



Application of Image Segmentation and Classification Techniques to Sentinel-2A Data for Monitoring Desertification: A Case Study in Southeastern Morocco

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Abstract: Monitoring land cover in arid and semi-arid zones through remote sensing is essential for understanding desertification processes and guiding sustainable land management strategies. This study assesses the performance of several unsupervised image segmentation and classification algorithms, namely K-means and ISODATA (integrated into QGIS), as well as SLIC, Mean Shift, and Felzenszwalb (implemented in Python), for land cover mapping in southeastern Morocco, a Saharan region highly vulnerable to land degradation. The analysis is based on Sentinel-2A remote sensing imagery acquired during the dry season (April), using three RGB band combinations (11/8/2, 12/11/4, and 8/4/3) to better distinguish key land cover units: sand dunes, desert crusts, sparse vegetation, wadi beds, and rocky plateaus.

The results indicate that each algorithm presents specific strengths and limitations depending on landscape complexity and segmentation parameters. K-means and ISODATA allow for rapid and easily interpretable classification but tend to confuse intermediate classes. However, advanced methods like SLIC (especially with 500 to 1000 segments), Mean Shift (which uses adjusted bandwidths), and Felzenszwalb (at a medium scale) provide better spatial delineation and thematic superiority, especially for vegetation and linear elements, although they require more computational resources.

These results highlight the importance of choosing methods according to the analysis objectives and the available resources. The use of these remote sensing techniques is an effective way to enhance desertification monitoring systems and support national projects, particularly those orchestrated by the High Commission for Water, Forests, and the Fight against Desertification.

Keywords: remote sensing, image segmentation, classification, Sentinel-2A, desertification, unsupervised algorithms



Primjena tehnika segmentacije i klasifikacije slika na podatke Sentinel 2A za praćenje procesa dezertifikacije: studija slučaja u jugoistočnom Maroku

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Sažetak: Praćenje pokrova zemljišta u aridnim i poluaridnim zonama pomoću daljinskog istraživanja ključno je za razumijevanje procesa dezertifikacije i usmjeravanje strategija održivog upravljanja zemljištem. Ovo istraživanje procjenjuje učinkovitost nekoliko nenadgledanih algoritama za segmentaciju i klasifikaciju slika, konkretno K-means i ISODATA (integrirani u QGIS), kao i SLIC, Mean Shift i Felzenszwalb (primijenjeni u Pythonu), u svrhu kartiranja pokrova zemljišta u jugoistočnom Maroku, saharskoj regiji izrazito osjetljivoj na degradaciju tla. Analiza se temelji na satelitskim snimkama Sentinel-2A prikupljenima tijekom sušne sezone (u travnju), pri čemu su korištene tri kombinacije RGB kanala (11/8/2, 12/11/4 i 8/4/3) radi boljeg razlikovanja ključnih jedinica pokrova zemljišta: pješčanih dina, pustinjskih kora, rijetke vegetacije, riječnih korita (wadi) i stjenovitih platoa.

Rezultati pokazuju da svaki algoritam ima svoje specifične prednosti i ograničenja ovisno o složenosti krajolika i parametrima segmentacije. K-means i ISODATA omogućuju brzu i lako tumačivu klasifikaciju, ali često miješaju međuklase. S druge strane, naprednije metode poput SLIC-a (posebno s 500 do 1000 segmenata), Mean Shifta (s prilagođenim širinama pojasa) i Felzenszwalba (na srednjoj skali) pružaju bolju prostornu razlučivost i tematsku preciznost, osobito za vegetaciju i linearne elemente, iako zahtijevaju više računalnih resursa.

Dobiveni rezultati naglašavaju važnost odabira metode u skladu s ciljevima analize i dostupnim resursima. Primjena tih tehnika daljinskog istraživanja predstavlja učinkovit način unaprjeđenja sustava praćenja dezertifikacije i podršku nacionalnim projektima, osobito onima koje koordinira Visoko povjerenstvo za vode, šume i borbu protiv dezertifikacije.

Ključne riječi: daljinsko istraživanje, segmentacija slike, klasifikacija, Sentinel-2A, dezertifikacija, nenadgledani algoritmi

1 Introduction

Monitoring land use in Saharan regions is a significant challenge due to the increasing threat of desertification, which is accelerated by climate change and intensified human activities such as overgrazing, unsustainable agriculture, and urban expansion (Boulos et al. 2016, Fan et al. 2020). In Morocco, the High Commission for Water, Forests and the Fight Against Desertification (HCEFLCD) plays a central role in monitoring and managing these fragile ecosystems, implementing strategies for sustainable land use and environmental protection (HCEFLCD 2018).

Accurate and up-to-date land use information is essential for understanding environmental dynamics, assessing land degradation risks, and designing effective mitigation strategies (Zribi et al. 2013, Li et al. 2024). Remote sensing has emerged as a powerful tool for land cover monitoring, enabling large-scale and timely assessments in regions where field-based surveys are challenging or costly. High-resolution satellite imagery, such as Sentinel-2A data with a 10-meter spatial resolution for visible and near-infrared bands, supports the identification of different land cover types and their temporal changes (Drusch et al. 2012).

Several studies have demonstrated the effectiveness of segmentation and classification techniques for land cover mapping. Unsupervised algorithms such as K-means and ISODATA are widely used for their simplicity and ability to classify images without prior knowledge of thematic classes (Pal, Mather 2005, Mahdianpari et al. 2019). More recent approaches, including superpixel-based methods like SLIC, clustering algorithms such as Mean Shift, and graph-based segmentation like Felzenszwalb, have shown improved spatial delineation, better handling of heterogeneous landscapes, and more precise detection of subtle transitions between land cover classes (Main-Knorn et al. 2017, Berdyev et al. 2024, Lamaamri et al. 2022). However, these advanced methods often require careful parameter tuning and higher computational resources, which can limit their operational application in large-scale monitoring programs.

Despite the advances in algorithm development, few studies have systematically compared multiple unsupervised segmentation and classification techniques on Sentinel-2A imagery in arid and Saharan environments. Moreover, there is a lack of standardized evaluation using different RGB band combinations to optimize the discrimination of bare soils, sparse vegetation, and geological formations. This study aims to fill this gap by assessing the performance of five unsupervised algorithms (K-means, ISODATA, SLIC, Mean Shift, and Felzenszwalb) for land

cover mapping in southeastern Morocco. By combining multiple band combinations and conducting a detailed comparative analysis, this research seeks to identify practical guidelines for selecting the most suitable algorithm for desertification monitoring.

The findings are expected to support the development of a robust, automated system for thematic mapping that can enhance ongoing monitoring and sustainable land management initiatives led by the HCEFLCD in desertification-sensitive Saharan regions.

2 Materials and methods

2.1. Study area

The study area is located in southern Morocco (Fig. 1). It is bounded by:

- the Beni Mellal-Khénifra region to the north
- the Algerian border to the south
- the Tafilalet region to the east
- the Souss-Massa region to the west.

This area is characterized by a diverse range of landscapes, including dry plateaus, acacia forests, mountain ranges, and valleys. It also contains one of the largest palm groves on the African continent, as well as the Wadi Drâa, which is located east of the sand dunes (HCEFLCD 2018).

The climate is distinguished by desert conditions, with long and excessively hot summers where temperatures often exceed 40°C, and moderate winters during the day followed by colder nights. For the year, the average precipitation is particularly low, around 61 mm, leading to marked drought throughout the year (Hanchane 2024).

2.2. Data used

This study relies on satellite imagery data obtained from the Sentinel-2A satellite, provided by the European Space Agency (ESA). The multiregional data, which covers the visible, near-infrared (NIR), and short-wave infrared (SWIR) spectra, has a spatial resolution ranging from 10 to 20 meters and includes thirteen spectral bands (Drusch et al. 2012).

An image taken in April, corresponding to the drought period, was selected due to the favorable weather conditions for surface observation. The image was extracted from the Copernicus Open Access Hub. The Sen2Cor tool was used to perform atmospheric correction, thus ensuring the accuracy and credibility of the data (Louis et al. 2016). The use of Sentinel-2 images in arid and Saharan regions facilitates accurate detection of vegetation movements and clear soil states,

1. Uvod

Praćenje korištenja zemljišta u saharskim regijama je značajan izazov zbog sve veće prijetnje dezertifikacije koju dodatno ubrzavaju klimatske promjene i pojačane ljudske aktivnosti poput prekomjerne ispaše, neodržive poljoprivrede i širenja urbanih područja (Boulos i dr. 2016, Fan i dr. 2020). U Maroku Visoko povjerenstvo za vode, šume i borbu protiv dezertifikacije (High Commission for Water, Forests and the Fight Against Desertification – HCEFLCD) ima središnju ulogu u praćenju i upravljanju tim osjetljivim ekosustavima, provodeći strategije za održivo korištenje zemljišta i zaštitu okoliša (HCEFLCD 2018).

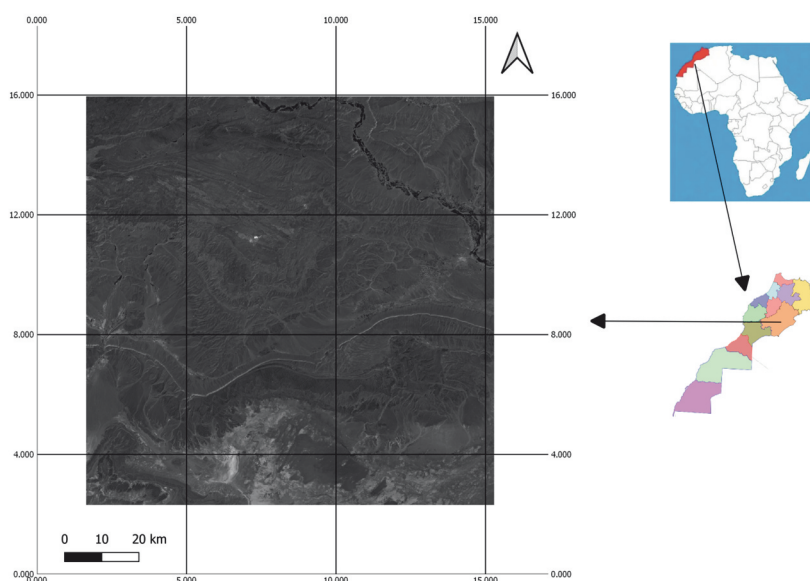
Točne i ažurirane informacije o korištenju zemljišta ključne su za razumijevanje dinamike okoliša, procjenu rizika degradacije tla te oblikovanje učinkovitih strategija ublažavanja posljedica (Zribi i dr. 2013, Li i dr. 2024). Daljinsko istraživanje pokazalo se kao snažan alat za praćenje pokrova zemljišta, omogućujući procjene velikih razmjera i u kratkom vremenu, osobito u područjima gdje su terenska istraživanja otežana ili skupa. Satelitske snimke visoke rezolucije, poput podataka Sentinel-2A s prostornom rezolucijom od 10 metara za vidljive i blisko infracrvene kanale, omogućuju prepoznavanje različitih tipova pokrova zemljišta i praćenje njihovih vremenskih promjena (Drusch i dr. 2012).

