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Developing a Transferable Object-Based Image Analysis (OBIA) Approach for the Detection and Classification of Urban Features

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Developing a Transferable Object-Based Image Analysis (OBIA) Approach for the Detection and Classification of Urban Features

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DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced. This work has not been previously evaluated or submitted to NOVA Information Management School or elsewhere.

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Developing a Transferable : Object-Based Image Analysis (OBIA) Approach for the Detection and Classification of Urban Features

Abstract

The analysis and usage of optical satellite images with very high spatial resolution, this has led to effective support for estimating and monitoring population, understanding urban changes and many other applications. The spatial data obtained from satellite images has become remarkably widespread and is increasing over the time due to the availability of different methods for processing remote sensing data.

In past studies, many researchers used object-based image analysis (OBIA) to closely examine and describe urban features in many different areas in great detail using a very high resolution satellite image. Detecting urban features within urban areas in an automated and adaptable way is challenge due to the variations in spatial and spectral Features.

This research focuses on the development of a Object-Based Image Analysis (OBIA) approach and create a flexible workflow and ruleset that can that easily adaptable across different study areas and datasets, enabling efficient and accurate urban feature detection and classification in diverse urban context and apply it to other study areas.

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CHAPTER 1: INTRODUCTION AND RESEARCH STRUCTURE

1.0 Introduction and Research Structure

This chapter aims to present a general overview of this research by identifying the research background, research problem, research aims, research questions, and research structure.

1.1 Research Background

There is a rapid and noticeable growth in urban areas, which poses challenges for the detection and classification of urban features such as buildings, roads and vegetation, which has made careful analysis of urban landscapes crucial for urban planning, environmental monitoring and infrastructure development (Sertel, E., 2015). inequality and high levels of energy use and pollution in urban areas are also other notable problems. Although the cities cover only 3 percent of the Earth's territory, they contribute to 60-80 percent of energy use and 75 percent of carbon emissions (United Nations. 2022).

The importance of urban mapping comes from the requirements for a very accurate and detailed knowledge of land use / land cover data and their distribution (Chen, J.2018). Ecosystems in urban areas provide social and ecological benefits but the assessing and monitoring their spatial extent is difficult due to the variety of diversity of these canopies (Moskal, L. M.,2011).

Remote sensing data covering large areas can be easily accessed and are being collected more frequently. However, dealing with such a massive amount of data requires automated or semi-automated systems to analyze images. By using computer vision and taking advantage of the increasing availability of data, we can create specific systems that automatically analyze and detect urban features (Camara, A., 2023).The increasing of very high resolution satellite images have advanced the ability to accurately mapping the land-use/land-cover (LULC) features (Lichtblau, E.,2019). Using VHR satellite imagery to classify urban land cover is a new and growing area of research in remote sensing. This type of imagery provides an incredibly detailed view of urban areas, allowing for the creation of highly accurate maps that capture specific details (Salehi, B. 2012).

Instead of the traditional, pixel-based approach, object-based image analysis (OBIA) or geospatial object based image analysis (GEOBIA) has been introduced to tackle the limitations of pixel-based and enhance the accuracy of information extraction from high resolution imagery (Han, R., 2020). Object-based image analysis (OBIA) have been suggested to include texture and other image object characteristics into the classification process (Bobáľová, H., 2021). OBIA is a useful method for detecting and classifying urban features. Very high- resolution imagery expected to provide detailed information's on land cover classes. Additionally, OBIA has emerged as a method for extracting these information's. challenges remain, such as difficulties in distinguishing between similar regions. When determining what something is, classifiers must consider its features and use the correct combination of parameters to accurately segment it (Kurniawan, A. 2020). OBIA segments images into meaningful objects based on their spectral, textural, and contextual object features, enabling a more comprehensive understanding of urban features. By considering objects as the fundamental units of analysis rather than individual pixels, OBIA offers improved accuracy, better contextual interpretation, and the ability to integrate diverse data sources (Blaschke, T., 2010).

OBIA is becoming increasingly popular within the scientific community, especially when combined with advanced classification methods such as random forest (RF), rule-based classification, and SVM. This integration has transcended into a more powerful method for image classification due to its ability to segment detailed objects, considering contextual setup, and incorporation expert rules. As a result, OBIA emerges as a more capable approach for accurate image classification (Labib, S. M., 2018).

The semi automation of image processing, closely associated with the emergence of very high-resolution imagery. While OBIA has great potential for urban analysis, its practical use is often limited due to the lack of transferability and standardization in existing approaches. Many OBIA methods are designed for specific study areas, which makes it difficult to apply them to different regions with diverse urban characteristics and environmental conditions.

This limitation hinders the scalability and widespread use of OBIA for detecting and classifying urban features (Phiri, D. 2017).

By conducting research on this topic, developing a Transferable Object-Based Image Analysis (OBIA) rule set Approach for identifying and categorizing urban features represents a significant advancement in urban analysis methods. This contributes to refining OBIA techniques for urban analysis, offering a more efficient and adaptable framework for identifying and categorizing urban features and improve our understanding of urban landscapes and facilitate sustainable urban development, enabling informed decision-making for urban planners. This study involved two main steps: the first is image segmentation, which is an important and crucial step in dividing the image into meaningful objects. the scale parameter (SP) plays a crucial role in determining the average size of image objects and directly influencing classification accuracy. The selection of an appropriate SP value for image segmentation can be problematic For rule-based classification (Bacha, A. S.,2020).

1.2 Research problem

The increase in the number of Very High-Resolution (VHR) satellite images, coupled with improvements in spatial and temporal resolution technologies present significant challenges for the detection and classification of urban features using semi-automated remote sensing techniques. that requires the development of effective and transferable methodological frameworks for information extraction analysis for many applications such as urban features mapping.

As a state of art, its critical to develop and propose a semi-automated and transferable data driven a process in VHR satellite images that can be easily customized and employed for many case studies.

1.3 Research aims/objectives

This Chapter aims to Creating a workflow/ruleset that easily adaptable and transferable to other study areas, so that it can be semi-automated used in different environments with different building types. To accomplish these goals, First develop a rule-based approach workflow using the extracted features after that Create sets of rules that are based on the spectral and spatial indices of urban features in first urban area. Secondly Evaluate and assess the transferability of the developed OBIA model by applying it in the second urban area third Analyze the results and compare them with the current OBIA and classification techniques. Finally, make a comparison to understand why these variations exist.

1.4 Research questions

1- What are the key features that need to be detected and classified using Object-Based Image Analysis (OBIA) in different study areas?

2- How can a workflow/ruleset be developed to facilitate the transferability and adaptability of OBIA for the detection and classification of urban features in different study areas?

3- How can an adaptable OBIA approach be developed to effectively detect and classify urban features across different geographic regions and datasets?

CHAPTER 2: LITERATURE REVIEW

This chapter focus on presenting the available literature review that generally explores the state-of-the-art in OBIA techniques for urban feature detection and classification, with a focus on the development of transferable rule-based OBIA methods using eCognition Trimble.

2.1. Introduction to Object-Based Image Analysis (OBIA)

After increasing dissatisfaction with pixel-by-pixel image analysis, it was apparent that this criticism wasn’t new. Several studies have noted that a hype in applications 'beyond pixels'. The shared factor among these applications has consistently been their reliance on image segmentation(Blaschke,T., 2010). High degree of within-class spectral variability and between-class spectral similarity of many land use/cover (LULC) types in VHR images results in low classification accuracies when these methods are employed. In last decades, object based image analysis (OBIA) has gained rapid popularity for acquisition of effective LULC classification(Kavzoglu, T., 2016).

Object-based image analysis (OBIA) has been defined as a sub-discipline of GIScience devoted to partitioning remote sensing (RS) imagery into meaningful image-objects and assessing their characteristics through spatial, spectral and temporal scale. The primary purpose of OBIA is to provide a method for analyzing high-spatial resolution imagery by using spectral, spatial, textural and topological characteristics (Hossain, M. D., 2019). OBIA offers a promising framework to address these constraints in heterogeneous wetland landscapes and to facilitate repeated monitoring of their composition and surface properties. , the images are first segmented into “objects” that are groups of pixels representing ground patches, entities or their elements (primitives) which subsequently can be classified into categories of interest by unsupervised, supervised or rule-based algorithms (Dronova, I., 2015)

2.1.1 OBIA Strengths and Weaknesses

The object-based image analysis (OBIA) approach shows strengths and weaknesses in the context of geospatial data analysis, as outlined in **Table 1**.

