A Comprehensive Review of Agricultural Parcel and Boundary Delineation From Remote Sensing Images

Recent progress and future perspectives

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Recent advances in diverse remote sensing sensors have enabled the acquisition of high-spatial-resolution imagery, offering unprecedented opportunities for cost-efficient and accurate agricultural inventory and analysis in an automated manner. Lots of studies that aim at providing an inventory of the level of each agricultural parcel have generated many methods for agricultural parcel and boundary delineation (APBD). This review article covers APBD methods for detecting and delineating agricultural parcels and systematically reviews the past and present of APBD-related research applied to remote sensing images. We conceptualize existing APBD studies as comprising three hierarchical levels: cropland identification (CI), boundary delineation (BD), and parcel segmentation (PS). With the goal to provide a clear knowledge map of existing APBD efforts, we conduct a comprehensive review of recent APBD papers to build a metadata analysis, including the algorithm, the study site, the crop type, the sensor type, the evaluation method, and so on. We categorize the methods into three classes: 1) traditional image processing methods (including pixel based, edge based, and region based), 2) traditional machine learning methods [such as random forests (RFs) and decision trees (DTs)], and 3) deep learning-based methods. With deep learning-oriented approaches

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contributing to a majority, we further discuss deep learning-based APBD methods, organizing them primarily by task into semantic segmentation-based and object detection-based approaches and, within each, distinguishing architectures based on convolutional neural networks (CNNs) and transformers. In addition, we discuss several APBD-related issues to further comprehend the APBD domain using remote sensing data, such as multisensor data in APBD tasks, comparisons between single-task learning and multitask learning in the APBD domain, comparisons among different algorithms and different APBD tasks, and so on. Finally, this article proposes some APBD-related applications and a few exciting prospects and potential hot topics in future APBD research. We hope this review helps researchers involved in the APBD domain to keep track of developments and trends.

INTRODUCTION

Agricultural parcels represent the fundamental spatial units for agricultural activities, and their precise delineation is crucial for efficient resource management and a wide range of critical applications, including crop mapping [1], yield estimation [2], and sustainable agricultural planning [3]. As the foundational layer for most geospatial agricultural analyses, the accuracy and quality of parcel boundary extraction directly influence downstream processes in precision agriculture [4], land use monitoring [5], and policy implementation [6]. Traditionally, field boundaries have been delineated manually or derived through rule-based image processing techniques that rely on spectral thresholds or vegetation indices. However, these methods often fall short in complex agricultural landscapes characterized by irregular field shapes, heterogeneous crop conditions, and indistinct or occluded boundaries resulting from natural variability or farming practices. Moreover, manual annotation is inherently time-consuming, labor-intensive, and unsuitable for large-scale or frequent updates. With the advent of high-resolution commercial satellites and rapid advancements in computational techniques, APBD has entered a new era. Modern approaches have evolved from classical machine learning algorithms, such as RFs and support vector machines (SVMs), to deep learning frameworks, including CNNs [7] and U-Net [8]. More recently, the emergence of foundation models, such as transformer architectures [9], the Segment Anything Model (SAM) [10], and vision language models (VLMs) [11], has further expanded the capabilities of APBD. These models, leveraging massive datasets and self-supervised learning, offer strong generalization ability, high adaptability, and improved performance across diverse agricultural scenarios when applied to high-resolution remote sensing imagery.

A wide range of review articles have extensively explored agricultural remote sensing applications [4], [17], [18], [19], [20], covering core tasks, such as crop mapping [1], [13], disease detection [21], growth monitoring [5], [15], [22], and yield estimation [2], among others. Some surveys focus on specific crop types, including paddy rice [23], [24], [25], maize [26], and wheat [27]. However, relatively few reviews have examined APBD in depth, particularly in relation to relevant datasets and deep learning-based methodologies. To address this gap, we summarize existing literature in Table 1, highlighting distinctions in methods, topics, tasks, and data sources. For example, Wang et al. [14] systematically analyze the farmland boundary extraction process, associated detection algorithms, and key influencing factors. Xu et al. [16] combine bibliometric and content analysis to provide a comprehensive overview of deep learning applications in APBD. Hadir et al. [28] focus specifically on the evaluation and comparative analysis of deep learning models for agricultural parcel delineation. By contrast, other surveys address only crop mapping [see "Crop Identification" ("Level 1") in Figure 1], without considering agricultural parcel BD [1], [12], [13], [15].

According to Table 1, most existing APBD reviews are limited in scope and focus mainly on crop identification, overlooking BD and recent advances driven by deep learning and foundation models. First, most of the reviews that were retrieved and screened contain fewer than 100 relevant publications, reflecting limited coverage of APBD and

TABLE 1. A SUMMARY OF EXISTING APBD-RELATED REVIEWS.

	REVIEWED APBD METHODS			REVIEWED APBD TASKS				
REVIEWED ARTICLES	TIP	TML	DL	CI	BD	PS	DATASETS	APPLICATIONS
Nagraj et al. [12]	✓	✓	×	✓	×	×	×	×
Joshi et al. [13]	×	×	✓	✓	×	×	×	✓
Alami et al. [1]	×	✓	✓	✓	×	×	×	×
Wang et al. [14]	✓	✓	×	×	✓	×	×	×
Omia et al. [15]	✓	✓	✓	✓	×	×	×	×
Xu et al. [16]	×	×	✓	×	✓	×	✓	×
Ours	✓	✓	✓	✓	✓	✓	✓	✓

TIP: traditional image processing-based APBD; TML: traditional machine learning-based APBD; DL deep learning-based APBD.
CI, BD, and PS denote three different levels of APBD tasks.

its associated tasks and applications, including crop classification, yield estimation, stress detection, and monitoring. Second, many of these reviews concentrate primarily on crop identification, often neglecting the equally critical task of BD. Before introducing our task taxonomy, it is essential to clarify our definition of agricultural parcels, as the literature presents two distinct conceptual frameworks. A small number of studies [14], [29] adopt a semantic-based definition, where parcels are defined as spatially contiguous areas cultivated with the same crop type. Under this framework, boundaries emerge at locations where crop types transition. In contrast, the predominant approach in the field, which we adopt in this article, is the physical boundary-based definition [30], [31]. This framework is also supported by other reviews [32] and practical applications [33], [34], defining parcels as land units delineated by permanent or semipermanent physical features, such as field ridges, roads, ditches, and hedgerows. Following this definition, an agricultural parcel is a continuous land unit whose boundaries are marked by these physical objects. Consequently, a parcel may contain either a single homogeneous crop or multiple crop types within its physical boundaries. This definition aligns with practical agricultural management and cadastral systems [35], where land units are defined by their structural organization rather than their temporary semantic content. In this article, we conceptualize APBD as including three hierarchical levels: CI, BD, and PS (see Figure 1 for details). CI, the simplest task, distinguishes cropland from the background (a two-class classification problem). BD focuses on precisely delineating parcel boundaries, whereas PS is the most challenging, requiring the segmentation of each parcel instance individually. To avoid confusion, we note that BD focuses on boundary lines and often produces boundary maps or polylines; it does not always separate adjacent fields into closed per-parcel instances. PS outputs closed, geographic information system (GIS)-ready polygons for each parcel and therefore implicitly includes the completion of BD for every parcel. Furthermore, the current body of literature does not fully capture the breadth of recent advances in APBD, especially those driven by state-of-the-art deep learning algorithms and foundation models. These emerging techniques offer substantial improvements in accuracy, robustness, and scalability yet remain insufficiently addressed in existing surveys.

Therefore, it is essential to synthesize the overall trends in APBD research over the past decade, offering readers a comprehensive perspective on APBD's historical evolution, current status, and future directions. The key contributions of this article are summarized as follows:

1) We provide the first systematic and in-depth review dedicated to APBD in the past decade. Our work includes a meta-analysis of existing literature, a detailed comparison of methodologies, an overview of practical applications, and an exploration of future research opportunities.
2) In response to rapid advances in computer science and their growing adoption in APBD, we analyze the strengths and limitations of existing approaches from three perspectives: traditional image processing, traditional machine learning, and deep learning. We further compare general-purpose deep learning models with their tailored applications in APBD.
3) We conduct an in-depth discussion of multisensor data utilization in APBD, dataset construction, algorithmic comparisons, and criteria for selecting appropriate methods. We also provide an extensive overview of APBD-related applications and tasks and outline promising research directions. We highlight that remote sensing data will remain a critical driver of APBD innovation in the foreseeable future.

The rest of this article is organized as follows. We present the meta-analysis of related literature in the "Meta-Analysis

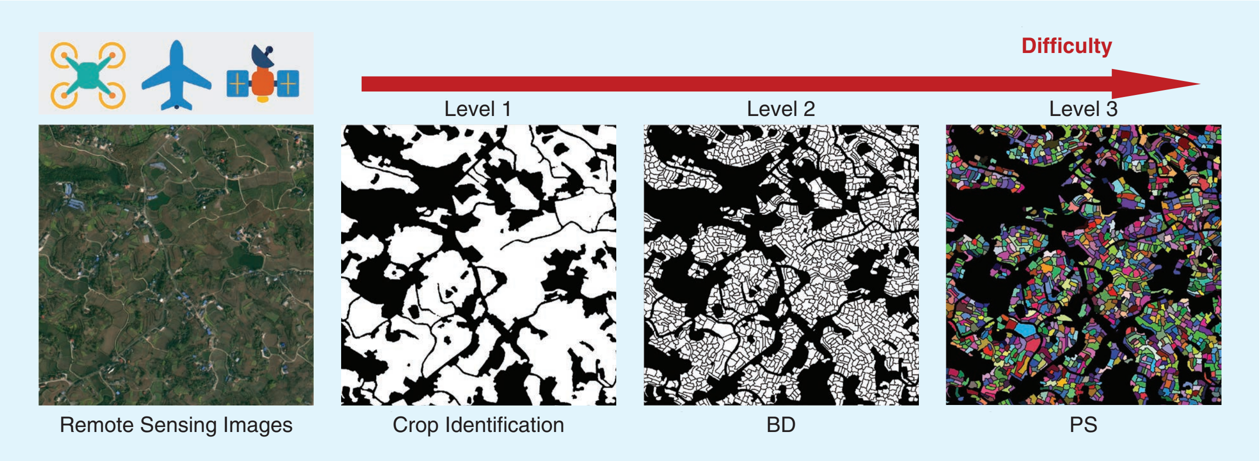

FIGURE 1. The three hierarchical levels of APBD tasks. These levels represent progressively increasing task difficulty, where level 1 (crop identification) distinguishes cropland from the background, level 2 (BD) advances further to delineate precise parcel boundaries, and level 3 (PS) achieves the most challenging goal: segmenting individual parcel instances. Each level accomplishes more refined extraction than the previous one, reflecting increasingly complex spatial granularity in agricultural parcel extraction from remote sensing imagery.

of Related Literature" section. Following that, we conduct a thorough review of the methodology of APBD in the "Methodology Review" section and an assessment (such as public datasets and different evaluation metrics) in the "Assessment" section. After that, we provide an in-depth discussion of comparisons between single-task learning and multitask learning in APBD tasks, the characteristics of different APBD methods, the criteria for choosing appropriate APBD methods, and so on in the "Discussions" section, followed by extensive APBD-related applications, such as crop type classification, yield estimation, stress detection, and so forth, in the "Agricultural Parcel and Boundary Delineation-Related Applications" section. We share our prospects for the APBD domain in the "Prospects" section. Finally, we conclude this review article in the "Conclusions" section.

META-ANALYSIS OF RELATED LITERATURE

As illustrated in Figure 2, the number of APBD-related studies leveraging remote sensing data has grown exponentially since 2019, making it increasingly challenging for researchers and practitioners in the field to stay abreast of the latest developments. This rapid expansion underscores the need for periodic reviews that synthesize recent advances, including newly implemented APBD methodologies, study areas, targeted crop and tree species, and the types of remote sensing data employed. In this section, we present a meta-analysis of the APBD domain to systematically examine these aspects, and this meta-analysis is based on a comprehensive literature review conducted until 20 August 2025, encompassing peer-reviewed journal articles indexed in major databases.

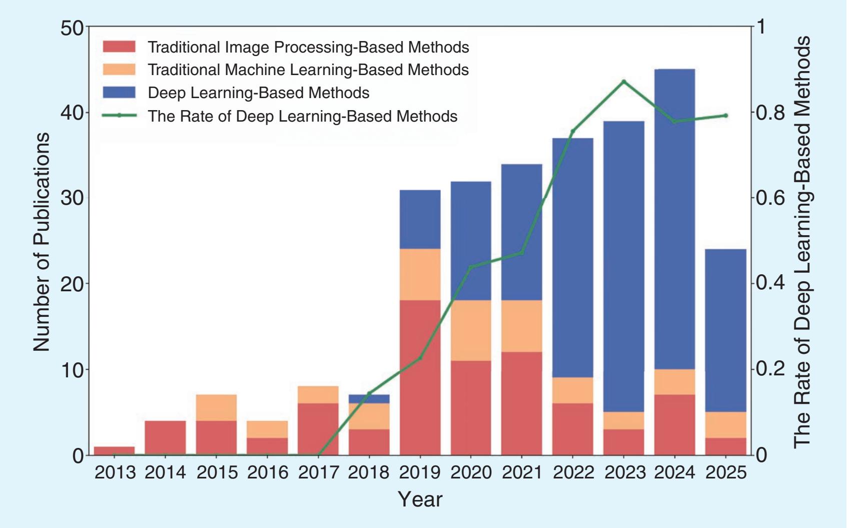

FIGURE 2. Publication trends of different APBD methodologies from 2013 to 2025 (data collected until 20 August 2025). The exponential growth since 2019, particularly in deep learning-based methods, reflects the increasing adoption of advanced artificial intelligence techniques in agricultural parcel extraction. Traditional image processing and machine learning methods have remained relatively stable, while deep learning approaches have become dominant in recent years.

