EFFECT OF SEGMENTATION PARAMETERS AND SPATIAL RESOLUTION IN SEGMENTATION ACCURACY AND LANDSCAPE HETEROGENEITY INDICES DERIVED FROM UAV IMAGERY

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JULY 2024

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ABSTRACT

The growing rate of biodiversity loss highlights the importance of effective conservation initiatives, such as rewilding, to restore and preserve natural landscapes. Accurate land cover mapping is essential for these initiatives, as it helps to identify and understand landscape structures. It is also crucial in monitoring landscapes, making informed decisions, and implementing conservation strategies. Additionally, landscape heterogeneity indices are essential for understanding landscape heterogeneity and ecological complexity, which will help in successful conservation strategies.

This study investigates the optimization segmentation parameters and compares classification accuracy and landscape heterogeneity indices at different spatial resolutions of UAV images. Specifically, this research focuses on analysing the impact of shape and compactness on the segmentation accuracy and the effect of the spatial resolution on land cover classification accuracy and evaluating the sensitivity of landscape heterogeneous indices across various resolutions. Based on the segmentation accuracy metrics, findings indicate that optimal segmentation parameters include shape values ranging from 0.05 to 0.3 and compactness values from 0.7 to 0.9, yielding the highest segmentation accuracy. High-resolution UAV imagery (3.5 cm) outperformed lower resolutions (12 cm and 25 cm) with an accuracy of 85%. This high-resolution imagery captures fine-scale landscape features necessary for accurate classification and effective conservation planning. The study highlights a significant improvement in classification accuracy with higher-resolution UAV imagery that captures detailed landscape features. Additionally, optimizing segmentation parameters, particularly shape and compactness, further enhances the accuracy of land cover classifications. The importance of variable selection is also emphasized, indicating that selecting fewer, more relevant variables improves the approach's efficiency by reducing computational requirements and time. Furthermore, the results show that the values of landscape heterogeneity indices are sensitive to different spatial resolutions. Higher-resolution images provided a detailed understanding of landscape structure, capturing subtle variations critical for conservation efforts. Implementing these methodologies across different ecosystems and geographical regions can generalise and adapt this approach to various environmental monitoring projects.

Keywords: UAV, Multi-Resolution Segmentation, Segmentation Accuracy, Segmentation Accuracy Metrics, Land Cover classification, Classification Accuracy, Spatial Resolution, Landscape Heterogeneity Indices, Environmental Monitoring.

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LIST OF ABBREVIATIONS

UAV	Unmanned Aerial Vehicle
DSM	Digital Surface Model
DTM	Digital Terrain Model
CHM	Canopy Height Model
OBIA	Object-Based Image Analysis
MRS	Multi-resolution Image Analysis
OS	Over-segmentation
US	Under-segmentation
QR	Quality Rate
AFI	Area Fit Index
MS	Multispectral
NIR	Near-infrared
VI	Vegetation Indices
RMSE	Root Mean Square Error
SFM	Structure From Motion
GCP	Ground Control Points
GNSS	Global Navigation Satellite System
NDVI	Normalized Difference Vegetation Index
NDRE	Normalized Difference Red Edge Index
SAVI	Soil Adjusted Vegetation Index
GRVI	Green-Red Vegetation Index
SD	Standard Deviation
MDA	Mean Decrease Accuracy
MDG	Mean Decrease Gini
OA	Overall Accuracy
PA	Producer Accuracy
UA	User Accuracy
SHAP	SHapley Additive exPlanations
TA	Total Area
PLAND	Percentage of Landscape
LPI	Largest Patch Index
ED	Edge Density
TE	Total Edge
PD	Patch Density
NP	Number of Patches
PRD	Patch Richness Density
IJI	Interspersion and Juxtaposition Index
SHDI	Shannon's Diversity Index
SIDI	Simpson's Diversity Index
SHEI	Shannon's Evenness Index
SIEI	Simpson's Evenness Index

1. INTRODUCTION

1.1. Background

Biodiversity is "the variety of life on Earth, in all its forms, from genes and bacteria to entire ecosystems such as forests or coral reefs"(United Nations, 2024a). It refers to the species in the ecosystem, the evenness of their distribution, and the differences in their interactions. Over the past decades, the effect of biodiversity loss has been the focus of much ecological research (Hooper et al., 2005). The 2030 Agenda for Sustainable Development's Goal 15 is to "protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and biodiversity loss" (United Nations, 2024b). Human activities continue to affect the environment locally and globally. This causes dramatic changes in ecological communities, which significantly affect the landscapes. Understanding the connectivity of various land cover within landscapes is essential for assessing the potential impacts of management interventions (Malanson & Cramer, 1999). Rewilding, a conservation strategy that focuses on protecting and restoring ecosystems and natural areas, is essential in maintaining and enhancing biodiversity (Svenning et al., 2016). It is a rapidly developing ecosystem management concept, a transformative approach to biodiversity conservation. Recently, rewilding has been broadly known as repairing or refurbishing ecosystem functions by reintroducing the selected species (Pettorelli et al., 2019). Rewilding also aims to increase the biodiversity and complexity of an ecosystem by allowing nature to take its course (Arya, 2023). Rewilding helps restore landscape heterogeneity, which is the spatial complexity and diversity of landforms, vegetation types, and habitats within an ecosystem (Svenning et al., 2016).This heterogeneity supports diverse species populations and genetic diversity, which is essential in the ecosystem's adaptability and resilience (Fahrig et al., 2011). Landscape heterogeneity is considered a significant indicator of biodiversity (Katayama et al., 2014). Landscape heterogeneity refers to the diverse nature of landscapes at different scale (Malanson & Cramer, 1999). The complexities and diversity in the spatial distribution of habitats are represented as landscape heterogeneity, and it is caused by the distribution of ecological systems (Kie et al., 2002). It consists of qualitative and quantitative differences in landscape components (Tonetti et al., 2023). Because of its role in reflecting habitat diversity and spatial complexity, landscape heterogeneity is essential in developing conservation strategies (Duflot et al., 2014). Quantifying spatial heterogeneity through Landscape heterogeneity indices (LHI) helps ecologists understand the effects of habitat fragmentation. This understanding is essential for conserving natural habitats and maintaining ecological balance (Navarro & Pereira, 2012).

1.2. Land cover mapping and Remote sensing

Land cover mapping is important in monitoring biodiversity conservation(Hansen et al., 2013). These maps contribute to identifying areas of high conservation importance, monitoring vegetation changes over time, and assessing the effects of environmental changes and human activities on ecosystems (Pettorelli et al., 2014). It is also essential to have a land cover map, as it plays a significant role in determining spatial distribution. Mapping land cover provides helpful information about natural and man-made environments locally and globally. A land cover map is required for effective conservation and restoration efforts (Xie et al., 2008). Since vegetation is interconnected with its surroundings. As a result, land cover maps are used in various fields, including landscape planning, agriculture, conservation, forestry, geography, and plant ecology (Dias et al., 2004).Mapping land cover is essential for identifying, assessing, and implementing management plans for natural areas (Dias et al., 2004). Remote sensing has emerged as an effective tool for vegetation and land cover mapping, with several advantages over traditional field methods (Xie et al., 2008). Remote sensing is the process of collecting information about the surface of the Earth without direct contact, usually through satellite or airborne sensors. These sensors collect data from multiple spectral bands, allowing for detailed analysis of vegetation characteristics (Asner et al., 2015). Using remote sensing imagery involves several considerations, processes, and techniques in Mapping land cover. There is a greater focus on addressing technical challenges in developing mapping techniques and improving precision in producing vegetation maps. The rapid growth of remote sensing technology has increased the availability of images at different spatial, spectral, and temporal resolutions. Studies show that using satellite images for land cover mapping is more efficient than aerial photographs (Kaneko & Nohara, 2014). However, satellite images from passive sensors have limitations, including cloud cover, spatial resolution, cost, and data availability. Unmanned aerial vehicles (UAVs) have evolved as a cost-effective solution to these limitations, offering very high spatial resolution and flexible data acquisition (B. Yang et al., 2019).

1.3. Role of UAVs in remote sensing

In recent years, UAVs have emerged as critical remote sensing tools, transforming how one perceives and studies our surroundings. UAVs have gained significant attention in remote sensing because of their unparalleled ability to capture high spatial resolution imagery with precision and efficiency (Colomina & Molina, 2014). The development of UAV remote sensing technology helps to increase data acquisition effectiveness (Huang et al., 2018). The increasing popularity of UAVs in remote sensing is due to their quickness and flexibility in data acquisition systems, which produce high-resolution data such as digital surface models (DSMs), orthoimages, and point clouds (Crommelinck et al., 2017). Using UAVs with mounted sensor systems is the most cost-effective method to get ultra-high-resolution images. The higher resolution of UAV-derived imagery enables scientists to conduct detailed analyses of habitat structure, species distribution, and ecological processes (Chabot & Bird, 2012). It produces precise vegetation mapping and helps monitor landscape changes (Yurtseven et al., 2019). The combination of low cost, high resolution, ability to operate at low altitudes, and not being affected by cloudy weather conditions have increased the use of UAVs in various fields of agriculture, forestry, and urban planning (Sibaruddin et al., 2018). According to the study of (Manfreda et al., (2018) UAVs can significantly improve environmental monitoring by providing high spatial detail over large areas. UAV-mounted sensors bridge the gap between field observations and traditional airborne and space-borne remote sensing. While UAV images are becoming more popular, some studies are comparing the advancements in UAV multispectral mapping with satellite data, as discussed by (B. Yang et al., (2019). Regarding adaptability, flexibility, rapid development, and high spatial and temporal resolution data, UAVs are better than manned airborne systems or satellites (Manfreda et al., 2018). UAVs are used in various fields, such as agriculture and environmental monitoring, to improve data efficiency for management and monitoring purposes (Kaneko & Nohara, 2014). UAV techniques have proven effective in mapping vegetation and providing precise classification in difficult on-the-ground investigation areas (Kaneko & Nohara, 2014).

1.4. Object-Based Image Analysis (OBIA)

UAVs provide higher spatial resolution and flexibility, enabling detailed data collection (Colomina & Molina, 2014). However, the extensive dimension and complexity of UAV imagery make it difficult to extract meaningful information. Object-based image analysis (OBIA) addresses these challenges by using the spatial consistency of image objects, thus improving feature extraction and classification accuracy (Feng et al., 2015). OBIA is widely used among other methods and helps achieve the most appropriate results (Yurtseven et al., 2019). The application of OBIA was established for very high-resolution (VHR) images and has been helpful in various remote sensing applications for over two decades (Johnson & Ma, 2020). OBIA techniques measure image objects' structure, form, and spectral properties (Kavzoglu & Tonbul, 2017). In addition to spectral properties, it considers shape and texture properties, establishing it as an advanced method (Sibaruddin et al., 2018). In OBIA, image segmentation is essential in analysing remotely sensed data and can be used in various fields, including land cover mapping (Costa et al., 2018). These methods depend on segmentation and classification processes, which are sequentially carried out (Ez-Zahouani et al., 2023). The accuracy assessment shows that object-based classification performs better than pixel-based classification when using multi-spectral Landsat imagery and the optimal segmentation method (Gao et al., 2011). Moreover, OBIA is essential for land cover classification, ecological monitoring, and urban planning applications. By delineating objects based on their spatial and spectral characteristics, OBIA allows for more precise and thematically accurate land cover classification (Blaschke, 2010).

1.5. Image segmentation in OBIA

In OBIA, Image segmentation is the primary step, which uses the segmentation algorithm to divide image objects into homogeneous polygons, representing the landscape features (Lin, 2008). Segmentation algorithms are essential in understanding the structure of landscapes and their important elements at different scales (Möller et al., 2007). Different segmentation algorithms are used for various images, but no segmentation method is applicable universally (Monteiro & Campilho, 2006). Because each segmentation algorithm can produce different types of outputs depending on the parameters' settings in each algorithm, selecting the segmentation algorithm becomes difficult (Costa et al., 2018). Image segmentation requires precise identification of image objects (Hao et al., 2021). Segmentation quality is essential and differs depending on precision, complexity, and effectiveness (Prabu & Gnanasekar, 2021). The accuracy of image classification is significantly affected by image segmentation quality(Kavzoglu & Tonbul, 2017). Evaluation and refinement of segmentation parameterisation are essential to ensure the segmentation results before moving on to image classification (Gao et al., 2011). Several studies, including (Kavzoglu & Tonbul, 2017)and (Monteiro & Campilho, 2006), have used segmentation evaluation metrics, like under-segmentation, over-segmentation, root means square, Area Fit Index (AFI) and Quality Rate (QR), and different numbers of segments. These metrics were applied using manually digitised reference objects. However, there is still room for improvement in results by developing quality measures (Kavzoglu & Tonbul, 2017).

1.6. Multi-resolution Segmentation (MRS) Algorithm

The multi-resolution segmentation (MRS) algorithm in OBIA is used in many applications that involve very high-resolution images. This multi-resolution segmentation algorithm significantly helps to segment the image objects (Chen et al., 2021)and is the most used and widely successful. Studies have shown significant improvements in segmentation accuracy and reliability achieved by MRS across various datasets, highlighting its efficacy in real-world applications (Haralick & Shapiro, 1985). The MRS algorithm represents a hierarchical segmentation approach that uses multi-scale analysis to divide images into homogeneous regions (Happ et al., n.d.).To proceed with this segmentation algorithm, scale parameters, image layer weights, shapes, and compactness must be defined. Determining these parameterisations is a challenging part. Usually, it is done through a trial-and-error method (Munyati, 2018). Studies such as (Drăguţ et al., 2010)proposed and developed the ESP (Estimation of Scale Parameter) tool, which helps define the scale parameter in the multi-resolution algorithm and determine the heterogeneity of the object within the scene by using the concept of local variance. However, there is a lack of studies that help determine the shape and compactness parameters to improve the segmentation algorithm's efficiency (Drăguţ et al., 2010).

Figure 1 (Herawan et al., 2021) provides a detailed visual representation of the parameters and criteria involved in the MRS algorithm. It explains the role of the Scale Parameter in defining the maximum standard deviation of the homogeneity criteria, which directly influences the size of the resulting objects. Homogeneity criteria work in pairs of shape and colour, balancing the overall segmentation processes further on the shape components, smoothness, and compactness. The figure detailed how smoothness and compactness are calculated and contribute to the overall segmentation. In the calculation, the variable b is a weighting factor that adjusts the influence of smoothness and compactness in shape parameters.

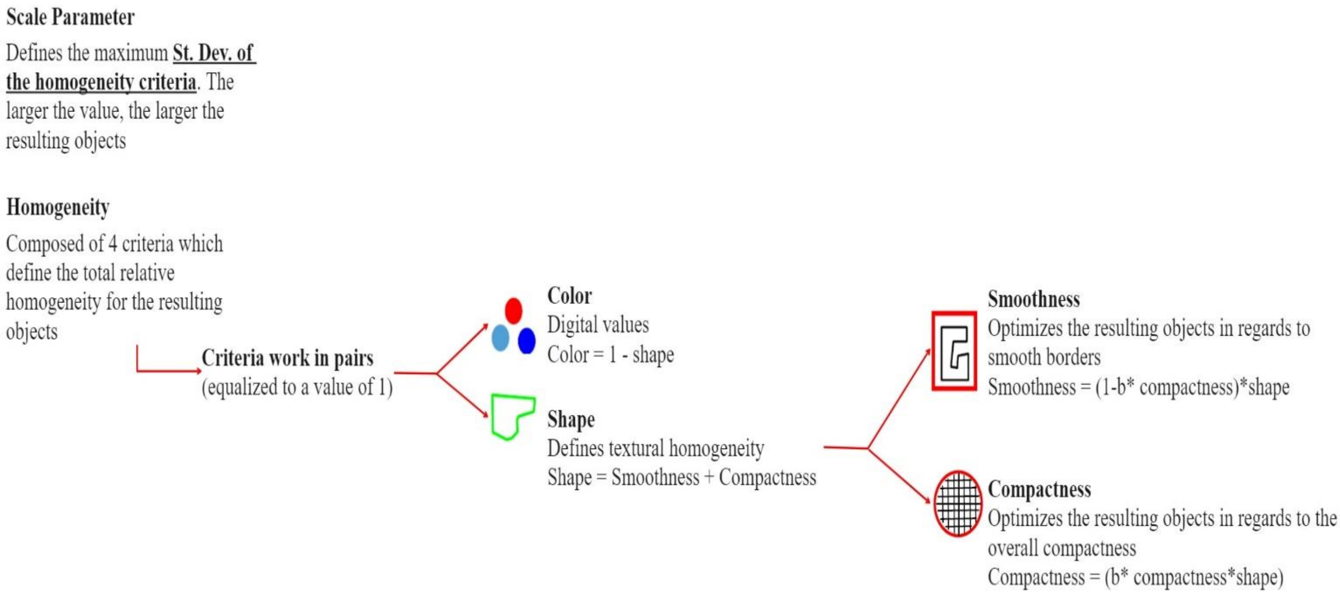


Figure 1: Multi-resolution segmentation concept flowchart (Source: (Herawan et al., 2021))

1.7. Segmentation Accuracy

Segmentation algorithms must be evaluated to measure their performance and determine the algorithm's effectiveness and its parameters (Zhang et al., 2015). Segmentation accuracy is essential in image analysis because it serves as a starting point for following classification and vegetation mapping processes (Zhang et al., 2015). Accurate segmentation ensures that objects of interest are precisely delineated, allowing for reliable feature extraction and further analysis. The primary challenges with segmentation accuracy are based on the resolution of the remotely sensed images. Low- to medium-resolution images produce results of low segmentation accuracy because of their large and mixed pixels. Reducing pixel size improves segmentation accuracy, indicating that higher spatial resolution leads to better segmentation accuracy (Lin, 2008). This kind of analysis is essential to improving the segmentation accuracy of image processing using different algorithms (Prabu & Gnanasekar, 2021).

Segmentation accuracy metrics are essential for evaluating and improving segmentation algorithm performance. Over-segmentation (OS) occurs when an object is split into multiple segments, whereas under-segmentation (US) occurs when multiple objects are combined into one segment. Both cases may affect an accurate representation of the landscape, influencing the following steps (Clinton et al., 2010; Kavzoglu & Tonbul, 2017) Quality Rate (QR) and Area Fit Index (AFI) are critical metrics for segmentation accuracy. QR assesses the overall quality of segmentation by considering both over-segmentation and under-segmentation of the segmented regions (El-naggar, 2018). AFI, on the other hand, assesses the geometric accuracy of the segmented areas, ensuring that the segments overlap the actual boundaries of the objects (Kavzoglu & Tonbul, 2017).High segmentation accuracy ensures precise classification of vegetation classes, which is essential for ecological studies, land use planning, and environmental monitoring (Guirado et al., 2021).

1.8. Classification Accuracy

Classification accuracy is essential in remote sensing applications, especially for vegetation and land cover mapping (Rwanga & Ndambuki, 2017). Classification accuracy is closely related to segmentation accuracy. Segmentation inaccuracy affects the classification process, which decreases the accuracy of land cover maps (Xie et al., 2008). The optimal segmentation resulted in the highest classification accuracy (Gao et al., 2012). High classification accuracy is necessary for making effective choices in environmental management and land use planning. Accurate classification allows policymakers and researchers to identify subtle changes in land cover, resulting in better conservation strategies and resource use (Rwanga & Ndambuki, 2017). Thus, improving classification accuracy is critical for effective biodiversity conservation and ecosystem management.

1.9. Landscape Heterogeneity Indices (LHI)

Landscape heterogeneity Indices (LHI) help to analyse the interaction between landscape structure and plant diversity, and they are also used for habitat assessment and modelling for species groups (Ndao et al., 2021). These metrics are becoming a popular topic in contemporary research on ecological landscapes (Uuemaa et al., 2009). The change in long-term patterns in fragmented areas is due to the increasing possibility of organism extinction (Tonetti et al., 2023). Using these metrics as an equal for fragmentation is significant even in human-dominated areas with frequently fragmented landscapes (Tonetti et al., 2023). Measuring landscape heterogeneity involves various methods requiring metrics of the effects of ecological processes (Ndao et al., 2021).Understanding these metrics using GIS analysis is essential for effective biodiversity conservation in the context of global change (Morelli et al., 2013). These metrics help to focus on estimating landscape changes in biodiversity and habitat analysis. The different relationships between landscape heterogeneity and species richness at various spatial scales are essential to understanding biodiversity (Katayama et al., 2014). Multiple studies indicate a positive relationship between biodiversity and landscape heterogeneity, particularly in historically diverse landscapes such as parts of Europe, North America, and East Asia (Katayama et al., 2014). Over the past three decades, landscape heterogeneity metrics have contributed to advancing both ecological theory and practical applications (Frazier & Kedron, 2017).

1.10. Research Gap

Several studies have been carried out to explore the effect of image resolution on classification accuracy and to evaluate various segmentation methods, including the methods developed by (Lu & He, (2018) and (Reyes et al., (2017). The study of (Mas et al., (2010) Specifically, it addressed the performance of classification methods on landscape heterogeneity metrics. On the other hand, studies including (Fynn & Campbell, (2019), (Sertel et al., (2018), and (Saura, (2004) Have focused on exploring the sensitivity of fragmentation indices (i.e., Landscape heterogeneity Indices) at various image spatial resolutions using satellite images. Furthermore, some studies compared segmentation methods and their accuracy (Kavzoglu & Tonbul, 2017). However, the sensitivity of LHI and segmentation accuracy influenced by segmentation parameterisation using different resolutions of UAV images is mainly unexplored. A study carried out by (Garcia & Saura, 2004) Found that LHI is sensitive to image resolution when using satellite images. However, as high-resolution UAV images become more widely available, it is essential to investigate the relationship between the segmentation algorithm, its accuracy, and LHI at different UAV image resolutions. This study aims to provide valuable insights into the optimal use of UAV imagery and segmentation methods with their parameterisation for enhanced sensitivity analysis in LHI.

