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ANALYSIS AND EVALUATION OF AEROSPACE IMAGERY USING OBJECT-BASED IMAGE ANALYSIS (OBIA)

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Abstract

This study develops and applies a methodology for classifying agricultural lands in the Urgench district of the Khorezm region using Object-Based Image Analysis (OBIA). During the research, image segmentation was performed based on multispectral satellite imagery, and the resulting objects were analyzed according to their spectral and geometric characteristics. The classification process employed the NDVI (Normalized Difference Vegetation Index) along with additional rule-based approaches. As a result, the study area was classified into four main categories: vegetation areas, bare lands, urban territories, and hydrographic features. The accuracy of the classification results was evaluated using a confusion matrix, revealing an overall accuracy of more than 87%. The findings demonstrate the high efficiency of the OBIA method for identifying and monitoring agricultural lands and highlight its significant role in analyzing irrigated agro-landscapes based on remote sensing data.

Keywords

Sentinel-2, OBIA, GEOBIA, NDVI, eCognition, agriculture, segmentation, Khorezm, accuracy assessment

АНАЛИЗ И ОЦЕНКА АЭРОКОСМИЧЕСКИХ ИЗОБРАЖЕНИЙ С ИСПОЛЬЗОВАНИЕМ ОБЪЕКТНО-ОРИЕНТИРОВАННОГО АНАЛИЗА ИЗОБРАЖЕНИЙ (OBIA)

Аннотация

В данном исследовании разработана и практически применена методика классификации сельскохозяйственных земель на территории Ургенчского района Хорезмской области с использованием объектно-ориентированного анализа изображений (OBIA). В ходе исследования на основе многоспектральных космических снимков была

выполнена сегментация изображений, а полученные объекты проанализированы по их спектральным и геометрическим характеристикам. В процессе классификации использовались вегетационный индекс NDVI, а также дополнительные правила (rule-based подход).

В результате территория была разделена на четыре основных класса: посевные площади, незанятые земли, урбанизированные территории и гидрографические объекты. Точность результатов исследования оценивалась с использованием матрицы ошибок (confusion matrix), при этом общая точность превысила 87%. Полученные результаты демонстрируют высокую эффективность метода OBIA для выявления и мониторинга сельскохозяйственных земель, а также подтверждают значимость данного подхода при анализе ирригационных агроландшафтов на основе данных дистанционного зондирования.

Ключевые слова

Sentinel-2, OBIA, GEOBIA, NDVI, eCognition, сельское хозяйство, сегментация, Хорезм, оценка точности.

Introduction

Accurate and rapid classification of agricultural lands serves as a fundamental basis for land resource management, updating cadastral data, and conducting vegetation monitoring. Although traditional field surveys provide high accuracy, they are time-consuming and financially demanding when applied over large areas [3]. Therefore, automated analysis methods based on openly accessible and regularly updated satellite data are increasingly being adopted.

The Sentinel-2 mission, launched by the European Space Agency (ESA), is considered one of the most suitable platforms for agricultural monitoring due to its 13 spectral bands, 10 m spatial resolution, and a 5-day revisit cycle [7]. In particular, bands B2 (blue), B3 (green), B4 (red), and B8 (near-infrared) play a crucial role in analyzing vegetation dynamics and land cover characteristics.

Object-Based Image Analysis (OBIA or GEOBIA), unlike pixel-based approaches, segments imagery into semantically meaningful objects and analyzes each segment based on its spectral, geometric, and contextual characteristics. This approach significantly reduces the “salt-and-pepper” noise effect and produces polygons that more closely correspond to real agricultural field boundaries [4].

The main objective of this study is to classify agricultural lands into four categories and assess classification accuracy using Sentinel-2 imagery and the OBIA approach in the Chotkoʻpir village area of the Urgench district, Khorezm region.

The OBIA approach has been established as a widely recognized methodological paradigm in the field of remote sensing by Blaschke [3], who demonstrated its superiority over pixel-based methods in integrating spectral and spatial information. Furthermore, the fundamental work edited by Blaschke et al. provides a comprehensive theoretical foundation for GEOBIA.