OVERALL TREND OF AGRICULTURAL PARCEL AND BOUNDARY DELINEATION DEVELOPMENT

Figure 3 presents representative APBD-related studies published between 2013 and 2025. Triangles, circles, and rectangles denote traditional image processing-based,

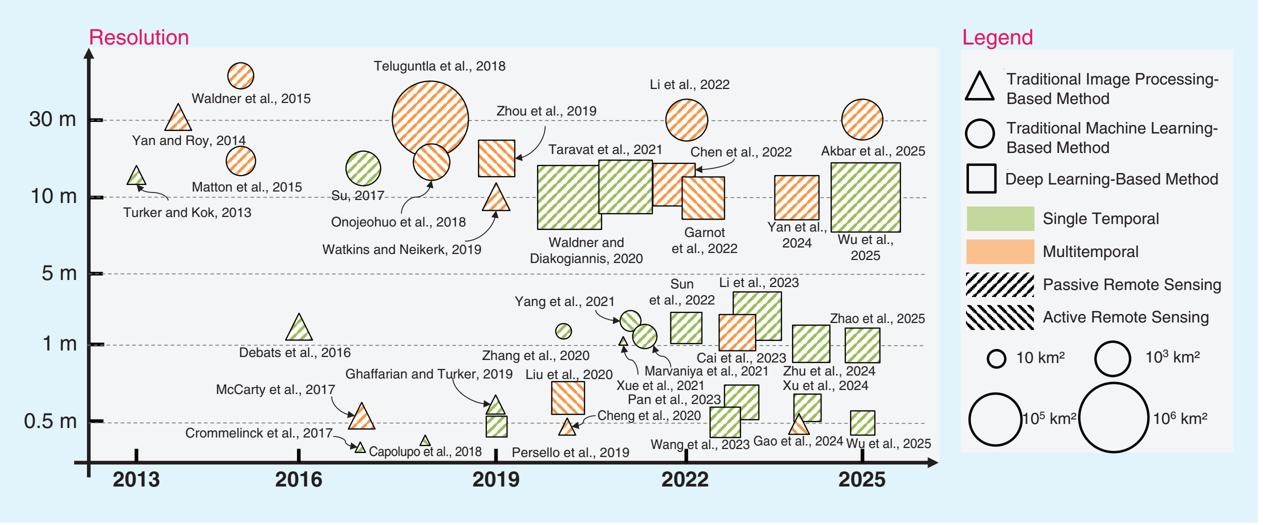

FIGURE 3. The evolution of APBD research from 2013 to 2025 (data collected until 20 August 2025), illustrated through representative studies. Different shapes represent different APBD methods, and boxes with different shading (such as colors and textures) represent different remote sensing data. The larger the size, the larger the study area.

traditional machine learning-based, and deep learning-based APBD methods. We can observe some tendencies in the APBD field.

1) The left side of Figure 3 is relatively sparse, whereas the right side, particularly the bottom-right corner, is densely populated. Since 2019, the number of APBD studies using very-high-resolution (VHR) remote sensing imagery has increased exponentially, driven initially by CNN architectures and more recently by the adoption of transformer-based models.
2) Early APBD research, constrained by both methodological limitations and the spatial resolution of available data, often relied on moderate-resolution imagery (e.g., *Sentinel* and *Landsat*). While some studies employed VHR imagery, their spatial extent was typically small ($<10\,km^2$). Before 2017, most methods were based on traditional image processing-based APBD algorithms; traditional machine learning-based APBD methods emerged gradually thereafter, and in recent years, deep learning-based APBD approaches have become dominant, enabling analysis over increasingly large areas.
3) Prior to 2018, APBD publications generally focused on small study areas (mostly $<1{,}000\,km^2$). The growing availability of VHR imagery, advances in computing resources, and the development of more robust artificial intelligence (AI) algorithms have facilitated a shift toward large-scale APBD studies, often integrating multiple VHR datasets.
4) Although VHR imagery (<0.5 m; the lower portion of Figure 3) enables high-accuracy APBD, it remains constrained to relatively small areas due to high storage and processing costs. Large-scale studies typically employ imagery with a spatial resolution above 10 m, often incorporating multitemporal datasets to balance accuracy, coverage, and storage demands.

QUANTITATIVE ANALYSIS

Alongside the collection of APBD-related publications, the following sections present quantitative analyses covering cropland types, study sites and their spatial extent, sensor types, and spatial resolution.

TYPES OF CROPLAND

Figure 4 provides a statistical overview of the crop types investigated in the reviewed literature. Publications were first classified based on whether they specified particular crop types. As shown in the pie chart, the majority (65.04%) focused on identified crops, while a considerable proportion (34.96%) did not distinguish among crop types. Given the wide variety of crops examined, the accompanying bar chart highlights only the 16 most frequently studied. The results reveal a strong emphasis on major staple crops, with corn being the most extensively investigated (91 publications), followed by wheat (80) and rice (68). Other commonly studied crops include soybeans (42), rapeseed (29), barley (25), and cotton (24). The remaining crops in the top 16 include potatoes (15), groundnuts (14), sugar beets (13), sorghum (12), alfalfa (11), and, finally, beans, grapes, peppers, and sunflowers, each appearing in nine publications.

STUDY SITES

Figure 5 gives the spatial distribution of study sites for APBD, based on our compiled database. The research is geographically concentrated, with a limited number of countries serving as major study areas. China emerges as the leading hub, with 130 studies, followed by the United States (19), The Netherlands (14), and India (11). Consistent with the distribution of research institutions, most study sites are clustered in East Asia, North America, and parts of Europe. By contrast, regions such as South America and Africa, despite their extensive agricultural lands and substantial research potential, remain underrepresented.

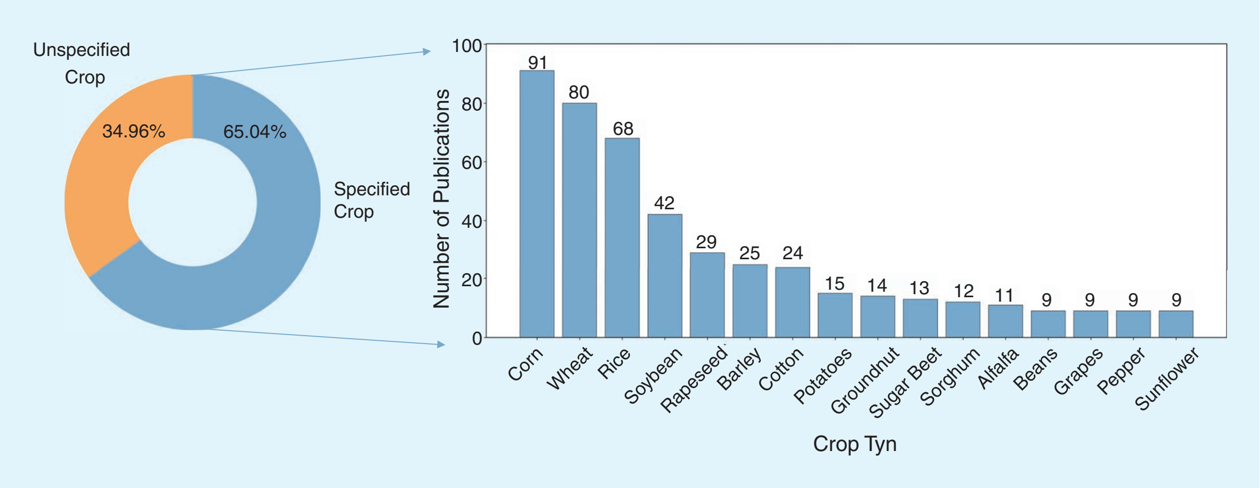

FIGURE 4. Crop types in APBD-related publications. We display only the top 16 most commonly studied crop types. The analysis reveals that 65.04% of studies focus on specific crop types, with major staple crops (corn, wheat, and rice) being the most extensively investigated, reflecting their global food security importance.

This imbalance may be explained by challenges such as the complexity of smallholder farming systems, persistent cloud cover affecting optical imagery, and difficulties in data acquisition and field surveys.

STUDY AREA

Among the studies that explicitly reported their study area size, analysis of the spatial scale over time reveals clear trends (Figure 6). A key finding is that the recent surge in very-large-scale research is predominantly driven by deep learning methods. In particular, the vast majority of studies covering extremely large regions (over 10,000 km^2) employ deep learning, with this pattern becoming especially evident after 2020. By contrast, while traditional image processing-based and traditional machine learning-based methods have been applied across various spatial scales, including some large-area studies in earlier years, their presence in research addressing the largest geographical extents is far less frequent compared to the more recent deep learning-based approaches.

SENSOR TYPE

The distribution of sensor types in the reviewed literature highlights a strong reliance on satellite-based platforms (Figure 7). Satellite imagery accounts for the overwhelming majority of data sources, representing 84% of the surveyed studies. Unmanned aerial vehicle (UAV) data and aerial imagery contribute smaller yet notable shares, at 10.8% and 5.2%, respectively. A closer examination of satellite data indicates a relatively balanced use of medium-resolution (10–100 m) and high-resolution (<10 m) sensors. Within the medium-resolution category, *Sentinel* (82) and *Landsat* (31) are the most widely used platforms. In the high-resolution group, a broader range of sensors is reported, with the *Gaofen* (*GF*) series (62) being the most prominent, followed by *WorldView* (13), *Satellite Pour l'Observation de la Terre* (*SPOT*) (7), and *Jilin-1* (7).

SPATIAL RESOLUTION OF DATA

An analysis of publications reporting the spatial resolution of their input data reveals a clear evolution in data preferences over the past decade, as described in Figure 8. A notable trend is the increasing reliance on high-resolution imagery (≤1 m), a shift that has become especially pronounced in recent years. Numerous studies now capitalize on the fine spatial details such data provide, particularly those employing deep learning methods. In contrast, although coarser-resolution data (>10 m) have historically been applied across various methodologies, their use in deep learning research has declined markedly in recent years. This trajectory suggests a growing convergence toward high-resolution datasets, likely driven by the ability of modern algorithms, such as deep neural networks, to effectively harness detailed textural and spatial information for more accurate plot extraction.

METHODOLOGY REVIEW

This section reviews and summarizes the development of APBD methodology. We categorize existing APBD methods into three classes: traditional image processing-based

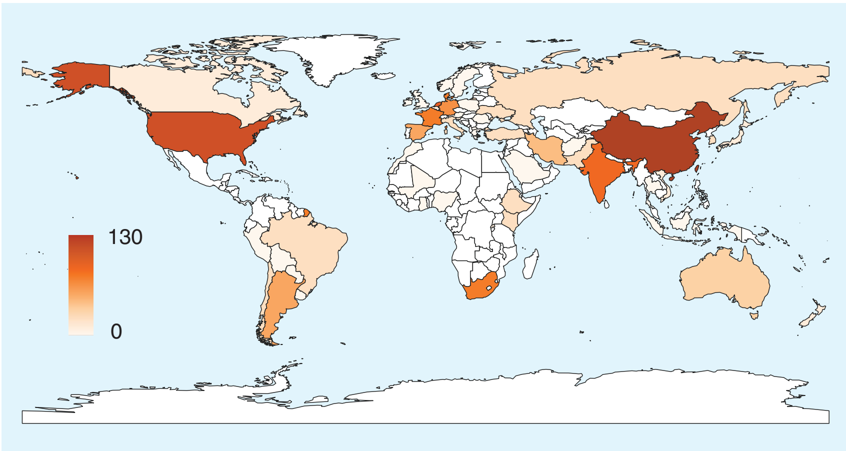

FIGURE 5. The global spatial distribution of APBD study sites. The geographic concentration in China (130 studies), followed by the United States, The Netherlands, and India, reflects both research capacity and agricultural importance.

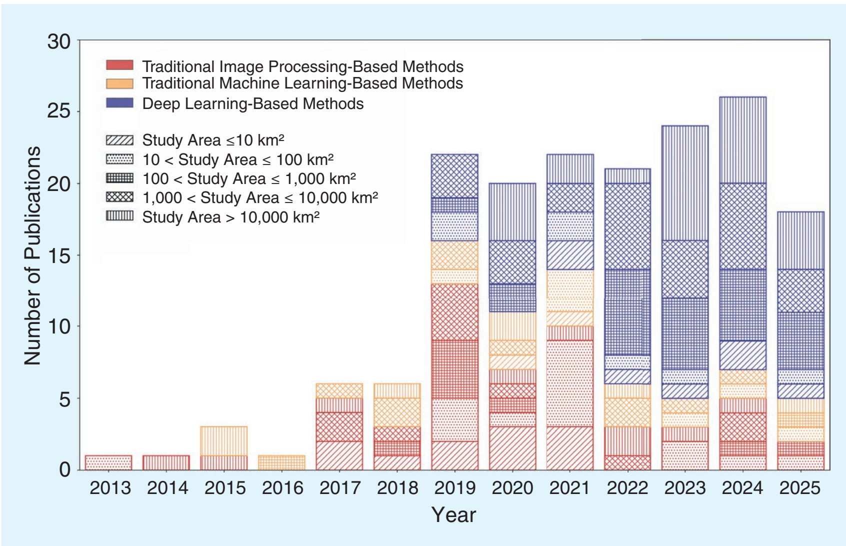

FIGURE 6. Temporal trends in study area sizes across different APBD methodologies from 2013 to 2025 (data collected until 20 August 2025). The increasing prevalence of very-large-scale studies (>10,000 km^2) after 2020 is predominantly driven by deep learning methods.

APBD, traditional machine learning-based APBD, and deep learning-based APBD methods. For deep learning-based APBD, we adopt a task-oriented taxonomy, primarily distinguishing between semantic segmentation-based and object detection-based approaches. Within each task category, we further differentiate methods based on their underlying network architectures, specifically CNNs and transformers.