OBIA Strengths	OBIA Weaknesses
The process of dividing an image into multiple objects is similar to how humans divide and comprehend the world around them.	Current software reliant on commercial objects offers excessively complex options under the guise of flexibility.
The implementation of image-objects as fundamental elements greatly reduces the computational overhead on classifiers, leading to a significant reduction in workload. The user can benefit from advanced methodologies, such as non-parametric techniques, through this method at the same time.	When dealing with very big datasets, there are several issues to contend with. Although OBIA is potentially more efficient than pixel-based methods, effectively segmenting a multispectral image that contains millions of pixels poses a significant challenge. It necessitates the implementation of efficient tiling or multiprocessing solutions.
For instance, single pixels do not contain the useful features that image-objects possess such as shape and texture and relation of context to another object.	Segmentation is a complex challenge that lacks a definitive solution, as it cannot be resolved with a one-size-fits-all approach. An illustrative instance of this is the possibility of generating diverse segmentations by adjusting the bit depth of the heterogeneity measure. It is important to remember that even professional photo-analysts will not observe identical elements.
The incorporation of image-objects is a more straightforward option in vector GIS than raster maps that are classified on a pixel-by-pixel basis.	there is a lack of agreement and a need for further research regarding the conceptual underpinnings of this emerging paradigm, particularly the correlation between image-objects (segments) and landscape objects (patches). One important issue that must be tackled is the rationale behind regarding segmentation-derived objects as precise depictions of landscape structural-functional units.
A large number of OBIA techniques and commercial software packages adopt the robust object-oriented (OO) paradigm.	The level of comprehension of the scale and hierarchical relationships between objects is limited and depends on different permissions in their acquisition.

Table 1:The Weakneesses and the Strengths of OBIA (Hay, G. J., 2006)

2.2. Traditional methods of urban feature detection and the challenges in handling VHR images.

The traditional methods of mapping the land cover are the interpretation of images and semi-automated sequencing classifications. Human analysts often rely on the principles of image interpretation (EII) to discern and classify features such as buildings, transportation infrastructure, agricultural fields, forests, wetlands, soils, and grasslands (Knight, J. F., 2015).

In recent decades, Traditional methods have heavily depended on human effort. However In order to optimize time efficiency, it is highly beneficial to create automated or semi-automated and real-time techniques for detecting urban areas in extensive datasets of remarkably detailed remote sensing images. The reason for this lies in the significant time consumption when processing high-resolution images in large-scale datasets (Tian, T., Li., 2018).

The challenge of analyzing multisource images lies in the misregistration problem between different source layers, such as high-resolution satellite imagery and vector data. Accurate alignment of these datasets has proven to be very challenging, especially in dealing with VHR images. The pixel size of such imagery, measuring below a meter, renders achieving pixel-by-pixel co-registration with vector data almost impossible. Consequently, traditional pixel-based classification methods fail to deliver satisfactory results in the classification of multisource data (Salehi, B., 2012).

2.3. Challenges in Handling VHR Imagery.

Handling Very High-Resolution (VHR) imagery presents several challenges due to the large amount of detailed information contained in the images. Some of the key challenges include:

2.3.1 Data Storage and Transmission

The storage and transmission of satellite images has become one of the biggest challenges. Therefore, the pressure became very important to these images (Hagag, A.. 2017). As a result of this, The current transmission, storage, and processing technologies are under significant pressure due to the large volume of images generated by ultra-high-resolution optical remote sensing satellites.(Ma, X.2023).In addition, the analysis of high-resolution images brings forth significant challenges. Converting raw data obtained through remote sensing into usable images or insightful information necessitates a deep understanding of data science, a substantial investment of time for computation, powerful processing capabilities, and ample financial resources. As the resolution continues to improve, the need for robust computational power and in-house expertise in data science also continues to rise. For instance, an uncompressed image capturing a large metropolis at a resolution of 30 cm would contain millions of pixels' worth of data (Santos, C. 2019).

2.3.2 Computational Complexity

The utilization of large multispectral images increases the computational load, leading to challenges in data storage and transmission. To address this issue, it is crucial and immediate to focus on data compression. However, the acquisition of multispectral data is costly, particularly considering their frequent utilization in analysis and processing tasks like classification or target detection. Therefore, it is necessary to employ lossless compression technology to reduce data volume without losing any information. However, for even greater compression, lossy image compression can be utilized, balancing an acceptable loss of information (Indradjad, A. 2019).

2.4. Image Segmentation

Image segmentation is the first stage of object-based image classification, which means identifying groups of pixels that collectively represent real-world objects(Blaschke, T., 2010). Since the launch of the Landsat-1 satellite, segmentation has been used in remote sensing image processing. However, the arrival of the high-resolution IKONOS satellite in 1999 marked a shift in image analysis from pixel-based to object-based methodologies. As a result, the objective of segmentation has been shifted from helping pixel labelling to object identification (Hossain, M. D., 2019). Mathematically, segmentation can be defined as follows: P() is the homogeneity criteria, R is the entire image and {Ri} will be a segment

of R if: (1) $Ri \subseteq R$ (2) $R = \bigcup_{i=1}^{n} R_i$ (3) $R_i \cap R_j = \emptyset$ (4) $P(R_i \cup R_j) = False$ when $i \neq j$ and R_i and R_j are neighbors (Hossain, M. D., 2019).

The segmentation process improves the representation of spatial, spectral, and textural features compared to analyzing individual pixels (Verbeeck, K. 2012). It can also be defined as the crucial process of dividing the entire scene into separate, non-overlapping regions. The careful selection of input layers greatly influences the segmentation process (Gianinetto, M. 2014). Moreover Image segmentation plays an important role in object-based image analysis (OBIA) , as it greatly affects the final feature extraction and classification results. The eCognition suite offers a variety of procedures derived from basic algorithms. Selection and modification of these algorithms requires a thorough understanding of segmentation theory and photogrammetry. Various segmentation algorithms are available, which are known to the public, such as Checkerboard, Quadtree, Contrast Split, Spectral Difference, Multiresolution (Dezso, B., 2012).

2.4.1. Scale Parameter Determination

Determining the appropriate scale parameter is important but can be tricky for effective image processing. Moreover it is time-consuming and impractical for large-area applications, However, modern OBIA techniques incorporate automatic, scene-specific scale determination methods. These techniques utilize spectral, textural, shape, and contextual information extracted from the images to define the optimal object sizes and boundaries (Chen, G., 2018).

The optimal segmentation scale should produce results that reveal the differences between various blocks while maintaining high internal homogeneity within each block .
Furthermore, there is no specific spatial scale for effectively analyzing and delineating features within a scene. Failure to determine the optimal scale may lead to insufficient selection of parameters for object-based image analysis when segmentation and classification are performed simultaneously. Without the appropriate division preceding the classification, the parameters suitable for classification may not be accurately determined (Ez-zahouani, B., 2023)

2.4.2. Multi-Resolution Segmentation

For remote sensing applications with high resolution (VHR), Multi-Resolution Segmentation (MRS) is a frequently used segmentation algorithm. The most significant difficulties of MRS involve optimizing parameters and evaluating segmentation quality. In order to overcome these issues, we introduce a new measure called the Normalized Segmentation Quality Index (NSQI) and employ level filtering to determine the most suitable parameters for the MRS algorithm. This approach focuses on maximising the level of homogeneity within objects and heterogeneity between them. (Chen, Y., 2021).

2.4.3 Semantic segmentation

Semantic segmentation aims to assign a categorical label to every pixel in an image, which plays an important role in image understanding and self-driving systems (Wang, P., 2018). Per-pixel segmentation classifies pixels by either assigning a single label to each pixel for high-resolution images, or assigning class membership on lower-resolution images because the resolution is not enough to contain an object (Neupane, B., Horanont, T.,2021).