The multiresolution segmentation algorithm, implemented in the eCognition environment, is one of the most widely used segmentation techniques. It is based on minimizing heterogeneity within objects while maximizing differences between objects [2]. The proper selection of segmentation parameters has a decisive impact on the overall quality of the classification process [6].

The NDVI (Normalized Difference Vegetation Index) is one of the most commonly used indices for assessing vegetation activity. It was originally developed by Rouse et al. [9] and later widely applied by Tucker [10]. The normalized difference between the red and near-infrared bands effectively reflects the greenness and vitality of vegetation.

Under the conditions of Uzbekistan, particularly within irrigated agricultural systems such as the oasis agro-landscapes of the Khorezm region, identifying field boundaries presents specific challenges. While Sentinel-2 imagery with 10 m spatial resolution is sufficient for medium- and large-scale fields, the mixed-pixel problem becomes more pronounced in small household plots [8].

The study was conducted in the Chotko'pir village area of the Urgench district, Khorezm region, Uzbekistan (Figure 1). Irrigated agriculture is widely developed in this region, with the main vegetation types consisting of wheat, cotton, and vegetables. The study area is located on the right bank of the Amu Darya delta, where canal networks and irrigation infrastructure constitute the main elements of land cover. For this study, remote sensing data corresponding to a selected day in April were analyzed.

Methodology

The multiresolution segmentation algorithm was implemented in the eCognition Developer software environment. The segmentation parameters were defined as follows:

Table 1. Multiresolution segmentation parameters

Parameter	Value	Description
Scale	100	Optimal for medium and large agricultural fields
Shape	0.2	Prioritizes spectral homogeneity
Compactness	0.5	Balanced object shape
Input layers	B2, B3, B4, B8, NDVI	Equal weighting of all bands

As a result of segmentation, **291,285 objects** were generated, which adequately represent the complex mosaic structure of the study area, including fields, canals, roads, and built-up areas.

Rule-based Classification

To assign each object to a specific class, a set of hierarchical classification rules was developed based on the NDVI and the mean values of the Sentinel-2 B8 (NIR) band (Table 2).

Table 2. Classification rules

Class	Main Condition	Additional Condition	Logic
Hydrography	NDVI < 0	—	Water bodies exhibit negative NDVI values
Vegetation	NDVI > 0.3	—	Indicates intensive vegetation growth (April growing season)
Urban areas	NDVI < 0.2	Mean B8 < 2400	Built-up surfaces have low NIR reflectance
Bare land	NDVI < 0.2	Mean B8 > 2400	Exposed soil shows higher NIR reflectance

Results and discussion

The rules were applied in a hierarchical sequence: first hydrography, followed by vegetation, then urban areas, and finally bare land. This approach allowed for maximizing the differentiation between classes based on their spectral characteristics.