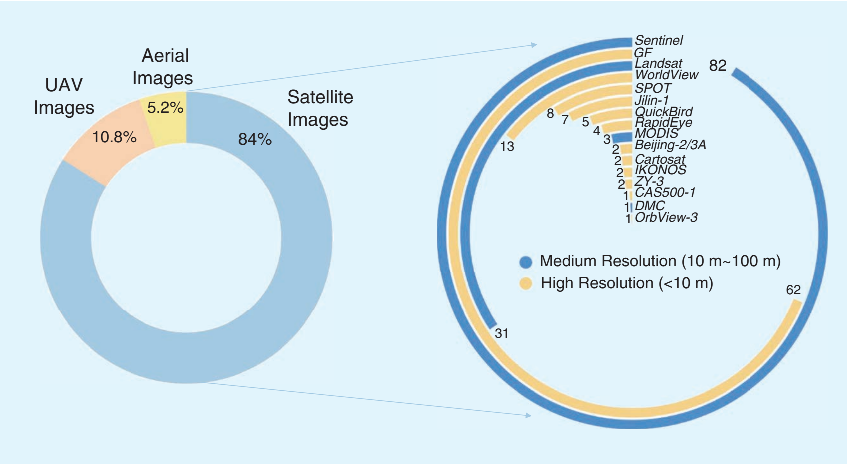

FIGURE 7. The distribution of sensor types in APBD research. Satellite imagery dominates (84%), with a balanced use of medium-resolution sensors (*Sentinel* and *Landsat*) and high-resolution platforms [*Gaofen* (*GF*) series and *WorldView*). The smaller proportions of unmanned aerial vehicle (UAV) (10.8%) and aerial imagery (5.2%) reflect the imagery's use in site-specific high-precision applications, while satellite data enable large-scale cost-effective monitoring. *SPOT*: *Satellite Pour l'Observation de la Terre*; MODIS: Moderate Resolution Imaging Spectroradiometer; *ZY-3*: *Ziyuan-3*; *CAS500-1*: *Compact Advanced Satellite 500-1*; DMC: Disaster Monitoring Constellation.

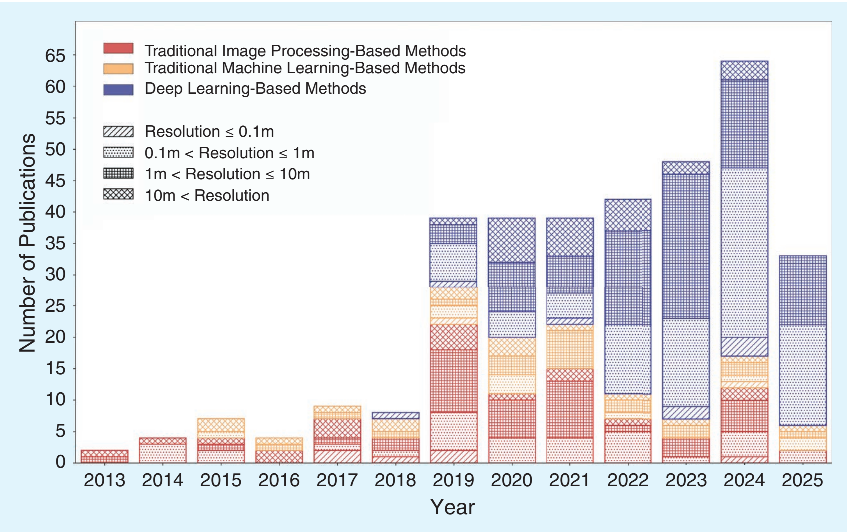

FIGURE 8. The evolution of spatial resolution preferences in APBD research from 2013 to 2025 (data collected until 20 August 2025). The increasing adoption of high-resolution imagery (≤1 m), particularly in deep learning-based studies, reflects the need for fine spatial details in BD. The decline in coarse-resolution data (>10 m) usage in recent deep learning research indicates a shift toward data sources that can better capture parcel-level features.

TRADITIONAL IMAGE PROCESSING-BASED AGRICULTURAL PARCEL AND BOUNDARY DELINEATION METHODS

Traditional image processing-based APBD methods mainly include image binarization, detection operators, the wavelet transform, watershed segmentation, the mean shift, and so forth. Inspired by previous segmentation surveys [36], [37], we can categorize them into three major types: pixel-based, edge-based, and region-based methods. Table 2 lists traditional image processing-based APBD methods and collected examples. Figure 9 displays some typical examples of traditional image processing-based APBD methods.

PIXEL-BASED METHODS

Pixel-based methods consist of image binarization and clustering segmentation in the feature space [37]. In this case, each spatially continuous unit needs to be assigned a unique label. Image binarization is a straightforward method to classify pixels or objects that belong to the parcel or the edge by comparing the thresholds. For example, Graesser and Ramankutty [61] adopt an adaptive threshold using temporal *Landsat* imagery across a South American region. Zhu et al. [39] propose a simple but effective method that converts detected continuous-valued texture results into binary boundaries using thresholding methods. Since the limitations of global thresholding make it challenging to address the issue of the coexistence of high-value noise and low-value boundaries in the detection results, the authors alternatively adopt local thresholding that calculates independent thresholds for each pixel based on neighboring pixels to effectively avoid this issue. As clustering segmentation methods depend on the features for each pixel, we assign clustering methods to pixel-based APBD methods. There are many classical unsupervised clustering algorithms applied in APBD scenarios, such as *k*-means [40], fuzzy *c*-means [41], ISODATA [62], AUTOCLUST clustering [63], Density-Based Spatial Clustering of Applications With Noise clustering [64], and so on.

EDGE-BASED METHODS

Edge-based methods first identify edges and then close them by using contouring algorithms, which assumes that between edges, the pixel properties change abruptly. The main challenge of APBD tasks is how to accurately detect the edges and boundaries between different parcels. Popular edge-based methods applied in APBD include detection operators, the wavelet transform, multiscale combinatorial grouping, the mean shift, the globalized probability of boundary (gPb), and so on. Traditional edge detection operators mainly involve locating the edge of the local area by using a differential operator to identify the place where the gray value abruptly changes in the image, such as the Canny operator [65], Sobel operator [66], Roberts operator, Scharr operator [42], and so forth, which are also called *gradient operators*. However, the extraction effect of simple traditional edge detection operators is usually not ideal [14]. The wavelet transform evolves from Fourier analysis, which has the advantages of multiresolution analysis and has good approximation characteristics for 1D signals. For instance, Ishida et al. [45] use a multiresolution wavelet transform from *SPOT* imagery to detect the edges of submerged paddy fields, which performs better than the difference-of-Gaussians filter. The gPb [67] combines the steps of image segmentation, line extraction, and contour generation with the ability to integrate image information at both local and global scales for texture, color, and brightness, which is an extremely advanced edge detection algorithm. For example, Marshall et al. [51] utilize the gPb to determine farm boundaries from *WorldView* imagery in highly fragmented agricultural landscapes of Ethiopia. In addition, the gPb is also applied in building boundary extraction [68]. Multiscale combinatorial grouping generates each boundary and region based on a structural forest edge detector, spectrum division, and global weighting, which usually has higher boundary extraction accuracy than the gPb and the classical edge detection Sobel algorithm [67]. The mean shift is a nonparametric density estimation algorithm that eliminates the need to assume a sample distribution model and determine the number of categories, which can effectively reduce intrafield variation and preserve edge information. Su et al. [48] propose a new image segmentation algorithm based on the mean shift to single out cropland in high-resolution remote sensing imagery.

TABLE 2. A SUMMARY OF TRADITIONAL IMAGE PROCESSING-BASED APBD METHODS.

TASKS	METHODS	EXAMPLES
Pixel based	Image binarization	[38], [39]
	Clustering	[40], [41]
Edge based	Detection operators	[42], [43]
	Wavelet transform	[44], [45]
	Multiscale combinatorial grouping	[46], [47]
	Mean shift	[48], [49]
	Globalized probability of boundary	[50], [51]
Region based	Object-based image analysis and geographic object-based image analysis	[52], [53]
	Watershed segmentation	[54], [55]
	Region growing	[56], [57]
	Local binary fitting	[58], [59]

REGION-BASED METHODS

The region-based methods start from the inside of an object and then expand outward until meeting the object

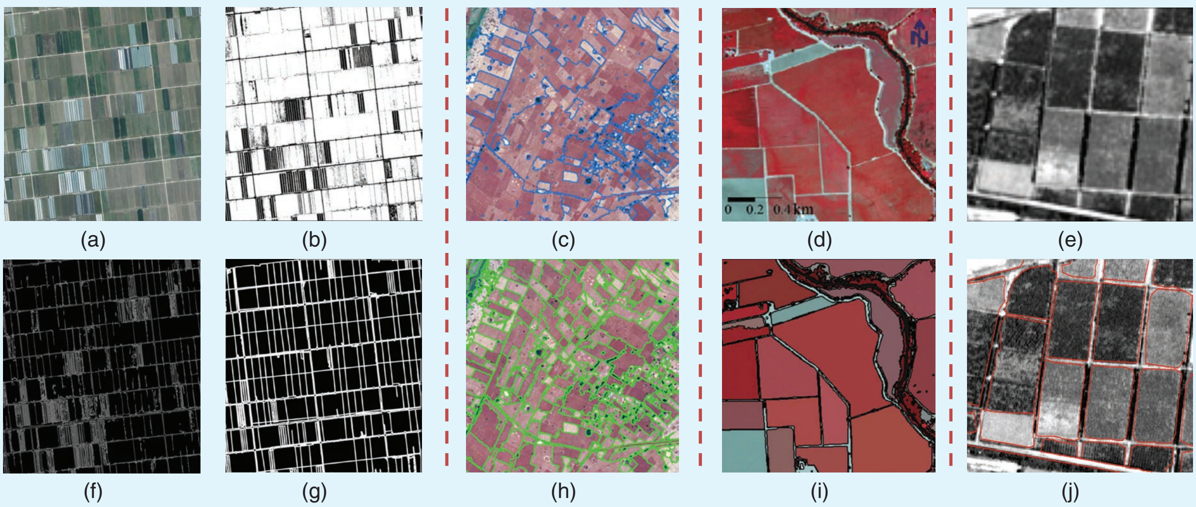

FIGURE 9. Examples of traditional image processing-based APBD methods. (a) The original aerial image from Hong et al. [60]. (b)–(d) The results of APBD using image binarization, the edge detection operator (Canny operator), and the Suzuki85 algorithm [60]. (e) and (f) The results of APBD using the globalized probability of boundary and multiresolution segmentation from [51]. (g) The original image by *OrbView-3*, located in western California, USA, from Su et al. [48]. (h) The results of APBD using the mean shift algorithm [48]. (i) The original image by *Cartosat-1*, located in Tehran, Iran, from Maghsoodi et al. [59]. (j) The results of APBD using the local binary fitting algorithm [59].

boundaries, assuming that neighboring pixels within the same region have similar values. Commonly, region-based APBD is addressed through two different conceptual levels: 1) object-based analytical paradigms, such as object-based image analysis (OBIA) or geographic OBIA (GEOBIA), and 2) specific region segmentation techniques, such as watershed segmentation, region growing, and local binary fitting. OBIA and GEOBIA [69] are subdisciplines of geographic information science devoted to partitioning remote sensing imagery into meaningful image objects and assessing their characteristics through the spatial, spectral, and temporal scales, which could analyze high-spatial-resolution imagery by using spectral, spatial, textural, and topological characteristics. Capolupo et al. [52] propose a method for automatic extraction of terraces from historical and contemporaneous aerial photos based on the OBIA approach. Watershed segmentation is a mathematical morphological segmentation algorithm that is based on topology theory, simulating the process of water immersion [70]. For example, Xue et al. [55] propose an improved watershed segmentation algorithm based on a combination of pre- and postimprovement procedures using *GF-2* remote sensing images with high time efficiency and segmentation accuracy. The watershed algorithm can obtain accurate boundary results for single-pixel localization; however, it is prone to oversegmentation. Region growing is the most popular and simple algorithm for region-based segmentation, which includes two main issues: selection of the seed region and similarity [71]. Wagner and Oppelt [57] propose a graph-based growing contours algorithm that is capable of extracting complex networks of boundaries present in agricultural landscapes and is largely automatic, with little supervision required in northern Germany using multitemporal *Sentinel-2* imagery. Local binary fitting is an energy-based segmentation algorithm that effectively segments images with an uneven gray scale, with good performance on satellite imagery of flatter farmland. For instance, Maghsoodi et al. [59] advance the local binary fitting model as a multiphase model with nonparametric active contours, followed by adding two texture layers to the input images and the development of the external energy function.

Besides the abovementioned region-based algorithms, other segmentation methods, such as multiresolution segmentation (MRS) [72], [73], [74], spatial–temporal information segmentation [75], [76] the variational region-based geometric active contour [54], [77], the Suzuki85 algorithm [60], [78], and so on, are also applied in many APBD scenarios. Many studies improve the original segmentation algorithms based on the computer vision domain. For example, the MRS algorithm is a well-known method for segmenting objects from images, but the segmentation quality depends on a priori knowledge of which scale, shape, and compactness values to use. Tetteh et al. [79] propose a sequential model-based optimization method based on MRS, which outperforms other segmentation optimization methods. Furthermore, some APBD-based research combines different traditional image processing-based APBD methods to simultaneously improve the results. For example, Watkins and Niekerk [42] combined the Canny edge detection operator and watershed image segmentation algorithm to produce accurate field boundaries, with an overall accuracy (OA) of 92.9%. Xu et al. [80] applied the mean shift and MRS using *GF-2* and *QuickBird* images to benefit the accurate extraction of farmland information. Borowiec and Marmol [74] propose a hybrid framework to identify agricultural land boundaries using lidar data. They combine Prewitt and Canny operators and MRS, along with principal component analysis and the Hough transform to attain precise determination of agricultural land boundaries.

TABLE 3. A SUMMARY OF FEATURE EXTRACTION AND ADOPTED CLASSIFIERS IN TRADITIONAL MACHINE LEARNING-BASED APBD METHODS.

ITEMS	METHODS	EXAMPLES
Feature extraction	Nonhandcrafted features	[81], [82]
	Handcrafted features	[83], [84]
		[85], [86]
		[87], [88]
Adopted classifiers	DT	[40], [89]
	Classification and regression trees	[90], [91]
	SVM	[87], [92]
	Genetic programming	[93], [94]
	RF	[88], [95]
	Maximum-likelihood classifier	[96], [97]
	Dynamic time warping	[98], [99]

TRADITIONAL MACHINE LEARNING-BASED AGRICULTURAL PARCEL AND BOUNDARY DELINEATION METHODS

The revolution in machine learning facilitates the development of APBD by offering powerful, adaptable, and accurate solutions. Generally speaking, for both agricultural parcel detection and BD, there are four steps in traditional machine learning-based APBD methods: 1) image preprocessing, 2) feature extraction, 3) classifier training, and 4) model prediction. Here, we focus more on the nature of APBD, which is progressing in feature extraction and classifier training. Table 3 reports traditional machine learning-based APBD methods and collected examples. This section does not separate agricultural parcel detection and BD because feature extraction and classifier training are both necessary for them, and the employed methods are similar.

