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REVIEW

Pixel to Parcel: Transformative Applications of Image Segmentation in Geospatial and Crop Research

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ABSTRACT

The rising need for precision farming and sustainable land management has catalyzed the requirement for sophisticated means of deriving practical data from remote sensing images. Image segmentation, or the process of dividing the image into semantically relevant parts, has become a groundbreaking technology that allows resolving the problem of transitioning the pixel-level data to a parcel-level analysis. This review is a synthesis of the segmentation methods and their use in crop research and geospatial science. The architectures of pixel-based, object-based, and deep learning (convolutional neural networks, U-Net, Mask R-CNN, and Transformer models) are considered in terms of principles, capabilities, and limitations. Multi-spectral, hyperspectral, LiDAR, and SAR data are integrated to improve the efficiency of segmentation, allowing the possible delineation of fields, the classification of crops, health monitoring, monitoring of yields, and stress identification. In addition to agriculture, segmentation helps in land use and land cover mapping, identification of temporal change, monitoring of the environment, and is used in combination with GIS-based spatial modeling. Nevertheless, issues related to data heterogeneity, mixed pixels, computational requirements, and inadequate availability of labelled data still exist despite the major progress. The future directions involve multi-source data fusion, pixel-to-parcel pipeline automation, and predictive models based on AI, which are used to enhance its scalability, robustness, and the ability to monitor in real-time. This review makes it clear that the use of image segmentation as a tool in generating precision agriculture, sustainable land use, and informed geospatial.

Keywords: Image Segmentation; Precision Agriculture; Geospatial Analysis; Crop Monitoring; Remote Sensing

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1. Introduction

Over the last several decades, there has been a radical change in agriculture and geospatial studies due to the growing accessibility of high-resolution imagery and new and highly developed computational techniques [1]. The universal food security, effective resource management, and sustainable agricultural practices have come into the limelight, whereby it is necessary to get accurate, timely, and scalable monitoring of the crops and land resources [2]. Historically, the most common methods of acquisition of information on the crop and land-use have been field observations and manual mapping. Although practical in small scales, these methods are labor-intensive, time-consuming, and highly likely to cause human error, which limits their application to large-scale or high-frequency monitoring.

The introduction of remote sensing technologies, which include satellites, aerial-based platforms, and unmanned aerial vehicles (UAVs), has transformed the process of observing and measuring both agricultural processes and environmental processes [3,4]. These platforms produce large quantities of imagery at different spatial, spectral, and temporal resolutions that allow researchers and practitioners to obtain detailed data on crop health, field boundaries, soil properties, and land cover dynamics. In spite of this development, issues of deriving significant and practical information from raw imagery are still a major challenge. Specifically, natural topography with its complexity and heterogeneity, the variability of the morphology of crops, and mixed pixels in medium- and coarse-resolution images are considered to be great challenges in traditional methods of image analysis.

Image segmentation -the act of breaking down an image to form semantically significant outcomes- has become the fundamental ticket to the coaxing between pixel image and agricultural communication [5,6]. Segmentation makes the pixels visible as coherent units, which allows individual fields and crop types, stress patterns, and other spatial features to be identified, which is important to crop management and geospatial research. In pixel-based segmentation, at the most detailed level, pixels are labeled, and spectral variations at the fineness of pixels are recorded. These pixels are combined into a meaningful amount of space at higher levels, with object/parcel-based segmentation, where landscape units that are common to the real world of agricultural and land management systems are grouped, e.g., fields or land plots, to enable easier analysis. Parcel-level analysis versus pixel-level analysis is a transitional move in image analysis towards a practical decision-making image analysis, with potential applications including precision agriculture, yield prediction, and sustainable land management.

It has recently been made possible due to recent advances in computational intelligence, especially in the field of deep learning, which has dramatically increased the capabilities of image segmentation [7,8]. CNNs, U-Net models, Mask R-CNNs, and newer Transformer-based methods have shown outstanding results when it comes to the segmentation of complex images, the processing of high-dimensional data, and cross-geographic and cross-crop generalization. The methods provide automated crop and land extraction at never-before-seen scales and resolutions, minimize the use of manual interpretation, and allow close-to-real-time monitoring. Also, object-based and AI-based segmentation models simplify multi-source data integration (multispectral, hyperspectral, LiDAR, and synthetic aperture radar (SAR) imagery) to enhance the quality and strength of agricultural and geospatial analyses.