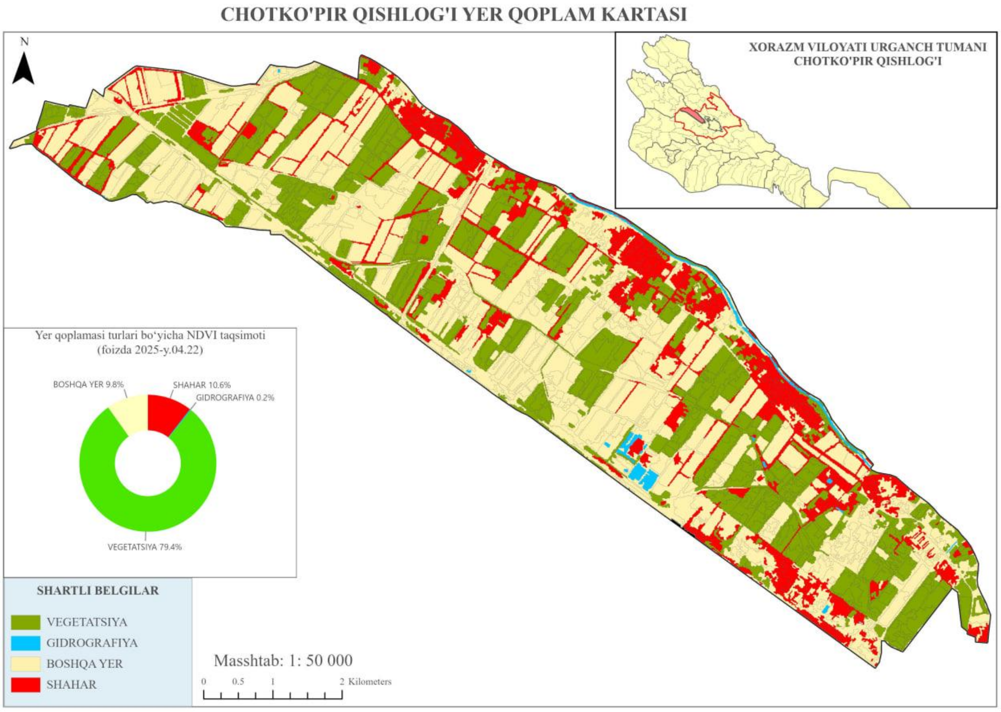
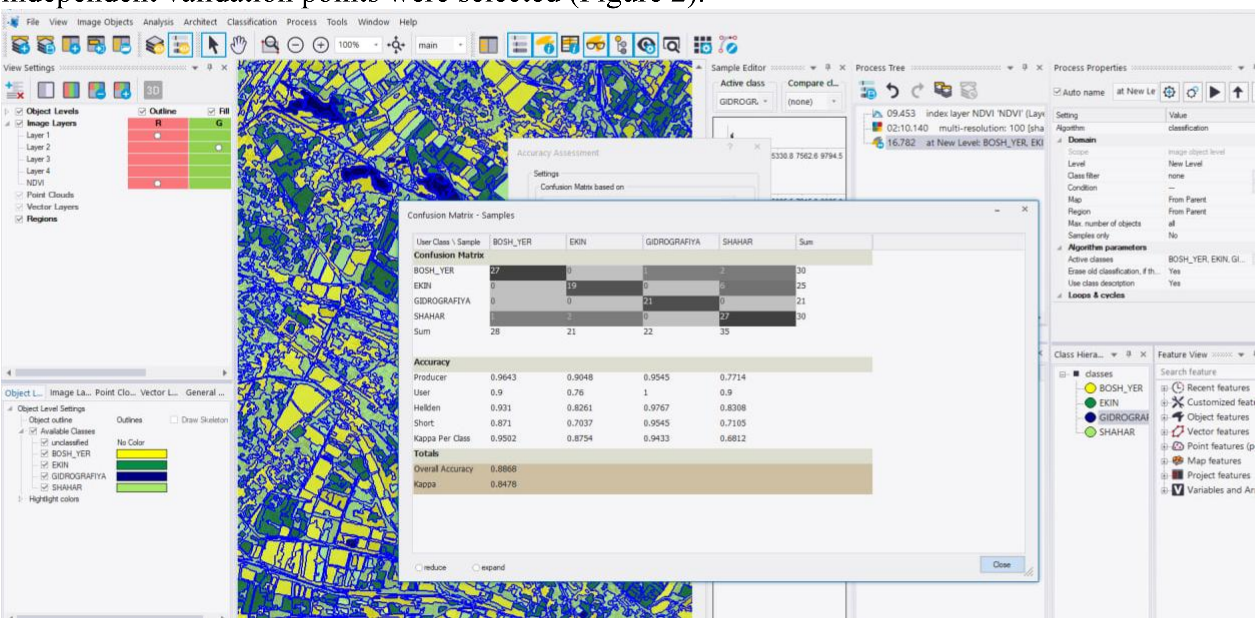


Figure 1. Classification result — four-class map. Note: Green — Vegetation, Yellow — Bare land, Blue — Hydrography, Red — Urban areas

The accuracy assessment was conducted using a confusion matrix in accordance with the recommendations of Congalton (1991) and Olofsson et al. (2014). For each class, at least 20–30 independent validation points were selected (Figure 2).