Mnoga su istraživanja potvrdila učinkovitost tehnika segmentacije i klasifikacije u kartiranju pokrova zemljišta. Nenadgledani algoritmi poput K-means i ISODATA često se koriste zbog svoje jednostavnosti i sposobnosti

klasifikacije bez prethodnog poznavanja tematskih klasa (Pal, Mather 2005, Mahdianpari i dr. 2019). Noviji pristupi, uključujući metode temeljene na superpikselima poput SLIC-a, algoritme klasteriranja kao što je Mean Shift te segmentaciju utemeljenu na grafovima poput Felzenszwalba, pokazali su poboljšanu prostornu razlučivost, bolje upravljanje heterogenim krajolicima i preciznije otkrivanje suptilnih prijelaza između klasa pokrova zemljišta (Main-Knorn i dr. 2017, Berdyayev i dr. 2024, Lamaamri i dr. 2022). Međutim, te napredne metode često zahtijevaju pažljivo podešavanje parametara i veće računalne resurse, što može ograničiti njihovu operativnu primjenu u programima praćenja velikih razmjera.

Unatoč napretku u razvoju algoritama, malo je istraživanja koja su sustavno usporedila više nenadgledanih tehnika segmentacije i klasifikacije na snimkama Sentinel-2A u aridnim i saharskim okolišima. Osim toga, nedostaje standardizirana evaluacija koja koristi različite kombinacije RGB kanala kako bi se optimiralo razlikovanje golih tala, rijetke vegetacije i geoloških formacija. Ovo istraživanje ima za cilj popuniti tu prazninu procjenom učinkovitosti pet nenadgledanih algoritama (K-means, ISODATA, SLIC, Mean Shift i Felzenszwalb) u kartiranju pokrova zemljišta u jugoistočnom Maroku. Kombiniranjem više kombinacija kanala i detaljnom komparativnom analizom, ovo istraživanje nastoji pružiti praktične smjernice za odabir najprikladnijeg algoritma za praćenje dezertifikacije.

Dobiveni rezultati trebali bi pridonijeti razvoju robusnog, automatiziranog sustava za tematsko kartiranje



Slika 1. Geografski položaj područja istraživanja.

Fig. 1 Geographic Location of Study Area.

thanks to the spectral abundance of the selected bands (Main-Knorn et al. 2017, Sola et al. 2018).

Numerous recent studies highlight the effectiveness of Sentinel-2 in monitoring desertification phenomena and mapping arid areas, primarily due to the integration of multispectral bands and sophisticated image classification techniques (Berdyev et al. 2024, Lamaamri et al. 2022). Reference data for this study, including field surveys, high-resolution aerial imagery, and existing land cover maps, were used to evaluate the accuracy of the classification results and the performance of the segmentation algorithms. The spectral bands used in this analysis are as follows:

- Band 2 (Blue, 490 nm)
- Band 3 (Green, 560 nm)
- Band 4 (Red, 665 nm)
- Band 8 (NIR, 842 nm)
- Band 11 (SWIR, 1610 nm)
- Band 12 (SWIR, 2190 nm)

To facilitate visual interpretation and support classification, three RGB composites were generated. These combinations (11/8/2, 12/11/4, and 8/4/3) were specifically selected to enhance the distinction of key land cover types in the study area. Using only three channels at a time allows for better visualization and separation of features while also reducing computational complexity. The selection of these particular bands was based on their spectral characteristics and their effectiveness in highlighting differences between sand dunes, desert crusts, sparse vegetation, wadi beds, and rocky plateaus.

- RGB 11/8/2: highlights bare soils and mineral surfaces
- RGB 12/11/4: enhances geological contrasts and structural features
- RGB 8/4/3: allows monitoring of sparse or stressed vegetation.

2.3. Data Preprocessing

Prior to applying the classification and segmentation algorithms, several preprocessing steps were conducted:

- *Atmospheric correction*: The image was corrected for atmospheric effects using the Sen2Cor module, enabling the conversion of reflectance values to surface reflectance (level-2A).
- *Study area delimitation*: The area of interest has been precisely defined, focusing on the areas affected by desertification
- *Spatial resampling*: To ensure uniform management, the 20-meter resolution bands have been reduced to 10 meters, thereby harmonizing all spectral elements used in the research.

2.4. Methodology

Classification and segmentation represent two complementary steps in the process of satellite image processing. Segmentation involves dividing an image into homogeneous areas based on specific criteria, whether spectral or spatial in nature (Blaschke et al. 2004, Serra 2006). In the subsequent process, classification assigns a label or category to each pixel or area based on its spectral signature (Pal, Mather 2005).

In the context of land use mapping, segmentation helps to distinguish coherent shapes, structures, or patterns such as vegetation, bare soils, or mineralized zones, while classification facilitates the thematic interpretation of these segments (Magee 2011, Dupas 2009).

Segmentation of an image I according to a homogeneity predicate P corresponds to a partition R of I such that:

1. $I = \bigcup_{r \in R} r$: Each pixel belongs to a region
2. $r_i \cap r_j = \emptyset$ For all $r_i, r_j \in R, i \neq j$: The regions are disjoint
3. $P(r) = \text{True}$ for all $r \in R$:

Each region is homogeneous according to a defined criterion (spectral values, texture, etc.)

4. $P(r_i \cup r_j) = \text{False}$ if r_i and r_j are adjacent :

Two adjacent regions should not be merged into a new homogeneous region

These conditions ensure that the segmentation results in a consistent division of the image, based on spectral and/or spatial similarity. Once segmentation is completed, classification enables labeling of the segmented regions according to their land cover type.

In this study, two software environments were used:

- *In QGIS*, two classical unsupervised classification algorithms were applied:
 - o *K-means*: partitions pixels based on their spectral similarity.
 - o *ISODATA*: an adaptive extension of K-means that allows automatic merging or splitting of classes during the iterative process.
- *In Python*, three advanced segmentation algorithms were implemented using custom-developed scripts:
 - o *SLIC (Simple Linear Iterative Clustering)*: a superpixel-based segmentation method, effective for detecting natural structures.
 - o *Mean Shift*: a density-based approach that is well-suited for identifying regions with gradual spectral transitions.
 - o *Felzenszwalb's method*: a graph-based segmentation algorithm that performs well in identifying objects with sharp contours.

These methods were applied to specific RGB composites derived from Sentinel-2A bands (particularly RGB 11/8/2, 12/11/4, and 8/4/3), selected for their ability to

koji može unaprijediti postojeće programe praćenja i inicijative održivog upravljanja zemljištem koje vodi HCEFLCD u saharskim područjima osjetljivima na dezertifikaciju.

2. Materijali i metode

2.1. Područje istraživanja

Područje istraživanja nalazi se u južnom Maroku (slika 1). Ono je ograničeno:

- na sjeveru regijom Beni Mellal-Khénifra
- na jugu granicom s Alžirom
- na istoku regijom Tafilalet
- na zapadu regijom Souss-Massa.

To područje karakterizira raznolik krajolik koji sadrži suhe plateau, šume akacije, planinske lance i doline. Sadrži i jednu od najvećih oaza palmi na afričkom kontinentu, kao i Oued (Wadi) Drâa, koji se nalazi istočno od pješčanih dina (HCEFLCD 2018).

Klima je izrazito pustinjska, s dugim i vrlo vrućim ljetima tijekom kojih temperature često prelaze 40°C, te umjerenim dnevnim zimama nakon kojih slijede hladnije noći. Na godišnjoj razini prosječne oborine su vrlo niske, oko 61 mm, što dovodi do izražene suše tijekom čitave godine (Hanchane 2024).

2.2. Korišteni podaci

Ova studija oslanja se na podatke satelitskih snimaka dobivene sa satelita Sentinel-2A, koje pruža Europska svemirska agencija (ESA). Multiregionalni podaci, koji pokrivaju vidljivi, blisko infracrveni (NIR) i kratkovalni infracrveni (SWIR) spektar, imaju prostornu rezoluciju od 10 do 20 metara i sadrže trinaest spektralnih pojaseva (Drusch i dr. 2012).

Za analizu je odabrana slika snimljena u travnju koja odgovara sušnom razdoblju zbog povoljnih vremenskih uvjeta za promatranje površine. Slika je preuzeta s Copernicus Open Access Hub-a. Alat Sen2Cor korišten je za atmosfersku korekciju, čime se osigurava točnost i vjerodostojnost podataka (Louis i dr. 2016). Upotreba slika Sentinela-2 u suhim i saharskim regijama omogućava precizno otkrivanje kretanja vegetacije i jasnog stanja tla, zahvaljujući spektralnoj raznolikosti odabranih pojaseva (Main-Knorn i dr. 2017, Sola i dr. 2018).

Mnoge nedavne studije ističu učinkovitost Sentinela-2 u praćenju fenomena dezertifikacije i kartiranju suhih područja, prvenstveno zbog integracije multispektralnih pojaseva i sofisticiranih tehnika klasifikacije slika (Berdyyev i dr. 2024, Lamaamri i dr. 2022). Referentni podaci za ovu studiju, uključujući terenska istraživanja, zračne snimke visoke rezolucije i postojeće karte pokrova tla,

korišteni su za procjenu točnosti rezultata klasifikacije i učinkovitosti algoritama segmentacije. Spektralni pojasevi korišteni u ovoj analizi su:

- Pojas 2 (plava, 490 nm)
- Pojas 3 (zelena, 560 nm)
- Pojas 4 (crvena, 665 nm)
- Pojas 8 (NIR, 842 nm)
- Pojas 11 (SWIR, 1610 nm)
- Pojas 12 (SWIR, 2190 nm)

Za olakšanu vizualnu interpretaciju i podršku klasifikaciji generirana su tri RGB kompozita. Te kombinacije (11/8/2, 12/11/4 i 8/4/3) posebno su odabrane kako bi se poboljšala distinkcija ključnih tipova pokrova tla u području istraživanja. Korištenje samo tri kanala u isto vrijeme omogućava bolju vizualizaciju i razdvajanje značajki uz smanjenje računalne složenosti. Odabir tih pojaseva temelji se na njihovim spektralnim karakteristikama i učinkovitosti u isticanju razlika između pješčanih dina, pustinjskih kora, rijetke vegetacije, korita wadija i kamenitih plateaua.