1.11. Research Objective and Questions

This study aims to evaluate the impact of various parameters on segmentation and classification accuracy and compare LHI using UAV imagery at different resolutions. The specific research objectives and questions are outlined as follows:

R.O.1: To Identify the impact of shape and compactness on segmentation accuracy at different spatial resolutions using the Multiresolution segmentation algorithm.

R.Q.1.1: How do the shape and compactness parameters in the multiresolution algorithm influence the segmentation accuracy at different spatial resolutions?

R.O.2: To assess the effect of different spatial resolutions of UAV images on classification accuracy and Landscape heterogeneity indices.

R.Q.2.1: How do different UAV image resolutions affect Land cover classification accuracy?

R.Q.2.2: What is the effect of different resolutions of UAV images on LHI?

2. STUDY AREA AND METHODS

2.1. Overview of the Study Area

The study area (Figure 2) for this research is the Pastos Solanillos, situated near the village of Mazarete in Guadalajara province, Spain. It is located at 40.957° N and 2.192° W and lies 5 km west of Anquela del Ducado. This area is in the Iberian Highlands, a significant part of the Iberian Chain in Spain. The region is known for its diverse ecosystems, including pine, oak, juniper forests, river canyons, and arid open spaces. The rewilding area of Pastos Sollanillos covers 1,515 hectares. It is an open forest containing pine trees (*Pinus Sylvestris, Pinus Nigra*), oak trees (*Quercus pyrenaica*), shrubs, grasslands, and other herbaceous vegetation. This area has its own ecological and environmental significance. It is connected to the region's historical heritage, highlighting its sustainable land use practices that have evolved over centuries. For this study, a specific area in the northeast, covering about 6.44 hectares, was chosen for detailed analysis.

Guadalajara has a diverse region divided into three main zones: The Castilian Plateau in the north and east consists of flat plains and isolated mountain ranges; the Central System Mountain range runs through the centre, with peaks exceeding 2,000 metres; and The Tagus River basin in the south includes fertile valleys and steeper terrain (*Inicio - Instituto Geográfico Nacional*, 2024). The study area lies within the Central System Mountain range. This region has a continental Mediterranean climate, with hot, dry summers, with an average temperature exceeding 25° C in July, and cold winters, with an average temperature below 5° C in January. Rainfall is usually scarce year-round, with the highest concentration in spring and autumn (Agencia Estatal de Meteorología - AEMET. Gobierno de España, 2024). The study area is dominated by Mediterranean forests that grow in the lower and middle altitudes, with *Pinus sylvestris, Pinus nigra*, and *Quercus Pyrenaica*. Scrubland vegetation in drier regions includes aromatic plants like thyme and lavender. Deciduous forests dominated by beeches (*Fagus Sylvatica*) and oaks (*Quercus Pyrenaica*) thrive at higher elevations in the more humid areas of the Central System mountains (Ministerio Para La Transición Ecológica y El Reto Demográfico, 2024).

Figure 2: Location of Pastos Sollinillos and study area

Rewilding Europe chose the Pastos Sollinillos area, part of the Iberian Highlands, Spain, as a project site to rejuvenate through natural grazing. Over half of the Rewilding Landscape's 850,000 hectares are protected, most of which are Natura 2000 sites. The sparsely populated Iberian Highlands, located at an interface of diverse climates and habitats, has emerged as a protection for a diverse range of species, including thriving populations of raptors such as Bonelli's eagle, peregrine falcon, and eagle owl. While livestock farming and hunting remain important, Nature tourism is also growing, providing an opportunity to strengthen and diversify local economies. With high biodiversity and low impact from humans, the conditions are ideal for nature tourism to begin taking a significant role.

Figure 3: Horses introduced in Pastos Sollinillos
Source: (https://rewildingeurope.com/landscapes/iberian-highlands/)

A portion of the study area was also affected by the forest fire in 2005, which destroyed 11,900 hectares of *Pinus sylvestris*, *Pinus nigra*, and *Quercus Pyrenaica* in the Iberian highlands. Burned trees were removed to help natural regeneration. However, after regeneration, it resulted in overly dense forests that lacked complexity, limiting acorn production. Horses were introduced (Figure 3) to help maintain the landscape. Their natural grazing behaviours have begun providing areas to light, encouraging structural diversity, and resulting in a mosaic landscape beneficial to long-term natural regeneration (*Iberian Highlands | Rewilding Europe*, 2024). This is part of Rewilding Europe's mission to provide more space for wildlife and natural processes, enhancing biodiversity and resilience to fire. The non-governmental organisation Rewilding took measures to protect this landscape and its biodiversity.

2.2. Data

The data used for this study includes primary data acquired by UAVs and field data collected on-site for training and validation purposes.

2.2.1. UAV data

The UAV-acquired data for this study was collected using the DJI Mavic 3M (Figure 3), a Quadcopter drone designed and equipped with advanced aerial imaging and mapping technology. This drone has a high-resolution RGB camera and a multispectral sensor (MS), which includes bands such as Green, Red, Red Edge, and Near-Infrared (NIR). For detailed specifications regarding the drone and its sensor capabilities, refer to the link (https://ag.dji.com/mavic-3-m/specs). The RGB camera operates as a panchromatic sensor with a resolution of 3.5cm per pixel at a flying altitude of 120 meters. Similarly, the MS sensor provides a resolution of 12cm per pixel at the same altitude. The dedicated bands in the NIR region are particularly useful for discriminating vegetation and monitoring its condition through vegetation indices (VIs). The flight operations were planned and executed with the DJI Pilot software, which integrates with the Android controller to ensure accurate navigation and data capture. The flights were conducted at a constant height of 120 meters above ground level, using the UAV system's onboard terrain-following feature, demonstrating the efficiency and reliability of the process. Real-time kinematic corrections ensure accuracy in the coordinates of every image, achieving a root mean square error (RMSE) of less than 2 cm in the X and Y dimensions and less than 3 cm in the Z dimensions. Furthermore, the data was collected on June 24, 2023, between 12:00 and 16:00, which introduced challenges such as a varying shadow affecting the interpretability of the images due to the sun’s position. The data was managed and stored to maintain its integrity and security while organising it for easy access and analysis. Despite the high-resolution data and advanced technology, limitations were identified caused by environmental factors such as shadows during the data collection phase. These factors were carefully considered during the later data processing and analysis phases to reduce their impact on the study's findings.

Figure 4: Mavic 3 Multispectral drone and its specifications
(source: https://ag.dji.com/mavic-3-m?site=ag&from=nav)

2.2.2. Field samples

The Rewilding Spain team collected field data to train the model and validate the classification results. The process involved direct observation within the study area and systematic ground sampling techniques to collect data on land cover types. The typology classes were chosen based on the dominant land cover types found in the landscape. The rewilding team performed a preliminary survey of the region's existing land cover classes. This analysis identified six key land cover classes: Trees, Shrubs, Herbaceous vegetation, Grass, Bare soil, and Rock. Additionally, extra class Shadows were included to ensure the precise classification derived from the visual interpretation of UAV images.

The sample points (Figure 5) were distributed across the study area and within each land cover class to ensure a balanced representation. This approach captures the heterogeneity in land cover distribution and minimizes sample biases. Furthermore, ultra-high-resolution UAV imagery complemented field observation sample points. A total of 310 samples were collected and evenly distributed across the study area and land cover classes. Within these, 210 were assigned for training, which was used to train the model and classify land covers. At the same time, the remaining 100 were chosen for validation, which was used to evaluate classification accuracy. These ground samples are a reference point for classifying various classes and validating the classification results of UAV imagery analysis in this study.

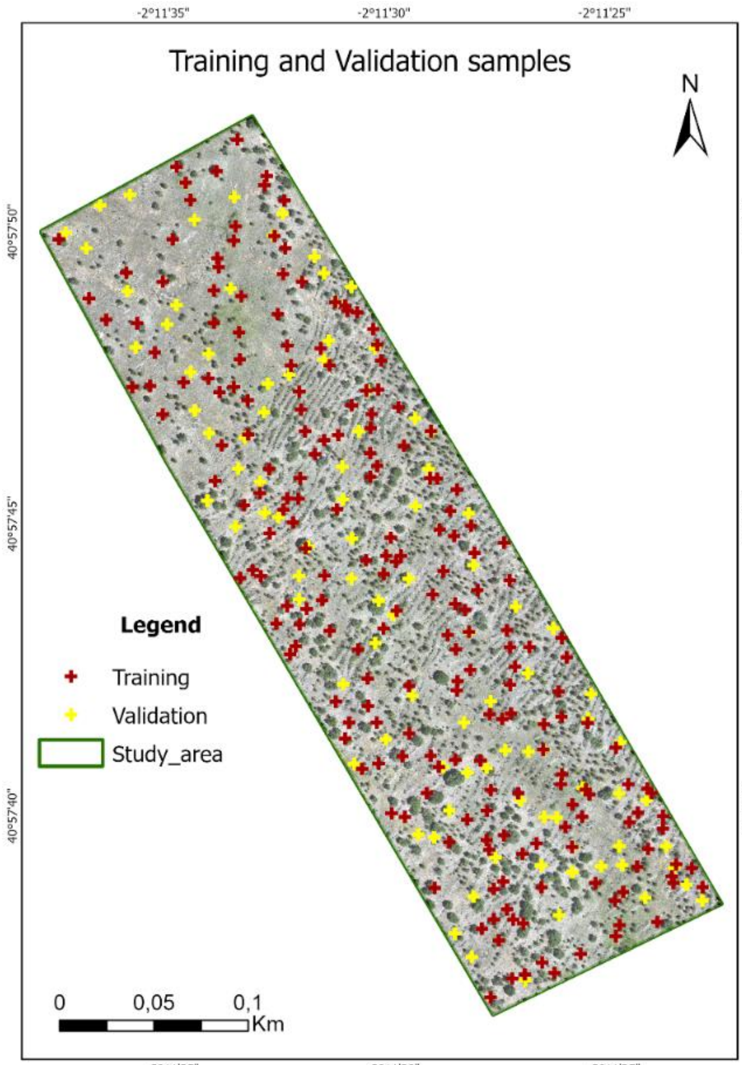


Figure 5: Training and Validation Samples

2.3. Methods

The proposed methodology uses UAV images to assess the landscape of Pastos Solanillos in Spain. The study includes segmentation, classification, and the computation of LHI. This workflow can help analyse the impact of segmentation parameters using a multiresolution segmentation algorithm and understand landscape structure through land cover classification and LHI. High-resolution images, combined with advanced methods and software, improve analysis reliability. The flowchart of the proposed methodology is shown below (Figure 6).

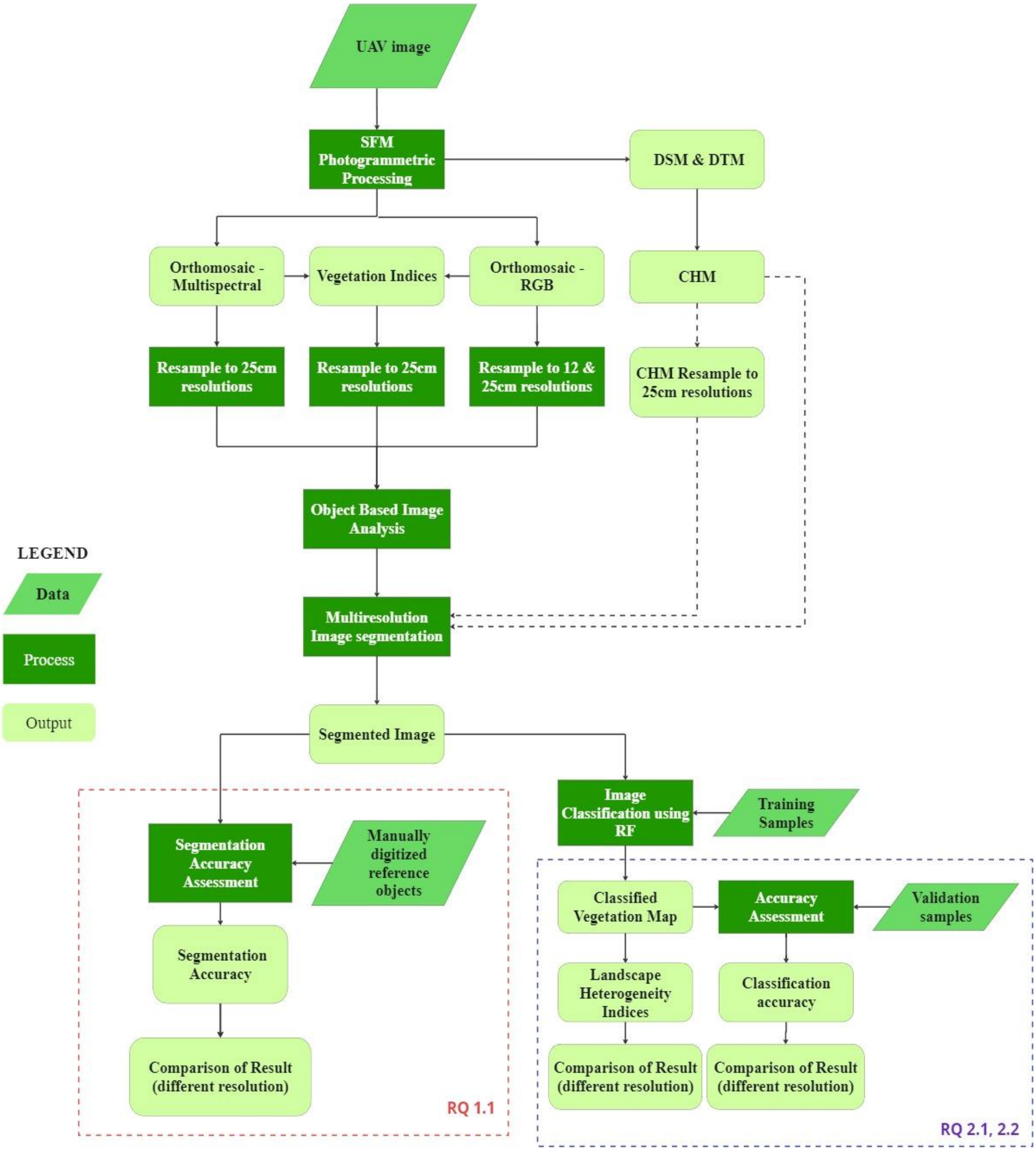


Figure 6: Methodology flowchart

2.3.1. UAV Data Processing

Data processing is required to convert raw aerial imagery into useful continuous data. This process consists of several steps, each intended to address a specific aspect of the data to ensure accuracy and efficiency of use. The key steps discussed here include UAV data processing, orthomosaic generation, and generating a canopy height model. Photogrammetry is the initial step in processing UAV imagery before proceeding to other processes. The process includes the generation of orthomosaics, Point clouds, a Digital Terrain model (DTM), a Digital Surface Model (DSM), reflectance orthomosaics and vegetation Indices. The images were processed in batches, which helped create orthomosaics and point clouds.

The data was processed using Pix4D mapper, a fully automated and highly accurate photogrammetric processing software. It converts large numbers of images into georeferenced point clouds, DEMs, and orthophoto mosaics (Chaudhry et al., 2020). Pix 4D data processing consists of three steps: initial processing, point cloud and mesh, DSM, orthomosaic, and index, all of which implement the Structure from Motion (SFM) algorithm (*Processing Steps - PIX4Dmapper*, 2024).

2.3.1.1. Orthomosaic Generation

SFM is a photogrammetric technique that generates 3D structures from overlapping 2D images (Westoby et al., 2012). The technique involves identifying matching characteristics between images to form an identical contiguous pattern (Gherga et al., 2020). This approach allows an accurate representation of the terrain being studied. Feature extraction is performed on each image during the initial processing step to identify unique features. These distinct features can be recognized across multiple images. The key matching points were identified and matched from one image to another. The tie points, which are the points visible in multiple images, serve as a reference for aligning the image in 3D space. An optimization process called bundle adjustments refines the image position by minimizing the re-projection error. This process helps create a sparse point cloud, a rough 3D representation of matched key points between the images (Processing Steps - PIX4Dmapper, 2024).

Furthermore, the dense 3D point cloud was generated, which helped to create a detailed 3D representation of the scanned area. From this dense point cloud, a DSM and DTM were generated using the inverse distance weighting algorithm, providing elevation data for both the surface and terrain. The images were then merged into a single tile and orthorectified to produce an orthomosaic. Reflectance maps were used to calculate vegetation indices (VIs). To ensure accurate measurements, reflectance data was corrected with an incoming radiation sensor and a radiometric correction panel. Using these corrected reflectance maps, vegetation indices such as NDVI, NDRE, SAVI, and GRVI (derived from the green and red bands of RGB imagery) were calculated to help classify the study area (Table 1).

Vegetation Indices	Equation	Reference
NDVI (Normalized Difference Vegetation Index)	(NIR-R) / (NIR-R)	(Rouse et al., n.d.)
NDRE (Normalized Difference Red Edge Index)	(NIR-RE) / (NIR-RE)	(Macintyre et al., 2020)
SAVI (Soil-Adjusted Vegetation Index)	((NIR-R) / (NIR+R+L)) * (1+L)	(Huete, 1988)
GRVI (Green-Red Vegetation Index)	(G-R) / (G+R)	(Tucker, 1979)

Table 1: Equations to calculate the vegetation indices and their references

After processing the data, Pix 4D generated a quality assessment report for reliability and accuracy. The original spatial resolution of UAV RGB is 3.5 cm, and UAV MS is 12 cm resolution. To address the study objectives and for further analysis, UAV RGB was resampled to 12 cm and 25 cm, and UAV MS was resampled to 25 cm.

2.3.1.2. Generation Canopy Height Model (CHM)

During UAV data processing, the 3D point clouds were used to generate DSM, representing vegetation elevation, and DTM, representing terrain elevation. The CHM is generated by subtracting the DTM from the DSM (Prins & Van Niekerk, 2020). The CHM helps estimate the vertical vegetation structure, including tree height, canopy cover, and biomass estimation. Its resolution is 12 cm, and it was resampled to 25 cm. CHM is essential in classification, providing detailed landscape and vegetation analyses.

2.3.2. Object-Based Image Analysis (OBIA)

OBIA consists of structured steps for processing, interpreting, and extracting meaningful spatial (land cover) information from data sources. This section outlines the key aspects of data analysis relevant to this research. The main steps in OBIA are image segmentation, image classification, segmentation, and classification accuracy assessment.

2.3.2.1. Image Segmentation

In this study, OBIA was used for image segmentation, which has proven to outperform pixel-based classification based on various studies (Liu et al., 2020; Makinde et al., 2016; Sibaruddin et al., 2018; K. Yang et al., 2022). OBIA is effective for high spatial resolution images. It involves segmenting meaningful homogenous pixels into objects. Then, these objects are classified based on their spectral, spatial, and contextual features (Ventura et al., 2018; K. Yang et al., 2022). The OBIA process involves two essential steps: image segmentation and image classification (Johnson & Ma, 2020; Ventura et al., 2018). In this study, these processes are performed using eCognition software. Image segmentation divides an image into meaningful objects or regions based on homogeneity (Ez-Zahouani et al., 2023). This process significantly impacts the quality of feature extraction and classification accuracy (Hossain & Chen, 2019). Over- and under-segmentation of objects causes misclassification, which reduces classification accuracy. The objects were delineated using a multi-resolution segmentation algorithm, which is the most used and effective in remote sensing applications (Chen et al., 2021). This segmentation algorithm depends on homogeneity criteria, using parameters such as scale, shape, and compactness.

The scale parameter directly affects the segmented objects' level of detail and size. A lower scale parameter value produces smaller objects and more detailed segments, with less spectral variation within each object, and vice versa. The shape parameter balances the importance of an object's spectral properties, whereas the compactness parameter influences the object's geometric properties, particularly how compact the segmented object is (Rejaur & Saha, 2008). The values of these optimal parameters are determined through an iterative process of trial and error (Liu et al., 2020). Optimizing these segmentation parameters is essential for improving the accuracy of segmentation and classification results (Ez-Zahouani et al., 2023). Segmentation used RGB, Multispectral (Green, Red, Red Edge, and NIR), CHM, and VIs layers like NDVI, NDRE, SAVI, and GRVI. Using trial and error, the scale parameters were determined to be 50, 20, and 10 for 3.5 cm, 12 cm, and 25 cm spatial resolutions, respectively. To identify the influence of shape and compactness on segmentation accuracy and to select the optimal parameter for each resolution for further analysis, six shapes (0.05, 0.1, 0.3, 0.5, 0.7, 0.9) and five compactness (0.1, 0.3, 0.5,0.7, 0.9), i.e. 35 parameter combinations were examined. This was repeated for the resolutions of 3.5 cm, 12cm and 25cm. At the 3.5

cm resolution, the RGB imagery and multispectral and VIs were maintained at their original resolutions of 3.5 cm and 12 cm, respectively. For the 12 cm resolution, the RGB imagery was resampled to match the resolution of 12 cm, while the multispectral data and VIs remained at their native 12 cm resolution. At the 25 cm resolution, all datasets, including RGB, multispectral, and VIs, were resampled to the target resolution of 25 cm before analysis.

2.3.2.2. Segmentation Accuracy

After generating the segments for each parameter combination using eCognition software, segmentation accuracy metrics, such as OS, US, QR, and AFI, were calculated using R studio with the built-in R function "Segmetric" (Costa et al., 2018). To calculate these segmentation accuracy metrics, the manually digitized 70 reference object polygons (Figure 7) were used to determine segmentation accuracy by comparing them with segmented image objects. To ensure the reference objects for computing segmentation accuracy, the objects selected are regular-shaped objects, such as Trees, Shrubs, and Shadows, avoiding objects of Bare soil and Rock.