2.4.4 Hierarchical object network

Hierarchical object network is an important component that provides many advantages in image analysis. The hierarchical object Network organizes image objects into a hierarchical structure based on their scale or level of object detail. This hierarchical arrangement allows for a better overall representation of the image scene, capturing features at different levels of resolution (Benz, U. C., 2004).

OBIA approach can analyse an image at different hierarchical levels. Segmentation process creates image object in hierarchical levels. Firstly, segmentation algorithm is applied to the pixel level to create the first an image object level, or to an existing image object level to refine it and to create new sub-levels or super-levels. At this level different image object levels are aware of each other and know their hierarchical relationships. Every Image object has its neighboring image objects at the same hierarchical level and the sub objects at the lower level and multiple image objects are part of a super-object in a higher hierarchical level. These hierarchical relationships among objects can be used to describe class properties (Truax, D. D. 2004).

This object network Objects constructed at different levels of scale can be connected to form a hierarchical object network, similar to the one illustrated in Figure 3. This hierarchical structure allowing for the integration of multi-scale information in image analysis tasks. By linking objects from finer to coarser scales, the hierarchical object network enables a more comprehensive representation of features within the image, facilitating tasks such as classification, segmentation, and feature extraction.

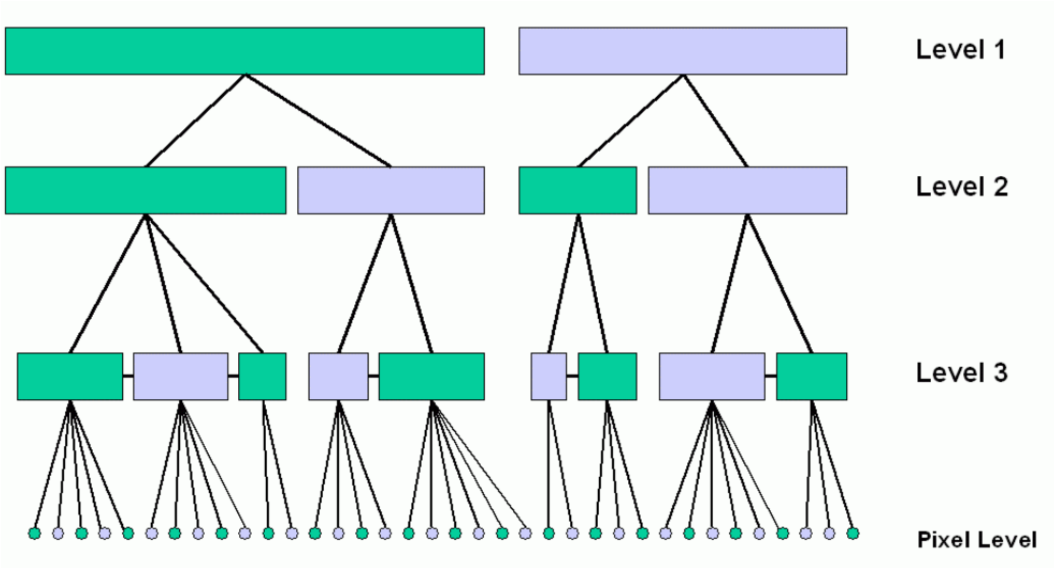

Figure 1: Hierarchical network of image objects *(Truax, D. D. 2004)*

2.5 Image classification

Image classification in Object-Based Image Analysis (OBIA) is a popular method used to analyze and extract land cover from remotely sensed images by grouping pixels into meaningful objects based on their spectral, spatial and contextual properties. (Kucharczyk, M., 2020). Traditional pixel-based classification techniques. take into account the spectral reflectance values of individual pixels of the images and then classify them into classes having define spectral values. Over the past few decades, many classification techniques have been developed. These techniques are aimed at classifying homogeneous features in the image being studied in similar classes. These pre-classification categories known as supervised classification can be defined or automatically defined by the software application using the clustering algorithm 22 also known as unsupervised classification((Gao, Y., Mas, 2007).

2.6 Ruleset transferability

Transferability refers to the ability of a method to produce comparable results with minimum of adaptations when used on images captured under different conditions. Therefore, it pertains to the capacity of a model developed for images taken at one time to be applicable to images taken at another time in the same area (Pratomo, J. 2018). Obia as a model has always performed spatially and objectively improved classification in the analysis of remote-sensed images from pixel-based approaches. Due to the high complexity of the image content, it is still very rare to have powerful and transformable object-based automatic solutions without human interactions. With different imaging conditions or different satellite sensors and their statistics, it is not possible to predict the variety of object characteristics. The rule-based approach in classification does not rely on sample data; instead, it is driven solely by the expertise of the user. In this method, the user formulates a set of conditions or rules, known as a rule set, for each target class based on their knowledge and understanding of the data. These rules incorporate various features of image objects, such as spectral characteristics, size, shape, texture, and contextual information. By integrating these features into the rule set, the user can effectively delineate and classify different classes within the image dataset (Anders, N. S., 2015).

2.7 Related Researches

The table presented below (Table 2) provides a comprehensive overview of various research studies related to the development of a Transferable Object-Based Image Analysis (OBIA) approach.

Title	Authors	Objective	Obia
Application of the trajectory error matrix for assessing the temporal transferability of OBIA for slum detection	Jati Pratomo, Monika Kuffer, Divyani Kohli & Javier Martinez	Evaluating the temporal transferability of OBIA for slum detection using the trajectory error matrix.	Bands : RGB and near infra-red Spatial resolution : 0.5 m
Transferable instance segmentation of dwellings in a refugee camp - integrating CNN and OBIA	Omid Ghorbanzadeh, Dirk Tiede, Lorenz Wendt, Martin Sudmanns & Stefan Lang	developing a transferable instance segmentation method for identifying dwellings in a refugee camp by integrating CNN and OBIA.	WorldView-3 Bands : RGB and near infra-red Spatial resolution : 2 WorldView-2 Bands : RGB and near infra-red GeoEye-1 Bands: RGB and near infra-red
Detailed intra-urban mapping through transferable OBIA rule sets using WorldView-2 very-high-resolution satellite images	Alireza Hamedianfar, Helmi Zulhaidi Mohd Shafri.	conduct detailed intra-urban mapping using transferable OBIA rule sets.	WV-2 include 8 spectral bands Spatial resolution : 2 WV-2 Spatial resolution : 2 WV-2 Spatial resolution : 0.5
TRANSFERABILITY OF OBIA RULESETS FOR IDP CAMP ANALYSIS IN DARFUR	D Tiede, S Lang, D Hölbling, P Füreder	assess the transferability of OBIA rulesets for analyzing Internally Displaced Persons (IDP) camps in Darfur	Two Images GeoEye-1 Spatial resolution : 0.5 m Bands : RGB and near infra-red

Table 2: Overview of OBIA Research Studies and Authors

CHAPTER 3: MATERIALS AND METHODS

3.0 Material and methods

This chapter is divided into three main sub-sections, namely: study area, data collection, and research method. These sub-sections will be presented as follows:

3.1 Study area/Case study

The chosen study area for this research is the city of Münster in Germany. Münster serves as an ideal setting due to its diverse urban landscape, characterized by a mix of historical structures, modern infrastructure, and varying land-use patterns. Münster, located in the North Rhine-Westphalia region in Germany.

3.1.1 Münster (Germany)

The chosen study area for this thesis is the city of Münster in Germany is located in the southwestern part of the city. Münster is located in the North Rhine-Westphalia region in Germany. Münster serves as an ideal setting due to its diverse urban landscape, characterized by a mix of historical structures, modern infrastructure, and varying land-use patterns. Münster includes a variety of places like commercial areas, parks, lakes, sports facilities, shopping centers, and more. Additionally, there are small forests, open spaces without buildings, and agricultural lands in certain areas. Finally, the choice of Münster as the study area elevates the significance of this thesis, as it allows for a thorough exploration of the proposed OBIA approach in a dynamic, diverse, and historically significant urban setting and the transferability of the developed OBIA approach to other urban areas is enhanced. The diverse urban characteristics, coupled with the detailed satellite imagery, contribute to a methodology that is adaptable and transferable to different geographic and urban contexts, thereby increasing the broader applicability of the research outcomes.