- RGB 11/8/2: ističe gole površine i mineralne slojeve
- RGB 12/11/4: poboljšava geološke kontraste i strukturne značajke
- RGB 8/4/3: omogućava praćenje rijetke ili oslabljene vegetacije

2.3. Predobrada podataka

Prije primjene algoritama klasifikacije i segmentacije provedeni su sljedeći koraci predobrade:

- *Atmosferska korekcija*: Slika je korigirana za atmosferske utjecaje korištenjem modula Sen2Cor, što omogućuje pretvorba vrijednosti refleksije u površinsku refleksiju (razina-2A).
- *Ograničenje područja istraživanja*: Područje interesa precizno je definirano, s naglaskom na dijelove zahvaćene dezertifikacijom.
- *Prostorna promjena uzorka (resampling)*: Kako bi se osigurala ujednačena obrada, pojasevi rezolucije od 20 metara smanjeni su na 10 metara, čime su svi spektralni elementi korišteni u istraživanju harmonizirani.

2.4. Metodologija

Klasifikacija i segmentacija su dvije komplementarne faze u procesu obrade satelitskih snimaka. Segmentacija je podjela slike na homogene površine prema određenim kriterijima, bilo spektralnim ili prostornim (Blaschke i dr. 2004, Serra 2006). U sljedećem koraku klasifikacija dodjeljuje oznaku ili kategoriju svakom pikselu ili području temeljem njegovog spektralnog potpisa (Pal, Mather 2005).

enhance key landscape features such as bare soils, vegetation, and lithological patterns. The objective is to identify the most suitable method(s) for automated land cover mapping in arid environments, considering the spectral heterogeneity of the land surface and the specific constraints of Saharan ecosystems.

K-means Algorithm

The K-means algorithm is an unsupervised classification method commonly used for non-hierarchical clustering of data. In the context of remote sensing, it enables the grouping of image pixels based on their spectral similarity without requiring prior knowledge of thematic classes. K-means operates by partitioning a dataset here, multispectral image pixels into k distinct groups, or clusters, in such a way as to minimize intra-cluster variance. This variance is defined as the sum of squared distances between each pixel and the centroid (spectral mean) of its respective cluster (Pant et al. 2025, Galluccio et al. 2012).

The algorithm follows an iterative procedure:

1. Random initialization of k centroids
2. Assignment of each pixel to the cluster with the nearest centroid (based on Euclidean distance)
3. Update of centroids by calculating the mean spectral value of each cluster
4. Repetition of steps 2 and 3 until convergence (i.e., cluster memberships stabilize or a maximum number of iterations is reached).

One of the main advantages of K-means lies in its ease of implementation, particularly in GIS environments such as QGIS, where the algorithm is readily integrated. However, the quality of the results is highly sensitive to the initial choice of centroids and the number of clusters k , which must be determined empirically. In this study, K-means was applied within QGIS to classify RGB composites derived from Sentinel-2A imagery. The aim was to assess its ability to automatically detect major land cover units in arid regions characterized by strong spectral heterogeneity.

ISODATA Algorithm

The ISODATA (Iterative Self-Organizing Data Analysis Technique) algorithm is an unsupervised classification method derived from K-means, offering greater flexibility. It is based on an iterative partitioning approach using Euclidean distance and allows for dynamic merging and splitting of clusters according to predefined criteria (Ball, Hall 1965, Abbas et al. 2016).

Unlike K-means, which requires the number of classes k to be set beforehand, ISODATA can automatically adjust

the number of clusters during the classification process by:

- *Merging* two clusters when the distance between their centroids falls below a predefined threshold (α),
- *Splitting* a cluster when its internal variance exceeds a predefined threshold (β).

This adaptive capacity makes ISODATA particularly well-suited to the spectral variability of natural environments, especially in heterogeneous arid and Saharan landscapes. In certain use cases, the ISODATA algorithm is implemented on the first principal component (PCA) to minimize spectral redundancy and improve processing efficiency. However, this statistical approach can occasionally blur the spectral signatures specific to certain land cover units (Dhodhi et al. 1999).

In this study, ISODATA was implemented using the unsupervised classification tools integrated into QGIS to generate thematic classes from the RGB composites derived from Sentinel-2A bands. The objective was to evaluate and compare its performance with that of K-means and advanced segmentation algorithms in identifying characteristic surface units in arid and desertified areas.

Simple Linear Iterative Clustering (SLIC) method

SLIC (Simple Linear Iterative Clustering) is an image over-segmentation technique that produces superpixels, it means, sets of pixels that share similar visual characteristics and exhibit spatial coherence. It modifies the k-means algorithm to adapt it to the 5D space that combines color and position, thus efficiently clustering pixels into compact and uniform areas. SLIC, unlike traditional k-means, limits aggregations to local neighborhoods, making it an extremely fast technique and suitable for natural and satellite images (Achanta et al. 2012, Van den Bergh et al. 2012). For unsupervised learning of satellite images in the mining or other sectors, the SLIC technique was configured with 500 superpixels, a compactness of 12 and a Gaussian pre-smoothing of $\sigma = 1,5$. This setting favors the capture of details of mining areas while maintaining a uniform segmentation of homogeneous regions such as vacant lots or vegetated surfaces. These values were chosen empirically to optimize fit to natural boundaries and regional consistency. An experimental study revealed that excessive values of $n_segments$ (e.g., ≥ 1000) lead to over-segmentation that visually resembles a near-reconstruction of the original image. While this phenomenon demonstrates SLIC's ability to observe local changes, it compromises the regional-scale simplification objective. In our experiments, we set an ideal value around 500 to maintain a satisfactory balance between spatial accuracy and semantic consistency.

U kontekstu kartiranja korištenja zemljišta, segmentacija pomaže u razlikovanju koherentnih oblika, struktura ili obrazaca poput vegetacije, golih površina ili mineraliziranih zona, dok klasifikacija olakšava tematsku interpretaciju tih segmenata (Magee 2011, Dupas 2009).

Segmentacija slike i prema predikatu homogenosti P odgovara particiji R slike i takvoj da:

1. $I = \bigcup_{r \in R} r$: Svaki piksel pripada nekoj regiji
2. $r_i \cap r_j = \emptyset$ Za sve $r_i, r_j \in R, i \neq j$: Regije su disjunktne
3. $P(r) = \text{Istinito}$ za sve $r \in R$:

Svaka regija je homogena prema definiranom kriteriju (spektralne vrijednosti, tekstura, itd.)

4. $P(r_i \cup r_j) = \text{Netočno}$ ako r_i, r_j su susjedne:

Ti uvjeti osiguravaju da segmentacija rezultira konzistentnom podjelom slike, utemeljenom na spektralnoj i/ili prostornoj sličnosti. Nakon dovršetka segmentacije, klasifikacija omogućuje označavanje segmentiranih regija prema njihovom tipu pokrova tla.

U ovom istraživanju korištena su dva softvera:

- U QGIS-u primijenjena su dva klasična algoritma nenadzirane klasifikacije:
 - o *K-means*: dijeli piksele na temelju njihove spektralne sličnosti.
 - o *ISODATA*: adaptivna ekstenzija K-means algoritma omogućuje automatsko spajanje ili razdvajanje klasa tijekom iterativnog procesa.
- U Pythonu primijenjena su tri napredna algoritma segmentacije koristeći prilagođene skripte:
 - o *SLIC (Simple Linear Iterative Clustering)*: metoda segmentacije utemeljena na superpikselima, učinkovita za otkrivanje prirodnih struktura.
 - o *Mean Shift*: pristup utemeljen na gustoći, pogodan za identifikaciju regija s postupnim spektralnim prijelazima.
 - o *Felzenszwalbova metoda*: algoritam segmentacije utemeljen na grafovima, učinkovit u prepoznavanju objekata oštrog kontura.

Te metode primijenjene su na specifične RGB kompozite izvedene iz pojaseva Sentinel-2A (posebno RGB 11/8/2, 12/11/4 i 8/4/3), odabrane zbog njihove sposobnosti da istaknu ključne značajke krajolika poput golih površina, vegetacije i litoloških obrazaca.

Cilj je bio identificirati najprikladniju metodu/metode za automatizirano kartiranje pokrova tla u suhim okolišima, uzimajući u obzir spektralnu heterogenost površine zemljišta i specifična ograničenja saharskih ekosustava.

Algoritam K-means

Algoritam K-means je metoda nenadzirane klasifikacije koja se često koristi za nehijerarhijsko grupiranje

podataka. U kontekstu daljinskog istraživanja omogućuje grupiranje piksela slike prema njihovoj spektralnoj sličnosti bez prethodnog poznavanja tematskih klasa.

K-means djeluje tako da dijeli skup podataka, ovdje multispektralne piksele slike, na k različitih grupa ili klastera, na način koji minimizira varijancu unutar klastera. Ta varijanca definirana je kao zbroj kvadrata udaljenosti između svakog piksela i središta (spektralnog prosjeka) pripadajućeg klastera (Pant i dr. 2025, Galluccio i dr. 2012).

Algoritam slijedi iterativni postupak:

1. Nasumična inicijalizacija k središta (centroida)
2. Dodjela svakog piksela klasteru s najbližim centroidom (utemeljeno na euklidskoj udaljenosti)
3. Ažuriranje centroida izračunavanjem prosječne spektralne vrijednosti svakog klastera
4. Ponavljanje koraka 2 i 3 dok ne dođe do konvergencije (tj. dok se članstva u klasterima ne stabiliziraju ili se ne postigne maksimalni broj iteracija).

Jedna od glavnih prednosti algoritma K-means leži u njegovoj jednostavnoj primjeni, osobito u GIS okruženjima poput QGIS-a, gdje je algoritam lako integriran. Međutim, kvaliteta rezultata vrlo je osjetljiva na početni izbor centroida i broj klastera k koji se mora odrediti empirijski.

U ovom istraživanju, K-means je primijenjen u QGIS-u za klasifikaciju RGB kompozita izvedenih iz snimaka Sentinel-2A. Cilj je bio procijeniti njegovu sposobnost automatskog prepoznavanja glavnih jedinica pokrova tla u suhim regijama karakteriziranim jakim spektralnom heterogenošću.

Algoritam ISODATA

Algoritam ISODATA (Iterative Self-Organizing Data Analysis Technique) je metoda nenadzirane klasifikacije izvedena iz algoritma K-means, koja nudi veću fleksibilnost. Utemeljena je na iterativnom pristupu podjele koristeći euklidsku udaljenost, a omogućuje dinamičko spajanje i razdvajanje klastera prema unaprijed definiranim kriterijima (Ball and Hall 1965, Abbas i dr. 2016).

Za razliku od K-means, koji zahtijeva da se broj klasa k zada unaprijed, ISODATA može automatski prilagoditi broj klastera tijekom procesa klasifikacije putem:

- Spajanja dvaju klastera kada udaljenost između njihovih centroida padne ispod unaprijed definiranog praga (α),
- Razdvajanja klastera kada njegova interna varijanca premaši unaprijed definirani prag (β).

Ova adaptivna sposobnost čini ISODATA osobito pogodnim za spektralnu varijabilnost prirodnih okoliša, posebno u heterogenim suhim i saharskim krajobrazima.