Image segmentation has a variety of uses in crop research. The delineation of field boundaries is done automatically, which increases the efficiency of the operations and the costs associated with surveying the fields. Classification of crops, monitoring their health, and detecting stress allow targeted interventions and maximize the use of inputs, as well as promote the work of precision agriculture. Moreover, segmentation forms the basis of sophisticated phenotyping and prediction of yield, the association of a visual pattern observed in the image with physiological and agronomic characteristics. Image segmentation is also used in the wider contexts of geospatial studies, such as land use and land cover mapping, change detection, and environmental monitoring, besides crop monitoring. Segmentation is useful as it transforms raw pixels into spatially coherent parcels (scales) that can be analyzed to determine ecosystem services, soil-water interactions, and land management practices, which are usually at policy and planning relevant scales [9–11].

These developments notwithstanding, there are still many challenges. Image resolution variability, seasonal and phenological variations, mixed system use, and sensor modalities make it difficult to segment and analyze an image. Moreover, some methods have a dependency on the computational cost of large-scale, high-resolution image processing and rely on labeled training samples in supervised training architectures. To overcome these difficulties, it is necessary to keep working on the strong, generalizable, and computationally effective segmentation techniques that can combine multi-source data and be applied in different agricultural and geospatial environments[12,13].

The subject of this review is the applications of image segmentation in geospatial and crop studies that are transformative, with special attention to the spectrum between the pixel-level classification and the parcel-level analysis. Our goal is to offer a broad generalization of the existing methodologies, sources of data, and practice, outlining the possibilities and shortcomings of the existing methods. This review aims to reveal the role of image segmentation in transforming the manner in which scholars and practitioners monitor, comprehend, and control the agricultural and land systems by synthesizing progress in the development of algorithms, remote sensing, and applied research. This way, it makes the significant importance of segmentation as the mediator between raw imagery and the actionable information a priority that can direct future studies and operational application in the quest to achieve precision agriculture and sustainable land management[14,15]. **Figure 1** illustrates the conceptual pixel-to-parcel workflow underpinning the segmentation-based analyses discussed throughout this review.

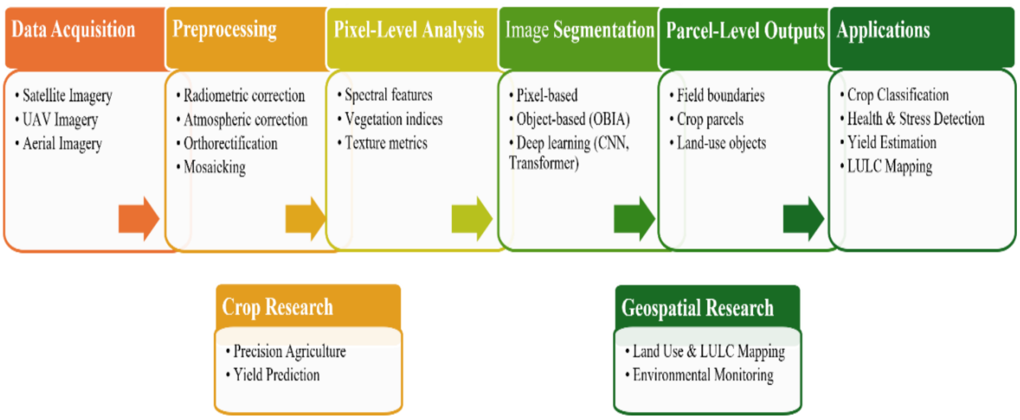

Figure 1. Conceptual workflow illustrating the transition from raw remote sensing imagery to parcel-level outputs through image segmentation.

2. Fundamentals of Image Segmentation

Image segmentation forms a staple of the current geospatial and crop studies because it represents the analytical interface between raw image and valuable spatial data. Segmentation is fundamentally the division of an image into homogeneous regions, in terms of particular characteristics, i.e., spectral reflectance, texture, geometry, etc. Segmentation uses a continuous field of pixel values to identify a set of semantically coherent structures, e.g., types of crops, field parcels, or land cover that are needed in precision agriculture, to monitor the environment, and to perform geospatial models. The selection of the segmentation method does not only require consideration of the spatial and spectral resolution of the data, but also the magnitude of the task at hand, the extent of the heterogeneity in the landscape, and the computer resources of the day[16–18].

2.1. Pixel-Based Segmentation

Segmentation at the pixel level is the most basic level of analysis, where each pixel is labelled with a label depending on its spectral or radiometric properties[19]. Conventional pixel-based approaches are usually based on thresholding approaches, clustering schemes, or spectral indices to distinguish between land-cover classes or crop stipulations. Thresholding techniques work by identifying features of interest by picking out certain ranges of spectral values, including those produced by vegetation indices. Clustering algorithms, such as the k-means and the hierarchical clustering algorithms, cluster the pixels by similarity to each other, thereby making the task of unsupervised classification possible without prior information about the landscape. Although it is simple, pixel-based segmentation is very sensitive to noise, mixed pixels, and changes in illumination or atmospheric conditions, resulting in fragmented or inaccurate delineations. This method, however, is also useful when fine-scale spectral analysis is needed or when it is necessary to find minute temporal variations in crop conditions.