FEATURE EXTRACTION

There is a variety of feature extraction methods, which can be simply classified into two types, i.e., nonhandcrafted features and handcrafted features. Nonhandcrafted features mainly utilize the obvious inner features of images themselves, such as spectral information [92], [100], vegetation indexes [82], [101], texture characteristics [40], [84], geometrical features [81], [83], climate variables [102], and so forth. Some studies also take homogeneity factors [103], temporal patterns [98], [104], [105], and point cloud data into consideration. On the other hand, handcrafted features are specific image representations that are crafted by domain knowledge and prior understanding of the data. These features are created by specific methods (e.g., the gradient direction histogram [87], the gray-level co-occurrence matrix [88], the differential of Gaussians [86], principal component analysis [85], and so on) to capture relevant information that is deemed important for APBD tasks.

The interpretability of these features makes them useful for understanding and reasoning about the content, as they are explicitly designed to capture certain visual attributes like shapes and edges of agricultural parcels [106], [107]. Compared to nonhandcrafted features, handcrafted features present more data-driven characteristics [108]. Still, due to the requirements of manual design and expert understanding, these features lack scalability and transferability to new scenarios [109]. In a nutshell, a full understanding of the characteristics and specific demands of specific APBD tasks is essential to harness the full potential of these features and is beneficial for later classifier training.

CLASSIFIER TRAINING

Classifier training is the most important part of traditional machine learning-based APBD methods. Potential classifiers contain DTs, the Gaussian maximum likelihood, linear discriminant analysis, SVMs, Bayesian optimization, RFs, multilayer perceptrons (MLPs), the *k*-nearest neighbor (*k*NN), classification and regression trees (CARTs), logistic regression, and so forth. Rahman et al. [110] investigated and tested six different classification algorithms to select the best algorithm for *Landsat* scenes between May and mid-August in the United States. The experimental results indicate that RFs achieve the best accuracy, followed by the *k*NN, SVM, DT, MLP, and Gaussian naive Bayes. In addition, some research adopts multimodel ensemble learning that combines the outputs of different machine learning classifiers. For example, Akbar et al. [102] developed an ensemble learning model that includes the RF, SVM, *k*NN, gradient tree boost, and CART in Google Earth Engine to achieve high-fidelity high-resolution (30-m) annual maps of irrigated areas from 2007 to 2022 in the Upper Red River Basin, USA, which improved the ground truth accuracy to 84%.

In summary, the performance of traditional machine learning-based methods in APBD relies on efficient feature extraction and powerful classifier training. Compared to traditional image processing-based methods, the ability to automatically learn and extract relevant features from raw data that involve specific expert understanding of traditional machine learning-based methods makes them more adaptable to more different scenarios for APBD. However, it is important to note that a set of high-quality and high-quantity input data is a sufficient condition for the promising performance of traditional machine learning-based methods. For example, if the study area is a small region with simple field targets and landscape invariance and the images are full of noise, traditional image processing-based methods may have better performance. Therefore, choosing or comparing traditional image processing-based and traditional machine learning-based methods depends on specific scenarios and data conditions. Also, to improve APBD results with limited labels, Estes et al. [100] utilized active learning. They created a platform that rigorously assesses and minimizes label error and used it to iteratively train an RF classifier with active learning, which identifies the most informative training sample based on prediction uncertainty.

Furthermore, some studies combine traditional image processing-based and traditional machine learning-based APBD methods to simultaneously improve the performance of APBD scenarios. For example, Yang et al. [103] propose an object-oriented multiscale segmentation method combined with an SVM, leveraging spectral reflectance, texture, and temporal differences between farmland and nonfarmland plots. This approach effectively improves farmland plot extraction accuracy, supporting crop type identification and advancing digital agricultural management. Belgiu and Csillik [98] first adopt a traditional image processing-based method (MRS) and then adopt two kinds of classifiers [i.e., time-weighted dynamic time warping (TWDTW) and RFs] using time-series *Sentinel-2* data. Experimental results show that TWDTW achieves comparable classification results to RFs in Romania and Italy, but RFs achieve better results in the United States.

DEEP LEARNING-BASED AGRICULTURAL PARCEL AND BOUNDARY DELINEATION METHODS

As successful cases emerge in various applications, today, many APBD methods adopt neural networks, achieving high-accuracy and real-time APBD results in complex and large-scale regions. Here, we review deep learning-based APBD methods by an extended taxonomy: semantic segmentation-based methods and object detection-based methods for agricultural parcel extraction. Table 4 reviews deep learning-based APBD methods. Figure 10 displays the number of deep learning-based APBD method-related publications since 2018.

There are many public datasets that could perform the crop identification task, which is the simplest task in APBD, such as UC Merced [143], AID [144], NWPU-RESISC45 [145], and so on. Many researchers have applied these public datasets or proposed new image-level datasets [146] in many agricultural applications, using deep learning algorithms to identify whether an image belongs to a crop field. However, they focus on scene classification, which is a coarse crop mapping method using a time-consuming sliding window-based scheme and beyond the scope of this article.

SEMANTIC SEGMENTATION-BASED AGRICULTURAL PARCEL AND BOUNDARY DELINEATION METHODS

Without requiring the time-consuming sliding window scheme, the semantic segmentation-based APBD method is an end-to-end algorithm, which is the most popular type of deep learning-based APBD method. Dissimilar to object detection-based methods that produce one label for a patch of an image, semantic segmentation methods aim at generating dense classes for each pixel in the whole image. Similar to object detection-based methods, semantic segmentation-based APBD methods also derive from semantic segmentation methods for natural images. Some state-of-the-art semantic segmentation architectures, such as DeepLab [147], U-Net [8], fully connected networks (FCNs), high-resolution networks (HRNets) [148], pyramid scene parsing networks (PSPNets) [149], and so forth, have been applied to the APBD domain in recent years. Some researchers have employed semantic segmentation-like models to generate confidence maps for agricultural parcel extraction [150], where pixels with high confidence indicate the locations of agricultural parcels. Many studies have also proposed modifying existing semantic segmentation models (like U-Net) for delineation tasks [151] or simultaneously using multitask learning methods to improve BD. For example, Li et al. [152] present a semantic edge-aware multitask neural network (SEANet) to obtain closed boundaries, which integrates three correlated tasks: mask prediction, edge prediction, and distance map estimation. Experiments show that SEANet is an accurate, robust, and transferable method for various areas and different remote sensing images. Xu et al. [153] develop a multitask network model to extract plot-level cropland information, consisting of a cascaded multitask network with integrated semantic and edge detection, a refinement network with fixed edge local connectivity, and an integrated fusion model. Cai et al. [154] propose a dual-branch spatio-temporal fusion network that integrates VHR images and medium-resolution satellite image time series to extract agricultural field parcels over various landscapes by exploiting important spectral, spatial, and temporal information from multimodal satellite data. Some researchers have explored the transferability of semantic segmentation-based APBD methods. For instance, Liu et al. [114] and Tian et al. [155] propose FieldSeg-DA and FieldSeg-DA2.0, respectively, to improve the performance of cross-regional and cross-temporal accurate boundary localization and parcel extraction, which borrow ideas from fine-grained adversarial domain adaptation.

TABLE 4. A SUMMARY OF DEEP LEARNING-BASED APBD METHODS.

TASKS	ARCHITECTURE	NETWORKS	EXAMPLES
Semantic segmentation	CNN	U-Net	[111], [112]
		DeepLab	[113], [114]
		Pyramid scene parsing network	[30], [115]
		Feature pyramid network	[116], [117]
		High-resolution network	[118], [119]
		D-LinkNet	[120], [121]
		Fully connected network	[122], [123]
		ResNet-like	[124], [125]
	Transformer	Vision transformer	[126], [127]
		Shifted window transformer	[128], [129]
		SegFormer	[130], [131]
		SAM	[133], [134]
Object detection	CNN	You Only Look Once	[134], [135]
		Mask Region-Based CNN	[136], [137]
		DeepSnake	[138], [139]
	Transformer	Mask2Former	[140], [141]

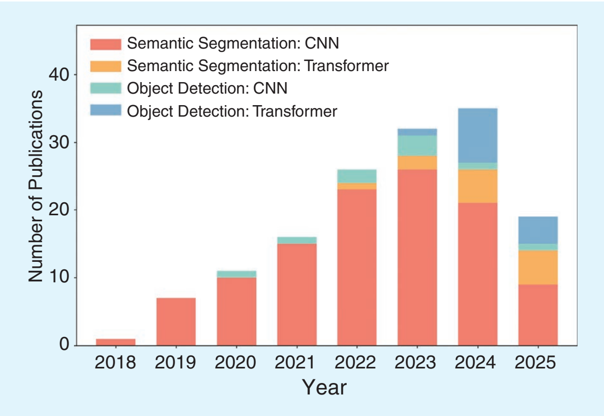

FIGURE 10. Growth trends in deep learning-based APBD publications from 2018 to 2025 (data collected until 20 August 2025). The exponential increase demonstrates the rapid adoption of neural network architectures in agricultural parcel extraction.

As the spatial complexity and heterogeneity of features resulting from high resolution make it difficult to obtain parcel-level information quickly and accurately, some semantic segmentation-based APBD methods may utilize traditional image processing-based APBD to improve low-level feature extraction and achieve better BD performance. For example, the hierarchical semantic boundary-guided network (HBGNet) [142] proposes a novel multitask learning framework, which employs a module based on a classical Laplace convolution operator to enhance model awareness of parcel boundaries (see details in Figure 11). Zhu et al. [30] utilize oriented watershed transformation and hierarchical region merging to address weak boundary loss from a modified PSPNet [115], leveraging the observational hierarchy of fields, resulting in stable parameters across regions and models. Furthermore, some semantic segmentation-based APBD methods first employ a deep learning-based method to delineate agricultural boundaries and then use a traditional machine learning method to exactly classify the crop types in each parcel. For example, Tang et al. [156] first apply SEANet [152] to delineate agricultural land parcel boundaries precisely. Subsequently, a parcel-scale RF model is developed to enable accurate crop type classification and spatial delineation of crop planting structures.

In recent years, transformer-based deep learning models, such as the vision transformer (VIT) [157], shifted window (Swin) transformer [158], SegFormer [159], and Relationformer [160], have gained attention for their ability in processing and understanding numerous remote sensing data. They leverage multihead self-attention, which computes pairwise interactions among all patches. Multihead self-attention makes them able to capture long-range dependencies among geographical features to be suitable for large-scale landscape analysis. Furthermore, technological advancements have shown the complementary advantages of vision and language in learning and understanding world knowledge, aiming to integrate the intuitive perception of vision with the deep understanding capabilities of language. Wu et al. design VLMs for farmland segmentation that combine a semantic segmentation model with a multimodal large language model (LLM) [161]. For example, FarmSeg_VLM [162] designs an image–text spatial alignment strategy under multilabel background priors and an image–text alignment adapter to further correct the spatial alignment mapping between the language descriptions and the corresponding visual features of ground objects (see details in Figure 12). Comparative experiments demonstrate that with the help of language description, the proposed method outperforms existing farmland segmentation methods in both generalization and segmentation accuracy.

In addition, some studies combine different kinds of deep learning-based methods to ensure good connectivity to repair fragmented edges that may appear in semantic edge detection. For example, Xia et al. [163] utilize D-LinkNet and Relationformer. This method relies on good connectivity to repair fragmented edges that may appear in semantic edge detection with effectiveness and robustness. Commonly, agricultural field results from traditional machine learning-based or deep learning-based methods are vector surface data; therefore, it is necessary to convert surface fields into vector contour boundaries. If we directly generated contour edge lines using a GIS software platform (such as QGIS, ArcGIS, and so on), the contour edge lines would not be guaranteed to be smooth and continuous, and adjacent field boundary adhesion issues could occur. It is critical to generate vectorized agricultural field parcels with closed boundaries from postprocessing methods for these models [154]. For example, Song et al. [164] use the Douglas–Peucker algorithm (DPA) [165] to optimize the edge contour and generate efficient and stable reconstruction

