Silva Rotta	Research paper	2020	Remote Sensing Applications: Society and Environment
External geo-information in the segmentation of VHR imagery improves the detection of imperviousness in urban neighborhoods	Klaartje Verbeeck, Martin Hermy, Jos Van Orshoven	Research paper	2012	International Journal of Applied Earth Observation and Geoinformation

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Title	Authors	Paper Type	Publication Year	Journal
A scale self-adapting segmentation approach and knowledge transfer for automatically updating land use/cover change databases using high spatial resolution images	Zhihua Wang, Xiaomei Yanga, Chen Lu, Fengshuo Yang	Research paper	2018	Int J Appl Earth Obs Geoinformation
Region Merging ConsideringWithin- and Between-Segment Heterogeneity: An Improved Hybrid Remote-Sensing Image Segmentation Method	Yongji Wang, Qingyan Meng, Qingwen Qi, Jian Yang and Ying Liu	Research paper	2018	remote sensing
Improvement of Region-Merging Image Segmentation Accuracy Using Multiple Merging Criteria	Haoyu Wan, Zhanfeng Shen, Zihan Zhang, Zeyu Xu, Shuo Li, Shuhui Jiao and Yating Lei	Research paper	2021	remote sensing
Evaluation of data fusion and image segmentation in earth observation based rapid mapping workflows	Chandi Witharana, Daniel L. Civco, Thomas H. Meyer	Research paper	2014	ISPRS Journal of Photogrammetry and Remote Sensing
Optimizing multi-resolution segmentation scale using empirical methods: Exploring the sensitivity of the supervised discrepancy measure Euclidean distance 2 (ED2)	Chandi Witharana, Daniel L. Civco	Research paper	2014	ISPRS Journal of Photogrammetry and Remote Sensing
A spatiotemporal cube model for analyzing satellite image time series: Application to land-cover mapping and change detection	Wenqiang Xi, Shihong Dua, Yi-Chen Wang, Xiuyuan Zhang	Research paper	2019	Remote Sensing of Environment
Multiscale Optimized Segmentation of Urban Green Cover in High Resolution Remote Sensing Image	Pengfeng Xiao, Xueliang Zhang, Hongmin Zhang, Rui Hu and Xuezhi Feng	Research paper	2018	remote sensing
A discrepancy measure for segmentation evaluation from the perspective of object recognition	Jian Yang, Yuhong He, John Caspersen, Trevor Jones	Research paper	2015	ISPRS Journal of Photogrammetry and Remote Sensing
Region merging using local spectral angle thresholds: A more accurate method for hybrid segmentation of remote sensing images	Jian Yang, Yuhong He, John Caspersen	Research paper	2017	Remote Sensing of Environment
A Scale - Synthesis Method for High Spatial Resolution Remote Sensing Image Segmentation	Lina Yi, Guifeng Zhang, and Zhaocong Wu	Research paper	2012	IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING
A supervised approach for simultaneous segmentation and classification of remote sensing images	Daniel Capella Zanottaa, Maciel Zortea, Matheus Pinheiro Ferreira	Research paper	2018	ISPRS Journal of Photogrammetry and Remote Sensing
Multi-scale Segmentation of High-Spatial Resolution Remote Sensing Images Using Adaptively Increased Scale Parameter	Xueliang Zhang, Xuezhi Feng, and Pengfeng Xiao	Research paper	2015	Photogrammetric Engineering and Remote Sensing
Segmentation quality evaluation using region-based precision and recall measures for remote sensing images	Xueliang Zhang, Xuezhi Feng, Pengfeng Xiao, Guangjun He, Liujun Zhu	Research paper	2015	ISPRS Journal of Photogrammetry and Remote Sensing
Toward combining thematic information with hierarchical multiscale segmentations using tree Markov random field model	Xueliang Zhang, Pengfeng Xiao, Xuezhi Feng	Research paper	2017	ISPRS Journal of Photogrammetry and Remote Sensing
Another look on region merging procedure from seed region shift for high-resolution remote sensing image segmentation	Xueliang Zhanga, Pengfeng Xiao, Xuezhi Feng, Guangjun He	Research paper	2019	ISPRS Journal of Photogrammetry and Remote Sensing