2.2. Object-Based Segmentation

Object-based image analysis (OBIA) resolves most of the shortcomings of pixel-based approaches since the groups of adjacent pixels are treated as objects or areas. Segmentation in OBIA is determined not only by the spectral homogeneity but also by the spatial and textural characteristics, i.e., shapes, size, and any adjacency. This method enables the formation of more coherent parcels that are more in line with the real practical fields of agricultural activities or natural landscape units. The object-based techniques have the advantage of being especially useful when dealing with high-resolution images, in which pixels can be smaller than the features of interest. OBIA improves the noise reduction and interpretability of pixels through aggregation into meaningful objects and enables the integration of the result with geographic information systems (GIS) to expand the capability of further spatial analysis. The use of OBIA frameworks in crop research has been massively applied to map field boundaries, classify crops, and monitor heterogeneous landscapes, allowing more actionable information to be provided to precision agriculture [20,21].

2.3. Deep Learning-Based Segmentation

The recent developments in the field of artificial intelligence, and especially deep learning, have transformed image segmentation capabilities [22,23]. CNNs and their variants, including U-Net and Mask R-CNN, have been shown to excel in terms of learning intricate spatial structures, being able to process data of high dimensionality, and being able to generalize to diverse landscapes. Methods based on deep learning are automatic feature learners that can also automatically extract hierarchical feature representations of raw data and, therefore, can segment complex structures, such as overlapping crops, irregular field shapes, and subtle vegetation health variations. Models of long-range spatial dependencies, such as transformer-based architecture, have advanced segmentation performance in large-scale geospatial applications. The methods are especially ideal in the context of incorporating multi-source data, multispectral, hyperspectral, and LiDAR data to offer highly robust and scalable solutions to pixel-to-parcel functions. **Table 1** provides an overview of the features, strengths, and weaknesses of the most popular segmentation techniques. Although they have benefits, deep learning-based segmentation models demand large volumes of labeled data to train and large amounts of computing power, making them inaccessible in resource-constrained settings.

Table 1. Summary comparison of pixel-based, object-based, and deep learning-based image segmentation approaches, highlighting principles, strengths, limitations, and representative applications.

Segmentation Approach	Principle	Strengths	Limitations	Typical Applications in Crop & Geospatial Research
Pixel-based	Assigns labels based on individual pixel spectral values	Simple, fine-scale analysis	Sensitive to noise and mixed pixels	Vegetation indices, early-stage crop detection
Object-based (OBIA)	Groups contiguous pixels based on spectral, spatial, and textural properties	Accurate parcel delineation reduces noise	Requires parameter tuning, less effective with very high heterogeneity	Field boundary mapping, LULC mapping
CNN/U-Net	Deep learning, hierarchical feature extraction	High accuracy, handles complex structures	Needs large labeled datasets, high computational cost	Crop classification, stress detection, phenotyping
Mask R-CNN/Transformers	Detects objects with instance segmentation, long-range spatial dependencies	Robust for overlapping objects, multi-scale	Computationally intensive, complex implementation	Multi-crop field monitoring, environmental parcel analysis

2.4. Evaluation Metrics

The quantitative assessment is imperative in determining the effectiveness of segmentation techniques. The most popular measures are the total accuracy, intersection over union (IoU), F1-score, and Dice coefficient, each of which can give different but equally informative information about the agreement between the segmentation prediction and the reference data. Mixed pixels, varying spatial resolutions, seasonality, and phenological variability are some of the complications that come about in evaluation in geospatial and crop studies. Therefore, both spatially explicit ground truth and temporal consistency should be rigorously validated to make sure that the segmentation results can be trusted and their results can be generalized [24,25]. **Table 2** provides the most popular metrics of segmentation evaluation.

Table 2. Commonly used quantitative metrics for evaluating image segmentation performance in crop and geospatial research.

Metric	Definition	Strengths	Limitations	Common Use Cases
Overall Accuracy	Ratio of correctly classified pixels/objects	Simple interpretation	Does not account for class imbalance	Crop classification, LULC mapping
Intersection over Union (IoU)	Overlap between predicted and reference regions/Union	Sensitive to spatial alignment	Can be low for small objects	Field boundary accuracy
F1 Score	Harmonic mean of precision and recall	Balances false positives and false negatives	Sensitive to class imbalance	Stress detection, crop type classification
Dice Coefficient	2 × (intersection)/(sum of predicted + reference)	Emphasizes spatial overlap	Less interpretable for multi-class	Parcel-level segmentation evaluation

The decision on which segmentation method to use is based on the study purpose, whether the imagery to be used is coarse or fine, and the degree of spatial coherence demanded. Finer spectral analyses should be done using pixel-based techniques, whereas object-based and neural networks would offer better parcel-level delineation and would be more easily connected to later geospatial analysis. It is necessary to be aware of the advantages, weaknesses, and calculating requirements of each method to build a strong and efficient segmentation workflow. The ever-growing advancement of algorithms and calculation capacities has gradually facilitated the incorporation of multi-source and high-resolution imagery, which preconditions the creation of groundbreaking uses in crop observation, precision farming, and geospatial studies [15,26].