SLIC – Algoritam Simple Linear Iterative Clustering

Input : color image $Img \in R^{M \times N \times 3}$ number of superpixels K , Compactness parameter m

Ulaz: slika u boji $Img \in R^{M \times N \times 3}$ broj superpikselâ K , parametar kompaktnosti m

Output : Image segmented into regions $R \in N^{M \times N}$

Izlaz: slika segmentirana u regije $R \in N^{M \times N}$

Color space conversion : / Pretvorba prostora boja:

Convert the RGB image to CIELAB space. / Pretvori RGB u CIELAB

Initialisation of the centers : / Inicijalizacija centara:

Calculate the grid size $G = \sqrt{M \times N / K}$

Izračunaj veličinu mreže $G = \sqrt{M \times N / K}$

Place the centers $C_k = (x_k, y_k, R_k, a_k, b_k)$ regularly spaced.

Postavi jednoliko raspoređena središta $C_k = (x_k, y_k, R_k, a_k, b_k)$.

Disruption of the centers : / Poremećaj centara:

Move each center to the minimum local gradient in a window 3×3 .

Premjesti svaki centar na minimalni lokalni gradijent unutar prozora 3×3 .

Main loop (iterative) : / Glavna petlja (iterativna):

Repeat for 10 iterations: / Ponovi 10 iteracija:

For each center C_k , consider a region $2S \times 2S$ around.

Za svaki centar C_k , razmotri područje $2S \times 2S$.

For each pixel i in this region : / Za svaki piksel i u tom području:

Calculate the combined distance : / Izračunaj kombiniranu udaljenost:

$$D = \sqrt{(d_c)^2 + (m/S)^2 (d_s)^2}$$

with d_c = color distance, d_s = special distance.

d_c = udaljenost boje, d_s = prostorna udaljenost

Associate the pixel with the nearest center (minimize D).

Poveži piksel s najbližim centrom (minimiziraj D).

Update the centers : / Ažuriraj središta:

Recalculate each center C_k as the average of the pixels associated with it.

Ponovno izračunaj svako središte C_k kao prosjek piksela povezanih s njim.

Post-processing (optional) : / Naknadna obrada (opcionalno):

Apply clustering to correct small, isolated regions.

Primijeni grupiranje kako bi se ispravile male izolirane regije.

Mean Shift

The Mean Shift method is a non-parametric data analysis technique used primarily for image clustering and segmentation (Comaniciu and Meer 2002). It allows finding modes (density peaks) in a data space, i.e., areas where points are most dense. In image processing, the Mean Shift technique is used for image segmentation by grouping pixels with similar characteristics (such as color, texture, etc.) together, without making strict assumptions

about the shape of the clusters. The key concept is to adjust each point by moving it closer to the local mean of adjacent points, based on a kernel specified by a bandwidth parameter, until convergence to a mode is achieved. The main characteristics of Mean Shift algorithm are non-parametric; there is no need to determine the number of clusters in advance. Robust against cluster geometry, able to identify clusters of undefined shape, unlike K-means which searches for spherical clusters. Mode search detects local peaks of

Algoritam Mean Shift / Mean Shift Algorithm

Za skup točaka $\{x_1, x_2, \dots, x_n\}$ u n dimenzionalnom prostoru / For a set of points $\{x_1, x_2, \dots, x_n\}$ in a n -dimensional space

Inicijalizacija: odaberite početnu točku x (često točka iz skupa podataka).

Initialization: Choose an initial point x (often a point from the dataset).

Izračunajte lokalni prozor oko x s jezgrom (npr. sferni ili Gaussov prozor) veličine h (širina pojasa).

Compute the local window around x with a kernel (e.g., a spherical or Gaussian window) of size h (bandwidth).

Izračunajte Mean Shift vektor kao razliku između ponderirane srednje vrijednosti točaka u prozoru i trenutne pozicije x :

Calculate the Mean Shift vector as the difference between the weighted average of the points in the window and the current position x :

$$m(x) = \frac{\sum_{i=1}^n K\left(\frac{|x_i - x|}{h}\right) x_i}{\sum_{i=1}^n K\left(\frac{|x_i - x|}{h}\right)} - x$$

gdje je K funkcija jezgre (npr. Gaussova). / Where K is the kernel function (e.g., Gaussian).

Ažurirajte položaj: / *Update the position:*

$$x \leftarrow x + m(x)$$

Ponavljajte korake 2 do 4 dok ne dođe do konvergencije (dok $m(x)$ postane blizu nule).

Repeat steps 2 to 4 until convergence (when $m(x)$ becomes close to zero).

Ponavljajte taj postupak za sve točke, a točke koje konvergiraju prema istom modu grupiraju se u isti klaster.

Repeat this process for all points, and points that converge to the same mode are grouped into the same cluster.

U određenim slučajevima algoritam ISODATA se primjenjuje na prvu glavnu komponentu (PCA) kako bi se smanjila spektralna redundancija i poboljšala učinkovitost obrade. Međutim, taj statistički pristup ponekad može zamagliti spektralne potpise specifične za određene jedinice pokrova tla (Dhodhi i dr. 1999).

U ovom istraživanju ISODATA je primijenjen za nenadziranu klasifikaciju pomoću alata integriranih u QGIS za generiranje tematskih klasa iz RGB kompozita izvedenih iz pojaseva Sentinel-2A. Cilj je bio procijeniti i usporediti njegovu učinkovitost s algoritmom K-means i naprednim algoritmima segmentacije u prepoznavanju karakterističnih površinskih jedinica u suhim i dezertificiranim područjima.

Metoda Simple Linear Iterative Clustering (SLIC)

SLIC (Simple Linear Iterative Clustering) je tehnika pre-segmentacije slike koja proizvodi superpiksele, što znači skupove piksela koji dijele slične vizualne karakteristike i pokazuju prostornu koherenciju. Algoritam

modificira K-means kako bi ga prilagodio 5D prostoru koji kombinira boju i položaj, čime se učinkovito grupiraju pikseli u kompaktna i ujednačena područja.

SLIC, za razliku od tradicionalnog K-means, ograničava agregacije na lokalne susjedstva, što ga čini izuzetno brzim algoritmom i pogodnim za prirodne i satelitske slike (Achanta i dr. 2012, Van den Bergh i dr. 2012).

Za nenadzirano učenje satelitskih slika u rudarstvu ili drugim sektorima, SLIC tehnika je konfigurirana sa 500 superpiksela, kompaktnosti 12 i Gausovim prethodnim izgladivanjem uz $\sigma = 1,5$. Ta konfiguracija pogoduje hvatanju detalja rudarskih područja, dok istovremeno održava ujednačenu segmentaciju homogenih regija poput neiskorištenih parcela ili vegetacijskih površina. Te su vrijednosti odabrane empirijski kako bi se optimirao prikladan odnos prema prirodnim granicama i regionalnoj konzistenciji. Eksperimentalno istraživanje pokazalo je da prevelike vrijednosti $n_segments$ (npr. ≥ 1000) dovede do prekomjerne segmentacije koja vizualno nalikuje gotovo rekonstrukciji originalne slike. Iako taj fenomen pokazuje sposobnost SLIC-a za promatranje

Felzenszwalb Algorithm / Felzenszwalbov algoritam

Model the image as an undirected graph / Modelirajte sliku kao neusmjereni graf

Each pixel is a connection point linked to its neighbors, whether 4-connected or 8-connected.

Svaki piksel je točka povezana sa svojim susjedima, bilo 4-povezana ili 8-povezanih.

The weights assigned to the edges reflect the difference (usually the Euclidean distance in color space).

Težine dodijeljene bridovima odražavaju razliku (obično euklidska udaljenost u prostoru boja).

Sort edges in ascending order of weight. / Sortirajte bridove u rastućem redoslijedu prema težini.

Merge regions using a conditional aggregation strategy: / Spajajte regije koristeći strategiju uvjetne agregacije:

An edge connecting two regions A and B is merged if: / Brid koji povezuje dvije regije A i B se spaja ako:

$Weights(A, B) \leq \min(Int(A) + \tau(A), Int(B) + \tau(B))$ / $Težina(A, B) \leq \min(Int(A) + \tau(A), Int(B) + \tau(B))$

Where / gdje su

$Weights(A, B)$ = dissimilarity between regions. / $Težina(A, B)$ = različitost između regija A .

$Int(A)$ = the greatest internal dissimilarity in region A .

$Int(A)$ = najveća unutarnja različitost u regiji A .

$$\tau(A) = k/|A|$$

k is an adaptive threshold function (k is a parameter).

k je adaptivna funkcija praga (k je parametar).

Stop: when all edges have been examined or the merge conditions are no longer met.

Zaustavi: kada su svi bridovi pregledani ili uvjeti za spajanje više nisu zadovoljeni.

density, which is valuable for image segmentation. Easy to implement and guaranteed convergence (within a limited number of iterations). Can be used in multi-dimensional spaces (color space, position space, etc.).

Experiments have shown that the algorithm identifies 4 clusters in the image when the bandwidth is set to 50 or 40. For a bandwidth of 20, it identifies 30 clusters. This fluctuation shows that the value of the bandwidth parameter directly influences the level of detail of the segmentation. When the bandwidth is high (50 or 40), the exploration window encompasses a large area, which merges several similar areas into a single cluster. This results in a rough segmentation, highlighting the main structures of the image. On the other hand, with a lower bandwidth (20), the window becomes narrower, allowing the identification of a greater number of local variations. This results in a precise division (30 clusters), but can also generate visual noise if the details are too small or insignificant.

Felzenszwalb's method

The hierarchical segmentation approach developed by Felzenszwalb and Huttenlocher (2004) is based on a

linked feature clustering algorithm. Its objective is to divide an image into homogeneous areas based on visual uniformity standards, while preserving object boundaries. It is based on a graph structure where each pixel is a node linked to its neighbors, with edges having weights based on their intensity difference. The strengths of this algorithm are: Extremely fast and efficient for large images (Felzenszwalb, Huttenlocher 2004). It ensures that object contours are closely followed (especially with a high sigma value). Intuitive adjustment of segment size using scale.

3 Results and Discussion

The analysis of the five segmentation and classification algorithms applied to land cover mapping reveals contrasted performances influenced by the nature of the algorithms, chosen parameters, and the RGB composites used. This evaluation is based on each method's ability to discriminate classes such as sands, sparse vegetation, desert crusts, dry wadi beds, and rocky formations, while considering spatial readability, fidelity to terrain structures, processing time, and ease of interpretation. The accuracy of the results was assessed using

lokalnih promjena, on kompromitira cilj pojednostavljenja na regionalnoj razini. U našim eksperimentima postavili smo idealnu vrijednost oko 500 kako bismo održali zadovoljavajuću ravnotežu između prostorne preciznosti i semantičke konzistencije.