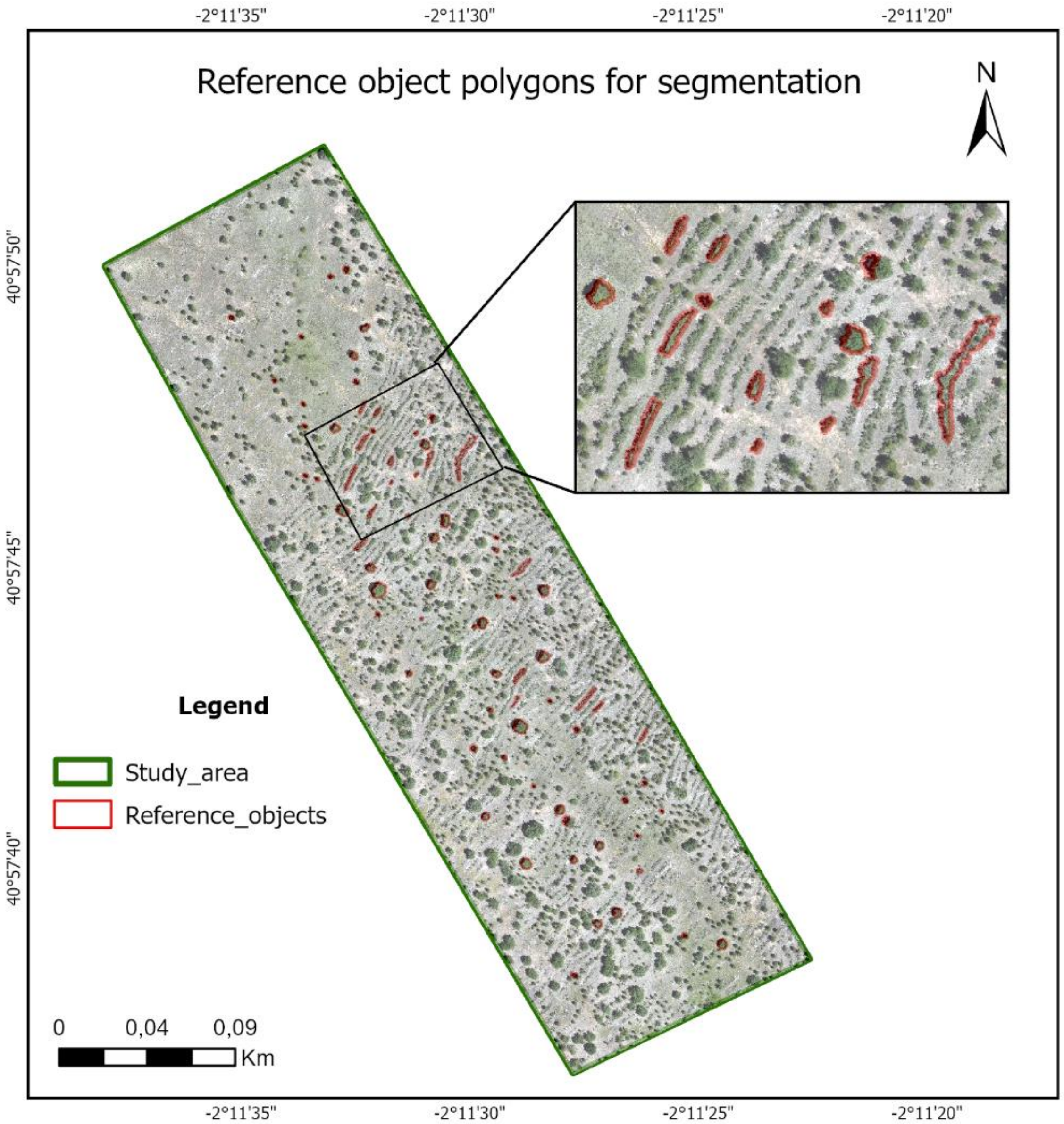


Figure 7: Reference object polygons for segmentation

OS occurs when segmented objects are smaller than reference objects, ranging from 0 (optimal) to 1. US occurs when the reference object is contained within the segmented results, also ranging from 0 (optimal) to 1 (Clinton et al., 2010; Kavzoglu & Tonbul, 2017)combines information about over-segmentation and under-segmentation, with values ranging from 0 (optimal) to 1 (El-naggar, 2018; Winter, 2000). AFI calculates the overlap percentage of the largest segments inside the objects, with an optimal value of 0. A reference object is over-segmented if the overlap is less than 100% and AFI > 0:0, and a reference object is under-segmented if the overlap is 100% and AFI < 0:0 (El-naggar, 2018; Lucieer & Stein, 2002).

The metrics are calculated based on the following equations:
OS = 1 - (A (reference object) ∩ A (segmented object) / A (reference object))
US = 1 - (A (reference object) ∩ A (segmented object) / A (segmented object))
QR = 1 - (A (reference object) ∪ A (segmented object) / A (reference object) ∩ A (segmented object))
AFI = A (reference object) - A (largest object) / A (reference object)
(Clinton et al., 2010; El-naggar, 2018; Kavzoglu & Tonbul, 2017; Lucieer & Stein, 2002; Winter, 2000)

After evaluating the segmentation accuracy at each resolution, optimal shape and compactness parameters were selected for further analysis.

2.3.2.3. Correlation analysis

Before the classification process, a correlation analysis was conducted to identify the relationship between the variables used. This analysis was executed using Python. The variables considered in the analysis included:
Mean values: RGB_1(Red), RGB_2(Green), RGB_3(Blue), CHM, Green, Red, Red Edge, NIR, NDVI, NDRE, SAVI, GRVI.
Maximum pixel value: CHM
Standard deviation (SD) values: RGB_1, RGB_2, RGB_3, CHM, Green, Red, Red Edge, NIR, NDVI, NDRE, SAVI, GRVI.

Groups of variables with correlation coefficients greater than 0.8 were identified as highly correlated. From these highly correlated groups, one variable was selected based on the results of a variable importance analysis, ensuring that the most significant features were retained for classification.

2.3.2.4. Variable Importance

The variable importance analysis was carried out in R Studio to determine and evaluate the importance of each input layer in classifying the data. This assessment is essential for determining which variables are significant in classification. It includes two main metrics: Mean Decrease Accuracy (MDA), which indicates how much accuracy would decrease if the variable were removed from the model, and Mean Decrease Gini (MDG), which measures each variable's contribution to the homogeneity of the nodes and leaves in the random forests model (Martinez-Taboada & Redondo, 2020).The variable importance plots generated from this analysis depict the significance of each variable in descending order.

2.3.2.5. Image Classification

The optimal shape and compactness parameter combinations for different spatial resolutions were selected based on the values of AFI and QR for the classification process. Following segmentation using the selected optimal shape and compactness combination, the segmented objects were classified using a supervised

approach based on training samples. The training samples are in point form (shapefile), representing land cover types as a thematic layer added in the eCognition software used to train the classifier model.
The model was trained using 210 field samples as training data, with 30 samples per class to ensure a balanced representation of the Land cover classes, as a random forest classifier is sensitive to the imbalance in the number of samples across classes. These land cover classes included Trees, Grass, Shrubs, Herbaceous vegetation, Rock, and Bare soil. Also, Shadows are determined as a separate class, which helps achieve better classification results. The supervised classification approach is carried out using the Random forests algorithm, which outperforms compared to other algorithms. For the source of feature space, the "sample statistics-based" method was used in eCognition (Adam et al., 2014; Tutorial-Sample Statistics and Accuracy Assessment, 2024).

2.3.2.6. Classification Accuracy Assessment

After classification, validation sample points, 100, were added as a thematic layer in eCognition, the same as training samples. Using an accuracy assessment tool in eCognition, an error matrix was generated for all land cover classes, which helps to see the performance of each class separately. It resulted in the overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and Kappa coefficient (K) values of the land cover class separately. When calculating OA, the total number of reference classes and the number of correctly classified classes. PA is the probability that a pixel belongs to a specific class and is correctly classified. UA is the probability that a pixel labelled as a specific class is correctly classified (Foody, 2020). The Accuracy assessment results of 3.5cm, 12 cm and 25 cm resolution were compared to analyse the difference in accuracies based on the image spatial resolution. This assessment is essential for assessing the classifier's performance and ensuring land cover classification accuracy.

2.3.2.7. Feature Importance in Land Cover Classification

Following classification, a feature importance analysis was conducted using SHAP (SHapley Additive exPlanations) in Python. SHAP is a method developed by (Lundberg et al., n.d.) That assigns an essential value to each feature based on its impact on the model's prediction. SHAP values provide a detailed understanding of how each feature influences the model's outcome. From this analysis, individual SHAP values for each feature were determined. These values show how each feature contributed to the prediction of each land cover class.

2.3.3. Landscape Heterogeneity Indices (LHI)

Both class and landscape level LHI were computed using classification results from different spatial resolution imagery. These indices were generated using Fragstats software (version 4.2-64) (https://fragstats.org/), which helps quantify the landscape's structure. These indices were selected based on their relevance to assessing landscape structure, widespread use in landscape ecology research, and ability to capture various aspects of landscape heterogeneity (Cushman & Neel, 993). The indices include Total (Class) Area, Percentage of Landscape (PLAND), Largest Patch Index (LPI), Edge Density (ED), Total Edge (TE), Patch Density (PD), Number of Patches (NP), Patch Richness Density (PRD), Interspersion and Juxtaposition Index (IJI), Shannon’s Diversity Index (SHDI), Simpson’s Diversity Index (SIDI), Shannon’s Evenness Index (SHEI), Simpson’s Evenness Index (SIEI). For more information on the indices and their description, refer to Appendix 3 (Landscape Heterogeneity Indices). Following the computation of these indices, a comparison of the indices produced from different resolutions of UAV images was conducted. This analysis will provide comprehensive results on the sensitivity of LHI influenced by imagery resolution. These LHI are essential for ecological conservation and management decisions.

3. RESULTS

This section presents the study's findings, focusing on three main areas: the impact of shape and compactness parameters on segmentation accuracy, the accuracy of land cover classification, and the estimation of LHI at three different spatial resolutions.

3.1. Effect of Shape and Compactness on Segmentation Accuracy

The following sections describe the variations in segmentation accuracy using different shape and compactness values. The accuracy metrics used are OS, US, QR, and AFI. These metrics were derived from analyzing 35 different combinations of shape (ranging from 0.05 to 0.9) and compactness (ranging from 0.1 to 0.9) parameters at image resolutions of 3.5 cm, 12 cm, and 25 cm. The analysis was conducted by keeping the shape constant while varying the compactness values and vice versa. This approach helps to assess how each parameter independently affects the segmentation accuracy metrics. The results provide an understanding of how shape and compactness affect segmentation performance, highlighting the best combinations for higher accuracy.

3.1.1. Segmentation Accuracy at 3.5 cm Resolution

3.1.1.1. Impact of Shape

The results show the impact of shape values on segmentation accuracy at a 3.5 cm resolution with varying levels of compactness. Figures 8 and 9 show the shape values ranging from 0.05 to 0.9 and their influence on the segmentation accuracy metrics under different levels of Compactness. At lower shape values (0.05 and 0.1), the OS ranges from 0.42 to 0.53. As the shape value increases, the OS ranges increase and reach a maximum value of 0.80. Like OS, US ranges from 0.18 to 0.21 when the shape value is low and increases with increasing shape value. The same pattern seems in the QR, with the highest value of 0.85 at a shape value of 0.9 and compactness of 0.9. The highest observed values for OS, US, and QR were recorded at shape 0.9, indicating that the highest shape values are not ideal for the segmentation. According to the AFI metric (Figure 9), the AFI is close to the optimal value when the shape value falls between 0.05 and 0.3. When the shape exceeded 0.3, the AFI showed significant fluctuation and increased value.

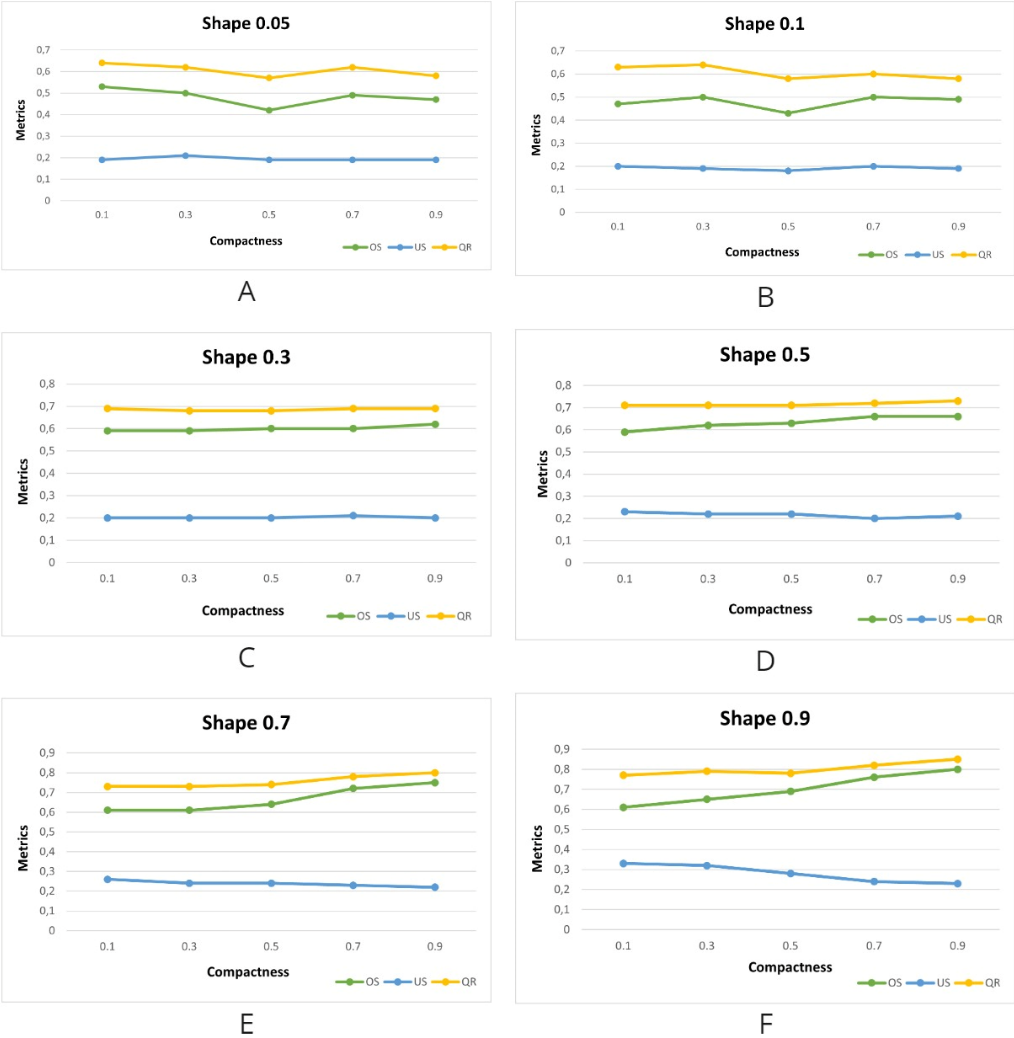


Figure 8: Impact of shape (OS, US & QR) at 3.5 cm resolution

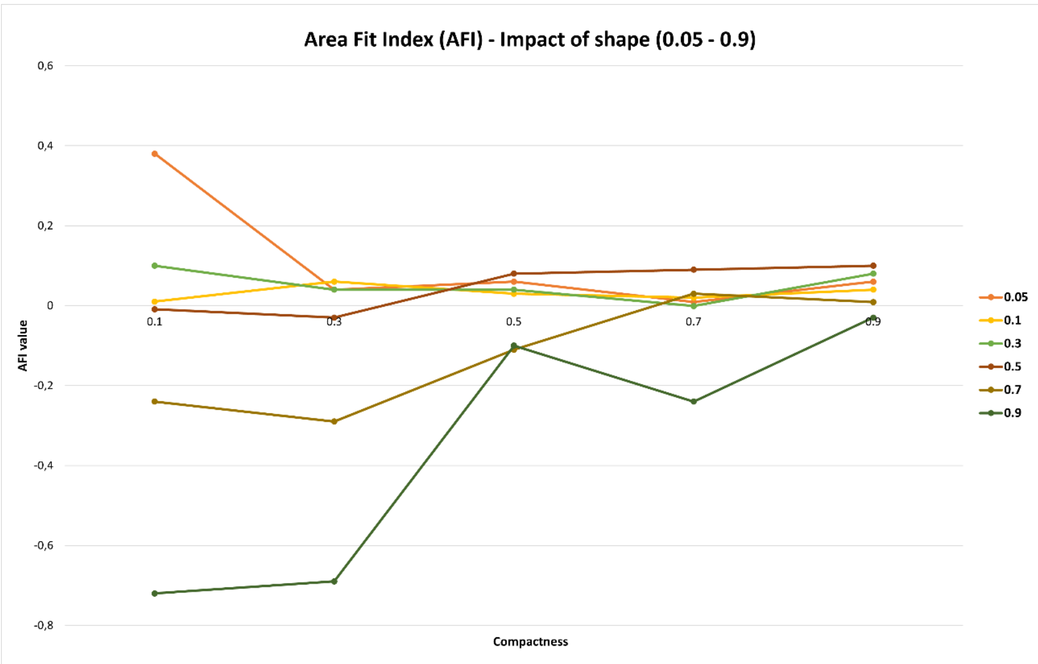


Figure 9: Impact of shape (AFI) at 3.5 cm resolution

3.1.1.2. Impact of Compactness

The following results show the impact of compactness values on segmentation accuracy at a 3.5 cm resolution with varying ranges of shapes (Figures 10 and 11). Results show that when the compactness is 0.1, OS starts at 0.53 and increases with the rising shape value. A similar pattern is observed across the compactness range of 0.3 to 0.9, with the OS reaching a maximum value of 0.80. Based on the US values, there are no significant variations in the values; they are stable across the compactness levels and slightly increase as compactness increases. This variation indicates that compactness has a less significant impact on under-segmentation. QR follows a pattern like OS at all compactness levels. Noticed that in all levels of compactness in shape values of 0.1 and 0.3, there is a sudden increase in the values of OS and QR compared to other shape values. In contrast to the impact of shape on AFI (Figure 11), the compactness shows minimal fluctuations in the higher value (0.7 and 0.9). The AFI range decreases as compactness increases. For compactness 0.1, AFI ranges from 0.58 to -0.72, while for compactness 0.9, it ranges from 0.06 to 0.03. This suggests that higher compactness results in near to optimal value.