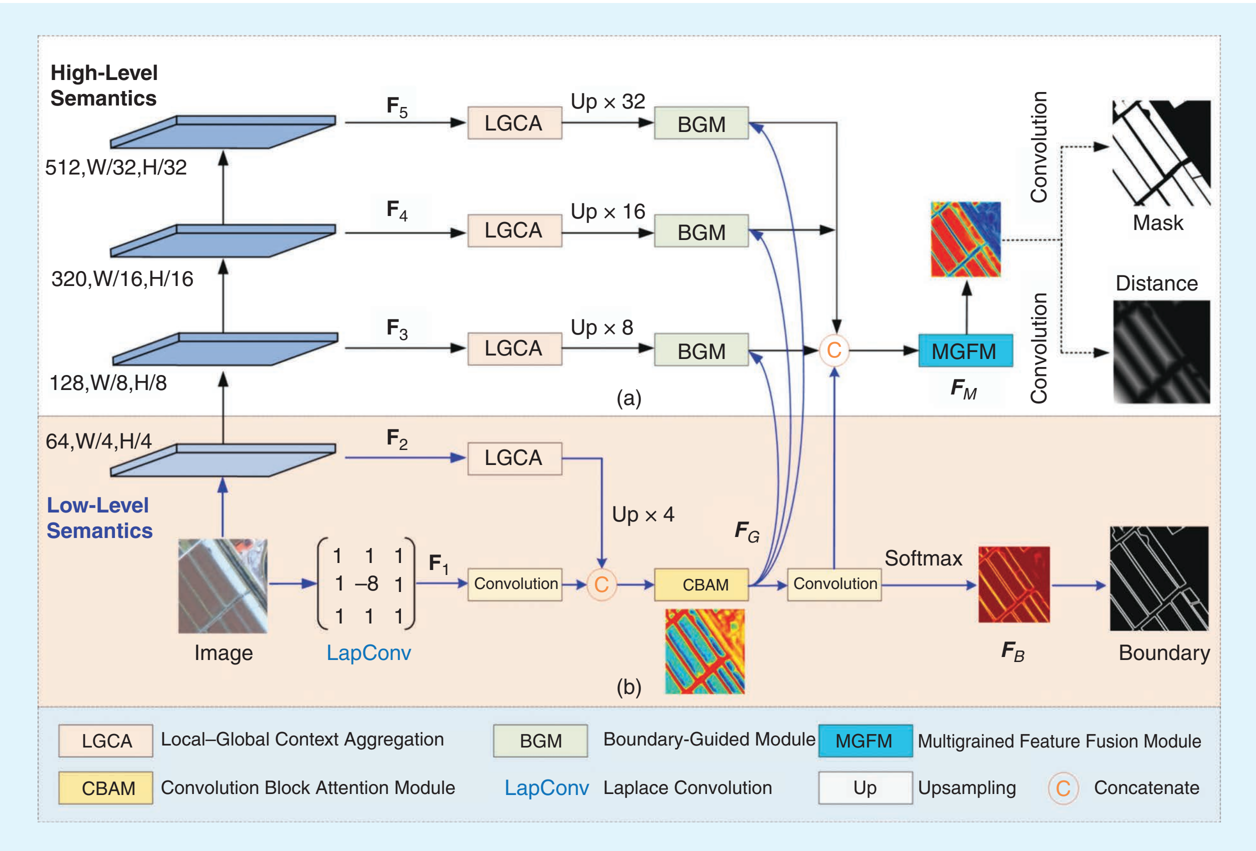

FIGURE 11. A typical example of a CNN-based semantic segmentation APBD method, HBGNet, proposed by Zhao et al. [142]. (a) The agricultural parcel feature extraction branch learns high-level semantic representations of agricultural parcels. (b) The parcel boundary feature extraction branch aims to obtain accurate boundary information by exploiting fine-scale spatial details from low-level features.

rules of smooth contour lines. The DPA is an algorithm that approximates a curve as a series of points and reduces the number of points. In addition, Wang et al. [166] point out that the deep learning model outputs field BD results but not separate crop fields. To obtain individual agricultural parcels (also called "instances"), they use a hierarchical watershed segmentation algorithm, which is a region-based algorithm that operates on a gray-scale image and treats it like a topographic map, with the brightness value of each pixel representing its height.

OBJECT DETECTION-BASED AGRICULTURAL PARCEL AND BOUNDARY DELINEATION METHODS

Object detection-based APBD frameworks, such as You Only Look Once (YOLO) [167], Mask Region-Based CNN (R-CNN) [168], Mask2Former [169], DeepSnake [170], and so forth, provide precise identification of agricultural parcel and boundary features, especially in farmland with complex and fragmented boundaries. The core of object detection-based methods is the region proposal before feature extraction and segmentation. The selective search algorithm extracts approximately thousands of class-agnostic region proposals from an input image, focusing on complete patches rather than pixels. By combining region generation with refined segmentation, these methods effectively address features such as cropland patches and agricultural boundaries. For example, inspired by DeepSnake, Pan et al. [138] propose the end-to-end vectorization of smallholder agricultural parcel boundaries for extracting the vertices of each parcel boundary individually, where the semantic contour interaction and topological loss through hierarchical instance representation are designed for aggregating foreground features and jointly establishing the topological relationship among instances to alleviate the topological overlap between parcel objects (see details in Figure 13). This method shows considerable gains on the iFLYTEK public agricultural parcel dataset compared to other object detection-based methods (such as the Mask

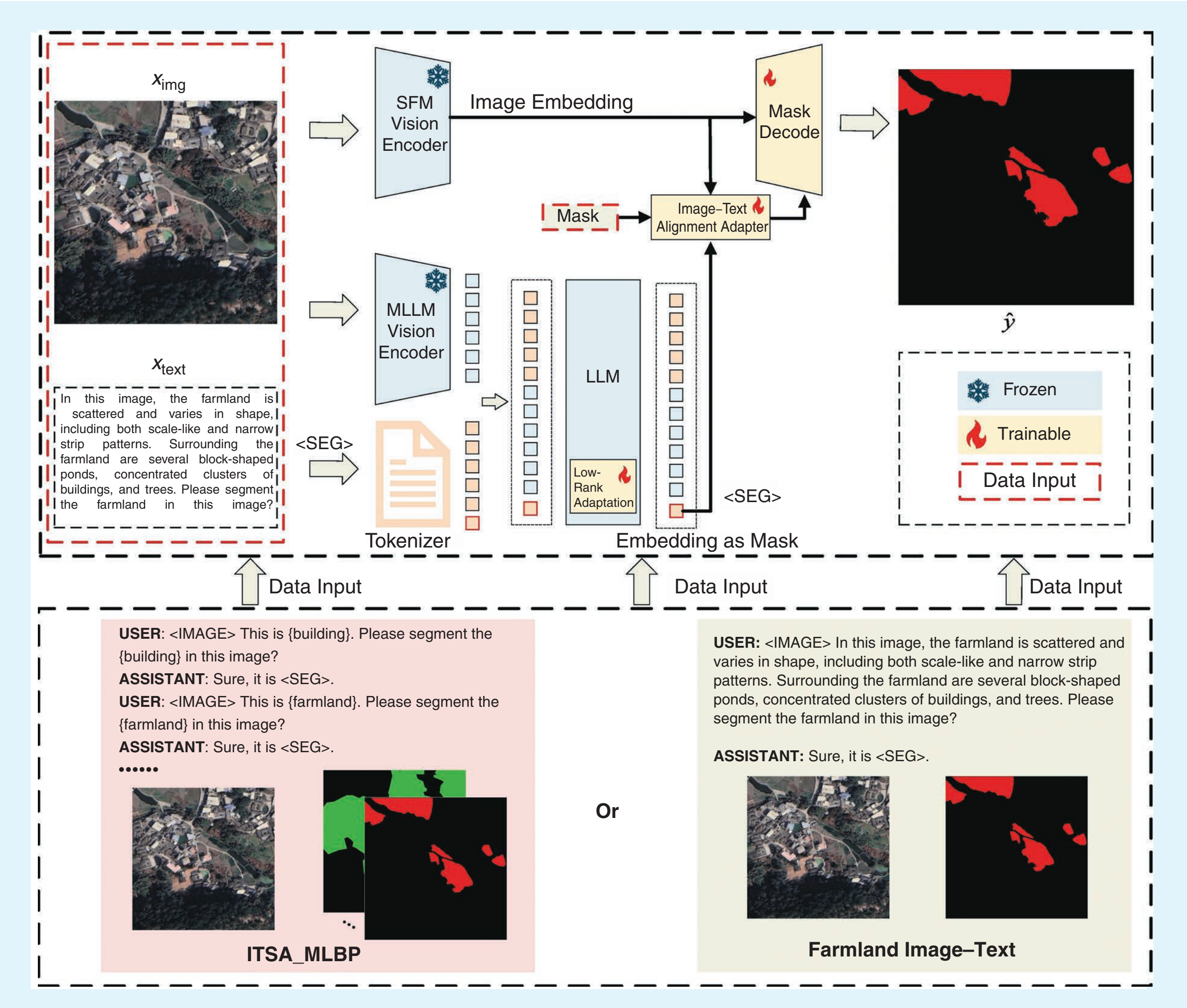

FIGURE 12. A transformer-based semantic segmentation APBD method, FarmSeg_VLM, proposed by Wu et al. [162]. SFM: structure from motion; MLLM: multimodal LLM.

R-CNN, E2EC, and DeepSnake). Cao et al. [171] propose an example segmentation method of Mask R-CNN based on a dual-attention mechanism feature pyramid network (FPN) to describe small farms, where the standard edge detection algorithm cannot accurately segment blurred farmland boundaries. Experiments indicate that this method could accurately depict small farms in VHR satellite images, which lays a foundation for the automatic segmentation of small farms.

However, traditional CNN-based object detection methods commonly perform slightly worse than semantic segmentation-based methods. Tetteh et al. [137] compare one object detection-based method (i.e., Mask R-CNN) with two semantic segmentation-based methods (i.e., U-Net and ResUNet) and one traditional image processing-based method (i.e., MRS based on supervised Bayesian optimization) for delineating agricultural parcels in Lower Saxony, Germany, from monotemporal *Sentinel-2* images. Experimental results show that ResUNet combined with a postprocessing approach generated the best segmentation results, closely followed by the optimized MRS approach.

Additionally, to further enhance instance-level extraction capabilities, transformer-based models show promise in few-shot learning, where pretraining and fine-tuning can mitigate the challenge of limited labeled agricultural parcel and boundary data. Some research uses SAM [10], a state-of-the-art image segmentation foundation model that functions as a generalized object extractor, as an auxiliary way to extract features and then adopt traditional machine learning-based methods (such as the RF, SVM, and so on) and deep learning-based methods (such as the CNN, long short-term memory, and so forth) to significantly improve the performance of classifiers and alleviate the sample scarcity problem [172]. Ferreira et al. [173] propose a new SAM-assisted crop field extraction framework using 2,022 *Sentinel-2* temporal composites and present the lessons learned using this foundational model in eight agricultural regions across the world. The large-scale applicability of this method is demonstrated in four countries (1 million km^2),

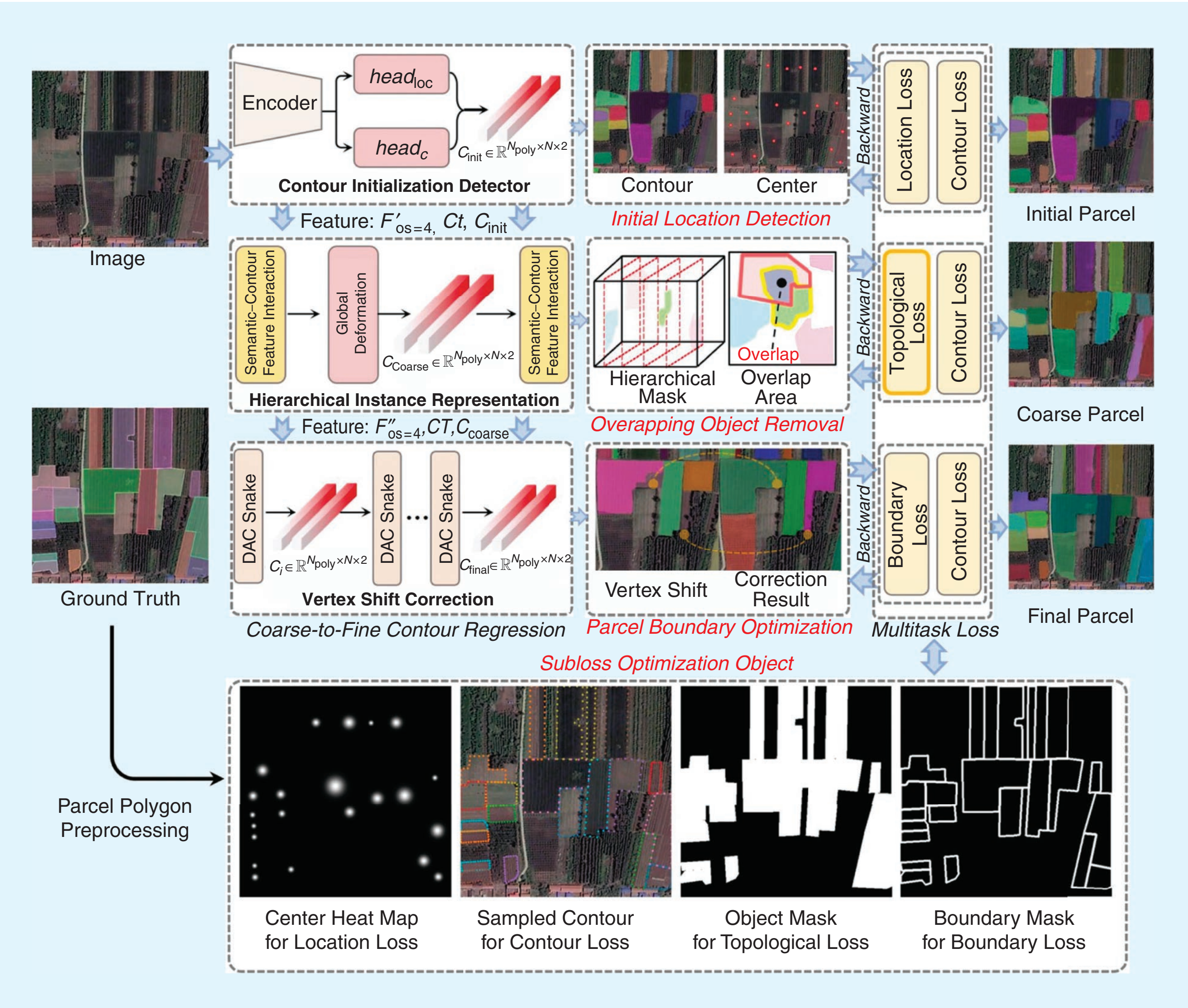

FIGURE 13. A CNN-based object detection APBD method, E2EVAP, proposed by Pan et al. [138]. DAC: deep attention contour.

showing promising results and the ability to generalize across different regions.

ASSESSMENT

PUBLIC DATASET FOR AGRICULTURAL PARCEL AND BOUNDARY DELINEATION

DATASET CONSTRUCTION

In the construction of a useful APBD dataset, four crucial indexes must be considered. First, the data source serves as the foundation for developing high-quality datasets. As evident in the selected APBD-related datasets in Table 5, these sources include high-resolution Earth observation satellites (e.g., *GF*, *Sentinel*, *Landsat*, and *SPOT*), aerial images, or geographic information programs. Second, resolution plays a vital role. APBD tasks necessitate high-resolution images, which provide fine-grained boundary information, and most of the publications in Table 5 have achieved resolutions finer than 30 m, with the highest resolution reaching 0.5 m. The third index pertains to the quantity of images. The datasets in Table 5 consistently involve manual annotation of a sufficient number of target samples for training, validation, and testing, taking into account the application domain and the complexity of model parameters. Especially for deep learning models that exceed 100 million parameters, such as transformers, an increase in the baseline number of annotated images is advisable. Finally, the geographic area covered by images is also an important consideration, as it relates to the diversity of agricultural parcels and boundaries. Using globally covered images for model training can enhance the generalization ability of the model.