Figure 2. The Study area of Munster, Germany

3.1.2 Cologne (Germany)

The second study area of Cologne, is located in the city center of Cologne, with a particular focus on the Port of Niehl situated along the Rhine River in Germany. the intention is to apply the rule set developed in the first study area. By transferring the selected set of rules, which were originally designed for fine-grained analysis of object-based images, the aim is to gain insight into the land cover characteristics and features of Niehl Harbor and its surroundings

Figure 3: The Study area of Cologne, Germany

3.2 Data Preparation and Software

As the objective of this research is to develop a rule set/workflow based on semi-automated extraction and classification of urban features is based on the use of very high resolution (VHR) satellite imagery and object-based image analysis (OBIA) software. Therefore, two VHR Images satellite scenes were used, image of part of Münster, Germany , and of centre of Cologne, Germany. The data was downloaded from geoportal of NRW powered by Esri, which holds all the rights for their distribution, a very high-resolution satellite image with RGB and near-infrared bands of the area was needed.

3.2.1 Münster (Germany)

Info	**Bands**	**Wavelengths (mm)**	**Resolution (m)**
Location: **Münster**	Red	450 - 495 nm	0.1
Date Acquired : 28 April, 2023	Green	500 - 550 nm	0.1
	Blue	620 - 750 nm	0.1
	NIR	750 - 900 nm	0.1

Table 3 Data description of Munster, Germany

The first Image of south-western part of Münster. The image captured on 28 April, 2023, is very high resolution with a spatial resolution of 0.1 meters and includes four spectral bands: Red (R), Green (G), Blue (B), and Near-Infrared (NIR). The projection used is ETRS89/UTM_Zone_32N.

3.2.2 Cologne (Germany)

Info	Bands	Wavelengths (mm)	Resolution (m)
Location: Cologne	Red	450 - 495 nm	0.1
Date Acquired : 24 May, 2023	Green	500 - 550 nm	0.1
	Blue	620 - 750 nm	0.1
	NIR	750 - 900 nm	0.1

Table 4 Data description of Cologne, Germany

The second image of the city center of cologne Shows the Port of Niehl on the Rhine River in Germany. The image captured on 24 May, 2023, is very high resolution with a spatial resolution of 0.1 meters and includes four spectral bands: Red (R), Green (G), Blue (B), and Near-Infrared (NIR). The projection used is ETRS89/UTM_Zone_32N.

3.2.3 Software

eCognition Developer software package was used in this thesis for development and creating adaptable rule-set of the OBIA. This software is designed with the goal of accelerating and automating the analysis of geospatial data. It enables remote sensing organizations to quickly extract accurate and reliable geo-information from any kind of geospatial data. eCognition Developer has a wide array of algorithms can be dynamically combined to create a personalized application that reflects the user's desired analysis approach and requirements.

QGIS software and ArcGIS software also was used to manage and manipulating GIS data, generating reference data for accuracy assessment, and produce final visualizations for maps.

3.3 Research Method:

The research methodology in this thesis consists of seven steps. The first step is pre-processing for the data by collecting and organizing it and Ensure the accuracy of the analysis. Next, the second step is the segmentation. The third step involves determining the key object features and run thresholds to classify different features. Next, the rule set is developed in step four, guiding the classification process. The fifth step is the final classification of the data based on the established rule-set and create land cover map. To ensure the accuracy of the results, the sixth step involves evaluating the accuracy and validating the LULC map. Finally, the transferability of the approach to the second study area is evaluated and the accuracy and validation are assessed to map, analyze and draw meaningful conclusions from the data in a structured manner.

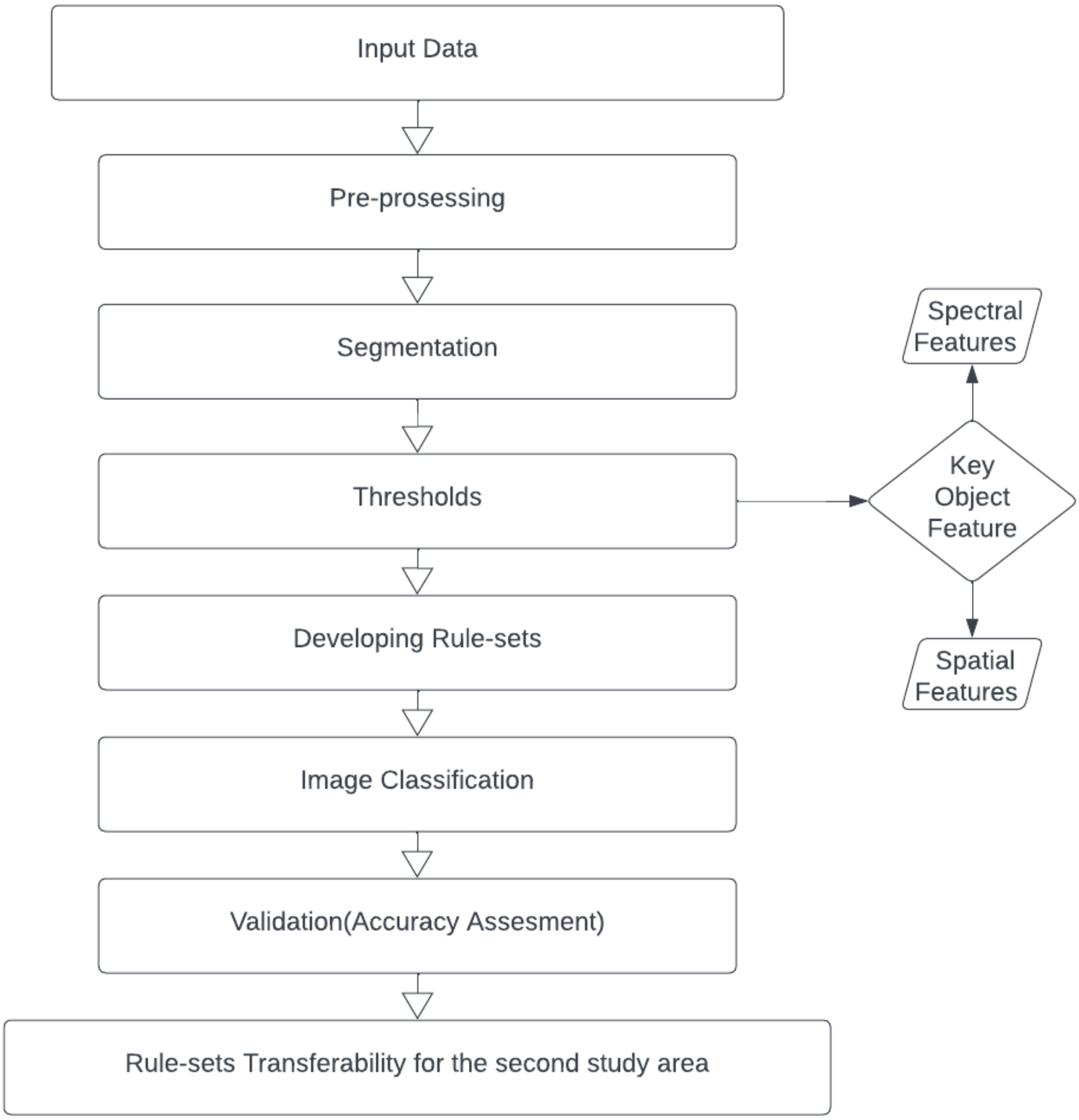

Figure 4: Workflow demonstrating the approach and the steps.

3.3.1. Data pre-processing

In the first step of the research, the focus was on preparing and optimizing the acquired data to develop an Object-Based Image Analysis (OBIA) approach directed toward detecting and classifying urban features. in this process involved downloading the relevant datasets. Then, to simplify the analysis, the rasters were combined into a single Geotiff format file t in order to use them in different software. This pre-processing step ensures that the data is well structured and ready for further segmentation, thresholding, rule set development and final classification, as explained in the larger context of the thesis. These additional processing allows to produce a cleaner vector segmentation output which can then be used in a GIS software.