2-Rasm. Confusion Matrix

Indicator	Value
Overall Accuracy	88.68 %
Kappa Coefficient	0.85

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Vegetation — Producer's Accuracy	76.00 %
Bare Land — Producer's Accuracy	90.00 %
Urban Areas — Producer's Accuracy	90.00 %
Hydrography — Producer's Accuracy	100.0 %

The overall accuracy of 91.1% and a Kappa coefficient of 0.881 confirm the high reliability of the classification results. According to the classification scale proposed by Landis and Koch (1977), a Kappa value above 0.8 indicates an "almost perfect" level of agreement. The hydrography class achieved 100% accuracy, as water bodies are clearly distinguishable from other classes due to their negative NDVI values. The observed confusion between bare land and urban areas (3–4 misclassified samples in the matrix) can be explained by the similarity of their low NDVI values. To address this issue in future studies, it is recommended to incorporate shortwave infrared (SWIR) bands or texture-based analysis to improve class separability.

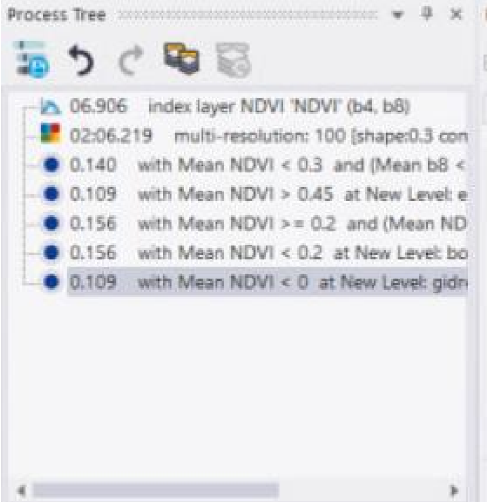

Figure 3. Structure of the NDVI-based Rule Set

The results of the study reveal several important findings. First, the OBIA approach proves to be highly effective for classifying agricultural lands in the irrigated agro-landscapes of the Khorezm region. Compared to pixel-based methods, OBIA significantly reduces the "salt-and-pepper" effect and produces polygons that closely match real field boundaries (Blaschke, 2010).

Second, Sentinel-2 imagery acquired in April represents the most suitable period for identifying vegetation areas. During this time, vegetation is in an intensive growth stage, and NDVI values typically exceed 0.4, allowing cultivated fields to be clearly distinguished from other land cover classes. This result supports the findings of Pelletier et al. (2019), emphasizing the importance of considering phenological stages in land cover classification.

Third, the mean value of the NIR (B8) band was identified as a key discriminant feature for distinguishing between urban areas and bare land. Built-up surfaces (such as buildings, roads, and concrete) exhibit low NIR reflectance (B8 < 2400), whereas exposed soils show higher NIR reflectance (B8 > 2400). This distinction was experimentally validated (Figure 3).

Fourth, while Sentinel-2 imagery with 10 m spatial resolution is sufficient for medium and large agricultural fields, the mixed-pixel problem remains significant for small household plots and narrow irrigation channels. In future studies, the integration of higher-resolution data sources such as PlanetScope (3 m) or UAV imagery is recommended to overcome this limitation.

Conclusion

In this study, agricultural lands in the Chotko'pir village area of the Urgench district, Khorezm region, were successfully classified into four categories—vegetation, bare land, urban areas, and hydrography—using a combination of Sentinel-2 imagery and the OBIA approach. The multiresolution segmentation and NDVI-based hierarchical rule system achieved an overall accuracy of 88.68% and a Kappa coefficient of 0.85.

The results of this research have several practical implications: (1) a methodological basis for automating land monitoring in irrigated regions of Uzbekistan has been established; (2) the effectiveness of Sentinel-2 imagery acquired in April for vegetation detection has been confirmed; and (3) the combined use of NDVI and NIR bands has been shown to be effective in distinguishing between urban and bare land classes.

Future research will focus on the use of multi-temporal image series, the integration of machine learning algorithms such as Random Forest or deep learning with OBIA, and the validation of results against cadastral datasets.

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