EXISTING DATASETS

Table 5 summarizes key statistics of representative APBD-related datasets, showcasing their diversity in terms of sources, resolutions, and scales. For instance, FHAPD [142], the first large-scale VHR agricultural parcel dataset sourced from *GF-1/2*, contains 68,982 images covering an area of less than 500 km^2, with resolutions ranging from 0.5 to 1 m and two labeled classes. On the other hand, datasets like EuroCropsML [180], derived from *Sentinel-2*, stand out with a large number of images (706,683) and 176 labeled classes, emphasizing versatility. Notably, GTPBD [181], the first multicontinental fine-grained dataset with broad geographic coverage of major terraced regions (with study areas primarily distributed across Asia, Africa, Europe, and Latin America), sourced from *GF-2* and Google Earth, consists of 47,537 high-resolution images with three-level labels and more than 200,000 complex terraced parcels, with manual annotation. The wide range of resolutions and geographic coverage highlights the heterogeneity of APBD datasets. Furthermore, while many datasets are suitable for three different levels of APBD tasks, it is evident that the variety in parcel types, geographic locations, and image sources leads researchers to develop tailored datasets for specific scenarios. This reinforces the need for standardization and encourages sharing annotated datasets to foster broader adoption.

EVALUATION OF AGRICULTURAL PARCEL AND BOUNDARY DELINEATION RESULTS

PIXEL-LEVEL EVALUATION METRICS

To evaluate segmentation accuracy in crop identification, five standard pixel-level metrics are commonly used in

TABLE 5. STATISTICS OF REPRESENTATIVE APBD-RELATED DATASETS.

DATASET	SOURCE	IMAGES	AREA (KM^2)	RESOLUTION (M)	CLASSES	GLOBAL COVERAGE	TASK: CI	TASK: BD	TASK: PS
FHAPD [142]	*GF-1/2*	68,982	<500	0.5–1	2		✓	✓	✓
GTM [174]	*Sentinel-2*	108,300	853,161	10	2	✓	✓		
FTW [175]	*Sentinel-2*	70,462	166,293	10	2	✓	✓	✓	✓
AI4B (S-2) [176]	*Sentinel-2*	7,831	51,321	10	2		✓	✓	✓
AI4B (Ortho) [176]	*Aerial*	7,598	1,992	1	2		✓	✓	✓
PASTIS [177]	*Sentinel-2*	2,433	3,986	10	19		✓	✓	✓
CP-Set [178]	*GF-2*	949	249	1	2		✓	✓	✓
GFSAD30 [179]	*Landsat 8*	64,800	18,740,000	30	2	✓	✓		
GloCAB [177]	*Sentinel-2*	190,832	N/A	10	2		✓	✓	✓
EuroCropsML [180]	*Sentinel-2*	706,683	>4,000	10	176		✓	✓	
AI4SmallFarms [176]	*Sentinel-2*	62	1,550	10	2		✓	✓	✓
India Smallholder Boundaries [166]	*SPOT-6/7*	10,000	30–50	1.5–4.8	2		✓	✓	✓
GTPBD [181]	*GF-2* and Google Earth	47,537	885	0.5–0.7	3		✓	✓	✓
CropLayer [182]	Mapbox and Google satellite	389,777	9.6 million	2	2		✓		

CI, BD, and PS denote three different levels of APBD tasks.

semantic segmentation tasks, including precision [150], [183], recall [130], [151], the intersection over union (IOU) [121], [133], OA [131], [152], and the F_1 score [184], [185].

Precision measures the proportion of correctly predicted agricultural pixels among all pixels predicted as agricultural. A higher precision indicates fewer false positives (FPs) in land parcel classification.

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}. \tag{1}$$

True positives (TPs) indicate the number of pixels correctly identified as agricultural parcels, while FPs indicate the number of pixels misidentified as agricultural parcels (i.e., mistakes).

Recall captures the proportion of true agricultural pixels that are correctly identified. A high recall reflects the ability of a model to minimize missed detections.

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{2}$$

where false negatives (FNs) indicate the number of pixels misidentified as nonagricultural parcels (i.e., omissions).

The IOU quantifies the spatial agreement between predicted and ground truth regions. The IOU is widely adopted in segmentation benchmarks due to its robustness to class imbalance.

$$\text{IOU} = \frac{\text{TP}}{\text{TP}+\text{FP}+\text{FN}}. \tag{3}$$

The OA calculates the proportion of correctly classified pixels across the entire image. The OA provides a global view of model performance and is especially informative for datasets with class imbalance.

$$\text{OA} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{FN}+\text{TN}}. \tag{4}$$

where true negatives (TNs) indicate the number of pixels correctly identified as nonagricultural parcels.

The F_1 score is the harmonic mean of the precision and recall, offering a balanced evaluation metric particularly useful under domain shift conditions or in the presence of noise and uncertainty.

$$F1 = \frac{2\cdot\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}. \tag{5}$$

EDGE DETECTION EVALUATION METRICS

For BD tasks in the APBD scenario, we evaluate model performance using three widely adopted metrics: the optimal dataset scale (ODS) F_1 score [77], optimal image scale (OIS) F_1 score [77], and average precision (AP) [139]. These metrics jointly assess the accuracy, adaptability, and robustness of predicted boundaries.

Let P_t and R_t denote precision and recall computed at threshold t, and let F_t be the corresponding F_1 score.

$$F_t = \frac{2\cdot P_t\cdot R_t}{P_t+R_t}. \tag{6}$$

The ODS F_1 score evaluates the global performance of an edge detector across the entire dataset using a single optimal threshold t^*.

$$\text{ODS} = \max_{t\in\mathcal{T}}\left(\frac{2\cdot P_t^{\text{dataset}}\cdot R_t^{\text{dataset}}}{P_t^{\text{dataset}}+R_t^{\text{dataset}}}\right) \tag{7}$$

where P_t^{dataset} and R_t^{dataset} are the aggregated precision and recall over the full dataset under threshold t.

The OIS F_1 score computes the mean of the per-image best F_1 scores, reflecting local threshold adaptiveness.

$$\text{OIS} = \frac{1}{N}\sum_{i=1}^{N}\max_{t\in\mathcal{T}}\left(\frac{2\cdot P_t^{(i)}\cdot R_t^{(i)}}{P_t^{(i)}+R_t^{(i)}}\right) \tag{8}$$

where $P_t^{(i)}$ and $R_t^{(i)}$ denote the precision and recall on the ith image under threshold t and N is the total number of images.

The AP is computed as the area under the precision–recall curve.

$$\text{AP} = \int_0^1 P(R), dR \tag{9}$$

where $P(R)$ is the precision as a function of the recall, evaluated across all thresholds.

OBJECT-LEVEL GEOMETRIC METRICS

To comprehensively evaluate the geometric quality of delineated agricultural parcels, we adopt three object-level geometric metrics to evaluate PS: the global overclassification error (GOC) [152], [186], global underclassification error (GUC) [132], [186], and global total classification error (GTC) [127], [155]. These indicators quantify segmentation accuracy in terms of spatial overreach, omission, and overall geometric consistency.

Let S_i denote the ith predicted parcel (segmentation), and let O_i represent the ground truth parcel that has the largest intersection area with S_i. Denote m as the number of predicted parcels. The object-wise evaluation is defined as follows.

The GOC measures the average extent to which predicted parcels exceed the spatial extent of their matched ground truth objects.

$$\text{OC}(S_i) = 1 - \frac{\text{area}(S_i\cap O_i)}{\text{area}(O_i)} \tag{10}$$

$$\text{GOC} = \sum_{i=1}^{m}\left(\text{OC}(S_i)\cdot\frac{\text{area}(S_i)}{\sum_{k=1}^{m}\text{area}(S_k)}\right) \tag{11}$$

where $\text{area}(\cdot)$ denotes the number of pixels in the respective region.

The GUC quantifies the proportion of each predicted parcel not covered by the corresponding ground truth.

$$\text{UC}(S_i) = 1 - \frac{\text{area}(S_i\cap O_i)}{\text{area}(S_i)} \tag{12}$$

$$\text{GUC} = \sum_{i=1}^{m}\left(\text{UC}(S_i)\cdot\frac{\text{area}(S_i)}{\sum_{k=1}^{m}\text{area}(S_k)}\right). \tag{13}$$

The GTC synthesizes both over- and underclassification errors into one holistic metric using a root-mean-square formulation.

$$\mathrm{TC}(S_i)=\sqrt{\frac{\mathrm{OC}(S_i)^2+\mathrm{UC}(S_i)^2}{2}} \tag{14}$$

$$\mathrm{GTC}=\sum_{i=1}^{m}\left(TC(S_i)\cdot\frac{\mathrm{area}(S_i)}{\sum_{k=1}^{m}\mathrm{area}(S_k)}\right). \tag{15}$$

DISCUSSIONS

APBD is of the utmost importance for a comprehensive understanding of food security on global and local scales. The presented meta-analysis is convenient to outline the past, current, and potential future of APBD for those who want to know about this specific domain. The thorough introduction of APBD algorithms in this article may be interesting to them. In this section, we discuss four APBD-related issues to further comprehend the APBD domain.

MULTISENSOR DATA IN AGRICULTURAL PARCEL AND BOUNDARY DELINEATION DOMAIN

Due to the extreme imbalance of categories in farmland boundary extraction tasks, the direct use of neural networks for boundary pixel prediction in remote sensing images often results in poor performance. Therefore, some studies investigate the beneficial effects of multisource and multisensor remote sensing data fusion to assist in boundary extraction. In addition, most of the existing research on farmland boundary extraction is based on optical remote sensing data. The quality of optical remote sensing images depends on the absence of clouds and rain [187]. Research in rainy and cloudy areas will be limited to some extent. Compared with this, remote sensing platforms based on polarized synthetic aperture radar (SAR) are not limited by clouds and rain and have the characteristic of all-weather conditions. For example, Kuang et al. [188] propose a novel cascaded model of semantic segmentation and edge detection for the boundary extraction task of farmland in northern Xinjiang, China, using the fused data of *Sentinel-1* dual-polarized SAR images with multiple temporal phases and *Sentinel-2* multispectral images. In addition, some studies also utilize different optical remote sensing images with multiresolution to extract different levels of features for cropland and boundaries. VHR images (such as *QuickBird*, *WorldView*, and so on) could easily distinguish field boundaries in areas with established croplands, while processing large volumes of VHR scenes for a region is computationally intensive and has previously been a cost-prohibitive task. On the other hand, although moderate-resolution satellite data (such as *Landsat*, *Sentinel*, and so on) do not have adequate spatial resolution to capture the total area occupied by smallholder farms, they have richer spectral information and time-series temporal characteristics, with easy accessibility. For example, McCarty et al. [189] combine the results from submeter *WorldView-1* and *WorldView-2* segmentation with the median phenology amplitude from *Landsat 8* data to map cropped areas for the rainfed residential cropland mosaic of the Tigray Region, Ethiopia, consisting mostly of smallholder farms.

SINGLE-TASK LEARNING VERSUS MULTITASK LEARNING

Currently, deep neural networks have been widely used in extracting thematic information due to their powerful feature extraction capabilities [190], [191], which could be categorized into two classes: single-task and multitask models. Single-task networks typically use an encoder–decoder architecture, where the encoder captures multiscale semantic features and the decoder subsequently refines these gathered features [115], [192]. Although these approaches produce satisfactory results, they tend to overlook the benefits of intrinsically related tasks that share optimal hypothesis classes, which could enhance generalization and reduce overfitting risk. Therefore, researchers have increasingly adopted multitask architectures that allow for joint representation learning across multiple related tasks [31], [152], [193]. For example, Long et al. [190] propose BsiNet, which learns three tasks: a core task for agricultural field identification and two auxiliary tasks for field boundary prediction and distance estimation, corresponding to mask, boundary, and distance tasks, respectively. However, such a method fails to fully consider multilevel boundary semantics, resulting in incomplete and unclosed parcel boundaries. To deal with these deficiencies, the dual-branch architecture performs the tasks of agricultural parcel detection and BD separately, using a shared encoder but distinct decoders, which improves the representation of boundary features, thus enhancing the accuracy of AP delineation in diverse areas (such as SEANet [152] and HBGNet [142]).

COMPARISON OF DIFFERENT AGRICULTURAL PARCEL AND BOUNDARY DELINEATION METHODS

Table 6 presents a qualitative assessment for different APBD methods in three aspects: annotations, efficiency, and accuracy. Here, we conduct in-depth discussions of them.

ANNOTATION

It is necessary and fundamental to conduct annotation work in supervised learning. Traditional image processing-based APBD methods have the least cost, and most of them are unsupervised learning methods and do not require any annotation work [44], [54]. The annotation work of deep learning-based APBD methods (especially for semantic segmentation-based methods) is the most difficult and complex among all methods since most of them are pixel-level annotation and have to carefully outline all kinds of fine-grained boundary shapes for agricultural parcels [115], [194]. As for most traditional machine learning-based APBD methods, we not only have to annotate samples of farmland but also have to annotate samples of other land cover types, such as bare land, water, trees, impervious areas, and so on. As for object detection-based methods, we have to annotate the location of the four corners of an agricultural parcel and generate a bounding box for each individual parcel [134]. Of course, for Mask R-CNN and Mask2Former, we further have to annotate the thorough shape of each agricultural parcel to conduct PS [140], [171]. The two abovementioned APBD methods are of moderate difficulty, and their annotation work is more difficult than traditional image processing-based APBD methods while easier than semantic segmentation-based APBD methods.