3. Remote Sensing Platforms and Data Sources

The success of the image segmentation method in geospatial and crop studies is inherently connected to the nature and the quality of the underlying image. The recent technological development of remote sensing allows the field of platforms and available sensors to dramatically increase, making it possible to observe agricultural landscapes and environmental processes on a multi-scale level. The choice of a proper platform and data source depends on the spatial, spectral, and temporal resolution needed for the study and on the focus of the study: field-level crop monitoring, landscape-scale land use mapping, or multi-temporal change detection [27]. The next passages give a summary of popular remote sensing platforms and sensor modalities and their applicability to the segmentation-based studies. From a pixel-to-parcel perspective, these segmentation approaches represent progressive steps in spatial abstraction, where raw pixel-level information is aggregated into increasingly meaningful spatial units. Pixel-based methods capture fine-grained spectral variability, whereas object-based and deep learning approaches enable the delineation of coherent parcels that correspond to real-world agricultural and geospatial entities.

3.1. Satellite Imagery

The satellite platforms are reliable, repeatable, and provide large-scale delivery of observations, and hence, they cannot be ignored in geospatial monitoring as well as agricultural research [28]. Moderate to high resolution satellites, i.e., Sentinel, Landsat, Planet Scope, and MODIS, vary in spatial, spectral, and temporal aspects capable of providing different advantages to the application. An example of this is the use of Sentinel-2 to give multispectral images at 10–20 m resolution and with high revisit periods, giving the chance to follow crop phenology, health of vegetation, and field delineation.

Landsat has a longer historical record, which enables time studies, such as land-use change and the long-term pattern of crop rotation. Commercial satellites such as PlanetScope have sub-meter spatial resolution, which provides fine-scale parcel delineation and can be used in field-level management decisions. Despite these benefits, there might be constraints on satellite imagery due to cloud cover, atmospheric effects, and mixed-pixel effects, especially in the heterogeneous agricultural landscape. From a pixel-to-parcel perspective, these segmentation approaches represent progressive steps in spatial abstraction, where raw pixel-level information is aggregated into increasingly meaningful spatial units. Pixel-based methods capture fine-grained spectral variability, whereas object-based and deep learning approaches enable the delineation of coherent parcels that correspond to real-world agricultural and geospatial entities.

3.2. Aerial and UAV Imagery

Owing to the high versatility of UAVs and manned aircraft services, they provide supplementary services on top of satellite imaging services [29,30]. The UAV platforms provide a particular opportunity to retrieve the imagery at the centimeter-level and customize the flight plan to track the stage of crop growth, factors of stress, and heterogeneity of the fields, in particular. Aerial imagery can be acquired depending on the spectral band involved, either near-infrared spectrum, thermal, or visible spectrum, to facilitate precise characterization of the vegetation indices, water stress, and canopy structure. UAV imaging is especially applicable to segmentation purposes that require the information at the parcel or intra-field level, such as early detection of pests, diseases, or nutrient deficiency. The drawbacks of aerial imagery, and the fact that it has a low coverage per flight, regulatory needs, and extensive computational resources needed to build high-quality pictures of an area into an orthomosaic.

3.3. Sensor Modalities

The sensor modality selected has a significant implication on the form and quality of information, which offers simplistic structural images and allows crop patterns and edges to be detected. This can be expanded by multi-spectral sensors that measure selected bands sensitive to vegetation health, chlorophyll levels, and water stress, e.g., red-edge and near-infrared. Hyperspectral sensors extend the spectral coverage to hundreds of narrow bands, enabling a fine discrimination between crop species, soils, and stress states. LiDAR sensors are capable of delivering three-dimensional structural data, including canopy height, biomass, and topography, which can be combined with spectral data to enhance the accuracy of segmentation. Synthetic aperture radar cameras provide imaging on a day-night basis and in all weather conditions, and are especially useful in areas where clouds tend to cover the sky or where optical cameras are unavailable. The combination of several sensor modalities improves the performance of the segmentation, which allows the recovery of both spectral and structural features to be used in the robust crop and land-use analysis [31–34]. A comparative summary of remote sensing platforms and the nature of data is given in **Table 3**, available to form a segmentation. Conventional RGB sensors can record visible light.