3.3.2 Image segmentation

Image Segmentation is an important step in the object-based image analysis. Segmentation techniques enhance automatic classifications using not only spectral features, but also shape, texture, hierarchical and contextual information. The choice of segmentation scale parameter plays an important role in the accuracy and reliability of ground object information extraction and recognition. The scale parameter dictates the size of the generated segments, while the shape and compactness weighting values influence their shape. A smaller scale value yields smaller segments, whereas a larger scale value produces larger segments. The shape and compactness parameters range from 0 to 1, with lower shape values prioritizing color, typically crucial for meaningful object creation. Shape and compactness values range from 0 to 1, with lower shape values placing more emphasis on color, which is important for creating meaningful objects. Higher compactness values make the object boundaries tighter, such as what you find in crop fields or buildings (Khadanga, G. 2014).

Several image segmentation algorithms are provided by the eCognition software package. The selection of algorithm depends on the application and the purpose of the segmentation process. To create rule set , Multiresolution Segmentation, Spectral difference segmentation, algorithms were mostly used.

3.3.2.1 Multiresolution Segmentation

The Multiresolution segmentation algorithm was created and implemented into the commercial software eCognition (Tian,J.,2007). Multiresolution Segmentation algorithm consecutively merges pixels or existing image objects. Essentially, the procedure identifies single image objects of one pixel in size and merges them with their neighbours, based on relative homogeneity criteria. This homogeneity criterion is a combination of spectral and shape criteria. Alternatively, With any given average size of image objects, multiresolution segmentation yields good abstraction and shaping in any application area. However, it puts higher demands on the processor and memory, and is significantly slower than some other segmentation techniques – therefore it may not always be the best choice (Atik, S. O., 2021). The Scale parameter plays a vital role in this algorithm, as it defines the maximum permissible spectral heterogeneity for the resulting objects. Essentially, this parameter dictates the size of the identified objects, with higher values indicating larger objects. When dealing with heterogeneous data, the resulting objects tend to be smaller compared to instances with higher data homogeneity. The Scale parameter, which measures the degree of object homogeneity, comprises three internal parameters: color, shape, and compactness. Multi-resolution segmentation with a specific set of parameters may be good at providing meaningful objects for one feature class but bad for another. Regarding the definition of meaningful objects, segmentation should be evaluated carefully according to the feature class of interest (Tian, J., 2007).

	Level (1)	**Level (2)**
Scale Parameter	100	45
Shape	2	3
Compactness	8	7

Table 5: Multiresolution Segmentation Parameters for Münster

In table 5 shows The delineates parameters utilized in multiresolution segmentation, a pivotal technique in image analysis for partitioning images into homogeneous regions. The "Scale Parameter" defines segment size, with a value of 100 for Level 1 resulting in larger segments and 45 for Level 2 leading to smaller ones. The Shape parameter influences segment regularity, with a value of 2 for Level 1 producing less uniform shapes and 3 for Level 2 yielding more uniform ones. Compactness determines the tightness of pixel clustering within segments, with a value of 8 for Level 1 indicating less smooth boundaries and 7 for Level 2 indicating smoother ones. These parameters govern segmentation, enabling customization of segment characteristics based on analysis requirements and data features. Adjusting them optimizes segmentation precision, aiding in extracting meaningful insights from images.

3.3.2.2. Spectral difference segmentation

The spectral difference segmentation algorithm allowed for merging of several neighboring image objects that in reality does not Show anything meaningful into larger image objects that often represent larger real world objects better. The vegetation often has spectral response similar to built-up objects similar to built-up objects. At this level, large and relatively homogeneous surfaces, such as bare soil or farm land are segmented by a single compact image object. This representation provide an opportunity to select and use the area features of these image objects to separate them them from the urban areas filled with buildings. Since built-up objects are usually smaller and less homogenous compared to agricultural bare soil fields.

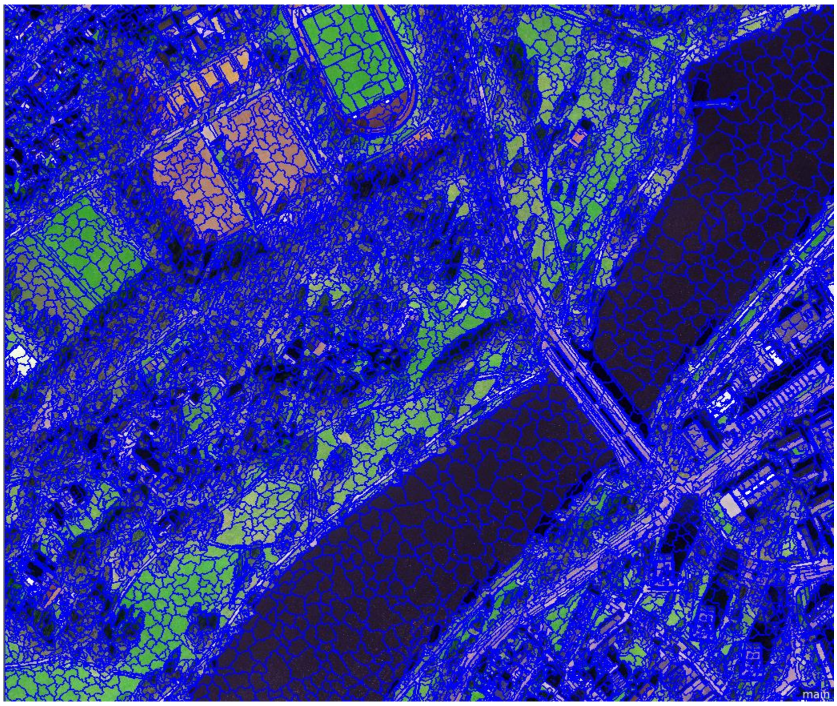

Figure 6 Result for Multiresolution Segmentation   (The center of study area Munster Level 1)

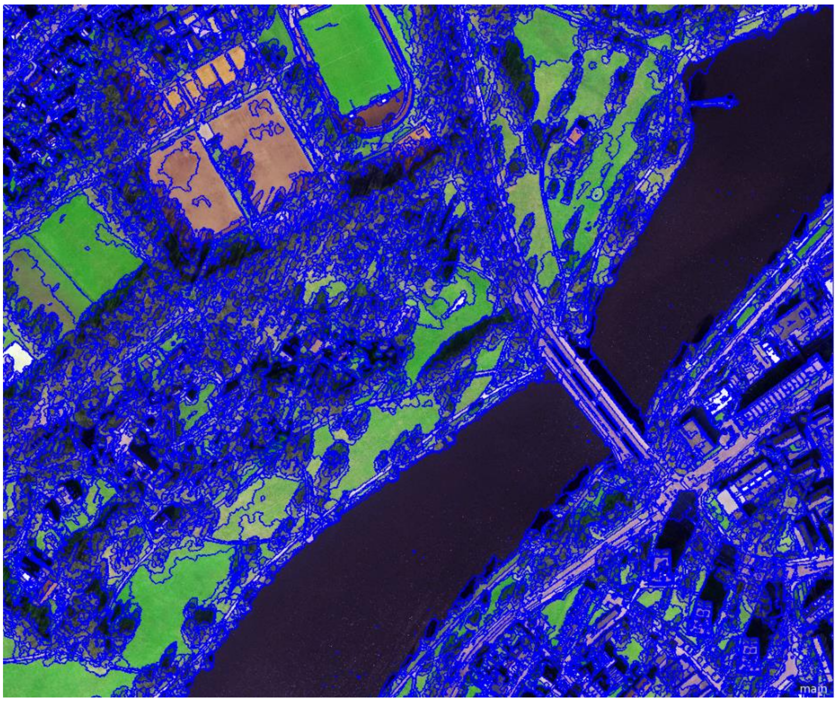

Figure 5 Result for Spectral difference Segmentation   (The centre of study area Munster Level 1)

3.3.3. Thresholds and features selection

In order to obtain a detailed land cover classification as this was one of the main steps to achieve the goal of this thesis, the image objects were classified at the analysis level into several land cover categories as follows: building, water, grass, trees, shade, and bare soil. Different spectral and spatial features were used in creating the classification rule set in order to reliably classify image objects into land cover classes. Multiple spectral object features and image operators were utilized to analyze the Very High-Resolution (VHR) images. These features served two main purposes: segmenting images and classifying different surfaces. Specifically designed features were employed to highlight specific surfaces such as vegetation, built-up areas, and water bodies. After computing these indices, appropriate thresholds were applied to classify the identified surfaces. Additionally, certain indices focused on delineating object edges, aiding in the precise delineation of objects during the image segmentation process. As Table 6 shows, each row represents a particular land cover class, detailing the spectral and spatial features used for classification. For example, built-up areas are extracted using the Natural Difference Vegetation Index (NDVI) and red band, While bodies of water are identified using a combination of Normalized Difference Water Index (NDWI), NDVI, and Near Infrared (NIR). while shadows are classified by the difference between NIR and NDVI. along with spatial features like asymmetry and area per pixel.