EFFICIENCY

Algorithm efficiency is a crucial factor in APBD applications, especially applied to large-scale study areas. Since most of the applications are unsupervised learning algorithms, traditional image processing-based APBD methods cost the most time in simple and basic image operations, usually with low computation complexity [42]. However, region-based methods may cost more iteration time than pixel-based and edge-based methods. Therefore, the efficiency of region-based methods is lower than the other two traditional image processing-based methods. Transformer-based semantic segmentation and transformer-based object detection APBD methods have the worst performance in algorithm and implementation efficiency, given that their parameters are huge, although their performance is the best. Traditional machine learning-based APBD methods usually require the time-consuming sliding window scheme to achieve the location and recognition of cropland [95]. In addition, classifiers or neural network training and parameter tuning phases worsen their efficiency. Although CNN-based semantic segmentation and CNN-based object detection APBD methods both have time-consuming neural network training work, they belong to end-to-end algorithms that allow the delineation of agricultural boundaries in the whole patch image [127]. To this end, these three algorithms are moderately efficient, better than transformer-based semantic segmentation and transformer-based object detection APBD methods while worse than traditional image processing-based APBD methods.

ACCURACY

Accuracy is the most important evaluation metric to judge whether the APBD algorithm is successfully applied to practical agricultural inventory. In general, deep learning-based methods perform the best in accuracy, with high robustness and generalization [114], [186]. In particular, deep learning-based APBD methods achieve more convincing and satisfying results in complex areas [122], [138]. Notably, transformer-based semantic segmentation and transformer-based object detection APBD methods have slightly better performance than CNN-based semantic segmentation and CNN-based object detection APBD methods. As for traditional image processing-based APBD methods, their accuracy is generally the lowest among the different algorithms, and they have satisfactory performance only in simple areas or under specific parameters or specific regions. When study sites involve varied topography, complicated environments, or regions with overlapping field boundaries, the accuracy may suffer a terrible deterioration. It is noteworthy that region-based methods usually perform best compared to pixel-based and edge-based methods [14]. The accuracy of traditional machine learning-based APBD methods is between that of deep learning-based APBD methods and traditional image processing-based APBD methods.

COMPARISONS OF GENERAL DEEP LEARNING MODELS AND THEIR APPLICATIONS IN AGRICULTURAL PARCEL AND BOUNDARY DELINEATION DOMAIN

In Figure 14, the top of the timeline shows the development of general deep learning architectures, and the bottom shows the years that these deep learning models were first used in the APBD domain.

Early research in APBD was predominantly driven by CNN-based semantic segmentation methods. These approaches frame the task as a pixel-wise classification problem, aiming to assign each pixel to a specific class, such as "parcel" or "background." As depicted, foundational models like the FCN, U-Net, and DeepLab were among the first to be adapted for this purpose, between 2018 and 2020. Subsequently, more sophisticated architectures, such as PSPNet, D-LinkNet, and HRNet, which offer improved

TABLE 6. A QUALITATIVE COMPARISON OF DIFFERENT APBD METHODS IN ANNOTATION, EFFICIENCY, AND ACCURACY.

METHODS		ANNOTATION	EFFICIENCY	ACCURACY
Traditional image processing-based APBD methods	Pixel based	+++	+++	+
	Edge based	+++	+++	+
	Region based	+++	++	++
Traditional machine learning-based APBD methods		++	++	++
Deep learning-based APBD methods	CNN-based semantic segmentation	+	++	+++
	CNN-based object detection	++	++	+++
	Transformer-based semantic segmentation	+	+	+++
	Transformer-based object detection	++	+	+++

Three plus signs (+++) denote methods that perform best, while one plus sign (+) denotes methods that perform the worst.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

context aggregation and multiscale feature representation, were also introduced to enhance the accuracy and completeness of the extracted parcel boundaries.

A subsequent evolution in methodology saw the adoption of CNN-based object detection frameworks, which treat each agricultural parcel as a distinct "instance." This paradigm shift enables the delineation of individual nonoverlapping field boundaries, a critical requirement for parcel-level analysis. Pioneering instance segmentation models like Mask R-CNN were first applied to APBD around 2020. This was followed by more advanced contour-based methods, such as DeepSnake, which directly regresses the boundary vertices, and sophisticated mask-prediction models like Mask2Former and YOLO, further improving the precision of individual parcel extraction.

The most recent phase in APBD research is characterized by the integration of transformer-based architectures. However, it is crucial to clarify that rather than constituting a new third category of methods distinct from the aforementioned approaches, this phase is largely characterized by the adoption of transformer-based backbones within both semantic segmentation and object detection-based APBD frameworks. These models, leveraging self-attention mechanisms, excel at capturing long-range dependencies and global contextual information, which is highly beneficial for understanding the complex layouts of agricultural landscapes. Furthermore, the advent of large foundation models introduced novel paradigms. SAM offers powerful segmentation capabilities through prompting. Similarly, LLMs like Llama represent a significant shift. In the context of APBD, Llama is not directly used for pixel-level segmentation; instead, it is typically fine-tuned using techniques like low-rank adaptation to function as an advanced instruction-following component. It interprets user textual requirements, such as "Extract only the irrigated rice paddies," and guides an underlying visual segmentation model to perform the specific extraction task, thereby enabling a more interactive and semantically aware parcel delineation process.

According to different deep learning models, we can complete different APBD tasks (see Table 6). General deep learning models can be directly applied to APBD scenarios. However, the following differences and modifications should be considered:

1) Since the size of a remote sensing image is too large to be data input for general deep learning models, we need to utilize an overlapping partition method to divide a large-scale remote sensing image into several subimages in the inference phase. After that, we apply coordinate transformation and merge the results of all the subimages to achieve the final APBD results [142], [166].
2) As for the design of deep learning architectures, we need to modify the sizes and the ratios of candidate anchor boxes in object detection-based APBD methods, due to the fact that the size of agricultural parcels is usually different from that of general objects. Furthermore, the number of channels in the first layer usually needs to be modified because of multispectral bands for remote sensing images, rather than only three bands for general images [173], [195].
3) Many deep learning-based methods need postprocessing procedures. For example, the results of semantic segmentation-based APBD methods are "confidence maps," so the approaches usually require the DPA [164] or watershed segmentation [166] to produce the final detection and delineation of individual parcels. Some

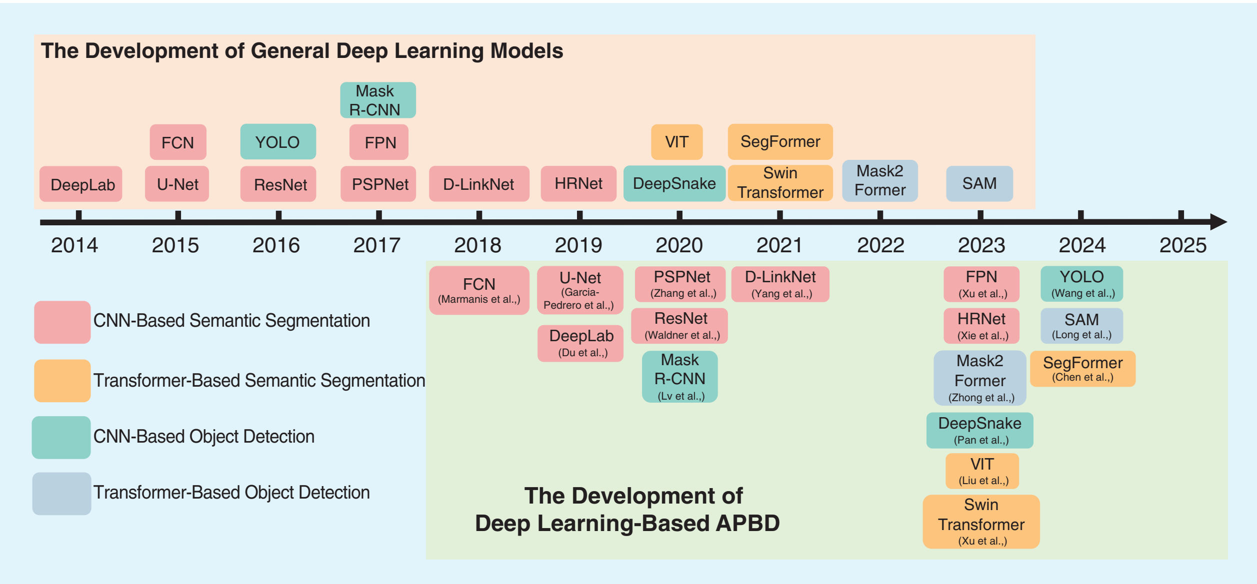

FIGURE 14. A timeline comparison between the development of general deep learning models and their adoption in APBD applications from 2014 to 2025 (data collected until 20 August 2025). The figure reveals a consistent two- to four-year lag between a model's introduction in computer vision and the model's application to agricultural parcel extraction.

studies design dedicated postprocessing strategies for vector generation and homogeneity checking to produce closed and discrete polygons [121], thereby improving the accuracy of the APBD model.

CRITERIA FOR CHOOSING APPROPRIATE AGRICULTURAL PARCEL AND BOUNDARY DELINEATION METHODS

Due to the complexity of different research subjects (e.g., mixed cropland, specific types of cropland, and so forth) with different attributes (e.g., areas, density, locations, and so on), it is desirable to design or select appropriate APBD approaches that address APBD tasks under different scenarios. In this section, we discuss multiple influencing factors of APBD approaches.

CROP TYPES

The accuracy of APBD is significantly influenced by the type of crops grown within each field. Different crops exhibit distinct canopy structures, texture features, and planting patterns, which directly affect the separability of parcel boundaries in remote sensing imagery. For example, large-scale crops, such as maize and wheat, are typically grown in regular rows with uniform canopy coverage, resulting in clear boundaries and homogeneous textures that facilitate accurate segmentation. In contrast, crops like vegetables, legumes, and mixed grains are often grown in small fields with diverse management practices, such as intercropping, crop rotation, or multiple harvests per year. These conditions lead to spectral heterogeneity and ambiguous boundaries, thereby reducing segmentation performance. The phenological stage of crops also plays a crucial role. For instance, paddy fields exhibit distinct boundaries during the early transplanting phase due to exposed soil and water backgrounds, but these boundaries become less distinguishable in later stages when the canopy closes and interparcel differences diminish. The fusion of multisource remote sensing data, particularly combining optical and SAR imagery, can improve robustness in complex agricultural scenarios by leveraging complementary spatial and spectral features. Overall, crop type is a key factor influencing parcel extraction performance, and careful consideration of crop-specific characteristics is essential for developing models with high generalizability and accuracy across diverse agricultural landscapes.

TERRAIN AND TOPOGRAPHY

Terrain and topography characteristics play a critical role in the accuracy of APBD from remote sensing imagery. These effects are manifested in the spatial morphology of parcels, the spectral expression of land surfaces, and the variability of cropping patterns across different landscapes. In flat areas, such as the North Plain or the Northeast Plain in China, agricultural fields tend to be large, regularly shaped, and managed uniformly. These conditions produce clear spectral signatures and well-defined boundaries in remote sensing images, enabling high-precision extraction using deep learning models. In contrast, in hilly and mountainous regions, parcels are often small, irregularly shaped, and constructed along slopes. These landscapes result in fragmented spatial patterns and complex boundary shapes, which significantly increase the difficulty of accurate delineation [196]. Topographic variation also affects the radiometric properties of remote sensing imagery. In areas with significant elevation changes, differences in slope and aspect alter the illumination geometry, causing uneven reflectance even within the same crop type. This intraparcel spectral inconsistency can lead to oversegmentation or misclassification. Additionally, terrain-induced shadows and occlusions are common in mountainous areas, obscuring boundary information and introducing errors in PS. These challenges are particularly pronounced when using single-date optical imagery, where shadow and lighting variation is not compensated for, resulting in reduced accuracy and robustness.

CROPPING PRACTICE AND MANAGEMENT

Cropping practice and management also exert a significant influence on the selection of appropriate APBD methods by shaping field characteristics [197]. In regions dominated by mechanized farming, such as large-scale grain-producing areas, agricultural parcels tend to be large, geometrically regular, and uniformly managed [31], [61]. For these scenarios, standard semantic segmentation models or OBIA are often sufficient to achieve high accuracy due to the spatial homogeneity and consistent texture [42], [190]. Conversely, smallholder farming systems, commonly found in mountainous regions and developing countries, present markedly different challenges, with smaller, irregularly shaped, and fragmented parcels [127]. In such systems, mixed cropping and the absence of distinct physical boundaries result in high intraparcel variability. Consequently, methods designed for these regions should go beyond simple spectral analysis. Approaches that incorporate topological constraints, instance-level reasoning, or boundary-aware loss functions are more suitable to address the fragmentation and lack of clear edges [138], [152]. Furthermore, regional variability implies that models trained on data from mechanized regions may not generalize to smallholder systems, necessitating the use of transfer learning or domain adaptation techniques when selecting methods for cross-regional applications [155].

CHALLENGES IN OPERATIONALIZING AUTOMATED AGRICULTURAL PARCEL AND BOUNDARY DELINEATION MODELS

Despite rapid advances in automated APBD methods, manual visual interpretation by trained experts remains the primary approach in operational agricultural monitoring programs [198], [199]. This gap between research innovation and practical deployment reflects fundamental technical challenges that limit the reliability of current automated methods in real-world production systems.

INHERENT AMBIGUITY OF PARCEL BOUNDARIES

A primary challenge is that agricultural parcel boundaries, unlike objects such as buildings, often lack distinct visual markers in remote sensing imagery [31]. Adjacent parcels may share the same crop and growth stage, creating a continuous spectral appearance with no clear transition. Boundaries might be defined by subtle changes in crop texture, narrow features like small drainage channels, or purely administrative lines that have no spectral signature at all [32]. This lack of consistent physical indicators means that even high-resolution imagery may not contain sufficient information to reliably identify all boundaries, posing a fundamental limitation for any automated approach.

PERFORMANCE DISPARITY ACROSS TERRAINS AND FARMING SYSTEMS

While the "Methodology Review" section discussed how farming systems influence method selection, a critical operational challenge lies in the stark performance gap of existing models across these systems. In flat regions with large-scale mechanized farming (e.g., the North China Plain or U.S. Midwest), automated methods achieve operational-grade accuracy [200]. However, performance degrades sharply in mountainous, hilly, or smallholder farming areas, which feature complex topographic effects and fragmented ownership [122], [166], [181]. This disparity creates a significant barrier to the global operationalization of APBD: regions where manual interpretation is most costly and automation is most urgently needed for food security monitoring (e.g., South Asia or Africa) are precisely where current automated models perform the worst [152], [201]. This inverse capability gap means that despite high reported metrics in the literature, the technology remains unreliable for practical deployment in complex agricultural landscapes, limiting its utility for global-scale monitoring programs.