Table 3. Overview of commonly used remote sensing platforms, spatial and temporal resolutions, sensor types, and typical applications in segmentation-based studies.

Platform	Spatial Resolution	Temporal Resolution	Sensor Types	Typical Applications
Sentinel-2	10–20 m	5 days	Multispectral	Crop monitoring, LULC mapping
Landsat	30 m	16 days	Multispectral	Historical change detection, crop rotation analysis
PlanetScope	3–5 m	Daily	Multispectral	High-resolution field delineation, precision agriculture
UAV/Drone	1–10 cm	Flexible	RGB, multispectral, hyperspectral, thermal	Parcel-level crop monitoring, disease detection
LiDAR	Sub-meter (3D)	N/A	Active laser scanning	Canopy structure, biomass estimation, topography
SAR	5–100 m	Days to weeks	Radar	All-weather monitoring, soil moisture, flood detection

3.4. Data Preprocessing

Raw imagery usually needs to undergo preprocessing before segmentation is possible to remove sensor and atmospheric distortions, as well as geometric distortions [35,36]. Radiometric correction makes the pixel values reflect the surface reflectance correctly, taking into consideration sensor-specific biases and atmospheric scattering. Orthorectification is a procedure that adjusts images to a geographic coordinate system and resembles that of the terrain and sensor viewpoint. Filtering and contrast adjustment are noise reduction and image enhancement techniques that increase the separability of features for segmentation algorithms. In the case of UAV and aerial imagery, further preprocessing would usually entail mosaicking and joining of several images to create one continuous orthomosaic that encompasses the area of study. It is important to do good preprocessing to reduce errors and increase the accuracy of segmentation outcomes, especially when using multi-temporal or multi-source data.

The choice of remote sensing platforms and sensor modalities should be determined by the spatial, spectral, and temporal needs of the application. Satellite images are widely ramified in space and time so that they can be used in regional and landscape analysis. High-resolution and flexible observations at the parcel and intra-field scales are offered by the UAVs and aerial platforms. The choice of sensors, both RGB and hyperspectral and LiDAR, influences what kind of features can be retrieved, whereas the preprocessing is taken very carefully to make sure that the quality of input data and its consistency are preserved to be used with segmentation algorithms [37–39]. When combined, these platforms and data sources provide a basis to scale up and accurately analyze pixels-to-parcels so that the researchers and practitioners can create actionable insights to support precision agriculture, environmental monitoring, and geospatial modeling. Collectively, these platforms and sensor modalities define the feasibility and accuracy of the pixel-to-parcel transition, influencing how effectively pixel-level observations can be transformed into parcel-level representations for downstream applications.

4. Applications in Crop Research

From a pixel-to-parcel perspective, segmentation enables the translation of fine-scale spectral information into field-level insights that directly support agricultural decision-making. Image segmentation used in crop science has become a revolutionary method of observation, allowing scaled and accurate observation of farm areas [40]. Segmentation enables information to be extracted, which is essential in managing crops, predicting the yield, and optimizing resources by transforming raw remote sensing data into semantically meaningful areas. In this section, the main uses of segmentation in crop research are addressed, which range from field delineation to high-end phenotyping and stress detection.

4.1. Field Delineation and Parcel Mapping

Closeness in field delineation is a basic requirement of contemporary crop management as well as precision agriculture. Conventional techniques, which involve manual surveying or crude resolution maps, are time-consuming and can easily be misleading. Image segmentation allows automatic recognition of individual fields or parcels in those similar pixels, both spectrally and spatially, which are put into units of coherence. This has been especially well done with object-based image analysis and deep learning-based methods, which can be used to extract field boundaries even in non-uniform landscapes with irregular forms. UAV images and satellite data of high resolution are being used more to create current field maps, which are used as a base for further analysis, including crop identification, harvest size estimation, and distribution of resources [3,41].

4.2. Crop Classification and Health Monitoring

Segmentation is crucial in the differentiation of types of crops and their health status [42,43]. Segmentation algorithms allow the classification of different agricultural systems with precision, as they identify coherent regions that represent particular crops. Vegetation indices (NDVI, red-edge indices) sensitive to chlorophyll content, biomass, and stress of plants can be extracted with multispectral and hyperspectral imagery, with the use of segmentation techniques. State-of-the-art deep learning methods, such as convolutional neural networks and transformer-based models, have already shown the capability of detecting fine-tuning to spectral and spatial patterns and thereby allow early discovery of nutrient deficiency, water stress, and pest infestation. This knowledge enables specific interventions that allow maximizing the use of fertilizers and irrigation with minimum negative effects on the environment.