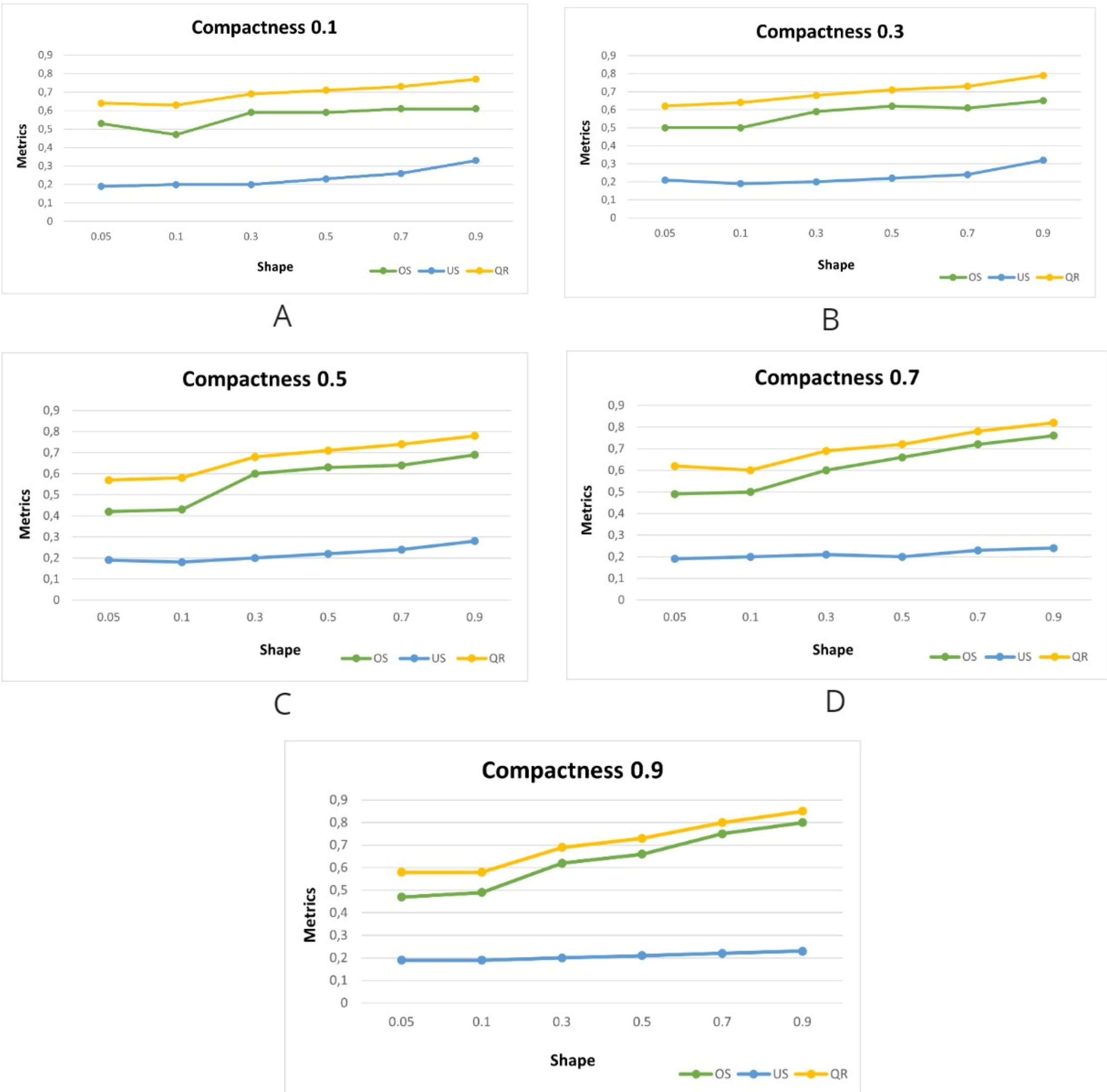


Figure 10: Impact of compactness (OS, US, & QR) at 3.5 cm resolution

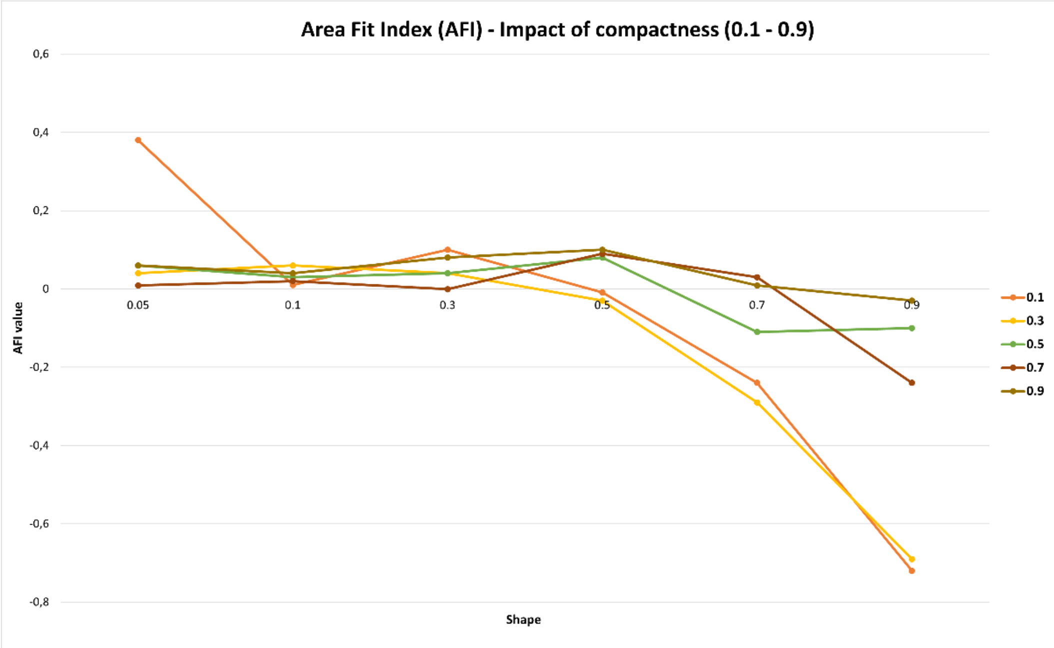


Figure 11: Impact of Compactness (AFI) at 3.5 cm resolution

3.1.2. Segmentation Accuracy at 12 cm Resolution

3.1.2.1. Impact of Shape

The analysis of the impact of shape on segmentation accuracy at 12cm spatial resolution (Figures 12 and 13) shows that when the shape parameter increases from 0.05 to 0.9, the OS value generally rises, indicating that higher shape values lead to more over-segmentation. Specifically, for a shape parameter of 0.05 (Figure 12 (A)), OS ranges from 0.27 to 0.36, whereas for a shape parameter of 0.9 (Figure 12 (F)), OS ranges from 0.34 to 0.67. This trend suggests that lower shape values result in higher segmentation accuracy based on OS. Similarly, US values significantly increase with the shape parameter up to 0.56. This pattern indicates that higher shape parameters negatively impact the US. Consequently, the QR value, which calculates accuracy based on over-segmentation and under-segmentation, shows consistently lower values for shape parameters of 0.05 and 0.1. At a shape value of 0.9, the QR value reaches 0.80, suggesting that the lower shape values produce higher accuracy segmentation. Furthermore, according to the trends shown in the AFI metric (Figure 13), the value of AFI is near the optimal level when the shape value is between 0.05 and 0.3, with some variation between compactness values. From shape 0.5 to 0.9, it is observed that the AFI values fluctuate drastically, and that indicates shape values ranging from 0.05 to 0.3 are preferable for achieving better accuracy.

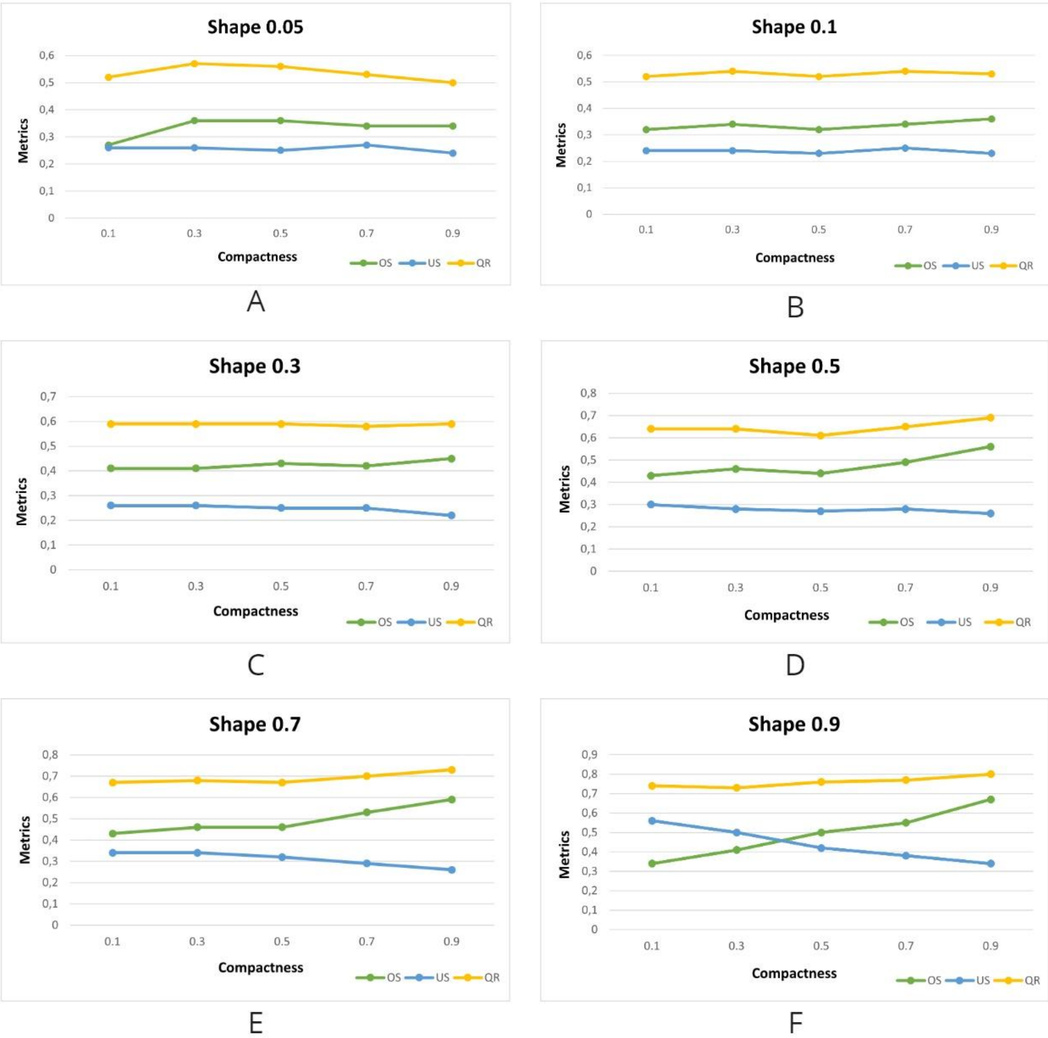


Figure 12: Impact of shape (OS, US & QR) at 12 cm resolution

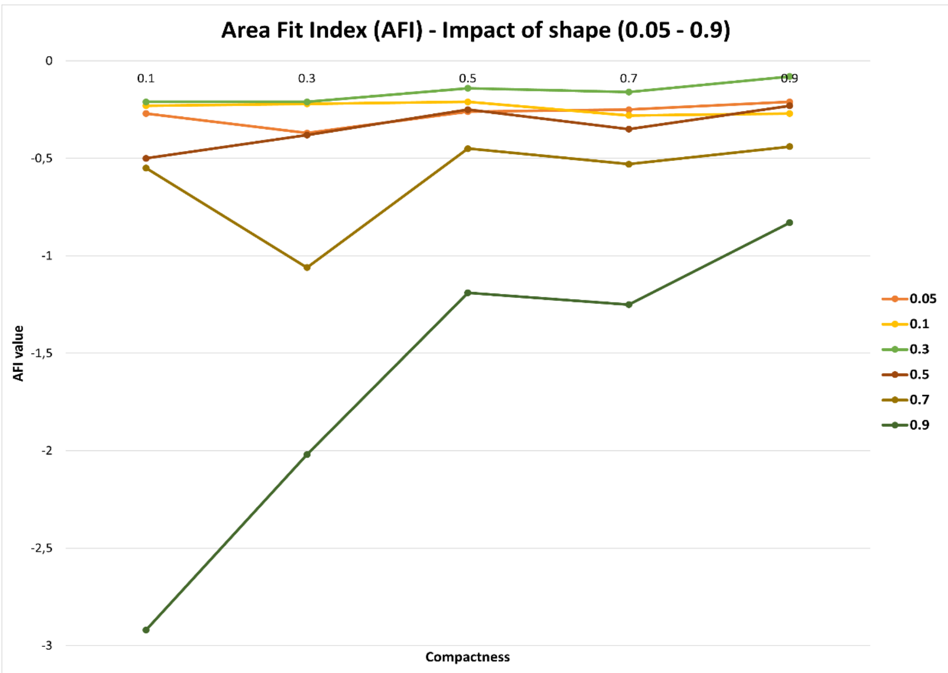


Figure 13: Impact of shape (AFI) at 12 cm resolution

3.1.2.2. Impact of Compactness

The following results show the impact of compactness values on segmentation accuracy at a 12 cm resolution with varying ranges of shapes (Figures 14 and 15). Figure 14 shows the trends of OS, US, and QR segmentation metrics when keeping the compactness constant. Results show a decreasing pattern with increasing compactness values ranging from 0.1 to 0.9. It is observed from Figure 14 A to E that with the increasing shape values in each compactness from 0.1 to 0.9, the metric value of OS, US and QR rises. Figure 14 E shows that with a compactness value of 0.9 and increasing shape values, the OS, US, and QR metrics are significantly higher. This observation shows that higher compactness values combined with lower shape values provide metrics values that are more favourable for achieving better segmentation accuracy. Figure 15 depicts that the AFI values decrease (near the optimal value), with the compactness increasing from 0.1 to 0.9. It is observed that the range of the values fluctuates more and suddenly decreases and increases within the compactness range of 0.1 to 0.7 compared to the compactness of 0.9. However, in the compactness value of 0.5 with the shape value 0.05 to 0.5, the AFI values are near the optimal. This trend in the graph indicates that higher compactness produces good segmentation results.

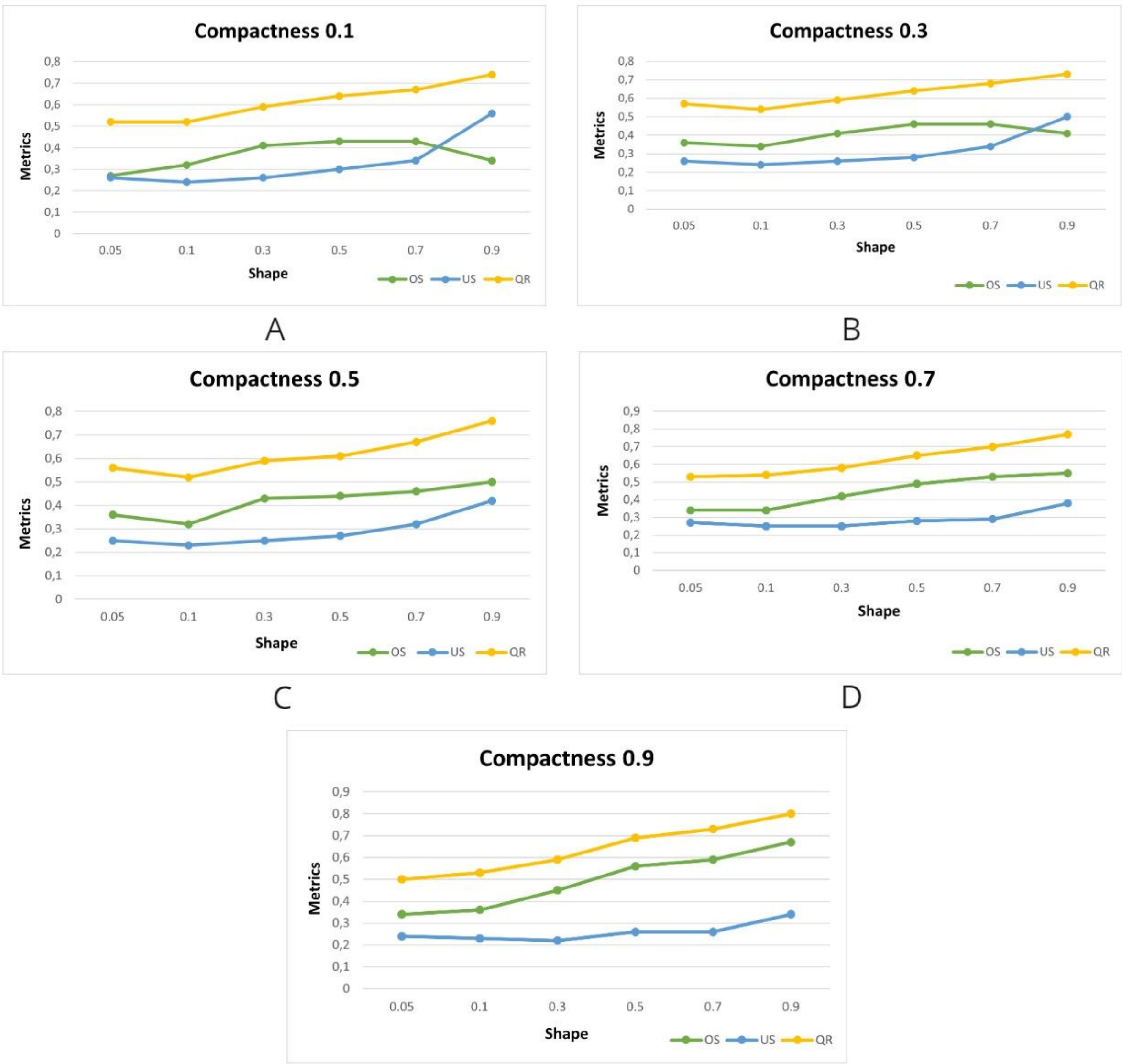


Figure 14: Impact of Compactness (OS, US & QR) at 12 cm resolution

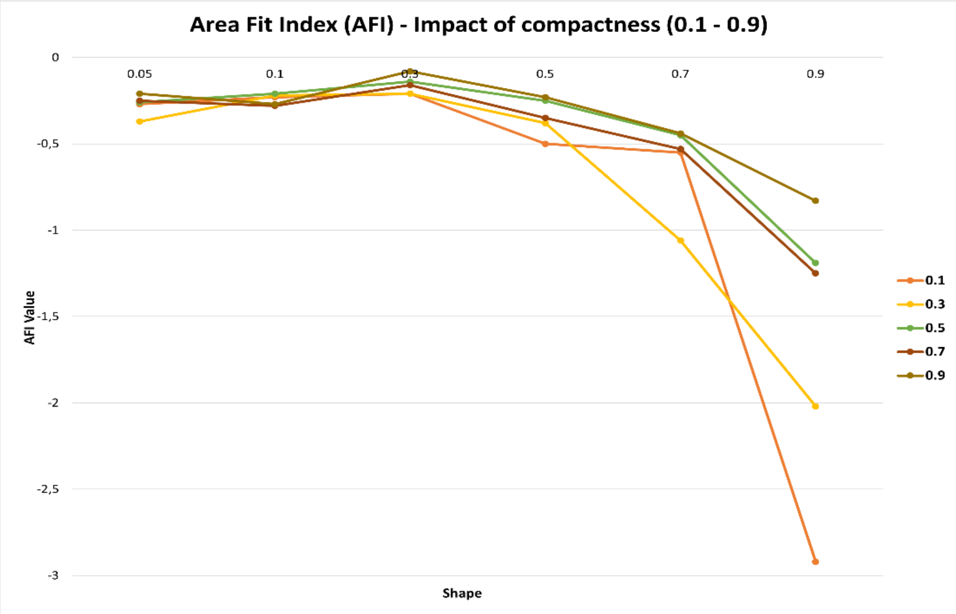


Figure 15: Impact of Compactness (AFI) at 12 cm resolution

3.1.3. Segmentation Accuracy at 25 cm Resolution

3.1.3.1. Impact of Shape

The following results show the impact of shape values on segmentation accuracy at a 25 cm resolution with varying levels of compactness (Figures 16 and 17). Results show that OS and US show similar trends with shape values of 0.05 to 0.5 (Figure 15). However, for the shape value of 0.7 (Figure 16 E), OS increases with increasing compactness, while US decreases. A similar pattern is noted for a shape value of 0.9 (Figure 16 F), where OS gradually increases with higher compactness and US slightly decreases. Overall, with an increasing shape value up to 0.9, the OS and US values reach 0.56 and 0.58, respectively. This trend suggests that the lower shape value ranges between 0.05 and 0.3 might be good for minimizing over-segmentation and under-segmentation. The values of QR also share trends similar to those of OS and the US. For a lower shape of 0.05, the value of QR is lower, ranging from 0.5 to 0.55. In contrast, with a shape value of 0.9, the QR value increases to 0.77. Therefore, to achieve better segmentation accuracy for 25 cm resolution imagery, the preferable shape range is between 0.05 and 0.3. This finding aligns with the AFI results for 3.5 and 12cm resolutions, where the shape values from 0.05 to 0.3 indicate values near the optimal AFI. It is also noted that the shape value of 0.5 with compactness values of 0.7 and 0.9 shows AFI values near the optimal range, while this is not the case for compactness values of 0.1, 0.3, and 0.5 (Figure 17). Then, the AFI values of shapes 0.7 and 0.9 show drastic changes and increase the AFI value, suggesting the shape range (0.05 to 0.3) is preferably a good option to have better segmentation.

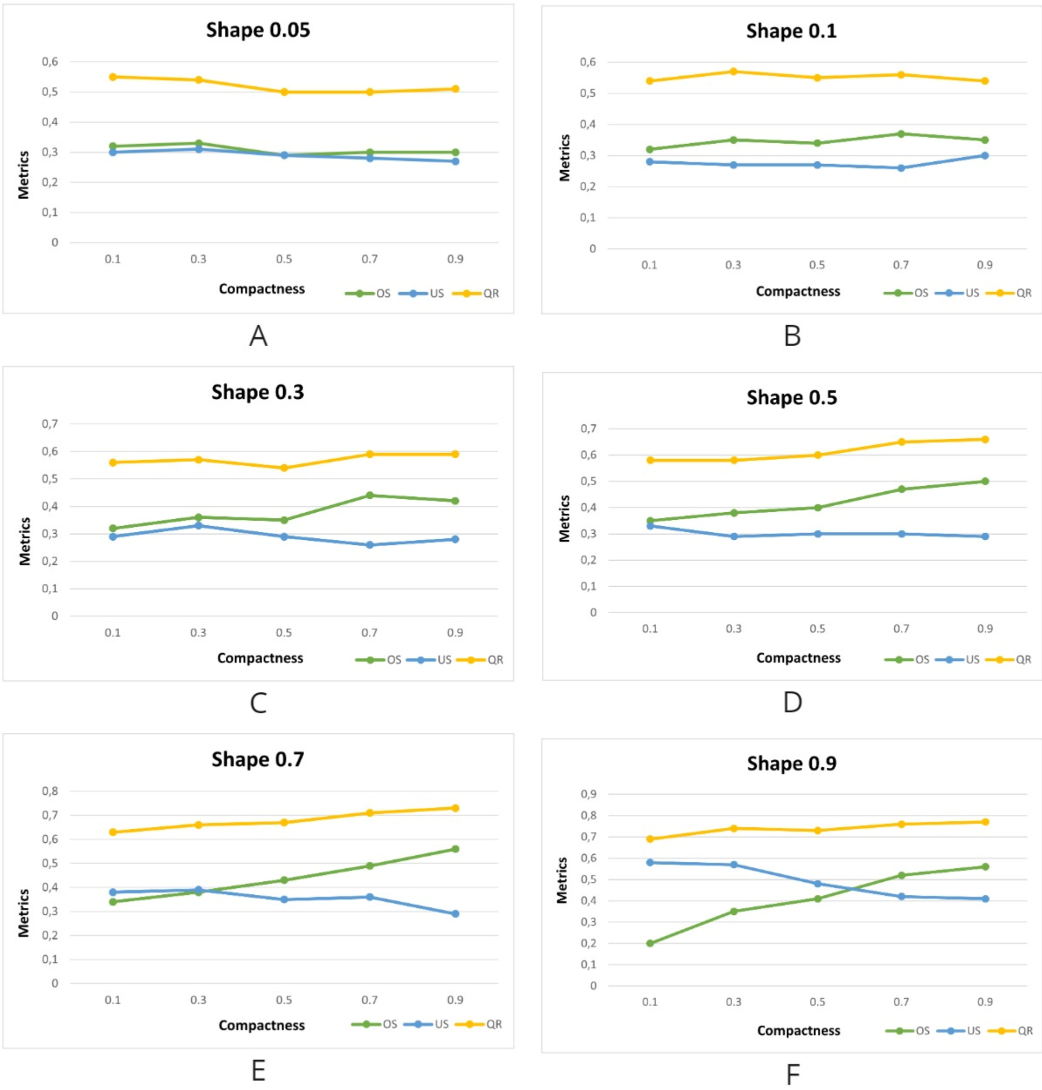


Figure 16: Impact of Shape (OS, US & QR) at 25 cm resolution

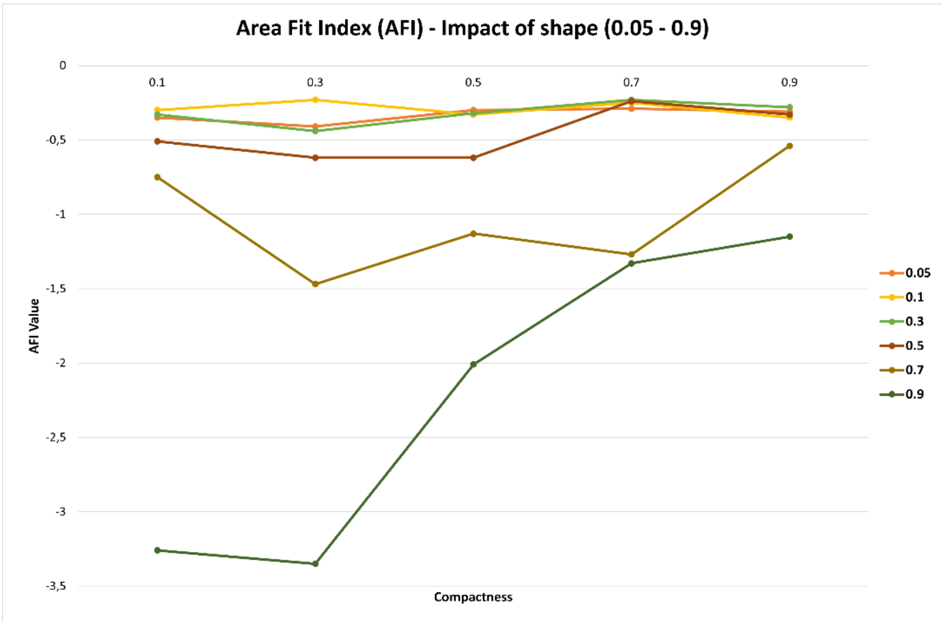


Figure 17: Impact of Shape (AFI) at 25 cm resolution

3.1.3.2. Impact of Compactness

The following results show the impact of compactness values on segmentation accuracy at a 25 cm resolution with varying ranges of shapes (Figures 18 and 19). Results show a trend like that observed at a 12 cm resolution; metrics such as OS, US, and QR decrease as compactness values increase from 0.1 to 0.9 (which means closer to optimal value). It is important to note that for each compactness value, an increase in shape values increases the metrics values, like in the 12 cm compactness results. Also, with the compactness values of 0.1 and 0.3 (Figure 18 (A & B)), it is observed that there is a sudden interchange with OS and US values in the shape values of 0.7 and 0.9. A similar pattern is also observed in the compactness value of 0.5 with a shape of 0.9. These observations suggest that lower shape values combined with the AFI values are closer to the optimal at a compactness value 0.7. Additionally, shape values of 0.05 to 0.5 provide preferable metrics values of OS, US and QR for segmentation. AFI values decrease (near the optimal value), with the highest compactness value of 0.9 (Figure 19). Compared to the AFI of 3.5 and 12 cm, AFI values at 25 cm show significant changes with sudden decreases and increases within the compactness range of 0.1 to 0.7. However, the AFI values are closer to the optimal at a compactness value of 0.7 and shape value of 0.05 to 0.5. This pattern suggests that higher compactness values produce suitable segmentation results.