Mean Shift

Metoda Mean Shift je neparametarska tehnika analize podataka koja se koristi prvenstveno za grupiranje i segmentaciju slika (Comaniciu, Meer 2002). Omogućuje pronalaženje modova (vrhova gustoće) u prostoru podataka, tj. područja gdje su točke najgušće. U obradi slika, tehnika Mean Shift koristi se za segmentaciju slika grupiranjem piksela sličnih karakteristika (poput boje, teksture itd.) bez strogih pretpostavki o obliku klastera. Ključni koncept je prilagodba svake točke pomicanjem bliže lokalnoj srednjoj vrijednosti susjednih točaka na temelju jezgre definirane parametrima širine pojasa, sve dok se ne postigne konvergencija na mod. Glavna karakteristika algoritma Mean Shift je da nije potrebno unaprijed određivati broj klastera. Otporan je na geometriju klastera, sposoban je identificirati klastere neodređenog oblika, za razliku od K-meansa koji traži sferične klastere. Pretraživanje modova otkriva lokalne vrhove gustoće, što je vrijedno za segmentaciju slika. Jednostavan je za primjenu i zajamčena je konvergencija (unutar ograničenog broja iteracija). Može se koristiti u višedimenzionalnim prostorima (prostor boja, prostor položaja itd.).

Eksperimenti su pokazali da algoritam identificira 4 klastera na slici kada je širina pojasa postavljena na 50 ili 40. Za širinu pojasa od 20, algoritam identificira 30 klastera. Ta fluktuacija pokazuje da vrijednost parametra širine pojasa izravno utječe na razinu detalja segmentacije. Kad je širina pojasa velika (50 ili 40), prozor istraživanja obuhvaća veliko područje, što spaja nekoliko sličnih područja u jedan klaster. To rezultira grubom segmentacijom, naglašavajući glavne strukture slike. S druge strane, kod manje širine pojasa (20), prozor postaje uži, omogućujući identifikaciju većeg broja lokalnih varijacija. To rezultira preciznom podjelom (30 klastera), ali također može generirati vizualnu šumovitost ako su detalji previše mali ili neznatni.

Metoda Felzenszwalba

Hijerarhijski pristup segmentaciji koji su razvili Felzenszwalb i Huttenlocher (2004) temelji se na algoritmu grupiranja povezanih značajki. Njegov je cilj podijeliti sliku u homogene površine na temelju standarda vizualne uniformnosti, pritom očuvajući granice objekata. Temelji se na strukturi grafa gdje je svaki piksel čvor povezan sa

svojim susjedima, s bridovima čije težine ovise o razlici u intenzitetu. Taj je algoritam izuzetno brz i učinkovit za velike slike (Felzenszwalb, Huttenlocher 2004). Osigurava da se konture objekata precizno prate (posebno s visokom vrijednošću σ). Podešavanje veličine segmenta korištenjem skale je intuitivno.

3. Rezultati i rasprava

Analiza pet algoritama za segmentaciju i klasifikaciju primijenjenih na kartiranje pokrova tla pokazuje kontrastne performanse koje ovise o prirodi algoritama, odabranim parametrima i korištenim RGB kompozitima. Ova se evaluacija temelji na sposobnosti svake metode da razlikuje klase poput pijeska, rijetke vegetacije, pustinjačkih korica, suhih korita wadija i kamenitih formacija, uzimajući u obzir prostornu čitljivost, vjernost terenskim strukturama, vrijeme obrade i jednostavnost interpretacije. Točnost rezultata procijenjena je korištenjem referentnih podataka, uključujući terenska istraživanja, zračne snimke visoke rezolucije i postojeće karte pokrova tla. Generirana je matrica zabune za usporedbu klasificiranih piksela s referentnim podacima, a izračunana su i ukupna točnost i Kappa koeficijent za procjenu performansi svakog algoritma.

Algoritam K-means, primijenjen u QGIS-u, pokazao je zadovoljavajuće rezultate u prepoznavanju velikih homogenih jedinica. Izvršava se brzo, zahtijeva malo resursa i jednostavan je za primjenu, što ga čini praktičnim rješenjem za standardne zadatke obrade. U RGB kompozitima (11, 8, 2) i (12, 11, 4), razdvajanje pijeska bilo je jasno zbog snažnog spektralnog odziva SWIR traka na razlike u vlazi i teksturi tla. Međutim, kompozit (8, 4, 3) pokazao je ograničenja u razlikovanju vegetacije i pustinjačkih kora zbog sličnih spektralnih karakteristika. Algoritam K-means također ovisi o arbitrarno fiksiranom broju klastera: premali broj klastera vodi do prevelikog generaliziranja, dok prevelik broj stvara fragmentirane particije. Preporučuje se kalibracija putem unakrsnog potvrđivanja (cross-validation) ovisno o ciljevima kartiranja. Osiguravanje dobre homogenizacije traka (resampling) također je ključno, jer nesukladnosti mogu iskriviti rezultate (slika 2).

Pristup ISODATA, također primijenjen u QGIS-u, pokazao se fleksibilnijim jer dinamički prilagođava broj klasa spajanjem ili razdvajanjem grupa na temelju statističkih udaljenosti. Ta sposobnost omogućila je bolju reprezentaciju prijelaznih zona, osobito između pustinjačkih kora i vegetacije ili između pijeska i suhih wadi korita. U kompozitu (12, 11, 4), ISODATA je uspješno identificirao slane kore koje su često bile pogrešno klasificirane pomoću K-means algoritma.

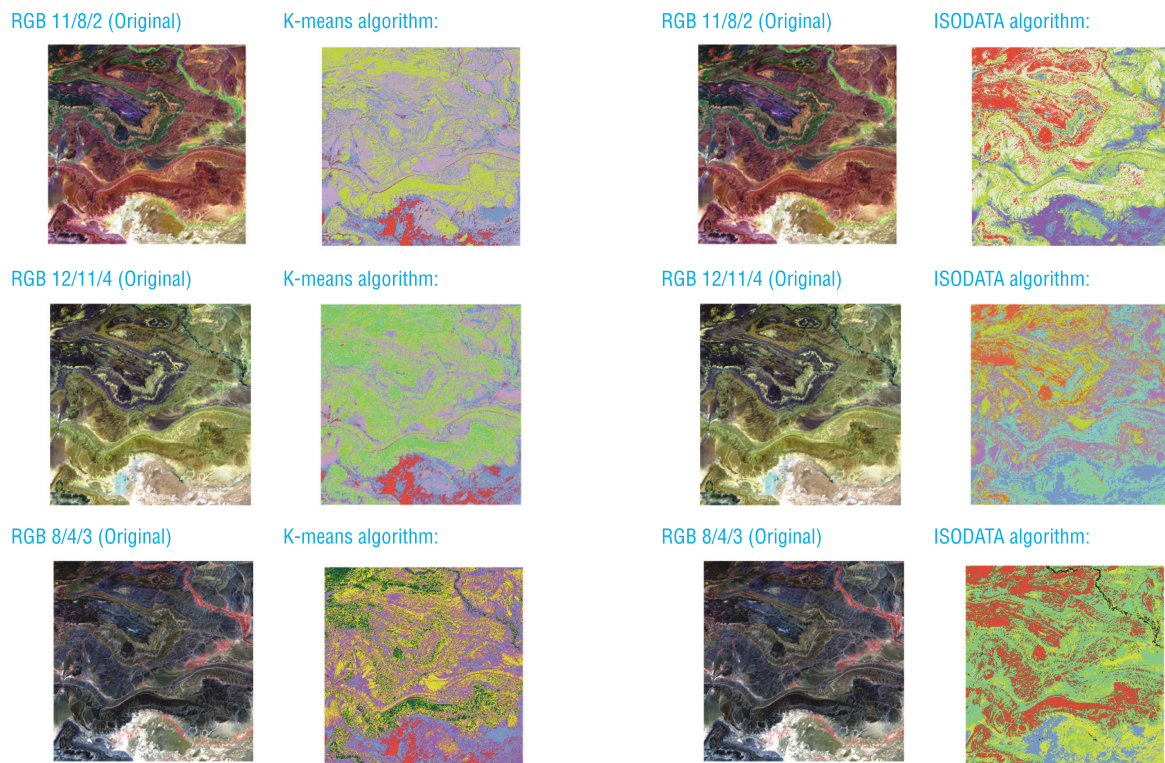


Fig. 2 Evaluation of K-means Classification Using Various RGB Composites.

Slika 2. Procjena K-means klasifikacije upotrebom različitih RGB kompozita.

Fig. 3 Evaluation of ISODATA Classification Using Various RGB Composites.

Slika 3. Procjena ISODATA klasifikacije upotrebom različitih RGB kompozita.

reference data, including field surveys, high-resolution aerial imagery, and existing land cover maps. A confusion matrix was generated to compare the classified pixels with the reference data, and both overall accuracy and the Kappa coefficient were calculated to evaluate the performance of each algorithm.

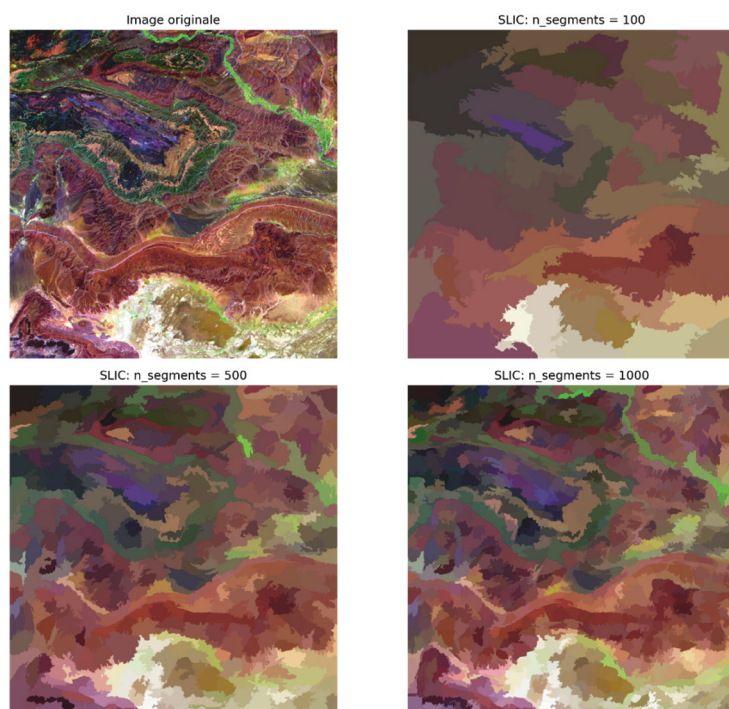
The K-means algorithm, implemented in QGIS, demonstrated satisfactory performance in identifying large homogeneous units. It is fast to execute, resource-efficient, and easy to implement, making it a practical solution for standard processing tasks. In the RGB composites (11, 8, 2) and (12, 11, 4), the separation of sands was clear due to the strong spectral response of the SWIR bands to moisture and soil texture differences. However, the (8, 4, 3) composite showed limitations in differentiating between vegetation and desert crusts due to their similar spectral signatures. K-means suffers from dependency on the arbitrarily fixed number of clusters: too few clusters lead to overgeneralization, while too many produce fragmented partitions. Calibration via cross-validation is recommended depending on mapping objectives. Ensuring good band homogenization (resampling) is also critical, as inconsistencies can bias results (Fig. 2).