4.3. Yield Estimation and Phenotyping

Image segmentation can help to measure quantitatively the crop characteristics that are highly related to yield and productivity[44,45]. Having demarcated crop plots and the spectral and structural features, it is possible to estimate the canopy cover, biomass, and leaf area index, among other important phenotypic features. High-throughput phenotyping can be made available using UAV-derived high-resolution imagery in conjunction with segmentation methods, which enable breeders and agronomists to assess large populations of crops in a non-destructive and fast manner. Temporal sequences of segmented images integration also aid in more dynamic observation of growth development stages and patterns, which could be used to improve the yield prediction model and guide management decisions to improve overall productivity.

4.4. Stress Detection and Disease Monitoring

It is essential to ensure that biotic and abiotic stresses are detected early to minimize crop losses and make the crops more resilient[46,47]. Segmentation helps in the determination of spatial patterns relating to diseases, pest outbreaks, and environmental stresses. Segmentation facilitates localized treatment in fields by isolating infected areas, and this is used in fields to apply pesticides or adaptive irrigation to minimize resource consumption and prevent loss of crops. Multispectral and hyperspectral measurements offer insightful spectral indicators of stress reactions, whereas segmentation models based on deep learning can differentiate between overlapping or comorbid stress factors, which justifies accurate and timely decision-making. The combination of machine learning and UAV and satellite imagery will also enable monitoring scales, both at the level of separate plants or an individual field in the center of an agricultural field. **Table 4** provides a summary of the applications of segmentation in crop research.

Image segmentation is a necessity in crop research, and it helps to eliminate the disparity between the raw image and useful information. Segmentation is used to accurately, scalably, and in a data-driven manner support agricultural management, whether it is outlining field boundaries, characterizing crops, tracking health, estimating yield, or identifying stress. The combination of developed sensor applications, high-resolution images, and machine learning has significantly improved the ability to study intricate agricultural systems. With further developments of these methodologies, it is anticipated that segmentation-based methodologies will become more central to precision agriculture, sustainable crop production, and agronomic decision-making of geospatial data more generally[5,40].

Table 4. Major crop research applications enabled by image segmentation, including segmentation level, data sources, and primary benefits.

Application	Segmentation Level	Data Used	Benefits	Example Outcome
Field Delineation	Parcel	UAV, Sentinel-2	Automated boundaries, reduce labor	Field maps for management zones
Crop Classification	Pixel/Parcel	Multispectral, Hyperspectral	Accurate crop type mapping	Identification of maize, wheat, rice
Health Monitoring	Pixel/Parcel	Multispectral, LiDAR	Early stress detection	Detection of water stress or nutrient deficiency
Yield Estimation	Parcel	UAV, Hyperspectral	High-throughput phenotyping	Biomass estimation, predicted yield
Pest/Disease Detection	Pixel/Object	RGB, Multispectral	Localized intervention	Early identification of fungal infection

5. Applications in Geospatial Research, Limitations, and Future Perspectives

Extending the pixel-to-parcel paradigm beyond agriculture, segmentation facilitates the aggregation of pixel-level observations into spatial units that underpin geospatial analysis and environmental monitoring. Image segmentation is not limited to crop studies alone, as it has a revolutionary impact on the geospatial domain. Segmentation allows the specific analysis of the land use, environmental processes, and landscape dynamics by transforming raw imagery into spatially coherent parcels[48]. The section examines how segmentation can be applied in geospatial studies and offers the existing limitations and future opportunities for research, which are paramount to the ongoing requirements of scientific knowledge and application.

5.1. Land Use and Land Cover Mapping

Segmentation is a basic land use and land cover (LULC) mapping tool whereby the spatial units of heterogeneous landscapes can be identified and classified. The classical pixel-based classification technique is usually unable to delimit consistent parcels, especially in areas of frigid land utilization or complicated terrain. By comparison, object-based and deep learning segmentation methods cluster pixels into meaningful objects that are related to real-world objects, e.g., forest patches, cities, bodies of water, or crops. It is effective at boosting classification accuracy, decreasing noise, and incorporating the spatial data into geographic information systems to manage the environment, urban planning, and agricultural surveillance [49,50].

5.2. Change Detection and Temporal Analysis

Temporal tracking is a key to the knowledge of dynamic processes in the environment. Segmentation allows the identification of the variation of land cover, patterns of crop rotation, and landscape structure through the consistent identification of the parcels across time. A segmentation algorithm can be used to analyze multi-temporal satellite imagery, UAV data, or aerial photography to detect changes in vegetation cover, deforestation, urban growth, or irrigation methods. Segmentation assists in seeing the individual components of the larger picture of land management, conservation, and policy planning by providing high-resolution information regarding spatial and temporal processes that would be challenging to realize due to the traditional pixel-based methodology [51].