Class	**Spectral features**	**Spatial features**
Built-up	NDVI-Red	Area (Pxl)
Bare soil	NDVI	
Water	NDWI- NDVI- NIR	Area (Pxl)
Trees	NDVI-NIR-Brightness	
Shadow	NIR-NDVI	Asymmetry- Area (Pxl)
Grass	NDVI	

Table 6 spectral and spatial features used.

3.3.3.1 Normalized Difference Water Index (NDWI)

The Normalized Difference Water Index (NDWI) is a spectral index that has been advanced to detect the existence of open water features in digitally captured remote sensing images (remotely-sensed digital imagery.). This index efficiently filters out non-water objects such as shadows, while highlighting the presence of water. By utilizing the reflected near-infrared radiation and visible green light, NDWI successfully suppresses soil and vegetation features. Although there is an alternative version of NDWI that employs short-wave infrared (SWIR) for monitoring changes in leaf water content, this study focuses on identifying and classifying water bodies. Hence, the SWIR bands were not available in the Very High Resolution (VHR) datasets utilized. As a result, the Normalized Difference Water Index NDWI algorithm (Ji, L. 2009) was chosen for this purpose. The NDWI Formula is :

$$NDWI = (GREEN - NIR)/(GREEN + NIR)$$

The NDWI values are obtained after conducting calculations using the Near Infrared and Green spectral bands, In NDWI, high values typically indicate the presence of water. This is because NDWI is calculated based on the difference in reflectance between near-infrared (NIR) and green or blue wavelengths. Water absorbs more strongly in the NIR range and reflects less, while it reflects more in the visible green or blue range. Therefore, when water is present, there is a high contrast between the NIR and visible bands, resulting in high NDWI values.

Resulting NDWI image, with high values in water surfaces can be seen in Figure 7.

Figure 7 NDWI calculated Result in Munster

3.3.3.2 Normalized Difference Vegetation Index (NDVI)

The NDVI is commonly employed to assess Vegetation Index and crop health in agricul ture land. Due to variations in soil characteristics across different areas within a field, varying amounts of nitrogen may be required to achieve optimal yield (Bhandari, A. K. 2012).

At the outset, researchers performed an analysis of land cover images by employing the widely accepted Normalized Difference Vegetation Index (NDVI). This index serves as a prominent tool in recognizing vegetated areas and has been extensively utilized in various studies to discern between regions with or without vegetation. The The NDVI is calculated as:

$$NDVI = (NIR - RED)/(NIR + RED)$$

The NDVI values are obtained after conducting calculations using the Near Infrared and Red spectral bands, and are measured on a scale ranging from -1 to 1.where NIR and RED are the mean values of all pixels (within the boundary of each object). Higher NDVI values are indicative of the presence of thriving green vegetation, whereas lower values may suggest stressed plants, barren soil, impervious artificial surfaces, and very low values indicate for bodies of water. Subsequently, NDVI was applied for the classification of vegetated areas. Based on visual verification and examination of the image objects representing vegetation. the lower threshold for the lower threshold for classifying vegetation areas was established at -0.20 in the study area of Munster.

Resulting NDVI image, with high values in Vegetation surfaces can be seen in Figure 8 .

Figure 8 NDVI calculated Result in Munster

3.3.4 Develop OBIA rule sets:

The detailed land cover classification was the aim of this project and In order to detect urban features, Image objects are classified at the analysis level into several land cover classes as following built up, water, grass, trees, Shadow and bare soil. Various spectral, spatial, textural or contextual features were employed in the classification rule set establishment in order to reliably classify image objects into land cover classes. Table 7 provided outlines a rule-set for classifying different urban features classes based on specific threshold values of remote sensing indices. the columns specify the thresholds used for classifying each class. For instance, areas classified as "Built-up" are characterized by having a Red band value greater than 175 and a Normalized Difference Vegetation Index (NDVI) less than -0.2. Similarly, Bare soil areas are identified by an NDVI ranging between -0.20 and 0, while Water areas are defined by a Normalized Difference Water Index (NDWI) greater than 0.6 along with specific thresholds on NDVI and Near-Infrared (NIR) bands. Each class is distinguished by combination of spectral and spatial feature and their respective threshold values, enabling Semi-automated classification of land cover types in remote sensing imagery.

Classes	**Thresholds used**
Built-up	Red > 175 NDVI < -0.2
Bare soil	-0.20 < NDVI < 0
Water	NDWI > 0.6 NDVI < -0.65 NIR < 13
Trees	NDVI < 0.33 NIR < 95
Shadow	NDWI < 35 NDVI > -55 Asymmetry < 0.85 Area(Pxl) < 10000
Grass	NDVI > 0 NIR > 110

Table 7 : Image object features and threshold used for Image classification.

3.3.5 Rule-Based Classification

Image classification, an important step, reveals how the set of rules generated, based on specific features, classifies different urban features. The results of this process give us a visual map showing where these urban features are located in the map. In order to extract urban features, image objects at the analysis level were classified into several land cover classes.as following (built-up, bare soil, water, trees, shadow, grass) Various spectral, spatial, textural or contextual features were employed in the classification rule set establishment in order to reliably classify image object .

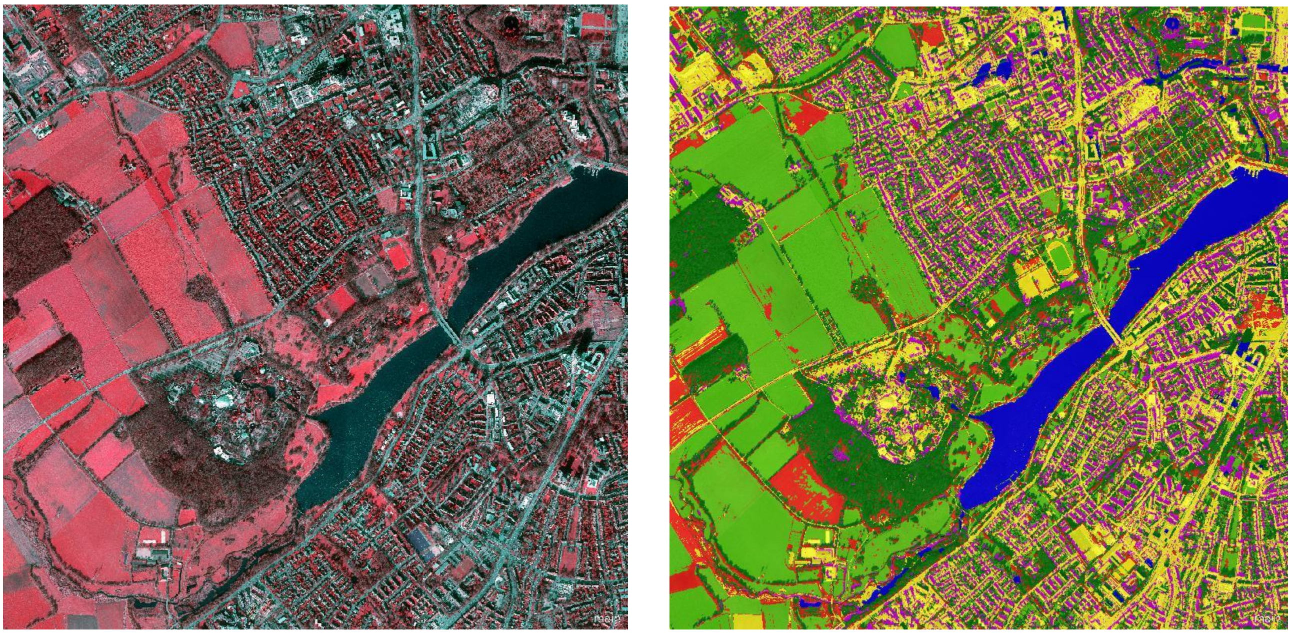

Figure 9: Result of rule based classification

(color: Yellow = built-up, Bare soil = red, water= blue, trees=dark green, shadow=magenta, grass=green)