The ISODATA approach, also implemented in QGIS, proved more flexible by dynamically adjusting the number of classes through merging or splitting groups based on statistical distances. This capability allowed better representation of transition zones, notably between desert crusts and vegetation or between sands and dry wadis. In the (12, 11, 4) composite, ISODATA successfully identified saline crusts often misclassified by K-means. However, ISODATA requires longer processing times and prior knowledge of merging and splitting thresholds to avoid incoherent classifications. A common mistake is using default parameters without adjustment, which can lead to arbitrary groupings. Nonetheless, the algorithm remains robust for heterogeneous arid zones such as the Maider basin (Fig. 3).

The SLIC (Simple Linear Iterative Clustering) algorithm, tested in Python with three values of the parameter `n_segments` (100, 500, 1000), showed the following trends: with `n_segments` = 100, superpixels were too large for fine landscape reading, clearly delineating only large units such as dune fields. At `n_segments` = 500, the results were balanced, correctly representing natural formations while avoiding over-segmentation. Sparse

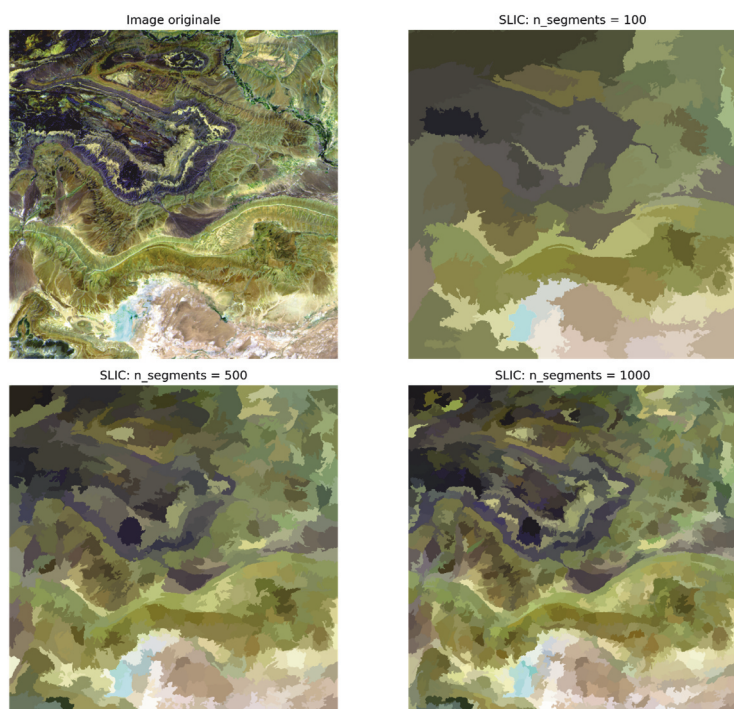
Međutim, ISODATA zahtijeva duže vrijeme obrade i prethodno poznavanje pragova za spajanje i razdvajanje kako bi se izbjegle nekonzistentne klasifikacije. Česta pogreška je korištenje zadane postavke parametara bez prilagodbe, što može dovesti do proizvoljnog grupiranja. Unatoč tome, algoritam ostaje robustan za heterogene suhe zone, poput bazena Maider (slika 3).

Algoritam SLIC (Simple Linear Iterative Clustering), testiran u Pythonu s tri vrijednosti parametra $n_segments$ (100, 500, 1000), pokazao je sljedeće trendove: s $n_segments = 100$, superpikseli su bili preveliki za detaljno čitanje krajolika, jasno razgraničujući samo velike jedinice poput dina. Pri $n_segments = 500$, rezultati su bili uravnoteženi, ispravno prikazujući prirodne formacije uz izbjegavanje prevelike segmentacije. Rijetka vegetacija bila je dobro izolirana u kompozitu (8, 4, 3), a wadi korita su dobro segmentirana u kompozitu (11, 8, 2). Suprotno tome, pri $n_segments = 1000$, prekomjerna segmentacija uzrokovala je pretjeranu fragmentaciju, otežavajući interpretaciju. Obrada pomoću SLIC-a relativno je brza, ali zahtijeva optimizaciju parametara u skladu sa željenom razinom detalja. Nepromišljeno povećavanje broja segmenata treba izbjegavati, osobito u područjima s niskom teksturom, kako bi se spriječila nepotrebna prostorna buka (slike 4-6).



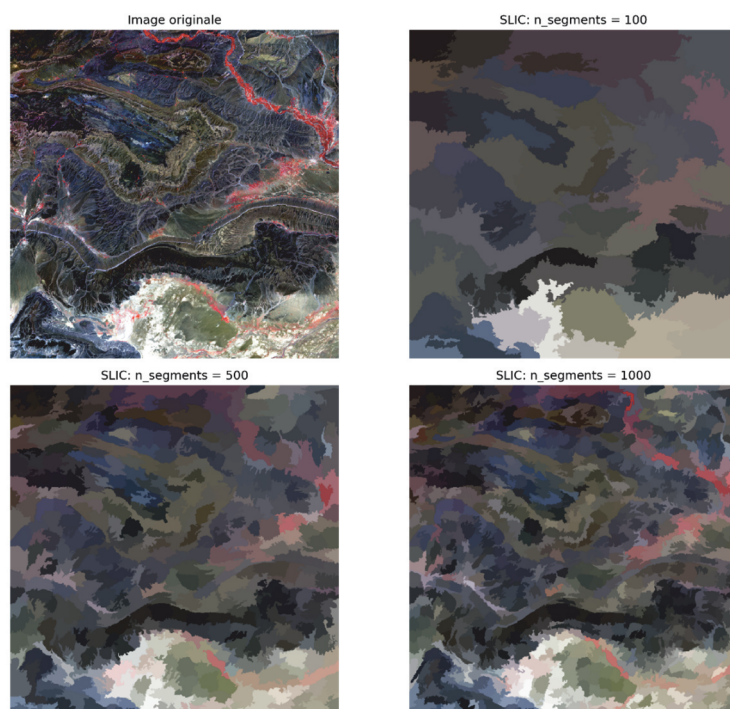
Slika 4. Utjecaj parametra $n_segments$ na SLIC segmentaciju upotrebom RGB 11/8/2.

Fig. 4 Effect of $n_segments$ Parameter on SLIC Segmentation Using RGB 11/8/2.



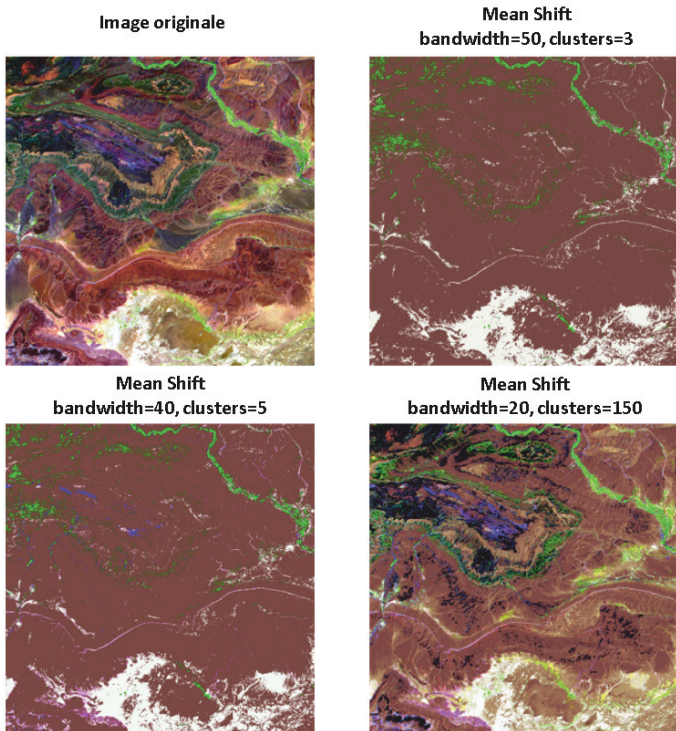
Slika 5. Utjecaj parametra $n_segments$ na SLIC segmentaciju upotrebom RGB 12/11/4.

Fig. 5 Effect of $n_segments$ Parameter on SLIC Segmentation Using RGB 12/11/4.



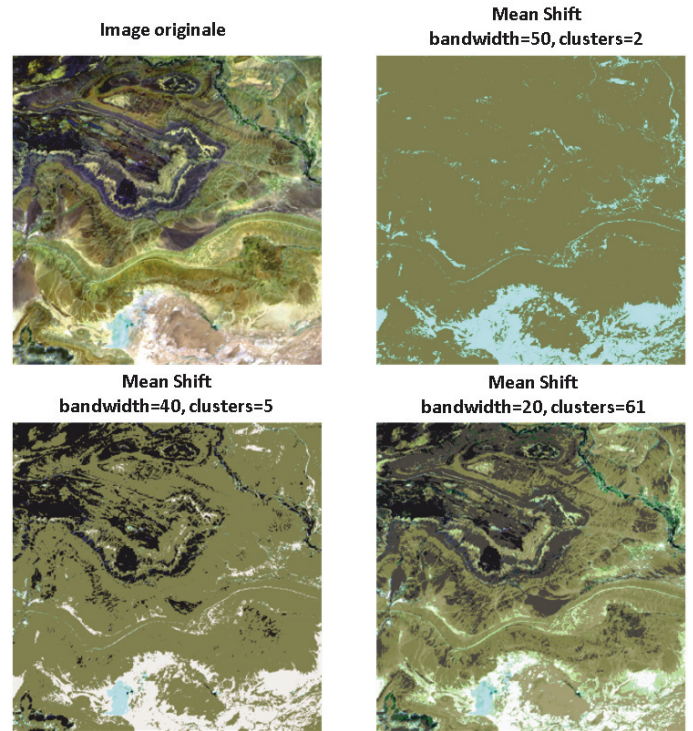
Slika 6. Utjecaj parametra $n_segments$ na SLIC segmentaciju upotrebom RGB 8/4/3.

Fig. 6 Effect of $n_segments$ Parameter on SLIC Segmentation Using RGB 8/4/3.



Slika 7. Svojstva algoritma Mean Shift pri promjenjivim parametrima propusnosti i klastera na RGB 11/8/2.

Fig. 7 Performance of the Mean Shift Algorithm with Varying Bandwidth and Cluster Parameters on RGB 11/8/2.



Slika 8. Svojstva algoritma Mean Shift pri promjenjivim parametrima propusnosti i klastera na RGB 12/11/4.

Fig. 8 Performance of the Mean Shift Algorithm with Varying Bandwidth and Cluster Parameters on RGB 12/11/4.