5.3. Environmental and Hydrological Monitoring

Segmentation is also useful in the examination of environmental processes such as soil-water, mapping of habitat, and monitoring of ecosystems. Through their isolation of coherent parcels, the researchers can relate spectral, structural, and topographic data with particular environmental processes. As an example, the segmentation of agricultural fields allows for accurately estimating the moisture of the soil, the efficiency of irrigation, and patterns of water use, whereas in the natural landscape, one can monitor the density of the vegetation, the fragmentation of the habitat, or the areas with high risks of erosion. Spectral and structural parcel-level information allows understanding environmental variability, which increases the possibility of sustainable resource management [52].

5.4. Integration with GIS and Spatial Modeling

Segmented imagery can be readily converted to geospatial units and therefore fitted in GIS and spatial modelling systems [53]. Predictive models, decision support systems, and resource allocation tools can use the information based on segmentation on a parcel level as input. Associating the spatial units with any ancillary data, e.g., soil property, topography, or climate variable, allows the researcher to simulate crop productivity, evaluate ecosystem services, or plan land use. The significance of segmentation as a technique in image processing is emphasized by this integration, but it is also a key element of a larger geospatial analytical process.

5.5. Limitations of Current Segmentation Approaches

Segmentation-based analyses have various shortcomings, regardless of the tremendous progress made. The accuracy and generalizability of models can be diminished due to such data heterogeneity as differences in spatial, spectral, and temporal resolutions. Both pixel-based and object-based methods have some problems with mixed pixels, complicated canopy shapes, and the complex structures of landscapes. Deep learning methods are powerful, but significant training data and high computation resources are needed; these methods may not be applicable in resource-limited scenarios. In addition, atmospheric errors, seasonal variations, and sensor noise may cause extra uncertainty, and preprocessing and validation should be done cautiously to use reliable outcomes [18,54,55].

5.6. Future Perspectives

The future of segmentation in geospatial and crop studies is in the form of multi-source, multi-temporal, and multi-scale data. Integrating satellite, UAV, aerial, LiDAR, and SAR images can be used to better extract features and also increase robustness on heterogeneous surfaces. The innovations in artificial intelligence, such as self-supervised learning and transformer-based models, among others, promise to help reduce the reliance on labeled data and enhance model generalization. Segmentation pipelines will be used to proactively monitor crop health, land cover change, and stressors on the environment in real time or near real time. Finally, more accurate, effective, and sustainable agricultural and geospatial management regimes will be facilitated by the creation of entirely automated "pixel-to-parcel workflows, which can assemble spectral, structural, and contextual information [56]. **Figure 2** integrates current geospatial applications of segmentation and outlines emerging future directions.