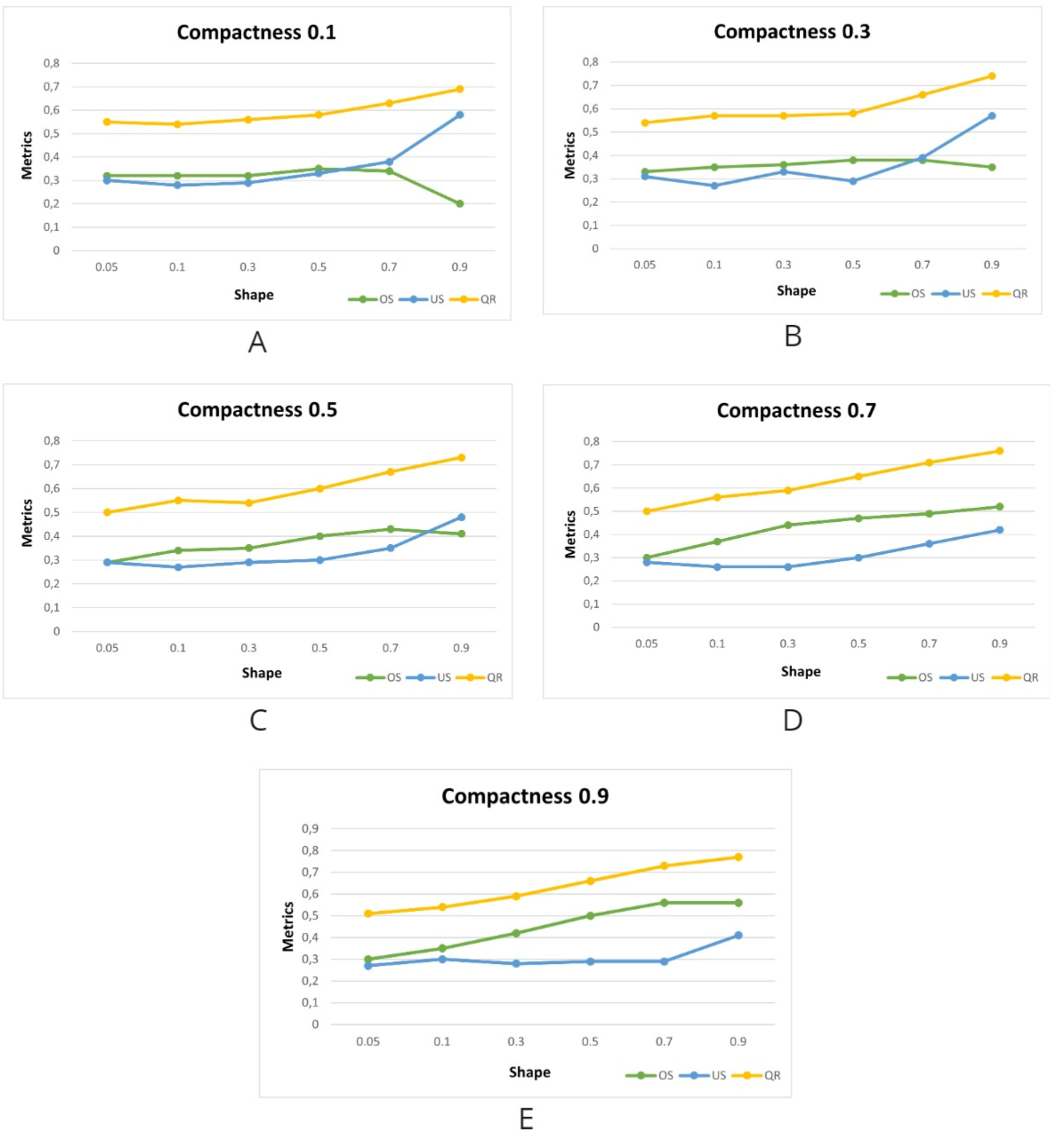


Figure 18: Impact of Compactness (OS, US, & QR) at 25 cm resolution

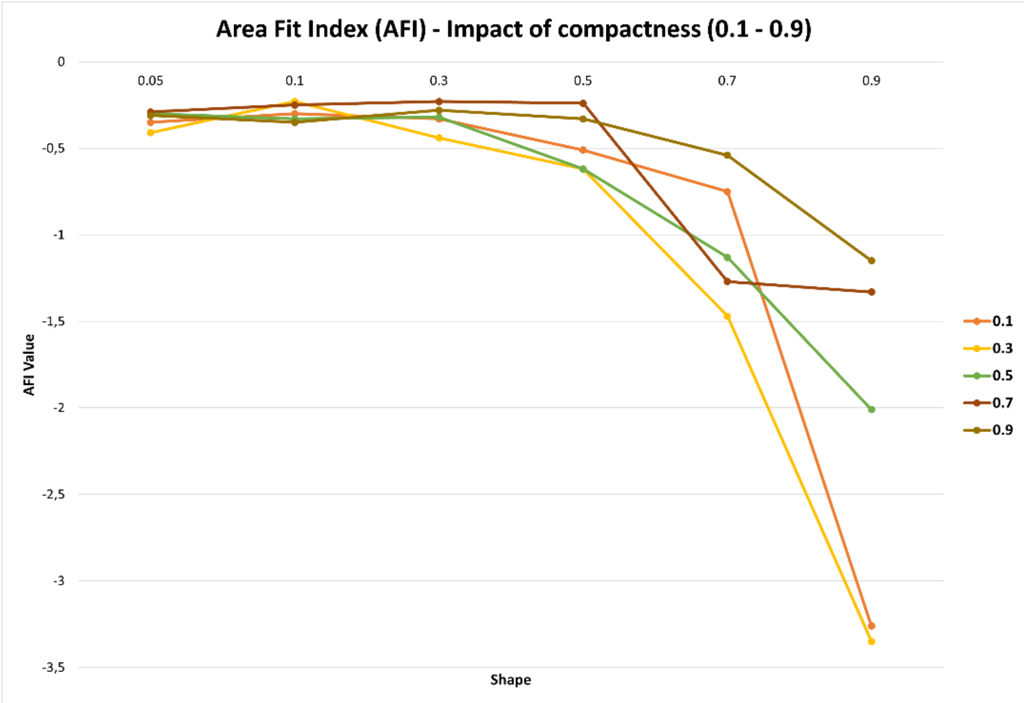


Figure 19: Impact of Compactness (AFI) at 25 cm resolution

3.2. Land Cover Classification Accuracy on Different UAV Image Spatial Resolutions

3.2.1. Selection of optimal shape and compactness parameter combinations at different spatial resolutions

Based on the segmentation accuracy metrics results (Figures 8-19), the best combinations of shape and compactness at each spatial resolution were selected based on the AFI and QR metric scores (Table 2). As mentioned in the methods section (3.3.2.2), QR is a metric that considers both OS and US. Therefore, only the AFI and QR metrics were considered when selecting the shape and compactness combinations. These selected combinations were subsequently used for classification.

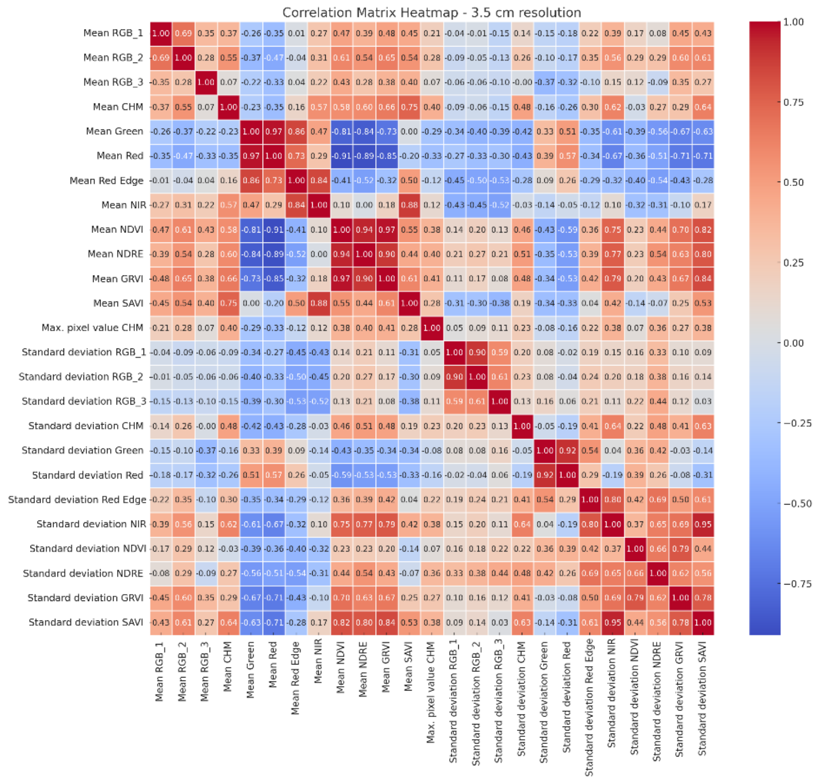
Resolution & scale factor	Best Performing Shape/compactness combination based on the **AFI score**	Best Performing Shape/compactness combination based on the **QR score**
3.5 cm (Scale 50)	0.05 / 0.7	0.05 / 0.5
12 cm (Scale 20)	0.3 / 0.9	0.05 / 0.9
25 cm (Scale 10)	0.3 / 0.7	0.05 / 0.7

Table 2: Best performing shape and compactness combinations

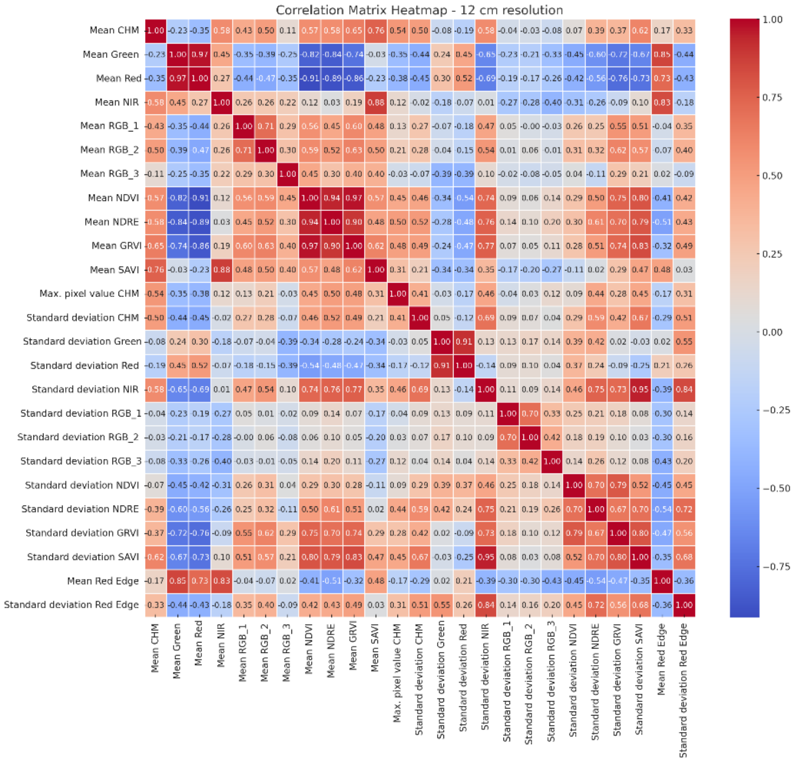
3.2.2. Correlation analysis

This section discusses the correlation analysis of the selected variables for the classification to identify highly correlated groups and optimize the classification process. Figure 20 presents the variable correlation matrix for resolutions of 3.5 cm, 12 cm, and 25 cm. These matrices illustrate how the variables are correlated with one another. The heat maps were used to identify pairs or groups of variables with correlation values above 0.8, which were considered highly correlated. Since the highly correlated group of variables contribute similarly to the classification, only one variable from each highly correlated group was selected for classification. The variable importance results were used as a reference for selecting which variable to use from each highly correlated pair.

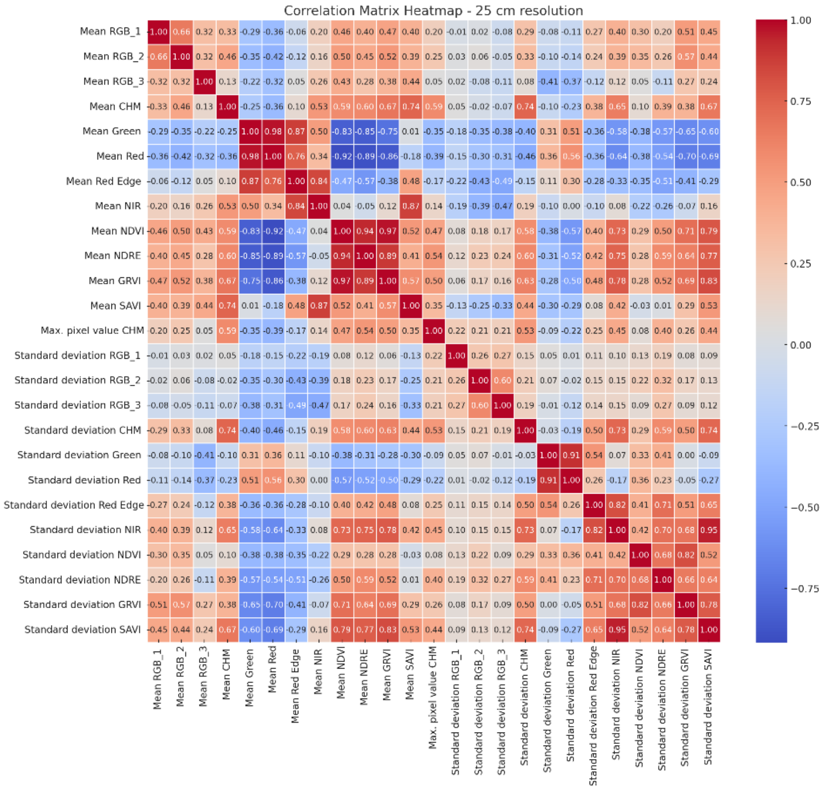
Several variables show strong correlations based on the correlation matrix at 3.5 cm spatial resolution (Figure 20 A). For example, the mean values of indices such as NDVI, NDRE, and SAVI strongly correlate with one another and other mean reflectance values. This suggests that these variables contain redundant information, and selecting one from each highly correlated group simplifies the classification process while keeping significant information. The 12 cm resolution correlation matrix (Figure 20 B) shows similar patterns, with mean reflectance values of Green, Red, NIR and Red edge and vegetation indices showing strong correlations. However, the values differ slightly from those at 3.5 cm resolution, indicating the resolution's impact on the data. However, the overall trend of high inter-correlation between certain groups of variables remains constant. The pattern of high correlations continues in the 25 cm resolution correlation matrix (Figure 20 C). The mean reflectance values remain strongly intercorrelated, particularly in the multispectral bands of green, red, red edge, and NIR. Furthermore, vegetation indices such as NDVI and NDRE show strong correlations with each other and mean reflectance values of Green, Red, NIR and Red edge.



A



B

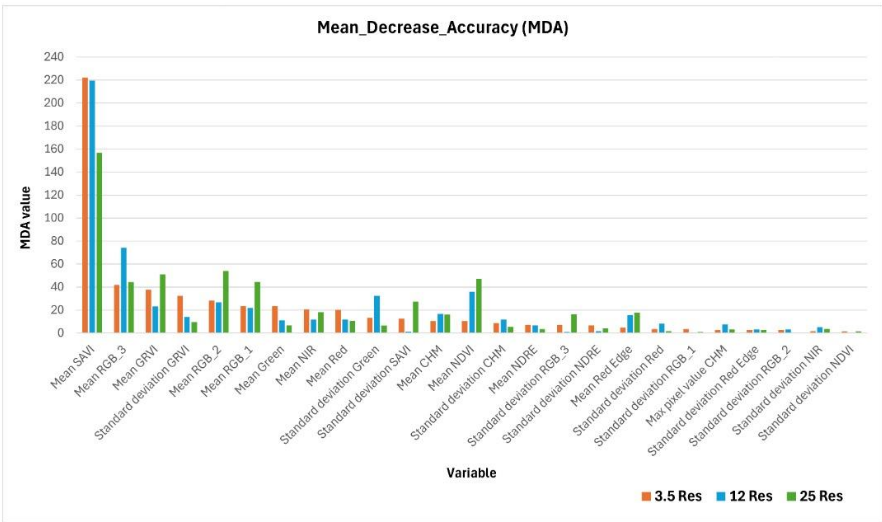


C

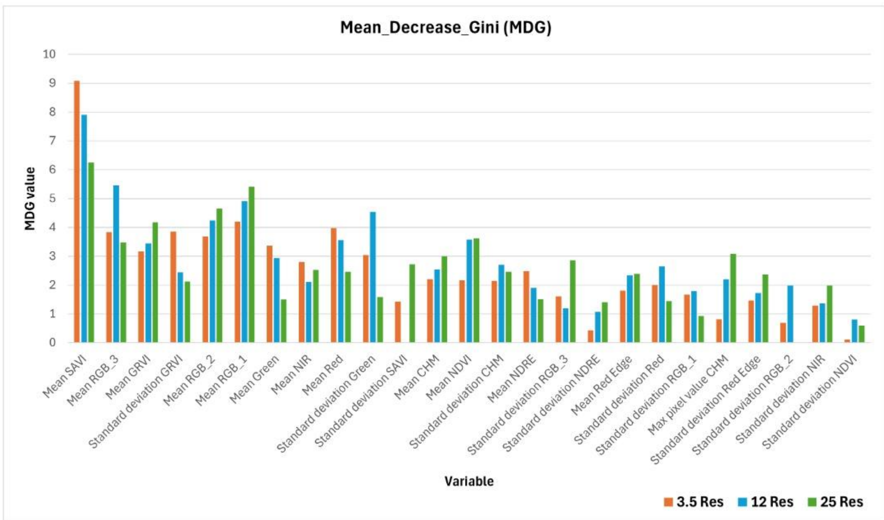
Figure 20: Correlation Matrix Heatmap A)3.5cm resolution B)12cm resolution C)25cm resolution

3.2.3. Variable Importance

Mean Decrease Accuracy (MDA) and Mean Decrease Gini (MDG) metrics were used to assess the variable's importance and select the most appropriate variable among the highly correlated variables. These results highlight the significance of each variable in the classification and help identify how each variable contributes to the model's accuracy. MDA (Figure 21 A) results show that variables such as Mean SAVI, Mean RGB_3(Blue), and Mean GRVI have the highest importance values across all resolutions, indicating a significant contribution to classification. Results from the MDG metric (Figure 21 B) highlight the significance of these variables, with Mean SAVI and Mean RGB_3 showing high importance values. It also highlights the significance of Mean RGB 1 and RGB 2, among others. These variables have consistently high importance across different resolutions (3.5 cm, 12 cm, and 25 cm), indicating their importance for classification. The correlation analysis results and insights of variable importance were combined to select the most relevant variables for classification. Specifically, between highly correlated pairs identified in the correlation matrix heat maps, the variable with the highest importance in the MDA and MDG graphs was selected for classification. This approach ensures that the selected variables provide unique information and significantly contribute to the model's performance.