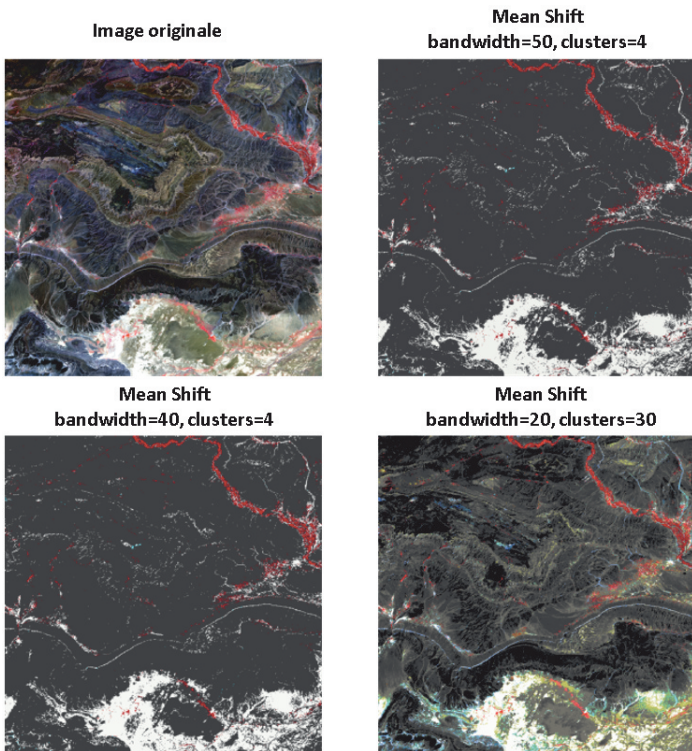


Fig. 9 Performance of the Mean Shift Algorithm with Varying Bandwidth and Cluster Parameters on RGB 8/4/3.

Slika 9. Svojstva algoritma Mean Shift pri promjenjivim parametrima propusnosti i klastera na RGB 8/4/3.

vegetation was well isolated in the (8, 4, 3) composite, and wadis were well segmented in (11, 8, 2). Conversely, at $n_segments = 1000$, over-segmentation caused excessive fragmentation, complicating interpretation. SLIC processing is relatively fast but requires parameter optimization according to the desired level of detail. Blindly increasing segment numbers should be avoided, especially in low-texture areas, to prevent unnecessary spatial noise (Fig. 4-6).

The Mean Shift algorithm, also developed in Python, was applied in three cases: (1) bandwidth = 50 and clusters = 4, (2) bandwidth = 40 and clusters = 4, and (3) bandwidth = 20 and clusters = 30. The first case produced a very smooth segmentation, useful for extracting large sand masses or thick crusts but less effective for detecting sparse vegetation. The intermediate case offered a good compromise: dry wadi beds and sparse vegetation were better isolated, particularly in SWIR-rich composites. The third case, with reduced bandwidth and many clusters, yielded highly detailed segmentation highlighting micro-variations such as vegetation alignments or rock outcrops, but at the cost of longer processing time and data overload, difficult to exploit without post-processing. It is

Tablica 1. Usporedna analiza algoritama segmentacije i klasifikacije silka za kartiranje pokrova tla u suhim područjima upotrebom podataka Sentinel-2.
Table 1 Comparative Analysis of Image Segmentation and Classification Algorithms for Land Cover Mapping in Arid Zones Using Sentinel-2 Data.

Algorithm	Korišteni parametri Parameters Used	RGB sastavi RGB Compositions	Dobro identificirane klase Well-Identified Classes	Snage Strengths	Slabosti Weaknesses	Vrijeme obrade Processing Time	Napomene i preporuke Remarks & Recommendations
K-means	Unaprijed definirani broj klasa (obično 4-6)	11/8/2, 12/11/4, 8/4/3	Pijesci, kore, suha riječna korita	Brzo, jednostavno, integrirano u QGIS	Loša obrada prijelaznih zona; ovisi o odabranom broju klasa	Vrlo brzo	Pažljivo kalibrirati broj klasa na temelju heterogenosti terena
K-means	Predefined number of classes (usually 4-6)	11/8/2, 12/11/4, 8/4/3	Sands, crusts, dry riverbeds	Fast, simple, integrated in QGIS	Poor handling of transitional zones; depends on chosen number of classes	Very fast	Carefully calibrate number of classes based on terrain heterogeneity
ISODATA	Automatsko spajanje/razdvajanje klasa	12/11/4, 8/4/3	Kore, rijetka vegetacija, pijesci	Fleksibilnije od K-means; dinamičko prilagođavanje	Manje stabilno; ovisi o pragovima za spajanje/razdvajanje	Brzo do umjereno	Zahtijeva precizno podešavanje pragova kako bi se izbjeglo pogrešno spajanje
ISODATA	Automatic class merging/splitting	12/11/4, 8/4/3	Crusts, sparse vegetation, sands	More flexible than K-means; dynamic adjustment	Less stable; depends on merging/splitting thresholds	Fast to moderate	Requires fine tuning of thresholds to avoid erroneous merges
SLIC	n_segments = 100 / 500 / 1000	11/8/2, 12/11/4, 8/4/3	Pijesci (veliki segmenti), suha riječna korita, kore	Dobra kontrola veličine segmenta; brzo procesiranje	Moguća prekomjerna segmentacija ako je n_segments previsok	Brzo	Optimalna vrijednost: 500; izbjegavati 1000 osim za studije vrlo fine skale
SLIC	n_segments = 100 / 500 / 1000	11/8/2, 12/11/4, 8/4/3	Sands (large segments), dry riverbeds, crusts	Good control over segment size; fast processing	Oversegmentation possible if n_segments too high	Fast	Optimal value: 500; avoid 1000 unless for very fine-scale study
Mean Shift	širina pojasa = 50/40/20; klasteri = 4/4/30	8/4/3, 11/8/2	Vegetacija, suha riječna korita, mikrojezaži	Izvršna lokalna diferencijacija; osjetljivo na teksturu	Vrlo sporo; teško za korištenje bez naknadne obrade	Sporo do vrlo sporo	Preporučena širina pojasa = 40 za dobar balans
Mean Shift	bandwidth = 50/40/20; clusters = 4/4/30	8/4/3, 11/8/2	Vegetation, dry riverbeds, micro-landscapes	Excellent local differentiation; texture sensitive	Very slow; difficult to use without post-processing	Slow to very slow	Prefer bandwidth = 40 for good balance
Felzenszwalb	skala = 50 / 100 / 150	11/8/2, 12/11/4	Suha riječna korita, pijesci, kore, vegetacija	Dobar balans između detalja i čitljivosti; prirodna segmentacija	Prekomjerna segmentacija (skala = 50) ili pretjerano pojednostavljivanje (skala = 150)	Umjereno	Preporučena skala = 100 za optimalan balans
Felzenszwalb	scale = 50 / 100 / 150	11/8/2, 12/11/4	Dry riverbeds, sands, crusts, vegetation	Good balance between detail and readability; natural segmentation	Oversegmentation (scale=50) or over-simplification (scale=150)	Moderate	scale = 100 recommended for optimal balance

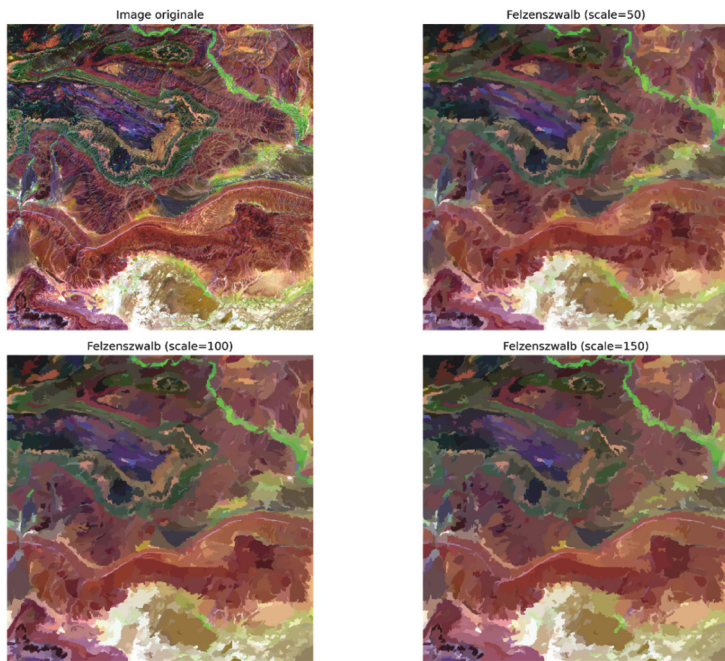


Fig. 10 Performance of the Felzenszwalb Algorithm at Different Segmentation Scales on RGB 11/8/2.

Slika 10. Svojstva Felzenszwalbova algoritma pri različitim skalama segmentacije na RGB 11/8/2.

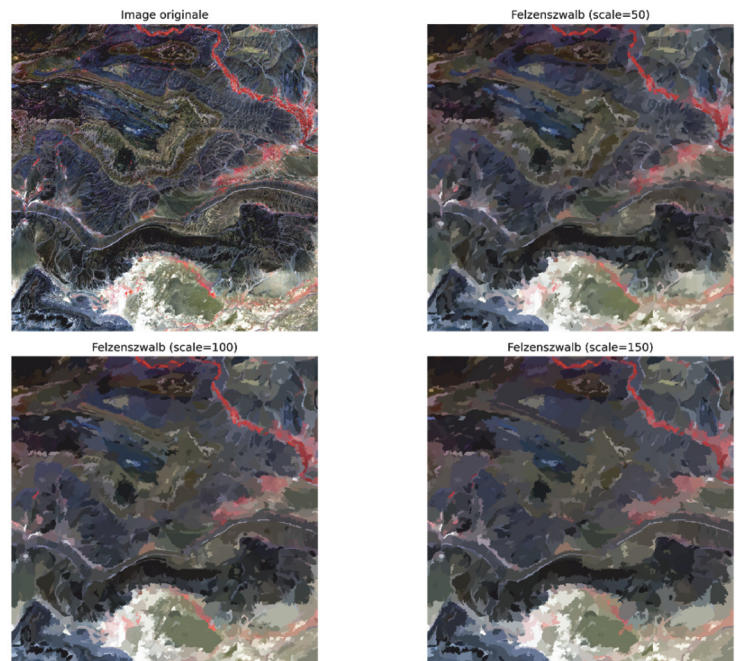


Fig. 12 Performance of the Felzenszwalb Algorithm at Different Segmentation Scales on RGB 8/4/3.

Slika 12. Svojstva Felzenszwalbova algoritma pri različitim skalama segmentacije na RGB 8/4/3.