MODEL LIMITATIONS IN PRESERVING GEOMETRIC DETAIL

While deep learning models excel at learning high-level patterns, they often fail to preserve the fine geometric details essential for accurate parcel delineation [8]. Standard CNN architectures tend to produce smoothed boundaries due to pooling and upsampling operations that reduce spatial precision [202]. Consequently, predicted boundaries can deviate from their true locations, and sharp corners are often rounded [203]. Thin linear features like irrigation ditches or farm tracks, which may be only a few pixels wide, are frequently missed entirely [204], [205]. These geometric inaccuracies have significant operational consequences for cadastral mapping or subsidy allocation, where even small errors can lead to incorrect area calculations or ownership disputes. As a result, automated outputs often require substantial manual correction, undermining the efficiency gains of automation [206].

RELIABILITY AND QUALITY CONTROL REQUIREMENTS

Operational agricultural monitoring demands not only high average accuracy but also predictable and auditable outputs [207]. Manual interpretation provides built-in quality assurance through human judgment and contextual reasoning [208]. In contrast, current automated models often function as "black boxes," making it difficult to diagnose the cause of an incorrect boundary, whether it stems from poor image quality, insufficient training data, or inherent ambiguity in the scene [209]. A critical limitation is the general lack of uncertainty estimates, which prevents operators from distinguishing high-confidence predictions from those requiring manual review [210]. This is a major barrier in applications with legal or financial stakes, such as land tenure documentation or agricultural subsidy payments, where trust and explainability are paramount [211].

In summary, the continued dominance of manual interpretation is rooted in real technical limitations. Closing this research–practice gap requires more than just incremental accuracy gains. It calls for fundamental advances in model robustness across diverse landscapes, geometric precision, and transparent reliability assessment to enable effective quality control in operational settings.

AGRICULTURAL PARCEL AND BOUNDARY DELINEATION-RELATED APPLICATIONS

In this section, we introduce some practical APBD-related applications. Other APBD applications include wildfire potential estimation, plant heterogeneity, wildlife protection and biodiversity research, and so forth. Most of the applications first conduct APBD and then further conduct other analyses on a single-plot scale. With the recent emergence of end-to-end deep learning techniques, we are able to achieve APBD, along with cropland classification or yield estimation in the meantime.

CROP TYPE CLASSIFICATION

APBD task is a preliminary step in crop type classification, which holds significant implications for cadastral management and agricultural land governance [49], [50]. However, most existing crop type classification is based on the first level of APBD, crop identification, without any BD or parcel extraction. In addition, existing parcel-level crop type classification is a two-stage framework, first conducting APBD for regions [212], [213] or directly using cropland parcel boundary vector data from others [83], [214], [215] and then getting the crop types for each individual parcel using another classifier or model. For example, Xie et al. [184] first adopt a boundary-enhanced U-Net model for farmland parcel extraction from *GF-2* data and then select RFs to achieve crop classification at the parcel level from both *Sentinel-2* and *Landsat 8* data. Therefore, as deep learning techniques emerged, end-to-end parcel-level crop type classification was proposed for application to larger areas with high efficiency.

YIELD ESTIMATION

Accurate and timely crop yield estimation is critical to realizing global food security, balancing international grain trade, and promoting sustainable agricultural development [2]. By providing consistent and large-scale observations, remote sensing technology has become indispensable in crop yield estimation across local, regional, and global scales. Over the past four decades, numerous crop yield estimation approaches have been developed. There is great potential to integrate AI and remote sensing technologies with process-based crop growth models through data assimilation techniques. However, most existing yield estimation studies are limited to the pixel level instead of the parcel level. Some parcel-level yield estimation conducts experiments only on very small-scale areas [216], [217] and may adopt existing open source field parcel boundary datasets [218] or manual delineation [219], which is actually a two-stage scheme. We think it is important to develop end-to-end parcel-level yield estimation algorithms using advanced deep learning methods in the future.

STRESS DETECTION AND HEALTH MONITORING

Multispectral information from remote sensing data, coupled with machine learning or deep learning techniques, plays a considerable role in crop stress [21], [216], crop phenology [22], [220], and other health monitoring [5], including disease, nutrient, and pest surveillance; growth status observation [221]; and so forth. Similar to cropland classification, previous popular health monitoring of individual parcels was two-stage work, although, as deep learning-based APBD methods emerge, existing crop health assessment becomes an end-to-end one-stage framework, accomplishing both individual parcel delineation and status observation. Compared to SAR/lidar data, deep learning may perform better on multispectral optical remote sensing data because of the data's rich semantic and texture information, which is also beneficial for capturing the intrinsic features of vegetation. As a matter of fact, employing comprehensive health monitoring is beneficial to improve productivity or yield and further increase the economic effect.

MULTITEMPORAL CHANGE DETECTION

On the one hand, multitemporal remote sensing images can facilitate more accurate agricultural parcel extraction from time-series features [29], [156], [222]. For example, Garnot [223] proposed a multimodal temporal attention-based model by leveraging both optical and radar time series to outperform single-modality models for crop mapping in terms of performance and resilience to cloud cover. On the other hand, multitemporal images could aid in exploring changes to cropland areas [224], crop types, growth processes [22], and so forth, evaluating variations of food production [225] and carbon stock [226] or the impacts of abandoned cropland [227], natural disasters [228], and conservation policies [229]. Also, multitemporal data contribute to better accomplishing APBD and APBD-related applications through seasonal spectral and texture variations [230], [231], [232]. However, similar to crop classification, existing single-parcel-level change analyses are all two-stage workflows [172]. Following the development of recurrent neural networks, we believe that coupling semantic segmentation-based and object detection-based APBD methods with time-series analysis may achieve real-time, high-accuracy, and end-to-end single-parcel-level change analysis using multitemporal remote sensing data.

PROSPECTS

Based on the above literature analysis, methodology review, and in-depth discussion, APBD-related prospects emerge, concerning past, current, and future trends. These prospects are introduced in this section.

MULTISOURCE AND MULTIRESOLUTION REMOTE SENSING DATA FUSION

The integration of multisource and multiresolution remote sensing data is expected to play a transformative role in advancing APBD. Traditional approaches often depend on single-source optical imagery, which is constrained by cloud cover, spectral limitations, and inconsistent resolution [187]. In contrast, data fusion enables the combination of complementary information across diverse platforms, including VHR optical imagery, medium-resolution time-series satellites (e.g., *Sentinel-2* and *Landsat*), SAR, lidar, and hyperspectral sensors, providing richer spatial, spectral, and temporal signals to support more accurate and robust delineation [187]. The synergy between spatial detail and temporal continuity improves both intrafield homogeneity and interfield separability, which are essential for high-quality segmentation. On the other hand, recent advances in deep learning facilitate more effective fusion of heterogeneous data [233]. Transformer-based models and attention mechanisms can learn from multiresolution and multimodal inputs, dynamically weighting relevant features according to the landscape context [185]. This enables more generalizable and adaptive parcel extraction models across diverse agroecological zones, especially when applied at continental or global scales. Therefore, the fusion of multisource and multiresolution remote sensing data represents a critical frontier for the future of APBD. Building intelligent, adaptable, and transferable frameworks will be essential for ensuring accurate delineation across variable landscapes, supporting both scientific research and operational applications in agriculture and land management.

KNOWLEDGE-GUIDED EXPLAINABLE DEEP LEARNING-BASED METHOD FOR AGRICULTURAL PARCEL AND BOUNDARY DELINEATION

As remote sensing technologies evolve toward higher spatial, spectral, and temporal resolutions, the challenge of accurate APBD becomes increasingly complex. In this context, knowledge-guided and explainable deep learning methods are emerging as a promising direction to improve the interpretability, generalizability, and reliability of models. Unlike purely data-driven approaches, knowledge-guided deep learning integrates domain-specific priors, such as agronomic patterns, crop growth cycles, and cadastral logic, into the model design to enhance performance in heterogeneous and data-scarce regions [234]. In addition, such models learn not only from raw imagery but also from structured knowledge graphs, spatial rules (e.g., field shape regularity and adjacency constraints), and temporal behaviors (e.g., plant–harvest cycles) [75]. This fusion of learning and reasoning facilitates more accurate detection of subtle or ambiguous field boundaries, especially in smallholder farming systems or terraced areas. Moreover, by embedding explainable components, such as attention visualization, saliency maps, and rule-based decision modules [235], these methods offer insights into model behavior, supporting trust and transparency in agricultural monitoring applications. In future developments, knowledge-guided models will be instrumental in enabling scalable, adaptive, and policy-aligned parcel extraction pipelines, and explainability mechanisms will support user validation, integration with cadastral databases, and collaborative decision making in precision agriculture and land management.

FINE-GRAINED CROP OR GROWTH STATUS CLASSIFICATION

Fine-grained cropland classification includes both fine-grained crop [236] and fine-grained growth status (such as different levels of disease, stress, and damage) classifications. The former is significant for understanding the distribution of crop types and ensuring food production. The latter not only observes damaged or diseased crops to prevent their proliferation but is also conducive to estimating yield and increasing the benefits for some economic crops. As for growth status observation, most growth statuses are classified into healthy and unhealthy croplands. By contrast, few studies are devoted to multiclass growth status classification. It is highly important to monitor cropland for more fine-grained health conditions, such as specific diseases. Until now, individual agricultural parcel classification work has been a two-stage scheme, first detecting or delineating the agricultural parcel and then completing type or growth status recognition [221]. Furthermore, fine-grained classification requires recognizing the slight differences among similar classes, which may need high-spatial-resolution and high-spectral-resolution remote sensing images. The data-fusing approaches mentioned in the "Multisensor Data in Agricultural Parcel and Boundary Delineation Domain" and "Multisource and Multiresolution Remote Sensing Data Fusion" sections would be effective solutions.

LARGE-SCALE AGRICULTURAL PARCEL AND BOUNDARY DELINEATION IN SPATIAL BIG DATA ERA

Undoubtedly, we are in the big data era and will continue to be in the future. Massive remote sensing images acquired by satellites, planes, UAVs, and even mobile phones create the spatial big data era. With these Earth observation data, we have the opportunity to achieve large-scale APBD and deeply comprehend global cropland resources. There are some global [237], national [238], and large-scale regional [115] crop mapping products. However, these works focus only on CI instead of fine-grained BD or individual parcel delineation. For example, despite the fact that Potapov et al. [224] estimate that there were roughly 1,244 Mha around the world in 2019, they only approximately map the global cropland distribution, without fine-grained agricultural parcel delineation. There are two major challenges in large-scale APBD work. The first is the capacity of model generalization. As we have to prepare multitemporal, multisource, and multiregional remote sensing data to conduct large-scale APBD, developing a more transferable, robust, and general model would be a powerful foundation, using advanced algorithms, such as domain generalization [239], [240], domain adaptation [241], [242], and transfer learning [243], [244]. Also, how to transfer our model to apply in complex areas, such as smallholder farmlands and terraced and mountainous areas [181], is very challenging, with scarce data. Another challenge is computational capacity to support the efficiency of APBD in large-scale areas. At present, few studies adopt high-performance computation platforms (such as field-programmable gate arrays and GPUs) to accelerate APBD algorithms. However, global, continental, or national-level APBD research has not been completed on higher-performance computing platforms, such as supercomputers, which may be a potential general platform for processing global observation issues [245], [246].

FOUNDATION MODELS FOR AGRICULTURAL PARCEL AND BOUNDARY DELINEATION

Building on initial successes, mentioned in the "Methodology Review" section, the future of foundation models in APBD holds transformative potential. One exciting frontier is the development of interactive human-in-the-loop workflows, where operators can use natural language to guide and refine delineations in a conversational manner. Another promising direction, rather than building a single monolithic model, is to create an ecosystem of coordinated models. Here, a powerful base model pretrained on remote sensing data would serve as a common foundation from which smaller specialized models were efficiently fine-tuned for distinct tasks like parcel delineation, crop classification, and yield estimation. This modular approach enhances efficiency and flexibility. Furthermore, the generative capabilities of these models could be harnessed for synthetic data generation, creating realistic agricultural imagery to address data scarcity in underrepresented regions.

However, operationalizing these models for APBD faces significant challenges. First, their immense computational and data requirements for training and fine-tuning pose high costs and accessibility issues. Second, a significant domain gap exists between the natural images used for pretraining most foundation models and the unique characteristics of remote sensing data, requiring sophisticated adaptation strategies [155]. Third, there is a tangible risk of model "hallucination," where a model generates linguistically plausible but factually incorrect boundaries or labels [247]. Finally, ensuring that the models produce geometrically precise and topologically correct outputs remains a key hurdle, as the models may still generate smoothed corners or disconnected segments, unacceptable for cadastral applications [138]. Addressing these practical challenges is as crucial as algorithmic innovation for the reliable deployment of foundation models in APBD.

CONCLUSIONS

This review article has systematically charted the evolution of APBD, presenting a comprehensive meta-analysis of research from the past decade and a detailed methodological survey that spans from traditional image processing to the latest deep learning paradigms. Our analysis reveals a significant shift toward deep learning and VHR imagery since 2019, which has enabled large-scale applications. However, it also highlights persistent challenges, including performance degradation in complex landscapes, such as fragmented smallholder farms and terraced regions, and a notable geographical imbalance in research focus. To address these gaps and propel the field forward, we propose several actionable research priorities. There is a critical need for public geographically diverse benchmark datasets, particularly for underrepresented agricultural systems. Methodologically, future efforts should focus on the fusion of multisource data and the development of knowledge-guided topology-aware models that directly generate analysis-ready vector-based outputs. Furthermore, the field should advance toward integrated end-to-end frameworks that couple parcel delineation with downstream tasks, such as fine-grained crop classification and yield estimation. Finally, leveraging the power of large-scale foundation models, including VLMs, will be crucial for enhancing model generalization across diverse regions and enabling interactive human-in-the-loop refinement workflows. By pursuing these directions, the research community can develop more robust, transferable, and operationally viable APBD solutions, ultimately strengthening their contribution to global food security and sustainable agricultural management.

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