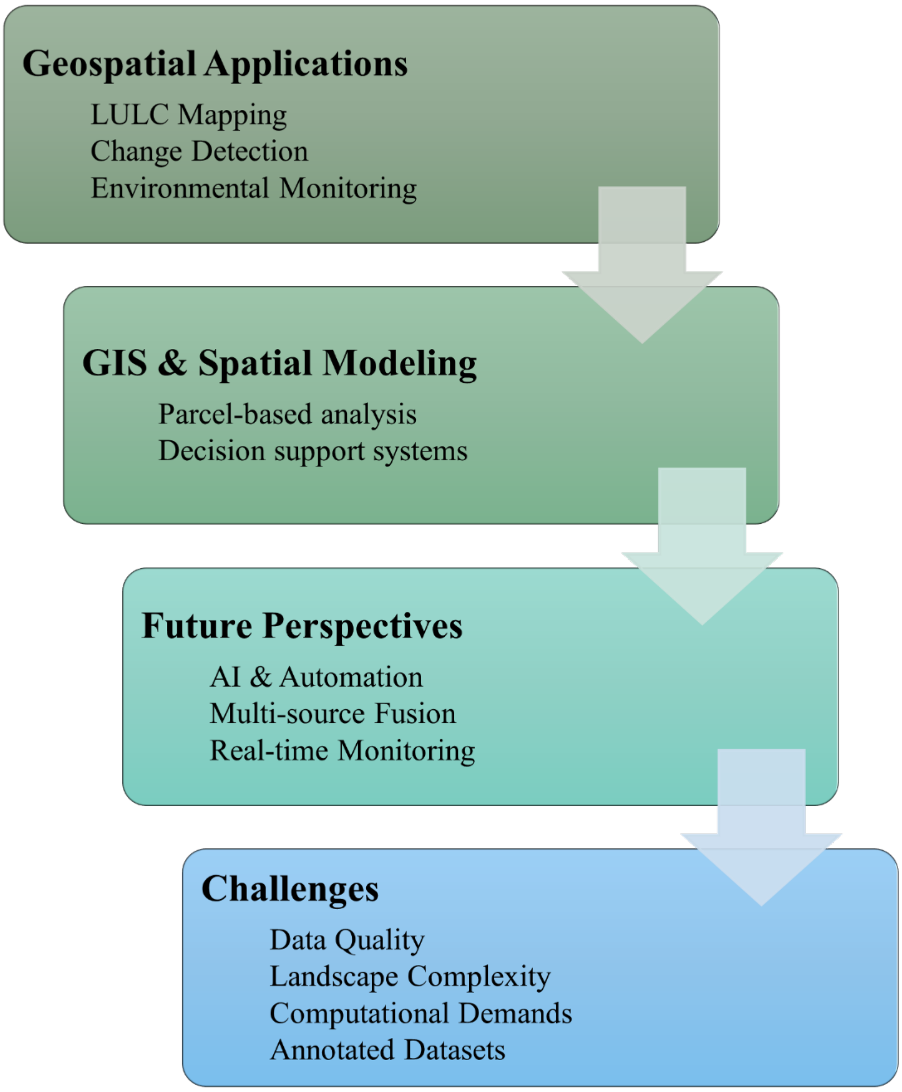

Figure 2. Conceptual representation of image segmentation applications in geospatial research, including land use mapping, change detection, environmental monitoring, and integration with GIS and predictive models, along with future development directions.

Future research in image segmentation for geospatial and crop applications should move toward more integrated, scalable, and application-driven solutions. A key priority is the development of algorithms for the synergistic fusion of multi-source data, such as combining Sentinel-2 optical imagery with Sentinel-1 SAR data to overcome cloud-related limitations in tropical and subtropical agricultural regions. Such approaches would enhance the robustness of parcel delineation under challenging environmental conditions. Another critical direction involves the design of lightweight, edge-deployable segmentation models that can operate on UAV platforms or in-field devices. These models would enable near-real-time detection of crop stress, nutrient deficiencies, or disease outbreaks, facilitating timely and localized interventions in precision agriculture.

Advances in self-supervised and semi-supervised learning are also expected to reduce dependence on large labeled datasets by leveraging vast amounts of unlabeled remote sensing data. Developing generalizable models capable of transferring across regions, crop types, and sensor modalities remains a key research challenge. Furthermore, integrating segmentation outputs with dynamic crop growth models and geospatial decision-support systems could enable predictive analytics at the parcel level, supporting yield forecasting, irrigation management, and climate adaptation strategies. Finally, the realization of fully automated pixel-to-parcel pipelines will require advances in computational efficiency, including cloud-based processing frameworks and optimized model architectures capable of handling large-scale, multi-temporal datasets in near real time.

6. Conclusions

Image segmentation has become a revolutionary method in crop science and geospatial science, and has been used to bridge the discontinuity between raw images and useful spatial data. Segmentation allows the accurate tracking of agricultural fields, the correct classification of the type of crops, the timely identification of stress and diseases, and the effective estimation of the phenotypic characteristics and yield, since pixel-level data can be converted into semantically meaningful segments and parcels. In addition to the field scale, segmentation enables the study of land use and land cover, temporal landscape change, and environmental processes to make important contributions to sustainable land management, ecosystem observation, and policy development.

Recent developments in object-based schemes and deep learning designs have extended the performance of segmentation, enabling the extraction of complicated spatial patterns in high-resolution, multi-source imagery with the help of automatic means. Such developments have greatly enhanced the scalability, precision, and efficiency of crop and geospatial analysis to aid in decision-making at various scales using space and time. In addition, the combination of segmentation outputs with the geographic information systems and predictive models contributes to their usefulness in precision agriculture, optimization of the resources, and managing the environment.

Although these have been achieved, there are still challenges. The imprecision of data, topographical intricacy, resource usage, and requirement of marked preparation datasets restrict the complete addition of segmentation technologies used in certain applications. To overcome these challenges, future methodological innovation, integration of multi-source data, and the construction of generalizable and automated pipelines that can be used in various agricultural and environmental contexts will be needed.

Finally, segmentation has been a key tool in the development of crop and geospatial science as it has provided a means of transition between pixels and parcels by which scholars, agronomists, and policymakers can track, comprehend, and control land and crop-based systems. The possibilities of segmentation to improve precision agriculture, encourage sustainable use of resources, and frame the large-scale environmental planning will only grow along with the further development of computational methods and remote sensing instruments, making segmentation one of the pillars of contemporary geospatial and agrarian science.

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All data and information supporting the paper are available in all publicly accessible domains.

Conflicts of Interest

The author declares no conflict of interest.

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