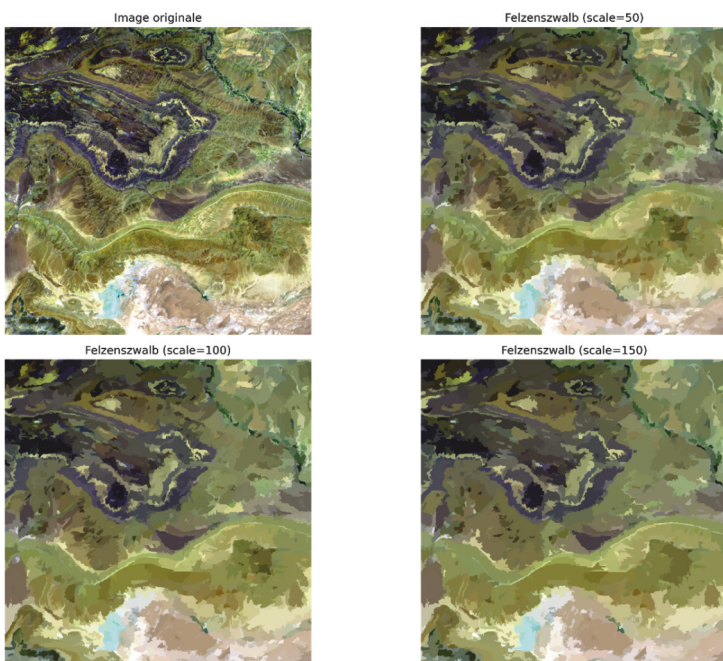


Fig. 11 Performance of the Felzenszwalb Algorithm at Different Segmentation Scales on RGB 12/11/4.

Slika 11. Svojstva Felzenszwalbova algoritma pri različitim skalama segmentacije na RGB 12/11/4.

advised to limit the bandwidth to intermediate values to maintain informative segmentation while avoiding proliferation of poorly interpretable classes (Fig. 7-9).

Finally, the Felzenszwalb algorithm was tested at three segmentation scales (scale = 50, 100, and 150). Scale = 50 produced very fine segmentation capturing details of linear structures like wadi beds but also generated an abundance of segments in crust or rocky zones. Scale = 100 was optimal for identifying relevant landscape units sands, crusts, vegetation, wadis while preserving satisfactory overall readability. Conversely, scale = 150 simplified the image structure excessively, suitable for small-scale maps but less informative locally. Felzenszwalb performs well in detecting spatial homogeneity breaks but requires moderate computation time (faster than Mean Shift) and good image preparation (noise removal, resampling). It is crucial not to apply this algorithm without prior quality assessment of radiometric and atmospheric corrections (Fig. 10-12).

Overall, each algorithm has specific strengths that can be leveraged depending on the targeted objectives: mapping residual vegetation, restoration areas, crusts, or mobile sands. The combined use of RGB composites (11, 8, 2), (12, 11, 4), and (8, 4, 3) proved essential to exploit the spectral potential of Sentinel-2A bands and enhance the interpretation of desert landforms.

Algoritam Mean Shift, također razvijen u Pythonu, primijenjen je u tri slučaja: (1) bandwidth = 50 i clusters = 4, (2) bandwidth = 40 i clusters = 4, i (3) bandwidth = 20 i clusters = 30. Prvi slučaj proizveo je vrlo glatku segmentaciju, korisnu za izdvajanje velikih pijesčanih masa ili debelih kora, ali manje učinkovit za detekciju rijetke vegetacije. Srednji slučaj pružio je dobar kompromis: suha korita wadija i rijetka vegetacija bolje su izolirani, osobito u kompozitima bogatim SWIR trakama. Treći slučaj, s reduciranom propusnošću i velikim brojem klastera, dao je vrlo detaljnu segmentaciju koja ističe mikrovarijacije, poput poravnanja vegetacije ili kamenih izdanka, ali uz dulje vrijeme obrade i preopterećenje podacima, teško iskoristivo bez naknadne obrade. Preporučuje se ograničiti propusnost (bandwidth) na srednje vrijednosti kako bi se održala informativna segmentacija, a istovremeno izbjegla proliferacija teško interpretabilnih klasa (slike 7-9).

Na kraju, Felzenszwalb algoritam testiran je na tri skale segmentacije (scale = 50, 100 i 150). Scale = 50 proizvela je vrlo finu segmentaciju koja je hvatala detalje linearnih struktura poput korita wadija, ali je također generirala veliku količinu segmenata u korama ili kamenitim zonama. Scale = 100 bila je optimalna za identifikaciju relevantnih jedinica krajolika poput pijeska, kora, vegetacije i wadija, uz održavanje zadovoljavajuće ukupne čitljivosti. Suprotno tome, scale = 150 pretjerano je pojednostavila strukturu slike, pogodna je za karte malog opsega, ali lokalno manje informativna. Felzenszwalb dobro detektira prekide prostorne homogenosti, ali zahtijeva umjereno vrijeme obrade (brže od algoritma Mean Shift) i dobru pripremu slike (uklanjanje šuma, resampling). Ključno je ne primjenjivati ovaj algoritam bez prethodne procjene kvalitete radiometrijskih i atmosferskih korekcija (slike 10-12).

Općenito, svaki algoritam ima specifične prednosti koje se mogu iskoristiti ovisno o ciljevima: kartiranje preostale vegetacije, područja obnove, kora ili pokretnih pijesaka. Kombinirana uporaba RGB kompozita (11, 8, 2), (12, 11, 4) i (8, 4, 3) pokazala se ključnom za iskorištavanje spektralnog potencijala traka Sentinel-2A i unapređenje interpretacije pustinskih reljefnih formacija.

Sljedeća tablica sažima rezultate vizualno-analitičke usporedne analize pet algoritama segmentacije i klasifikacije primijenjenih na kartiranje pokrova tla u suhim područjima. Evaluacija je temeljena na vizualnoj interpretaciji izlaza klasifikacije u usporedbi s originalnim snimkama Sentinel-2A, potkrijepljena referentnim informacijama iz terenskih opažanja i visokorazlučivih zračnih snimaka. Tablica ističe ključne parametre korištene za svaku metodu, testirane kombinacije RGB traka

Sentinela-2A, klase pokrova tla koje su najuspješnije identificirane, kao i glavne prednosti i ograničenja koja su uočena. Također su navedena vremena obrade i praktične preporuke za optimiranje performansi svakog algoritma. Taj pregled željeli smo usmjeriti čitatelje na izbor najprikladnijeg algoritma ovisno o specifičnim ciljevima i karakteristikama područja istraživanja.

4. Zaključak

Ovo istraživanje pokazalo je učinkovitost satelitskog daljinskog istraživanja, posebno snimaka Sentinel-2A, u kombinaciji s nenadgledanim algoritmima segmentacije i klasifikacije, za precizno kartiranje pokrova tla u suhim saharским područjima pogođenim dezertifikacijom. Korištenje tri kombinacije RGB pojasa (11/8/2, 12/11/4 i 8/4/3) omogućilo je jasnu vizualnu diskriminaciju ključnih klasa pokrova tla, poput pijesaka, pješčanih kora, rijetke vegetacije, suhih korita wadija i kamenih formacija.

Komparativna vizualna analiza otkrila je značajne varijacije u učinkovitosti algoritama. K-means i ISODATA, integrirani u QGIS, pružili su brze i lako interpretabilne klasifikacije, ali su pokazali ograničenja u prijelaznim zonama i u razlikovanju kora od pijeska. SLIC je ponudio snažnu ravnotežu između prostorne detaljnosti i tematske čitljivosti, posebno pri 500 segmenata. Mean Shift postigao je najbolju delinaciju vegetacije i linearnih elemenata, ali je zahtijevao najdulje vrijeme obrade. Felzenszwalb, na srednjoj skali (100), proizveo je prirodnu i koherentnu segmentaciju prikladnu za heterogena područja, dok su ekstremne skale rezultirale prekomjernom ili premalom segmentacijom krajolika.

Rezultati ukazuju da nijedan algoritam univerzalno ne nadmašuje ostale; izbor ovisi o cilju analize, složenosti krajolika i računalnim ograničenjima. Za operativno praćenje dezertifikacije, SLIC i Felzenszwalb preporučuju se za detaljno kartiranje, dok K-means i ISODATA ostaju korisni za brze procjene na velikim područjima.

Rezultati pružaju konkretnu metodološku osnovu za unapređenje kartiranja pokrova tla i strategije praćenja dezertifikacije u Maroku. Također nude praktične smjernice Visokom povjerenstvu za vodu, šume i borbu protiv dezertifikacije za odabir prikladnih tehnika prema specifičnim ciljevima projekta. Buduća istraživanja mogla bi uključivati fuziju više metoda, spektralne indekse vegetacije i tla (npr. NDVI, BSI) te pristupe dubokog učenja poput konvolucijskih neuronskih mreža (CNN) za poboljšanje točnosti klasifikacije i automatizaciju dugoročnog praćenja dinamike pokrova tla.

The following table summarizes the results of a visual analytical comparative analysis of five segmentation and classification algorithms applied to land cover mapping in arid environments. The evaluation was based on the visual interpretation of classification outputs in comparison with the original Sentinel-2A imagery, supported by reference information from field observations and high-resolution aerial images. The table highlights the key parameters used for each method, the Sentinel-2A RGB band combinations tested, the land cover classes that were most effectively identified, as well as the main strengths and limitations observed. Processing times and practical recommendations for optimizing each algorithm's performance are also provided. This overview aims to guide the selection of the most appropriate algorithm depending on the specific objectives and characteristics of the study area.

4. Conclusion

This study demonstrated the effectiveness of satellite remote sensing, particularly Sentinel-2A imagery, combined with unsupervised segmentation and classification algorithms, for accurate land cover mapping in arid Saharan environments affected by desertification. The use of three RGB band combinations (11/8/2, 12/11/4, and 8/4/3) enabled clear visual discrimination of key land cover classes such as sands, desert crusts, sparse vegetation, dry wadi beds, and rocky formations.

The comparative visual analytical evaluation revealed significant variations in algorithmic performance.

K-means and ISODATA, integrated in QGIS, provided rapid and easily interpretable classifications but showed limitations in transitional zones and in differentiating crusts from sands. SLIC offered a strong balance between spatial detail and thematic readability, particularly at 500 segments. Mean Shift achieved the best delineation of vegetation and linear features but required the longest processing times. Felzenszwalb, at a medium scale (100), produced natural and coherent segmentations suitable for heterogeneous terrains, while extreme scales either over- or under-segmented the landscape.

These results indicate that no single algorithm universally outperforms the others; rather, the choice depends on the analysis objective, the complexity of the landscape, and computational constraints. For operational desertification monitoring, SLIC and Felzenszwalb are recommended for detailed mapping, whereas K-means and ISODATA remain valuable for rapid large-scale assessments.

The findings provide a concrete methodological basis for improving land cover mapping and desertification monitoring strategies in Morocco. They also offer practical guidance to the High Commission for Water, Forests and the Fight against Desertification for selecting suitable techniques according to specific project goals. Future research could integrate multi-method fusion, vegetation and soil spectral indices (e.g., NDVI, BSI), and deep learning approaches such as convolutional neural networks (CNNs) to enhance classification accuracy and automate long-term monitoring of land cover dynamics.

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