A



B

Figure 21: A) Mean Decrease Accuracy (MDA) B) Mean Decrease Gini (MDG)

3.2.4. Selected Variables for the classification

After analyzing correlation and variable importance, the variables for classification were selected based on their high importance. Additionally, variables that were not highly correlated with others were considered, even if they showed a lower importance value. The variables selected for each resolution include mean values and standard deviations of specific bands and vegetation indices. Table 3 shows the list of selected variables for each resolution.

3.5 cm resolution	12 cm resolution	12 cm resolution
Mean RGB_1(Red)	Mean RGB_1(Red)	Mean RGB_1(Red)
Mean RGB_2(Green)	Mean RGB_2(Green)	Mean RGB_2(Green)
Mean RGB_3(Blue)	Mean RGB_3(Blue)	Mean RGB_3(Blue)
Mean CHM	Mean CHM	Mean CHM
Mean Green	Mean Green	Mean Red
Mean GRVI	Mean NDVI	Mean SAVI
Mean SAVI	Mean SAVI	Mean GRVI
Max pixel value CHM	Max pixel value CHM	Max pixel value CHM
Standard deviation RGB_1(Red)	Standard deviation RGB_1(Red)	Standard deviation RGB_1(Red)
Standard deviation RGB_3(Blue)	Standard deviation RGB_2(Green)	Standard deviation RGB_2(Green)
Standard deviation CHM	Standard deviation RGB_3(Blue)	Standard deviation RGB_3(Blue)
Standard deviation Green	Standard deviation CHM	Standard deviation CHM
Standard deviation Red Edge	Standard deviation Green	Standard deviation Green
Standard deviation NDVI	Standard deviation NIR	Standard deviation NDVI
Standard deviation NDRE	Standard deviation NDVI	Standard deviation NDRE
Standard deviation GRVI	Standard deviation NDRE	Standard deviation SAVI

Table 3: Selected variables for the classification at different Resolution

3.2.5. Land Cover Classification Map

Figures 22 - 24 show Land cover classification maps for each resolution (i.e. 3.5 cm, 12 cm, and 25 cm) using two different combinations of shape and compactness determined by the segmentation accuracy metric AFI and QR score. The land cover classes used for classification included Bare soil, Herbaceous vegetation, Grass, Rock, Shadow, Shrubs, and Trees. The results using the combination of shape and compactness based on AFI and QR metrics at 3.5 spatial resolution show a detailed land cover classification (Figure 22). This classification map derived from the highest spatial resolution imagery distinguishes between closely related vegetation types, such as Herbaceous vegetation and Grass. This high resolution enables the precise identification of small features and fine spatial patterns, particularly in heterogeneous landscapes. The high spatial resolution captures more detail and smaller features, allowing for more accurate and detailed classification of land cover types. The increased number of pixels per unit area ensures the model differentiates between closely related land cover classes.

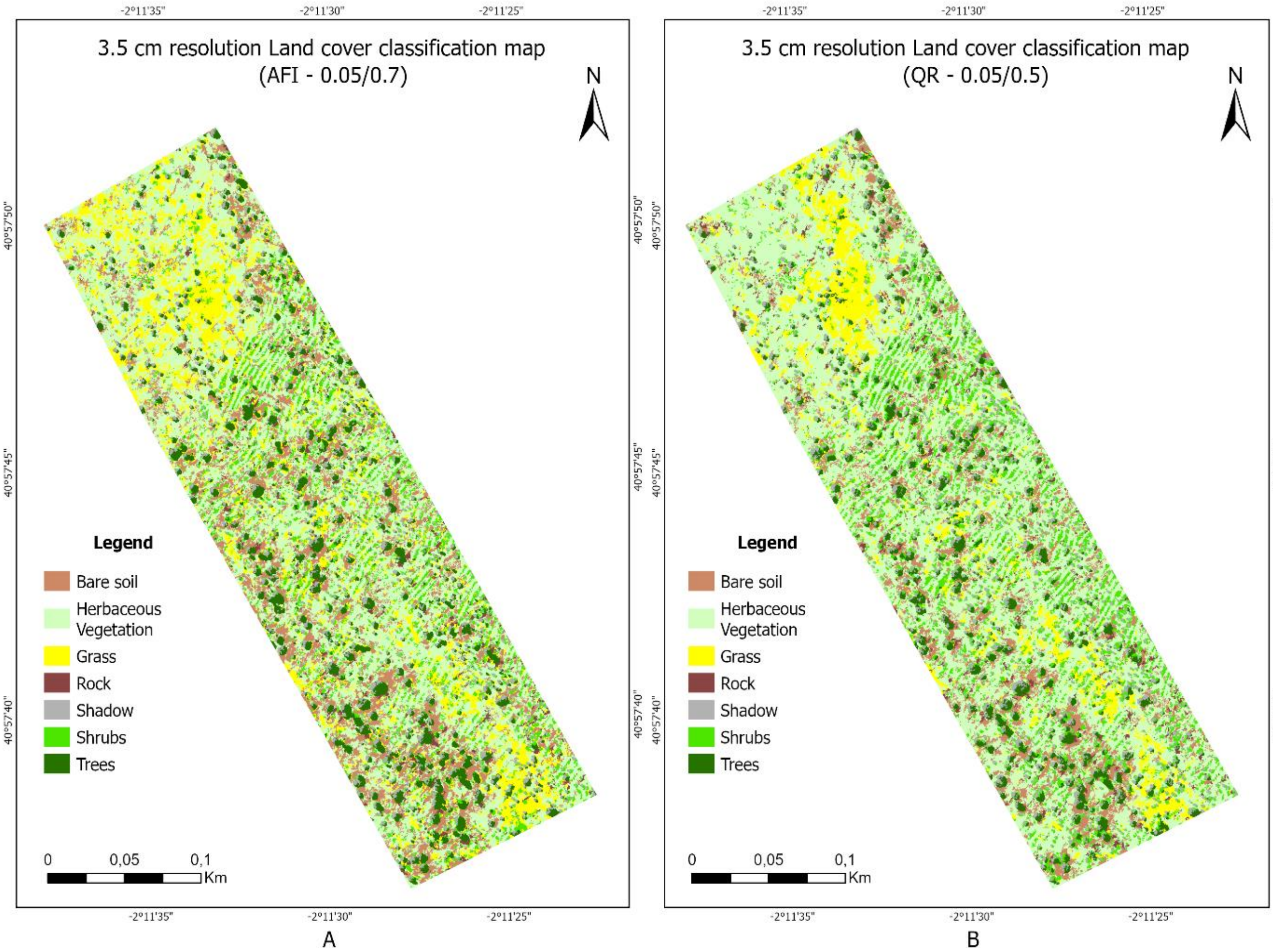
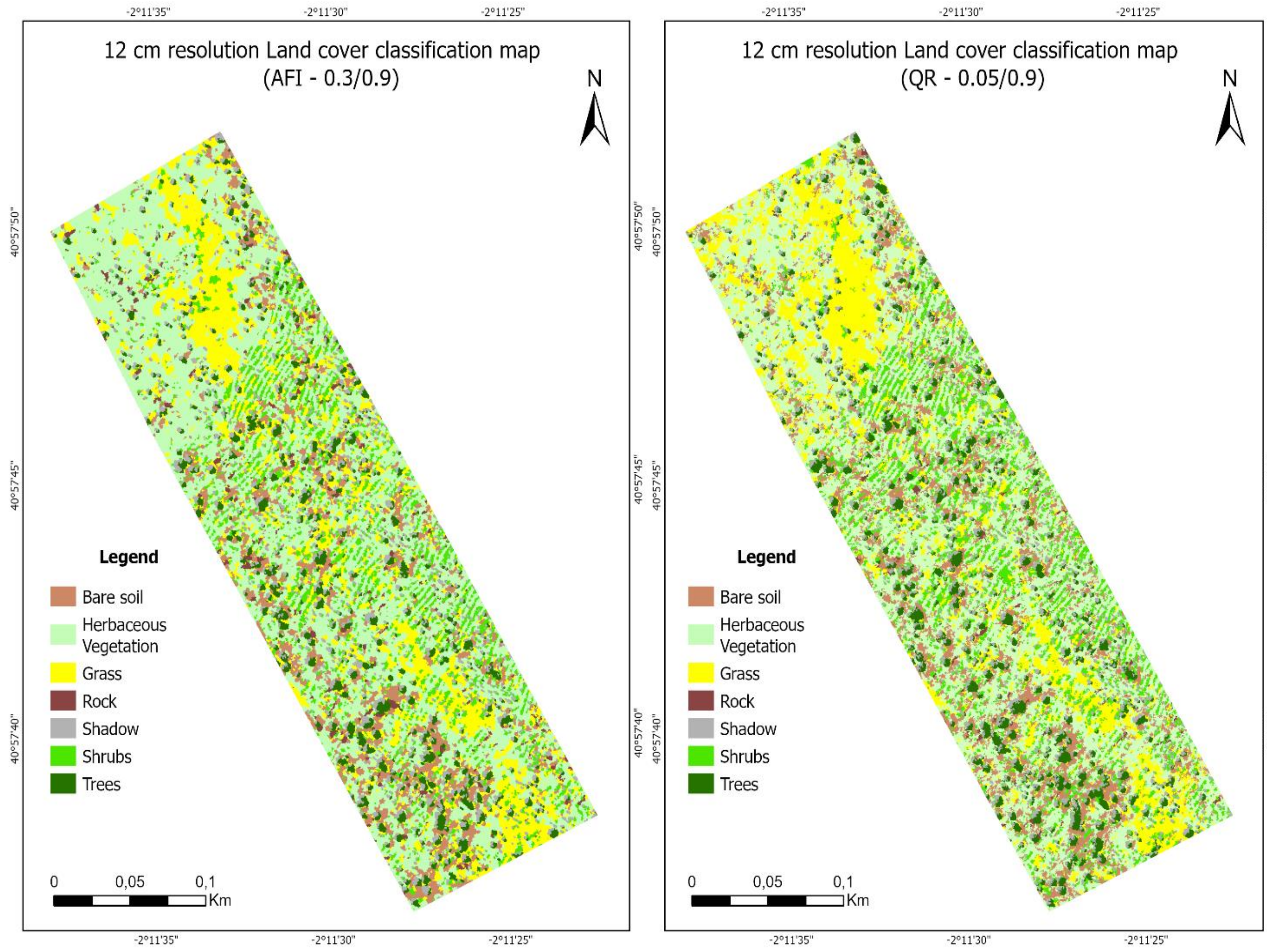


Figure 22: Land cover Classification Map 3.5cm A) AFI - 0.05/0.7 B) 0.05/0.5

The classifications at 12 cm resolution (Figure 23) were slightly less detailed than the 3.5 cm maps. While major land cover types remain identifiable, smaller features and finer distinctions between similar classes, such as Herbaceous vegetation and Grass, become less prominent. As resolution decreases with larger pixels, the classification becomes more generalized. While spatial resolution decreases, it is important to note that lower spatial resolution often comes with higher spectral resolution, which includes the NIR bands. Even though the boundaries between land cover types were less precise with the mixed pixels, affecting the overall classification accuracy.



A B

Figure 23: Land cover Classification Map 12cm A) AFI - 0.3/0.9 B) 0.05/0.9

At a 25 cm resolution (Figure 24), the maps show a smoothing effect between the land cover classes. Larger patches of land cover types, such as Trees and Shrubs, are identified, but finer details and small-scale variations are difficult to distinguish. The classification at this resolution is suitable for homogenous landscapes with broader land cover classes and larger landscape features, but it lacks the granularity observed in higher resolutions. Because of the larger pixel size at lower resolution, small features are frequently merged into larger homogeneous areas, reducing the ability to distinguish between closely related land cover types. Lower resolution is less sensitive to fine variations in the landscape, making it better suited for identifying major land cover classes than detailed mapping. It is observed in the maps that closely related classes, such as Bare soil and Rock, as well as Herbaceous vegetation and Grass, are not captured in detail. This results in a loss of detail and precision in land cover classification.

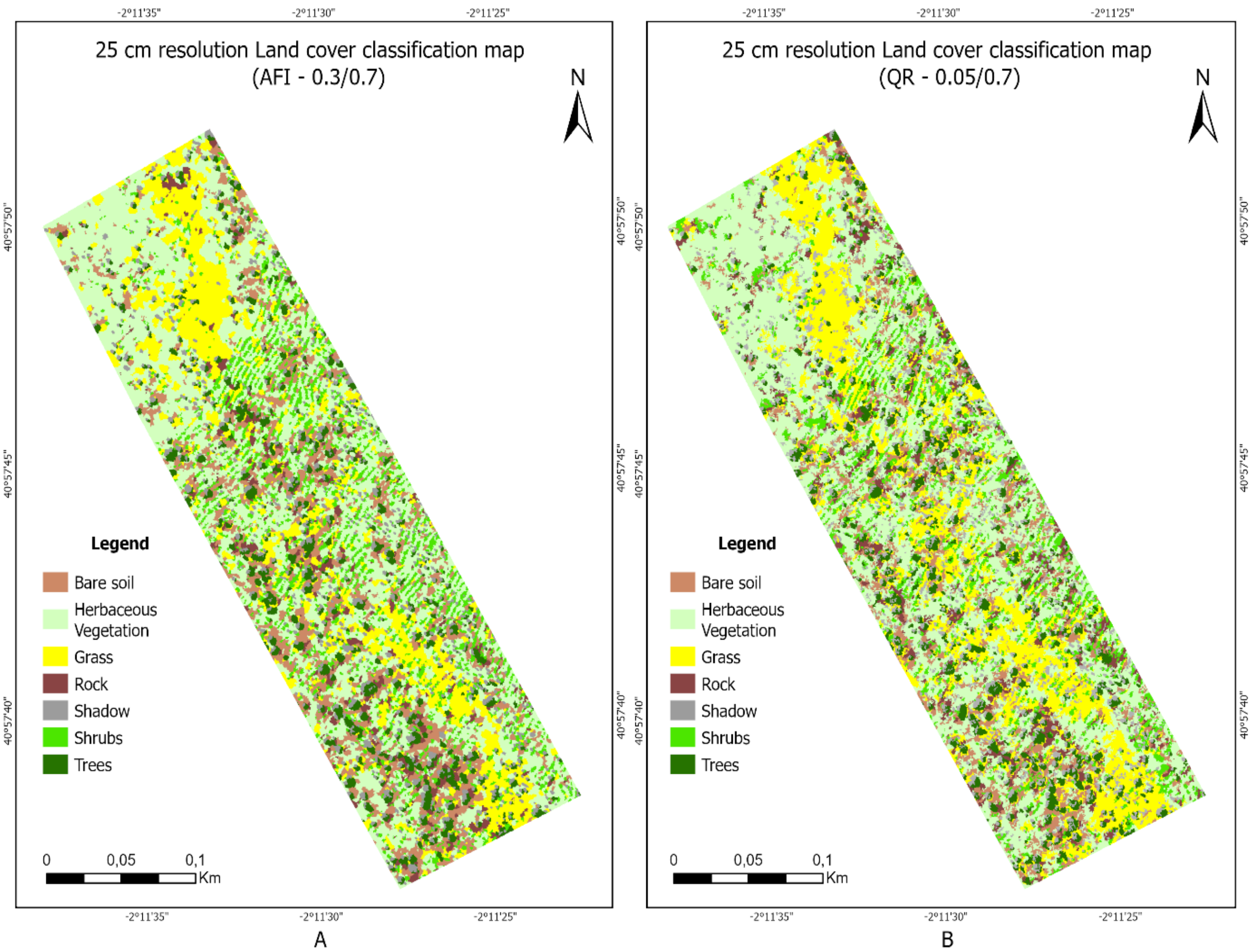


Figure 24: Land cover Classification Map 25cm A) AFI - 0.3/0.7 B) 0.05/0.7

3.2.6. Land Cover Classification Accuracy

The accuracy assessment of land cover classification shows significant differences between the performance of each land cover class at different spatial resolutions. The influence of image resolution on classification performance was assessed by comparing the results of confusion matrices for each resolution and within each resolution using two different shape and compactness combinations based on AFI and QR segmentation accuracy metric scores. The detailed confusion matrix on each resolution and AFI and QR score-based classification are provided in Annex (1) for reference. Table 4 shows the Producer, user, overall accuracy, and kappa values at different resolutions.

At 3.5 cm resolution, the classification performance is comparatively high, with slight variations between the AFI and QR-based classification confusion matrix. Comparing the AFI and QR-based confusion matrix in 3.5 cm resolution, the QR-based confusion matrix shows better accuracy in classes such as Bare soil and Rock. In both the accuracy results, Shadows and Tree classes show high producer and user accuracy, indicating the precise classification due to higher spatial resolution. At 12 cm resolution, the overall accuracy is slightly lower than at 3.5 cm, with no huge difference in the accuracies. Similarly, to 3.5 cm, the QR-based classification shows slight improvement compared to the AFI-based classification. It is observed that due to the coarser resolution, the accuracy of classes such as Grass and Rock decreases, leading to some misclassification. At 25 cm resolution, each class's overall accuracy, producer, and user accuracy drop compared to higher resolution. Both AFI and QR-based classifications yield the same overall accuracy. The performance of the closely related classes like Grass and Herbaceous vegetation decreases due to the impact of spatial resolution, which merges the smaller features into larger homogeneous areas due to the larger pixels.

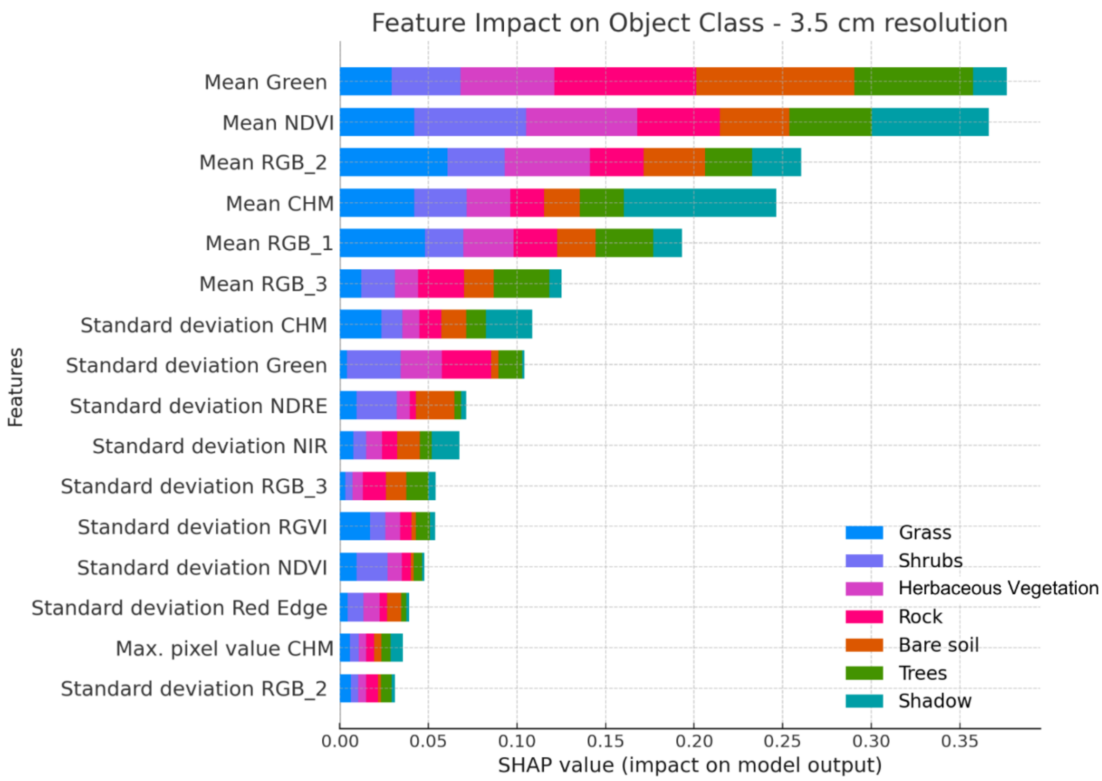
When comparing the accuracy in all land cover classes at different resolutions, we can highlight the key observation (Table 4): The accuracy for Herbaceous vegetation reduces at the 25 cm resolution. Similarly, the same pattern can be observed in each land cover class. In the case of Rock, the AFI-based classification shows lower accuracy than the QR-based classification at different resolutions. For Grass, the classification at 12 cm resolution produced lower accuracy compared to both 3.5 cm and 25 cm resolutions. Additionally, results indicate that major land cover classes like Trees and Shrubs are often misclassified at lower resolutions. Results show no huge difference between the overall accuracy of AFI and QR-based classification. However, when examining the accuracy of individual classes, the QR-based classification generally performs better. At the 25 cm resolution, there is no difference in overall accuracy between AFI and QR-based classifications. In general terms, Results indicate that QR-based classification is generally more effective, and higher spatial resolutions significantly improve the accuracy of land cover classifications, particularly in heterogeneous landscapes.