3.3.5.1 Merge Region

The Merge Region algorithm combines neighboring image objects of created classes into a single larger object and representative shapes (ecognition). This step is important to decrease the number of objects. This type of algorithm can be useful in many applications such as image segmentation, object recognition, and scene understanding.

3.3.5.2 Reclassification

In the this step the image objects were reclassified and assigned to different classes in order to correct the first classification errors. The aim of reclassification is to bring the land cover image representation the closest possible to the reality. In the last step, after the classification was completed the resulted built-up class excluded the shadows in the builtup classification because the built-up areas in the shadows have lower reflectance values in all bands. Since the shadows are not real physical surfaces and they may change over time with the angle of the Sun, and they should not be mapped. They should be reassigned to their neighboring classes where they most likely belong to as shadows. Shadows that are near built-up areas most likely belong to other built-up areas, such as lower buildings road, parking lots and other infrastructure objects. Based on the above assumption, the image objects that classified as shadows which were very close to built-up image objects, has been reclassified into built-up class. The reclassification has been done using class related features that include distance to image objects of built-up class or common border with image objects.

3.3.6. Accuracy assessment (Münster, Germany)

After completing the land cover classification and creating a land cover map, an accuracy assessment was performed to evaluate the classification results.The Reference points for each land cover class were obtained through visual interpretation of the original VHR image. The classes include Bare soil, Built-up, Grass, Shadow, Trees, and Water. The points were randomly distributed throughout the entire scene. 30 reference points was collected for both Bare soil and water while 45 reference points for built-up area and shadow and 60 points for the grass and trees because the portion of grass class on the whole image was much higher in comparison to other classes. A standard classification confusion matrix was produced for the land cover map and the Overall accuracy were calculated.

3.3.7 Rule-sets Transferability

After conducting an accuracy assessment of land cover classification in the first study area, Munster, the obtained rule sets were compared with those necessary for classification in the second study area (Cologne), to determine their transferability and adaptability. Table 8 shows the specific thresholds used for various land cover classes in both study areas. In comparing the two rule-sets of thresholds, It's clear that certain rules stay the same in both study areas. For example, in the classification of built-up class, Münster relies on a combination of thresholds related to red band intensity and NDVI values, with a higher threshold for the former (>175) compared to that of Cologne (>70).

	Study Area (Münster)	**Study Area (Cologne)**
Class	**Thresholds used**	**Thresholds used**
Built-up	Red > 175 NDVI < -0.2	Red > 70 NDVI < 0.15
Bare soil	-0.20 < NDVI < 0	0.6 < NDVI < 0.9
Water	NDWI > 0.6 NDVI < -0.65 NIR < 13	NDWI > 0.35 NDVI < -0.27
Trees	NDVI < 0.33 NIR < 95	NDVI < 0.7 NIR < 140
Shadow	NIR < 35 NDVI > -55 Asymmetry < 0.85 Area(Pxl) < 10000	NIR < 78 NDVI > -30 Area(Pxl) < 100000
Grass	NDVI > 0 NIR > 110	NDVI > 0.108 NIR > 92

Table 8: Comparison of Land Cover Classification Thresholds between Münster and Cologne Study Areas

CHAPTER 4: RESULTS AND DISCUSSION

4.1.1 Land cover classification (Münster, Germany)

After the rule-based classification, we conducted a thorough review and refinement process to address specific classification issues, such as the misidentification of shadowed areas. Shadows pose a challenge in accurately categorizing urban features due to their variable intensity and spectral characteristics. To mitigate this issue, we implemented targeted reclassification strategies. Specifically, we reclassified objects located in shadowed regions, utilizing spectral and spatial features to reallocate them to their appropriate land cover classes.

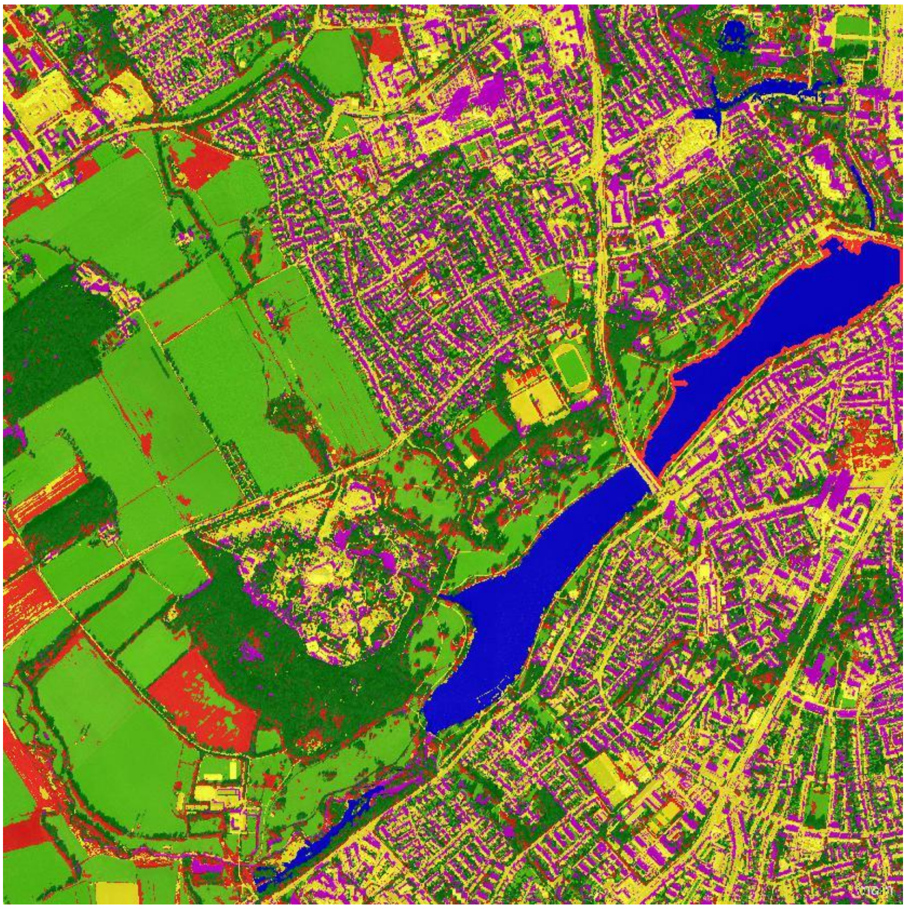

Figure 10: Result of land cover classification (Munster)

4.1.2 Land cover area statistics (Münster, Germany)

Following the final result of the land cover, some statistics were calculated for the result of the land cover map, These statistics include the total area and relative area of each class, in order to clarify the quantitative result of the distribution of land cover. The findings are presented in **Table 9** offering a detailed overview of the area occupied by each class and facilitating a comprehensive understanding of the relative proportions of different land cover types within the studied region.