Identifying and mapping individual plants in a highly diverse high-elevation ecosystem using UAV imagery and deep learning	Ce Zhang, Peter M. Atkinson, Charles George, Zhaofei Wen, Mauricio Diazgranados, France Gerard	Research paper	2020	ISPRS Journal of Photogrammetry and Remote Sensing
Object-specifi optimization of hierarchical multiscale segmentations for high-spatial resolution remote sensing images	Xueliang Zhang, Pengfeng Xiao, Xuezhi Feng	Research paper	2020	ISPRS Journal of Photogrammetry and Remote Sensing
Contextually guided very-high-resolution imagery classification with semantic segments	Wenzhi Zhao, Shihong Du, Qiao Wang, William J. Emery	Research paper	2017	ISPRS Journal of Photogrammetry and Remote Sensing
A multiscale approach to delineate dune-field landscape patches	Zhijia Zheng, Shihong Du, Shouji Du, Xiuyuan Zhang	Research paper	2020	Remote Sensing of Environment
Image Processing Techniques for Analysis of Satellite Images for Historical Maps Classification—An Overview	Anju Asokan, J. Anitha, Monica Ciobanu, Andrei Gabor, Antoanela Naaji and D. Jude Hemanth	Review paper	2020	applied sciences
MRF-based segmentation and unsupervised classification for building and road detection in peri-urban areas of high-resolution satellite images	Ilias Grinias, Costas Panagiotakis, Georgios Tziritas	Research paper	2016	ISPRS Journal of Photogrammetry and Remote Sensing
An object-based image analysis approach for detecting penguin guano in very high spatial resolution satellite images	Chandi Witharana, andHeather J. Lynch	Research paper	2016	remote sensing

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Title	Authors	Paper Type	Publication Year	Journal
ESP: a tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data	Lucian Dragut, Dirk Tiedec and Shaun R. Levick	Research paper	2010	International Journal of Geographical Information Science
Semivariogram-based spatial bandwidth selection for remote sensing image segmentation with mean-shift algorithm	Dongping Ming, Tianyu Ci, Hongyue Cai, Longxiang Li, Cheng Qiao, Jinyang Du	Research paper	2012	IEEE Geoscience and Remote Sensing Letters
A local approach to optimize the scale parameter in multiresolution segmentation for multispectral imagery	F. Cánovas-García & F. Alonso-Sarría	Research paper	2015	Geocarto International
Scale-variable region-merging for high resolution remote sensing image segmentation	Tengfei Su	Research paper	2019	ISPRS Journal of Photogrammetry and Remote Sensing
Efficient graph-based image segmentation	Pedro F. Felzenszwalb	Research paper	2004	International Journal of Computer Vision
A Multi-Band Approach to Unsupervised Scale Parameter Selection for Multi-Scale Image Segmentation	Jian Yang, Peijun Li, Yuhong He	Research paper	2014	ISPRS Journal of Photogrammetry and Remote Sensing
Scale Object Selection (SOS) through a Hierarchical Segmentation by a Multi-Spectral Per-Pixel Classification	Marco Chini, Alessandro Chiancone, Salvatore Stramondo	Research paper	2014	Pattern Recognition Letters
A regression modelling approach for optimizing segmentation scale parameters to extract buildings of different sizes	Shahab E. Jozdani, Mehdi Momeni, Brian A. Johnson & Mehran Sattari	Research paper	2018	International Journal of Remote Sensing
Region based segmentation of QuickBird multispectral imagery through band Ratios and fuzzy comparison	Ben Wuest, Yun Zhang	Research paper	2009	ISPRS Journal of Photogrammetry and Remote Sensing
A MRF model-based segmentation approach to classification for multispectral imagery	A. Sarkar, M.K. Biswas, B. Kartikeyan, V. Kumar, K.L. Majumder, D.K. Pal	Research paper	2002	IEEE Transactions on Geoscience and Remote Sensing
Size-constrained region merging (SCRM): an automated delineation tool for assisted photointerpretation	Guillermo Castilla, Geoffrey J Hay, José Reyes Ruiz-Gallardo	Research paper	2008	Photogrammetric Engineering and Remote Sensing
Multispectral image segmentation by a multichannel watershed-based approach	P. Li, X. Xiao	Research paper	2007	International Journal of Remote Sensing