Class	**3.5cm (AFI 0.05 / 0.7)**		**3.5cm (QR 0.05 /0.5)**		**12cmc (AFI 0.3 / 0.9)**		**12cm (QR 0.05 /0.9)**		**25cmc (AFI 0.3 /0.7)**		**25cm (QR 0.05/ 0.7)**	
	PA	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**
Bare soil	0.87	0.62	0.93	0.78	0.80	0.75	1	0.71	0.71	0.65	0.87	0.81
Herbaceous vegetation	0.80	0.86	0.80	0.71	0.80	0.75	0.60	0.75	**0.73**	**0.69**	**0.67**	**0.63**
Grass	0.83	0.83	0.75	0.90	**0.67**	**0.62**	**0.67**	**0.62**	0.75	0.75	0.67	0.80
Rock	**0.33**	**0.67**	0.67	0.89	**0.58**	**0.70**	0.50	1	**0.58**	**0.74**	0.75	0.75
Shadows	1	1	1	1	1	1	1	1	0.86	0.93	0.77	0.80
Shrubs	0.94	0.84	0.82	0.82	0.94	0.89	1	0.85	**0.79**	**0.80**	**0.76**	**0.8**
Trees	0.94	1	0.94	0.94	0.88	0.94	0.94	1	**0.71**	**0.83**	**0.82**	**0.93**
Totals												
Overall Accuracy	0.83		**0.85**		0.82		**0.83**		**0.79**		**0.79**	
Kappa	0.80		0.82		0.79		0.80		0.75		0.75	

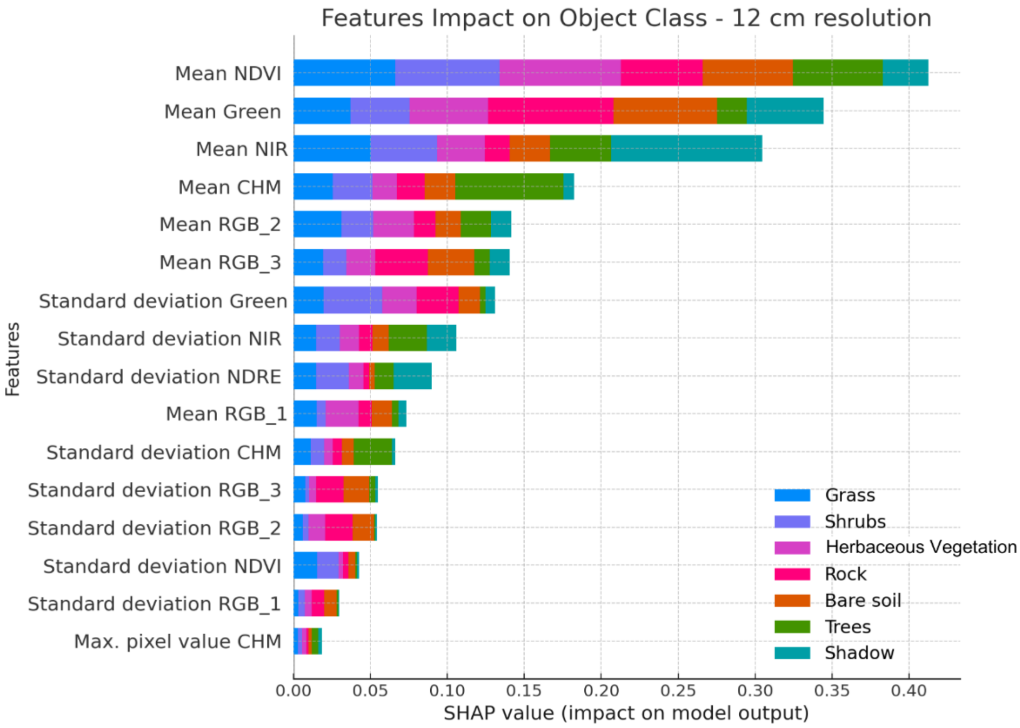
Table 4: Land cover classification accuracy at different spatial Resolution

3.2.7. Impact of the feature on each land cover class at different resolution

The SHAP analysis was performed to understand better the impact of various features on land cover classification at different spatial resolutions (3.5 cm, 12 cm, and 25 cm). Figure 25 (A) shows the impact of features on each land cover class in the classification model. Mean Green, at 3.5 cm resolution, is important for classifying Rock, Bare soil, and Trees. Mean NDVI is important in distinguishing Shrubs from Herbaceous vegetation. Standard deviation features, particularly the standard deviation of CHM, are also essential in detecting texture differences. This high resolution allows these features to capture fine details in the landscape, leading to better differentiation between classes. Similarly, at 12 cm resolution (Figure 25 B), Mean Green and Mean NDVI features remain highly significant for the Grass and dwarf shrub classes. It is also observed that Mean NIR becomes more significant in this resolution for distinguishing Grass and Shrubs. Mean CHM is an important factor in classifying Trees and Shrubs. Standard deviation features such as the NIR, NDRE, and Green are also significant, highlighting the importance of texture within classes. While features such as Mean Green and Mean NDVI are still important, their overall impact is slightly reduced compared to 3.5 cm resolution, reflecting the coarser resolution. At 25 cm resolution (Figure 25 C), the features with the greatest impact are Mean GRVI, which is important for classifying Grass and Shrubs, and Mean Red and Mean SAVI, which are important for distinguishing these classes. Mean CHM and Mean RGB_3(Blue) play a significant role in identifying Bare soil and Trees. Comparing feature importance across resolutions, Mean Green remains important across all resolutions, with its impact highest at 3.5 cm and decreasing slightly at lower resolutions. Mean NDVI is highly important at 3.5 cm and 12 cm but less so at 25 cm, where other features such as Mean GRVI and Mean Red take the lead. Mean CHM is significant at all resolutions but has the greatest impact at higher resolutions, capturing finer structural details. The SHAP analysis shows that higher-resolution data allows for greater dependence on detailed spectral and structural properties.



A



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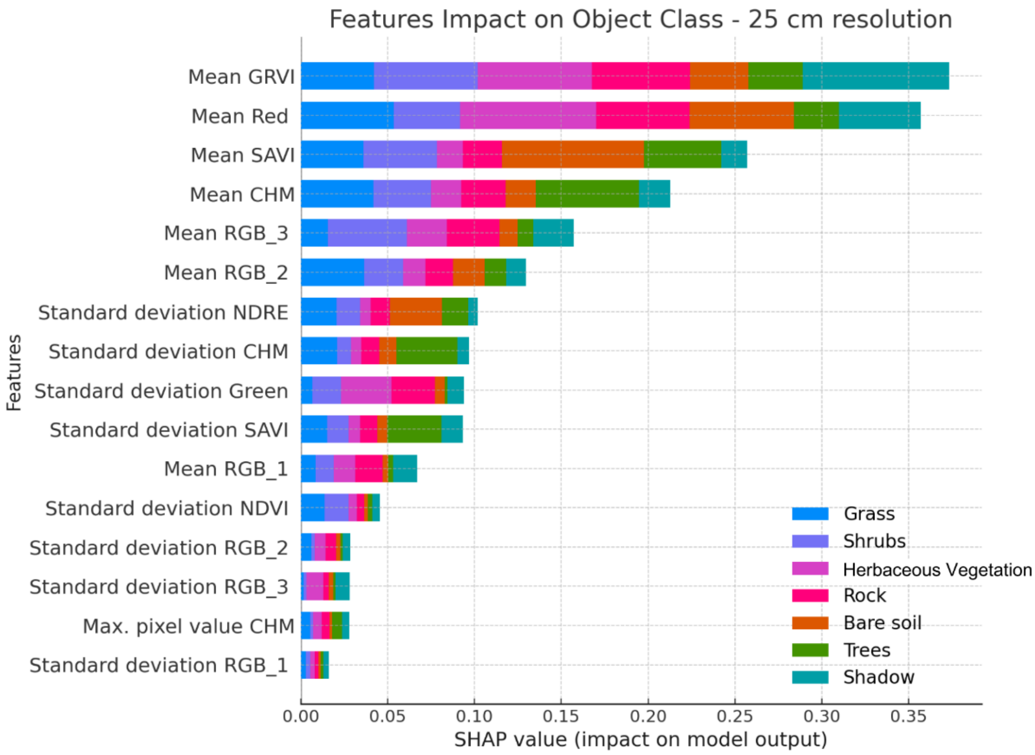

C

Figure 25: Feature Impact on land cover classes A)3.5cm resolution B)12cm resolution C)25cm resolution

The impact of different combinations of shape and compactness on classification accuracy was evaluated across three different resolutions: 3.5 cm, 12 cm, and 25 cm. Table 5 summarizes the results:

Resolution & scale factor	Best combination of Shape/compactness based on the AFI score	Classification overall accuracy	Best combination of Shape/ compactness based on QR score	Classification overall accuracy
3.5 cm (Scale 50)	0.05 / 0.7	0.83	0.05 / 0.5	0.85
12 cm (Scale 20)	0.3 / 0.9	0.82	0.05 / 0.9	0.83
25 cm (Scale 10)	0.3 / 0.7	0.79	0.05 / 0.7	0.79

Table 5: Shape and compactness combinations and classification accuracy

For further analysis of landscape heterogeneity metrics, classifications based on the QR were selected for all resolutions because results show that the QR metric is more comprehensive for assessing segmentation accuracy than the AFI metric. QR is a metric that combines over-segmentation and under-segmentation information to evaluate segmentation accuracy comprehensively. The study (Winter, 2000) highlights the limitations of metric AFI, which focuses primarily on the overlap percentage without considering over- and under-segmentation. It is also noted that single-focus metrics may miss important aspects of segmentation quality captured by more comprehensive metrics such as QR. Thus, QR-based classification results were preferable for computing landscape heterogeneity metrics, offering a balanced measure of segmentation quality and making it a preferable choice for further analysis.

3.3. Effect of different resolutions of UAV images on Landscape Heterogeneity Indices

3.3.1. Class level Indices

The analysis of LHI across different resolutions reveals significant variations in landscape structure. Tables 6-8 show the class-level LHI at three resolutions: 3.5 cm, 12 cm, and 25 cm. These indices help to understand the landscape structure and show how landscape features change based on classification at different spatial resolutions. The Indices include CA, PLAND, LPI, TE, and ED. CA and PLAND metrics, at a higher resolution of 3.5 cm, show that Herbaceous vegetation dominates the landscape with values of 3.25 and 50.42 for CA and PLAND, respectively, which remains consistent but with slightly decreased values at lower spatial resolution. A similar trend was observed in other classes, such as Bare soil, Grass, and Trees, but with slight variations in their values. The LPI values decrease at higher resolution (43.68 for Herbaceous vegetation), indicating more fragmented patches. The values of LPI reduced at lower resolutions (8.02 (12 cm) and 10.91 (25cm) for Herbaceous vegetation). This trend is consistent in other land cover classes, indicating that higher resolution captures finer patches, whereas lower resolution merges into larger, more dominant patches. The values of TE and ED are higher at higher spatial resolution, indicating more detailed and complex landscape structures. For instance, at 3.5 cm resolution, Shrubs have a TE value of 62262.66 and an ED value of 9666.71, which decreases with lower resolution. The edge complexity was reduced at 12 cm (TE: 36281.28, ED: 5631.62) and further at 25 cm (TE: 18986.75, ED: 2949.29), suggesting that lower resolution simplifies the landscape by reducing the delineation of edges and boundaries.

The results show that higher-resolution UAV images (3.5 cm) provide a better understanding of the landscape by capturing finer spatial heterogeneity and edge complexities. This is particularly significant for understanding landscape composition and structure because higher-resolution imagery can detect smaller patches and more complex boundaries. Lower-resolution images (12 cm and 25 cm) combine these finer details into larger patches, reducing landscape fragmentation and edge complexity.

CLASS	CA	PLAND	LPI	TE	ED
Bare soil	0.65	10.10	0.22	40484	6285
Herbaceous vegetation	3.25	50.42	43.68	107439	16680
Grass	0.64	9.98	2.97	32094	4982
Rock	0.18	2.67	0.03	12646	1963
Shadow	0.38	5.95	0.05	19896	3089
Shrubs	0.91	14.11	0.09	62262	9666
Trees	0.44	6.77	0.11	17018	2642

Table 6: Class-level LHI - 3.5 cm resolution

CLASS	CA	PLAND	LPI	TE	ED
Bare soil	0.80	12.46	0.22	31407	4875
Herbaceous vegetation	2.65	41.12	8.02	69507	10788
Grass	1.16	18.07	4.53	35821	5560
Rock	0.05	0.77	0.03	2522	391
Shadow	0.47	7.24	0.04	17457	2709
Shrubs	0.83	12.91	0.26	36281	5631
Trees	0.48	7.44	0.12	13041	2024

Table 7: Class-level LHI - 12 cm resolution

CLASS	CA	PLAND	LPI	TE	ED
Bare soil	0.60	9.34	0.15	17841	2771
Herbaceous vegetation	2.50	38.82	10.91	38383	5962
Grass	1.25	19.41	5.06	24250	3766
Rock	0.33	5.20	0.22	9549	1483
Shadow	0.61	9.46	0.04	19302	2998
Shrubs	0.62	9.64	0.14	18986	2949
Trees	0.52	8.14	0.15	12262	1904

Table 8: Class-level LHI - 25 cm resolution

3.3.2. Landscape-level Indices

Tables 9-11 show the Landscape-level LHI at three resolutions: 3.5 cm, 12 cm, and 25 cm. The Indices include Total Area (TA), Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Total Edge (TE), Edge Density (ED), Interspersion and Juxtaposition Index (IJI), Patch Richness (PR), Patch Richness Density (PRD), Shannon's Diversity Index (SHDI), Simpson's Diversity Index (SIDI), Shannon's Evenness Index (SHEI), and Simpson's Evenness Index (SIEI). At the highest spatial resolution (3.5 cm), the results show more patches (NP: 10913) and a higher patch density (PD: 169431.97). This suggests that higher resolution can detect smaller patches, resulting in a more fragmented landscape. As the resolution (12 cm and 25 cm) decreased, larger patches were identified due to coarser resolution. This trend is consistent with other indices such as LPI, TE, and ED. The value of IJI increases with lower resolution

(72.82 at 3.5 cm to 90.89 at 25 cm), indicating an even distribution of different patch types. Higher IJI values at lower resolutions indicate that the landscape appears distributed when the image resolution is coarser, as smaller patches are combined into larger ones. The value of diversity indices (SHDI and SIDI) and evenness indices (SHEI and SIEI) show increasing values with decreasing resolution. This trend reflects a more even distribution of patch types. The increase in value of SHDI (1.53 to 1.71), SIDI (0.70 to 0.78), SHEI (0.79 to 0.88), and SIEI (0.81 to 0.90) from 3.5 cm to 25 cm resolution indicates that coarser resolutions present a more balanced landscape structure.

The results clearly show that the spatial resolution significantly impacts LHI. Higher-resolution images (i.e. 3.5 cm) show a more detailed and fragmented landscape with greater patches, edge complexity, and a larger dominant patch. As the resolution (12 cm and 25 cm) decreases, the landscape becomes less fragmented and more homogenized. Thus, we can conclude that the resolution of the classification map plays a crucial role in determining LHI. Higher resolutions provide detailed insights into landscape structure and composition, while lower resolutions lower resolutions provide a broader perspective.

TA	NP	PD	LPI	TE	ED
6.44	10913	169431	43.68	145921	22655
IJI	**PR**	**PRD**	**SHDI**	**SIDI**	**SHEI**
72.82	7	108.68	1.53	0.70	0.79

Table 9: Landscape-level LHI - 3.5 cm resolution

TA	NP	PD	LPI	TE	ED
6.44	8839	137199	8.02	103019	15990
IJI	**PR**	**PRD**	**SHDI**	**SIDI**	**SHEI**
76.99	7	108.65	1.62	0.76	0.83

Table 10: Landscape-level LHI - 12 cm resolution

TA	NP	PD	LPI	TE	ED
6.44	5434	84408	10.91	70288	10918
IJI	**PR**	**PRD**	**SHDI**	**SIDI**	**SHEI**
90.89	7	108.73	1.71	0.78	0.88

Table 11: Landscape-level LHI - 25 cm resolution

4. DISCUSSION

4.1. Importance of Segmentation Accuracy

Segmentation accuracy is essential in object-based image analysis, mainly when calculating landscape heterogeneity indices using UAV imagery. Accurate segmentation ensures the precise delineation of objects, which influences the reliability and quality of feature extraction(Blaschke, 2010). The findings of this study show that the best combination of shape and compactness parameters for achieving high segmentation accuracy is shape values ranging from 0.05 to 0.3 and compactness values ranging from 0.7 to 0.9. For instance, at a 3.5 cm resolution, the combination of shape 0.05 and compactness 0.7 yielded the highest segmentation accuracy metrics values. In contrast, the study (Akcay et al., 2018) found that moderate shape and compactness values were more consistent than lower and higher values. These findings highlight the importance of fine-tuning segmentation parameters to achieve optimal accuracy. The outcomes of this research show that high segmentation accuracy captures fine landscape features, which are critical for ecological monitoring, vegetation, and land cover mapping. This is consistent with (Foody, (2020), who highlighted the importance of accurate vegetation type identification for effective biodiversity conservation and ecosystem management. Additionally, the findings highlight that segmentation accuracy is important in heterogeneous landscapes because of its spatial complexity and diversity of land cover types, as noted in the study of (Blaschke, (2010). One of the difficulties in achieving high segmentation accuracy is choosing appropriate segmentation parameters. The research observed that the optimal parameters vary with image resolution. At a 12 cm resolution, a shape value of 0.3 and compactness of 0.9 was optimal, whereas, at a 25 cm resolution, the best results were obtained with a shape value of 0.3 and compactness of 0.7. While these variations are relatively small, they highlight the need for careful parameter selection and refinement (Costa et al., (2018) state that this variability necessitates continuous evaluation and refinement of segmentation parameters to maintain high accuracy. Compared to (Chen et al., (2021) study, which also assessed segmentation parameter optimization for very high-resolution remote sensing images, our findings indicate a similar trend in the need for specific parameter settings to achieve high accuracy. Similarly, (Munyati, (2018) proved that the sensitivity of segmentation parameters to image resolution is essential for optimal feature extraction, which supports the findings of this study that parameter refinement is required at different resolutions.

According to the findings, shape and compactness play a significant role in segmentation accuracy, affecting classification accuracy. In contrast, the study (Torres-Sánchez et al., 2015) says that the parameters, such as shape and compactness, showed minimal influence on the classification accuracy compared to the scale parameter. The findings of this study underscore the necessity for a continuous process of refinement and optimization of shape and compactness parameters on segmentation. This effort is crucial to adapting to various landscapes' diverse requirements and ensuring the accuracy of the segmentation results. The practical implications of segmentation accuracy are significant, particularly in precision agriculture, which enables precise mapping of crop types, monitoring crop health, and urban planning for detailed land use mapping and infrastructure. The study shows that the high segmentation accuracy obtained in UAV imagery can enhance the decision-making processes in these fields by providing reliable and detailed spatial data. This aligns with the study by (Manfreda et al., (2018), which showed significant improvements in spatial data reliability due to high segmentation accuracy in UAV imagery.

4.2. Comparison of segmentation accuracy on different UAV image resolutions

The resolution of UAV imagery is a crucial factor that significantly impacts the segmentation. This study provides a comprehensive analysis of segmentation accuracy at three different resolutions, highlighting the variations in the segmentation accuracies. These findings align with the study (You et al., 2023), demonstrating that spatial resolution affected the segmentation results. This study's findings help to understand how image resolution influences and affects segmentation accuracy, the changes in segmentation parameterization, and the practical implications of UAV imagery. This study examined the impact of parameter selection on segmentation accuracy at different resolutions. It is also important to note that segmentation accuracy is influenced by the choice of segmentation algorithm. Based on previous research findings (Chen et al., 2021; Haralick & Shapiro, 1985), multi-resolution segmentation, which has shown better performance, was used in this study. However, many other options for land cover classification are present, so selecting the segmentation algorithm needs to be considered during the analysis. Higher resolutions enhance the delineation of intricate landscape features, which are particularly useful for applications requiring fine-scale analysis, such as vegetation mapping. Similar results were observed by

(Dandois & Ellis, (2013), who found that high-resolution imagery significantly improves the identification of small-scale landscape features.

This study found that this higher resolution results in a lower value of over-segmentation and under-segmentation, suggesting improved segmentation accuracy. It is observed that higher-resolution segmentation accuracy is achieved by fitting smaller pixels better to reference polygons, reducing errors in delineating objects. Segmentation accuracy metrics, such as QR and AFI values, indicate better segmentation results at higher resolutions. It is clear from this study that higher spatial resolution helps to delineate landscape features precisely, providing accurate spatial information useful for applying ecological monitoring and conservation initiatives. However, the improved accuracy at this higher resolution might also be due to the reference objects being digitized using the same high-resolution images, which introduces a potential bias. Despite the accuracy benefits, the higher resolution needs significant data storage, processing power, and time, which is a practical limitation for large-scale studies and real-time applications, as noted by (Manfreda et al., 2018). Medium resolutions balance the need for detailed spatial data and the practical aspects of data processing and storage. While less detailed, these images provide sufficient accuracy for urban planning, land use classification, forestry management, and disaster monitoring applications. Lower resolution causes a significant loss of landscape detail as smaller features are merged into larger, homogeneous segments. This results in higher over-segmentation and under-segmentation values, which indicate lower segmentation accuracy. The reduced accuracy at this resolution influences the reliability of classification results, which can have significant implications for applications requiring detailed spatial differentiation, such as ecological monitoring and habitat mapping. Lower resolution may be sufficient for broad-scale landscape analysis, but it is inadequate for detailed studies requiring high precision. The study by (Foody, (2020) Suggests that lower-resolution imagery requires less data storage and processing, and the trade-off in segmentation accuracy may not be justified for applications requiring fine-scale detail. This highlights the importance of conducting a cost-benefit analysis when determining the best image resolution for a specific study objective.

Thus, the study highlights the effect of segmentation parameters on segmentation accuracy at different image resolutions. The cause-and-effect relationship is clear from this study, as adjusting segmentation parameters directly impacted accuracy metrics. Lower shape values consistently reduced OS and US at all resolutions, improving segmentation accuracy. Likewise, increasing compactness values improved segmentation accuracy, as shown by lower OS and US values. These findings highlight the importance of fine-tuning segmentation parameters to achieve optimal accuracy. Additionally, it highlights the importance of improving segmentation accuracy to maintain high classification accuracy and for further analysis of the generation of LHI under various conditions, such as various spatial resolutions and different landscape structures. This helps to ensure the consistent performance of segmentation processes, enhancing UAV image analysis's reliability (Munyati, 2018).

4.3. Variable Importance

Variable selection is an important aspect of classification. Determining which features are most relevant for classification and improving the model's accuracy is essential. In this study, 26 variables were initially considered, and 16 were chosen based on correlation analysis and variable importance. This selection process involved keeping one variable from highly correlated groups while including all other features with low correlation. These criteria are specific to this study, but classification can also be performed using fewer variables. However, this would necessitate a more detailed analysis, such as determining the most important variables using conditional variable importance. It provides a more in-depth discussion of the importance of uncorrelated variables (Akcay et al., 2018). In this case, the highly correlated variables were reduced to one representative variable, while all other low-correlated variables were retained. Choosing which variables to use for training is essential because variable importance analysis indicates their contribution to classification. This study identified several key variables that influenced the model's performance. Specifically, the Mean SAVI, Mean RGB_3(Blue), and Mean GRVI were identified as the most important variables across all resolutions, as indicated by high Mean Decrease Accuracy (MDA) and Mean Decrease Gini (MDG) values. This aligns with (Akcay et al., 2018), Mean RGB_3(Blue) was the most effective variable in the landcover classification. Additionally, mean CHM also plays a role, but not as much as the variables like mean SAVI, RGVI, and RGB_3(Blue). This is similar to the study (Z. Xie et al., 2019), which found that height features in multiple source data had no or minimal effects on improving land cover classification. However, classification accuracy was improved for tree species. In this study, CHM mainly contributes to identifying specific land cover classes like trees and shrubs. This is consistent with the understanding that CHM provides information on vertical vegetation structure, which helps to classify these classes accurately.

These findings align with the previous studies, highlighting the importance of vegetation and spectral features in land cover classification. For instance, (Kang et al., (2021) found the importance of vegetation indices such as NDVI and NDRE in improving the classification accuracy in crop mapping. Although NDVI and NDRE were among the selected variables in this study, they were not as important as SAVI and GRVI. Additionally, the study aligns with (Z. Xie et al., (2019), who emphasized the importance of combining spectral bands, vegetation indices, and textures to improve land cover and forest classification accuracy. It is important to note that the random forests algorithm generates each tree from a random subset of variables, avoiding dependency on any single feature. This improves model reliability and applicability (Breiman, 2001; Liaw & Wiener, 2002). Additionally, it improves the efficiency as fewer variables are considered, which saves computational time and resources. The algorithm effectively manages variable importance by averaging variable contributions across multiple trees, thereby reducing potential bias toward specific variables (Gao et al., 2011).), improving classification accuracy.

4.4. Importance of Classification Accuracy

Classification accuracy affects the reliability of the results derived from the data and influences the decision-making processes in environmental management. It determines how well the algorithm can differentiate between different land cover types. Higher accuracy ensures that classifications reflect the landscape structure, essential to producing precise maps. This study illustrates that different UAV image resolutions impact classification accuracy. Higher-resolution images provide more detailed and accurate classifications, which are critical for detecting fine-scale heterogeneity in landscapes. For example, high-resolution imagery enabled more precise detection of small landscape features missed in lower-resolution images, aligning with similar findings (Anderson & Gaston, (2013). The choice of classifier significantly impacts classification accuracy. In this study, the Random Forest classifier was used, which is known for its high precision and reliability when working with large datasets. Several studies have supported the effectiveness of the RF classifier. For example, (Adam et al., (2014) showed that RF classifiers performed better in achieving high accuracy in heterogeneous coastal landscapes. The effectiveness could be due to the Random Forest improving prediction accuracy by combining results from multiple decision trees. However, it is important to note that this study does not compare RF with other classifiers; thus, the choice was based on existing research findings. This study observes that high accuracy in the classification results is also likely due to the use of multiple data sources, including RGB, MS, and CHM, which are important for distinguishing land cover types. This is supported by a study (Z. Xie et al., 2019) that showed the use of multi-source data – spectral bands, vegetation indices, textures and topographic factors significantly improved land cover classification accuracy compared to relying simply on spectral bands. Furthermore, a study by (Sharma, 2022) found that using multispectral sensors when combined with RGB imagery significantly improved classification accuracy since Multispectral data provides additional spectral information, which allows better differentiation between vegetation types, particularly in heterogeneous landscapes.

Accurate vegetation maps are essential for biodiversity monitoring and conservation. In this regard, (Navarro & Pereira, (2012) Indicate how precise land cover maps can help with habitat conservation by identifying areas that need to be conserved or restored. These accurate maps help conservation initiatives by organizations like Rewilding Spain, which aims to make Europe wilder by creating more space for wild nature, wildlife, and natural processes. This study identifies some sensitivities and potential inaccuracies. The heterogeneity of the landscape can affect the classification accuracy, which classifiers deal with difficulties distinguishing between diverse land cover. This difficulty arises from the variations in spectral signatures and structural differences within the heterogeneous landscapes. Studies showed that areas with higher structural and compositional differences in vegetation have higher species diversity, making accurate classification more difficult (Stein et al., 2014). To produce more accurate classification results, the study (Sharma, 2022)examined and found that combining data from multiple seasons improves classification accuracy. Seasonal variations in vegetation phenology can provide critical information to improve the differentiation between land cover types. While finer spatial resolutions generally improve classification accuracy, they remain challenged in highly fragmented landscapes (Matyukira & Mhangara, 2023). Therefore, Understanding and addressing these challenges is essential for improving classification reliability and producing accurate mapping results in complex landscapes.

4.5. Comparison of Landscape Heterogeneity Indices on different UAV image resolutions

Our research shows how UAV image resolution influences the estimation of LHI. This study's findings indicate that resolution impacts these indices' level of detail and precision, which are necessary for understanding ecological complexity. High-resolution UAV imagery provides detailed representations of landscape heterogeneity. The Shannon Diversity Index (SHDI) and Simpson's Diversity Index (SIDI) values observed in high-resolution images indicate a detailed depiction of the landscape, including fine-scale variations and small patches of different land covers. This precision is essential for detailed ecological studies like habitat assessments and species distribution modelling, which require fine spatial details (Liu et al., 2020; Lu & He, 2018). While high-resolution images capture fine details, they can also reduce within-class variance by accurately representing each land cover class (Blaschke, 2010). This level of detail may result in over-segmentation, in which the landscape is divided into small patches, complicating the analysis (Kim et al., 2011). On the other hand, lower resolution provides a broader perspective by merging fine details into larger, more homogeneous patches, which can be helpful in large-scale ecological studies. This generalization is valuable for landscape planning and management, where broader patterns are more important than fine-scale details. It enables the detection of large-scale ecological processes and patterns without being complicated by excessive information (Wu, 2004). In this study, higher resolution increased the NP and PD, indicating a more fragmented landscape. This aligns with the research (States, (1995), which has shown that high-resolution images show more fragmentation and edge complexity. As resolution decreases, these indices show fewer patches and less edge complexity, indicating a more generalized landscape structure. These differences can enhance the effectiveness of UAV-based ecological monitoring and landscape management efforts.

4.6. Applications of results

The results of this study provide valuable insights and practical applications for ecological conservation and management, especially in rewilding initiatives and habitat restoration efforts. High-resolution UAV imagery can help monitor habitat fragmentation and landscape heterogeneity. The ability to capture fine-scale landscape features with high spatial resolution is essential for accurate land cover classification and conservation planning. However, it is important to understand the limitations of temporal resolution. Frequent data acquisition may be limited by logistical and environmental constraints. While this study does not focus on temporal aspects, it is important to note that when conducting temporal analysis, maintaining a consistent spatial resolution is essential. This consistency ensures that LHI reflects landscape change. UAV-derived LHI may significantly benefit the management of protected areas at the landscape scale. For instance, monitoring changes due to the introduction of large herbivores is essential for the initiatives taken by Rewilding Spain. These indices enable the quantification of landscape changes over time, helping to assess the effectiveness of interventions and guide future actions linked to biodiversity and reduced fire risk. Low-heterogeneous areas may benefit from reintroducing diverse species to increase habitat complexity and ecological resilience. Conservationists can use this information to prioritize restoration activities, ensuring that resources are directed to areas where they will have a significant effect.

This study recommends high spatial resolution to monitor habitat structure and composition changes. For this purpose, UAVs flying at low altitudes provide more detail. Although flying at higher altitudes can cover larger areas more quickly, there is a trade-off between the data acquisition speed and the level of detail captured. The highest possible resolution is preferable for applications requiring detailed spatial data, such as identifying small-scale habitat features or assessing the impact of conservation interventions. In contrast, for broader landscape assessments requiring extensive area coverage but fine detail is less important, flying higher to cover larger areas faster may be more practical. Understanding the application's specific requirements will guide the selection of flying altitudes. This approach ensures that the data collected is most appropriate for the conservation and monitoring objectives. Therefore, combining high-resolution UAV imagery and LHIs provides an effective ecological monitoring and conservation method. It offers detailed and up-to-date information on landscape changes, allowing for proactive interventions to protect biodiversity and ensure sustainable ecosystem management.

4.7. Limitations of the research

- This main study's significant limitation is the reduced size of the study area, which is about 6 hectares. This constraint was due to the computational resources and processing time required for high-resolution UAV imagery. While this limitation helps to manage the data effectively, it also limits the potential for generalization of our findings. To validate the reliability of these findings across multiple landscapes, it is essential to consider a more diverse study area that can confirm the results.
- The Estimation of Scale Parameter (ESP) tool was not used to select scale parameters in segmentation due to the computational processing power required by eCognition software. As a result, the scale parameter was determined using the trial-and-error method.
- The findings are limited to the specific ecosystem studied and do not apply to all types of landscapes. Different ecosystems have unique features that depend on variations in UAV image resolution. To ensure broader applicability, further research is needed to validate our findings in diverse ecological settings.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

This study examined the impact of shape and compactness parameters on segmentation accuracy, the effect of UAV image resolutions on land cover classification accuracy, and the Landscape Heterogeneity Indices (LHI). The following conclusions address each research question:

R.Q.1.1: How do the shape and compactness parameters in the multiresolution algorithm influence the segmentation accuracy at different spatial resolutions?

The study identified that shape and compactness parameters significantly impact segmentation accuracy across spatial resolutions. Lower shape values (0.05 to 0.3) and higher compactness values (0.7 to 0.9) consistently produced better segmentation results, resulting in fewer over-segmentation and under-segmentation, which is determined by the results of the segmentation accuracy metrics. In between the range of shape and compactness, there are no huge variations, but higher values in shape and lower values in compactness affect the segmentation accuracy. The optimal shape and compactness parameters resulted in a more precise delineation of landscape features, which improved segmentation accuracy.

R.Q.2.1: How do different UAV image resolutions affect Land cover classification accuracy?

The spatial resolution of UAV images influences land cover classification accuracy. At 3.5 cm resolution, overall classification accuracy was 85%, compared to 83% at 12 cm and 79% at 25 cm resolution. Producer accuracy and user accuracy also varied with resolution. Higher-resolution images provide more detailed and accurate classifications, which are required for detecting fine-scale heterogeneity in landscapes. As resolution decreased, smaller features merged into larger homogeneous areas, resulting in lower classification accuracy. This highlights the importance of high-resolution imagery in capturing detailed spatial patterns required for accurate land cover classifications.

R.Q.2.2: What is the effect of different resolutions of UAV images on LHI?

The study found significant variations in LHI across different spatial resolutions. Higher-resolution images (3.5 cm) provided a more detailed understanding of landscape structure by capturing finer spatial heterogeneity and edge complexities. On the other hand, lower resolution (12 cm and 25 cm) resulted in a generalized landscape structure with fewer patches and less edge complexity. LHI, such as Patch Density (PD) and Edge Density (ED), was higher at 3.5 cm resolution, indicating that it captures a more fragmented and complex landscape. Indices like PD, LPI, TE and ED are also highly sensitive to changes in image resolution. Other indices like SHDI, SIDI, and SHEI are less sensitive to image resolution, making them more useful for comparative studies on environmental monitoring and conservation management. The study confirmed that higher resolutions yield more accurate measurements of landscape heterogeneity, which is crucial for detailed habitat analysis and biodiversity conservation. However, lower resolution may be appropriate for large-scale ecological studies but less effective for detailed habitat analysis.

Thus, this study demonstrates the importance of optimizing segmentation parameters and utilizing high-resolution UAV imagery in improving the accuracy of land cover classification and landscape heterogeneity assessments. These insights are essential for environmental monitoring, conservation planning, and effective natural resource management. Implementing these methodologies can lead to more accurate and detailed analyses across various ecosystems, ultimately contributing to better-informed biodiversity conservation and landscape management decisions.

5.2. Recommendations for further studies

- Future research should concentrate on developing automated tools and techniques for tuning shape and compactness parameters for segmentation processes. A potential recommendation is to create a model that runs multiple parameter combinations and calculates the Quality Rate (QR) and Area Fit Index (AFI). This approach would allow users to select optimal values, reducing dependence on trial-and-error methods and enhancing the efficiency of these processes.
- Additionally, machine learning algorithms can predict optimal parameters based on image characteristics, thereby automating the selection process. For example, selecting scale parameter values automatically using a tool like ESP in eCognition may help improve the segmentation process. While current studies employ this tool to select scale parameters, it does not work optimally in certain cases. Therefore, future research should understand why these tools may not perform optimally in specific scenarios.
- Also, for further analysis, remove the variables that do not contribute to the classification using variable analysis graphs (SHAP values). Focusing only on the most impactful variables would help the model, reduce computational load, and potentially increase classification accuracy.
- Furthermore, applying the study's methodologies and findings to various ecosystems and geographical regions would help validate its applicability and identify ecosystem-specific difficulties and solutions.
- Future studies might focus on long-term monitoring and quantification of LHIs. By quantifying and analyzing LHIs over time, studies may better understand the impact of conservation initiatives. This approach would better understand how conservation efforts affect landscape heterogeneity, allowing for more informed decision-making and adaptive management strategies.

6. ETHICAL CONSIDERATIONS

The study analyses the impacts of UAV image resolution on segmentation accuracy and landscape heterogeneity indices. It contains no human, animal, or private information and avoids ethical issues. Rewilding Europe Spain provided field data for the study area. This organization has granted permission and rights to use the data in this thesis, ensuring that it was obtained and used ethically and legally. The University of Twente provided the UAV data, which was acquired in compliance with European regulations and standards. All the data in this thesis is securely stored, backed up, and used solely for this research.

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APPENDICES

During the preparation of this work, the author used ChatGPT to assist in writing code (Python) for the feature Importance analysis in SHAP (SHapley Additive exPlanations). After using this tool, the author reviewed and edited the content as needed and took (s) full responsibility for the content of the work.

Appendix 1 - Confusion Matrix

Confusion Matrix – 3.5 cm (AFI 0.05/0.7)								
Class	Bare soil	Herbaceous vegetation	Grass	Rock	Shadow	Shrubs	Trees	Sum
Bare soil	13	0	0	8	0	0	0	21
Herbaceous vegetation	0	12	2	0	0	0	0	14
Grass	0	1	10	0	0	1	0	12
Rock	2	0	0	4	0	0	0	6
Shadow	0	0	0	0	12	0	0	12
Shrubs	0	2	0	0	0	16	1	19
Trees	0	0	0	0	0	0	16	16
Sum	15	15	12	12	12	17	17	
Accuracy								
Producer	0.87	0.8	0.83	0.33	1	0.94	0.94	
User	0.62	0.86	0.83	0.67	1	0.84	1	
Totals								
Overall Accuracy	0.83							
Kappa	0.80							

Confusion Matrix – 3.5 cm (QR 0.05/0.5)								
Class	Bare soil	Herbaceous vegetation	Grass	Rock	Shadow	Shrubs	Trees	Sum
Bare soil	14	0	0	4	0	0	0	18
Herbaceous vegetation	0	12	3	0	0	2	0	17
Grass	0	0	9	0	0	0	0	10
Rock	1	0	0	8	0	0	0	9
Shadow	0	0	0	0	12	0	0	12
Shrubs	0	2	0	0	0	14	1	17
Trees	0	0	0	0	0	1	16	17
Sum	15	14	12	12	12	17	17	
Accuracy								
Producer	0.93	0.8	0.75	0.67	1	0.82	0.94	
User	0.78	0.71	0.9	0.89	1	0.82	0.94	
Totals								
Overall Accuracy	0.85							
Kappa	0.82							

Confusion Matrix – 12 cm (AFI 0.3/0.9)								
Class	Bare soil	Herbaceous vegetation	Grass	Rock	Shadow	Shrubs	Trees	Sum
Bare soil	12	0	0	4	0	0	0	16
Herbaceous vegetation	0	12	4	0	0	0	0	16
Grass	0	2	8	1	0	1	0	13
Rock	3	0	0	7	0	0	0	10
Shadow	0	0	0	0	12	0	0	12
Shrubs	0	1	1	0	0	16	0	18
Trees	0	0	0	0	0	0	15	15
Sum	15	15	13	12	12	17	15	
Accuracy								
Producer	0.8	0.8	0.67	0.58	1	0.94	0.88	
User	0.75	0.75	0.62	0.7	1	0.89	1	
Totals								
Overall Accuracy	0.82							
Kappa	0.79							

Confusion Matrix – 12 cm (QR 0.05/0.9)								
Class	Bare soil	Herbaceous vegetation	Grass	Rock	Shadow	Shrubs	Trees	Sum
Bare soil	15	0	0	6	0	0	0	21
Herbaceous vegetation	0	9	3	0	0	0	0	12
Grass	0	0	8	0	0	1	0	13
Rock	0	0	0	6	0	0	0	6
Shadow	0	0	0	0	12	0	0	12
Shrubs	0	1	1	0	0	17	1	20
Trees	0	0	0	0	0	0	16	16
Sum	15	15	12	12	12	17	17	
Accuracy								
Producer	0.71	0.75	0.67	0.5	1	1	0.94	
User	0.71	0.75	0.62	1	1	0.85	1	
Totals								
Overall Accuracy	0.83							
Kappa	0.80							

Confusion Matrix – 25 cm (AFI 0.3/0.7)								
Class	Bare soil	Herbaceous vegetation	Grass	Rock	Shadow	Shrubs	Trees	Sum
Bare soil	12	1	0	4	0	0	0	17
Herbaceous vegetation	1	11	3	1	0	0	0	17
Grass	0	2	9	0	0	0	1	12
Rock	2	0	0	7	0	0	0	9
Shadow	0	0	0	0	12	0	0	12
Shrubs	0	1	0	0	0	16	2	19
Trees	0	0	0	0	0	0	12	12
Sum	15	15	12	12	12	17	15	
Accuracy								
Producer	0.71	0.73	0.75	0.58	1	0.94	0.71	
User	0.65	0.75	0.75	0.78	1	0.84	1	
Totals								
Overall Accuracy	0.79							
Kappa	0.75							

Confusion Matrix – 25 cm (QR 0.05/0.7)								
Class	Bare soil	Herbaceous vegetation	Grass	Rock	Shadow	Shrubs	Trees	Sum
Bare soil	13	0	0	3	0	0	0	16
Herbaceous vegetation	0	10	4	0	0	2	0	16
Grass	0	2	8	0	0	0	0	10
Rock	2	1	0	9	0	0	0	12
Shadow	0	2	0	1	12	0	0	15
Shrubs	0	0	0	0	0	13	3	16
Trees	0	0	0	0	0	1	14	15
Sum	15	15	12	12	12	16	17	
Accuracy								
Producer	0.87	0.67	0.67	0.75	1	0.76	0.82	
User	0.81	0.63	0.8	0.75	0.8	0.81	0.93	
Totals								
Overall Accuracy	0.79							
Kappa	0.75							

Appendix 2 – eCognition processing tree for classification

Appendix 3 – Landscape Heterogeneity Indices and its Descriptions

Name of the metrics	Description
CA: Total (Class) Area	The class area measures landscape composition, precisely, how much of the landscape comprises a particular patch type.
PLAND: Percentage of Landscape	PLAND equals the sum of the areas (m2) of all patches of the corresponding patch type, divided by total landscape area (m2), multiplied by 100 (to convert to a percentage); in other words, PLAND equals the percentage of the landscape comprised of the corresponding patch type. Note that total landscape area (A) includes any internal background present.
LPI: Largest Patch Index	The most extensive patch index at the class level quantifies the percentage of the total landscape area comprised by the most significant patch. As such, it is a simple measure of dominance.
ED: Edge Density	Edge density reports edge length per unit area on a basis that facilitates comparison among landscapes of varying sizes.
TE: Total Edge	Total edge is an absolute measure of the total edge length of a particular patch type. In applications that compare landscapes of varying sizes, this index may not be as helpful as edge density (see below). However, total edge and edge density are completely redundant when comparing landscapes of identical size.
PD: Patch Density	Patch density is a limited but fundamental aspect of landscape patterns. Patch density has the same essential utility as the number of patches as an index, except that it expresses several patches on a per unit area basis that facilitates comparisons among landscapes of varying sizes.

NP: Number of Patches	The number of patches of a particular patch type is a simple measure of its extent of subdivision or fragmentation.
PRD: Patch Richness Density	Patch richness density standardises richness on a per-area basis, facilitating landscape comparison. However, this metric is redundant regarding both patch richness and relative patch richness.
IJI: Interspersion and Juxtaposition Index	The interspersion and juxtaposition index are based on patch adjacencies, not cell adjacencies, like the contagion index. IJI approaches 100 when all patch types are equally adjacent to each other. It is a good indicator of isolation between habitat patches.
SHDI: Shannon's Diversity Index	Shannon's diversity index is a popular measure of diversity in community ecology. It is applied here to landscapes. Shannon's index is more sensitive to rare patch types than Simpson's diversity index.
SIDI: Simpson's Diversity Index	Simpson's diversity index is another popular diversity measure borrowed from community ecology. It is less sensitive to the presence of rare types and has a much more intuitive interpretation than Shannon's index. Specifically, the value of Simpson's index represents the probability that any 2 pixels selected randomly would be of different patch types.
SHEI: Shannon's Evenness Index	Shannon's evenness index expresses that an even area distribution among patch types results in maximum evenness. As such, evenness complements dominance. Shannon's Diversity and Evenness Index reflects the relative distribution in the area between patch types. Spatial distribution is not accounted for.
SIEI: Simpson's Evenness Index	Simpson's evenness index is expressed such that an even area distribution among patch types results in maximum evenness. As such, evenness complements dominance.