An efficient parallel multi-scale segmentation method for remote sensing imagery	Haiyan Gu, Yanshun Han, Yi Yang, Haitao Li, Zhengjun Liu, Uwe Soergel, Thomas Blaschke and Shiyong Cu	Research paper	2018	remote sensing
A Novel Technique for Optimal Feature Selection in Attribute Profiles Based on Genetic Algorithms	Mattia Pedergnana, Prashanth Reddy Marpu, Mauro Dalla Mura, Jón Atli Benediktsson, Lorenzo Bruzzone	Research paper	2013	IEEE Transactions on Geoscience and Remote Sensing
Image segmentation based on constrained spectral variance difference and edge penalty	Bo Chen, Fang Qiu, Bingfang Wu and Hongyue Du	Research paper	2015	remote sensing
Fusion of images and point clouds for the semantic segmentation of large-scale 3D scenes based on deep learning	Rui Zhang, Guangyun Li, Minglei Li, Li Wang	Research paper	2018	ISPRS Journal of Photogrammetry and Remote Sensing
Image segmentation evaluation: a survey of unsupervised methods	Hui Zhang, Jason E. Fritts, Sally A. Goldman	Research paper	2008	Computer Vision and Image Understanding
River channel segmentation in polarimetric SAR images: Watershed transform combined with average contrast maximization	Marcin Ciecholewski	Research paper	2017	Expert Systems with Applications
Morphological Profiles Based on Differently Shaped Structuring Elements for Classification of Images with Very High Spatial Resolution	Zhi Yong Lv, Penglin Zhang, Jon Atli Benediktsson, Wen Zhong Shi	Research paper	2014	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing
Marker-Controlled Watershed-Based Segmentation of Multiresolution Remote Sensing Images	Raffaele Gaetano, Giuseppe Masi, Giovanni Poggi, Luisa Verdoliva, Giuseppe Scarpa	Research paper	2015	IEEE Transactions on Geoscience and Remote Sensing
An Edge Embedded Marker-Based Watershed Algorithm for High Spatial Resolution Remote Sensing Image Segmentation	Deren Li, Guifeng Zhang, Zhaocong Wu, Lina Yi	Research paper	2010	IEEE Transactions on Image Processing
Object-based large-scale terrain classification combined with segmentation optimization and terrain features: A case study in China	Jiaming Na, Hu Ding, Wufan Zhao, Kai Liu, Guoan Tang, Norbert Pfeifer	Research paper	2021	Transactions in GIS
EdgeFlow: a technique for boundary detection and image segmentation	Wei-Ying Ma and B. S. Manjunath	Research paper	2000	IEEE Transactions on Image Processing

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Title	Authors	Paper Type	Publication Year	Journal
Multiobjective multiple features fusion: A case study in image segmentation	Cong Liu, Tingting Bian, Aimin Zhou	Research paper	2021	Swarm and Evolutionary Computation
Region-line association constraints for high-resolution image segmentation	Min Wang, Jiru Huang, Dongping Ming	Research paper	2017	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing
Object-based image analysis through nonlinear scale-space filtering	Angelos Tzotsos, Konstantinos Karantzalos, Demetre Argialas	Research paper	2011	ISPRS Journal of Photogrammetry and Remote Sensing
Hierarchical Multiple Markov Chain Model for Unsupervised Texture Segmentation	Giuseppe Scarpa, Raffaele Gaetano, Michal Haindl, Josiane Zerubia	Research paper	2009	IEEE Transactions on Image Processing
Region Merging Method for Remote Sensing Spectral Image Aided by Inter-Segment and Boundary Homogeneities	Yuhan Zhang, Xi Wang, Haishu Tan, Chang Xu, Xu Ma andTingfa Xu	Research paper	2019	remote sensing
Multi-scale segmentation of very high resolution remote sensing image based on gravitational field and optimized region merging	Ai Zhu Zhang, Gen Yun Sun, Si Han Liu, Zhen Jie Wang, Peng Wang & Jing Sheng Ma	Research paper	2017	Multimedia Tools and Applications
Road extraction in remote sensing data: A survey	Ziyi Chen, Liai Deng, Yuhua Luo, Dilong Li, José Marcato Junior, Wesley Nunes Gonçalves, Abdul Awal Md Nurunnabi, Jonathan Li, Cheng Wang, Deren Li	Research paper	2022	International Journal of Applied Earth Observation and Geoinformation
Edge-Guided Image Object Detection in Multiscale Segmentation for High-Resolution Remotely Sensed Imagery	Yongyue Hu, Jianyu Chen, Delu Pan, Zengzhou Hao	Research paper	2016	IEEE Transactions on Geoscience and Remote Sensing
Segmentation for High-Resolution Optical Remote Sensing Imagery Using Improved Quadtree and Region Adjacency Graph Technique	Gang Fu, Hongrui Zhao, Cong Li and Limei Shi	Research paper	2013	remote sensing
Landscape analysis of wetland plant functional types: The effects of image segmentation scale, vegetation classes and classification methods	Iryna Dronova, Peng Gong, Nicholas E. Clinton, Lin Wang, Wei Fu, Shuhua Qi, Ying Liu	Research paper	2012	remote sensing
Metaheuristics for supervised parameter tuning of multiresolution segmentation	Victor Andres Ayma Quirita, Pedro Achanccaray Diaz, Raul Q. Feitosa, Patrick N. Happ, Gilson A. O. P. Costa, Tobias Klinger, Christian Heipke	Research paper	2016	IEEE Geoscience and Remote Sensing Letters
Accuracy assessment measures for object-based image segmentation goodness	Nicholas Clinton, Ashley Holt, Li Yan, Peng Gong	Review paper	2010	Photogrammetric Engineering and Remote Sensing
Discrepancy measures for selecting optimal combination of parameter values in object-based image analysis	Yong Liu, Ling Bian, Yuhong Meng, Huanping Wang, Shifu Zhang, Yining Yang, Xiaomin Shao, Bo Wang	Research paper	2012	ISPRS Journal of Photogrammetry and Remote Sensing
Optimization in multi-scale segmentation of high-resolution satellite images for artificial feature recognition	J. Tian & D.-M. Chen	Research paper	2007	International Journal of Remote Sensing
Hybrid region merging method for segmentation of high-resolution remote sensing images	Xueliang Zhang, Pengfeng Xiao, Xuezhi Feng, Jiangeng Wang, Zuo Wang	Research paper	2014	ISPRS Journal of Photogrammetry and Remote Sensing
Image Segmentation Parameter Selection and Ant Colony Optimization for Date Palm Tree Detection and Mapping from Very-High-Spatial-Resolution Aerial Imagery	Rami Al-Ruzouq, Abdallah Shanableh, Mohamed Barakat A. Gibril and Saeed AL-Mansoori	Research paper	2018	remote sensing
Remote sensing image analysis by aggregation of segmentation-classification collaborative agents	Andrés Troya-Galvis, Pierre Gançarski, Laure Berti-Équille	Research paper	2017	Pattern Recognition
A Comparison of Unsupervised Segmentation Parameter Optimization Approaches Using Moderate- and High-Resolution Imagery	Heather Grybas, Lindsay Melendy & Russell G. Congalton	Research paper	2017	GIScience and Remote Sensing
Segmentation performance evaluation for object-based remotely sensed image analysis	Padraig Corcoran, Adam Winstanley & Peter Mooney	Review paper	2010	International Journal of Remote Sensing
Adaptive scale selection for multiscale segmentation of satellite images	Ya'nan Zhou, Jun Li, Li Feng, Xin Zhang, Xiaodong Hu	Research paper	2017	IEEE Journal ofSelected Topics inApplied Earth Observations and Remote Sensing
Object-based classification of vegetation species in a subtropical wetland using Sentinel-1 and Sentinel-2A images	Luis Fernando Chimelo Ruiz, Laurindo Antonio Guasselli, João Paulo Delapasse Simioni, Tássia Fraga Belloli, Pâmela Caroline Barros Fernandes	Research paper	2021	Science of Remote Sensing
Accuracy assessment measures for image segmentation goodness of the Land Parcel Identification System (LPIS) in Denmark	Alessandro Montaghi, René Larsen, Mogens H. Greve	Research paper	2013	Remote Sensing Letters

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Title	Authors	Paper Type	Publication Year	Journal
A region merging segmentation with local scale parameters: applications to spectral and elevation data	Maria Dekavalla and Demetre Argialas	Research paper	2018	remote sensing
Modified ALV for selecting the optimal spatial resolution and its scale effect on image classification accuracy	Dongping Ming, Jianyu Yang, Longxiang Li, Zhuoqin Song	Research paper	2011	Mathematical and Computer Modelling

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