Munster- LULC Statistics		
Classes	**Area_ha**	**Percentage %**
Built-up	42.464864	4.7917%
Bare soil	89.048212	10.0482%
Water	128.887396	14.5437%
Trees	197.139108	22.2452%
Shadow	211.430084	23.8578%
Grass	217.238936	24.5133%
Total	**886.2086**	**100**

Table 9: Area and percentage occupied by each land cover in Munster, Germany

The land cover information for the region of Munster offers valuable insights into the distribution of various land use and cover types. Grass dominates the landscape, covering the largest proportion of land at 24.51%, closely followed by shadow at 23.86%. also contribute significantly, occupying 22.25% of the landscape. Water bodies and bare soil are prominent features, accounting for 14.54% and 10.05% respectively, while built-up areas make up 4.79% of the land. These statistics provide a comprehensive overview of Munster's diverse land cover, highlighting the harmonious balance between natural elements such as trees, grass, and water, as well as the influence of human-made structures like built-up areas. These informations are crucial for urban planning, environmental monitoring, and sustainable development efforts in the region.

4.1.3 Accuracy assessment (Münster, Germany)

Münster classification - confusion matrix							
Classification	**Reference (px)**						
	Bare soil	Built-up	Grass	Shadow	Trees	Water	**Grand Total**
Bare soil	16	1	2				19
Built-up	7	43		2	2		54
Grass	4		54		1		59
Shadow				43	10	1	54
Trees	3	1	4		47		55
Water						29	29
Grand Total	30	45	60	45	60	30	270
Overall Accuracy = (232/270) 85.9259%							

Table 10: Confusion matrix for Land Cover classification - Münster city

The confusion matrix above shows an accuracy assessment of the land cover classification map for Münster city. The diagonal cells represent correct classifications, showing the number of pixels accurately identified for each land cover class. In contrast, the off-diagonal cells display misclassifications, pinpointing areas where classification errors occurred. Table 9 shows that in the row corresponding to Bare soil, 16 pixels were correctly classified as Bare soil, while 7 pixels were misclassified as Built-up. Similarly, in the Built-up row, 43 pixels were correctly classified as Built-up, while 1 pixel was misclassified as Bare soil. The overall accuracy of approximately 85.92% signifies the percentage of correctly classified pixels out of the total number of reference pixels, demonstrating the effectiveness of the classification process.

4.1.4 Land cover classification (Cologne, Germany)

After applying and transferring the developed rulesets to the second study area (Cologne), it's essential to conduct a thorough evaluation to assess the performance of the classification in this new area. The segmentation algorithm and parameters utilized were the same for both image scenes. Nonetheless, the classification rules used to arrange some land cover classes must be optimized and improved for each image. The segmentation algorithm and parameters utilized were the same for both image scenes. Nonetheless, the classification rules used to arrange some land cover classes must be optimized and improved for each image. Nonetheless, after effectively classifying the land cover and extracting the urban features. all the accompanying image processing algorithm and calculations were utilized similarly, with similar parameters on the two images.

Figure 11: Result of land cover classification using the developed ruleset in Cologne

4.1.5 Accuracy assessment (Cologne, Germany)

After transferring the rule sets to the second study area (cologne) and performing the classification, an accuracy assessment was conducted to validate the classification results. The Reference points for each land cover class were obtained through visual interpretation of the original VHR image. The classes include Bare soil, Built-up, Grass, Shadow, Trees, and Water. The points were randomly distributed throughout the entire scene. 30 reference points was collected for both Bare soil and water while 45 reference points for built-up area and shadow and 50 points for the grass and trees because the portion of grass class on the whole image was much higher in comparison to other classes. A standard classification confusion matrix was produced for the land cover map and the Overall accuracy were calculated as shown in table 10.

Cologne classification - confusion matrix							
Classification	**Reference (px)**						
	Bare soil	Built-up	Grass	Shadow	Trees	Water	**Grand Total**
Bare soil	18	4	1				19
Built-up	8	40		1	1		54
Grass	2		46		4		59
Shadow				42	2		54
Trees	2	1	3	2	43		55
Water						30	29
Grand Total	30	45	50	45	50	30	250
Overall Accuracy = (219/250) 87.6000%							

Table 11: Confusion matrix for Land Cover classification - Cologne city

4.2 Discussion

This discussion delves into the key findings, implications, and future directions stemming from the research. The aim of this thesis was to create a rule set that could be easily adapted and transferred to different study areas based on careful analysis of selected spectral and spatial features. Threshold values were established for various classes including built-up areas, bare soil, water bodies, trees, shadow, and grass. These thresholds were customized for each study area, reflecting the unique spectral signatures of urban features in Munster and Cologne. One of the crucial aspects that significantly influenced the success of the developed OBIA approach was the careful consideration of the segmentation parameter scale. The segmentation scale determines the size and shape of image objects used for classification. Selecting an appropriate segmentation parameter scale. can be challenging and requires a balance between capturing fine details and avoiding over-segmentation. the segmentation scale parameter was optimized to ensure accurate object delineation for classification.

One of the challenges encountered rule sets based on classification is distinguishing between shadows and water bodies, Shadows cast by buildings and trees can exhibit spectral characteristics similar to water bodies, making it difficult to differentiate between the two classes. The Similarity in spectral signatures can lead to misclassification and reduce the accuracy in detecting water bodies. The NDWI and NDVI are useful features for extracting water bodies and vegetation. However, the values of these features of the shadows may resemble those of water bodies, which complicates the classification process. As a result, relying only on spectral features may not be enough to accurately distinguish shadows from other land cover types.

Incorporating spatial features into the classification process provides additional contextual clues that can help extract shadows from other classes or extract new urban features from the scene and improve classification accuracy. For example in first study area(Münster), the asymmetry of object shapes and the size of image objects in terms of area (pixels) was a useful spatial features for extracting the shadows from water bodies. While in second study area (cologne), area (pixels) was enough to separate the shadow from the water bodies.

To summarize that we can say that the more urban features are incorporated into the classification process, the better the algorithm can differentiate between different land cover classes. Additionally, the complexity of the urban landscape and the scale of the image also play important roles in determining the adequacy of the features used.

As we have seen from the results of the land cover classification in both study areas, the quantitative assessments of these outcomes, our proposed techniques. The assessment of the developed OBIA approach revealed high classification accuracies for both Munster 85.92% and Cologne 87.60%. It was noticed that in the first study area (Münster), 7 points were incorrectly classified as built-up areas within bare soil, and 10 points were mistakenly classified as shadows within trees. This highlights the need to include more features to enhance accuracy in these classes. In the second study area (Cologne), 10 points were mistakenly classified as shade within trees, 8 points were misclassified as built-up areas within bare soil, and 4 points were incorrectly classified as grass within trees.

The developed ruleset was conducted on two different study areas. It would be better to test the created ruleset on a third VHR image from different urban environments to see the results compare them and confirm these conclusions. To enhance the transferability and the adaptability of the developed ruleset to be used with other VHR imagery and minimize classification optimization efforts, input images should be standardized in some way and taken at the same time of the day with similar illumination conditions, or the same season with similar phenological conditions, or by proper atmospheric corrections or histogram matching or image equalization techniques. To improve the accuracy of the land cover classification.

CHAPTER5:CONCLUSION,RECOMMENDATIONS, AND FUTURE WORK

In this chapter two sections are presented, the first section represents the conclusion of the study, and the second section is Recommendations and future plan.

5.1 Conclusion

This thesis has aimed to develop a rule set for semi-automated land cover classification in very high-resolution (VHR) satellite images. The primary objective was to create a transferable methodology adaptable to various urban environments, with a focus on the cities of Munster and Cologne. The research successfully established a rule set based on spectral and spatial features designed for different study areas. this was achieved by the careful selection of key spectral and spatial features. coupled with the appropriate selection of segmentation parameters. The approach was implemented in eCognition software and a rule-based classification map. The results demonstrated promising classification accuracies for both Munster (85.92%) and Cologne (87.60%) study areas, It can be concluded from this research that first attempting to classify urban features at a single segment level may not be possible due to variations within urban landscapes. which present a multitude of features with unique characteristics, making it challenging to accurately delineate them using a uniform, second The Shadowing is a common challenge in very high-resolution images affecting feature accuracy and classification. third Different rule sets need to be developed based on features of different objects and separated into one comprehensive map. Third the Spectral features alone may not be sufficient to differentiate shadows from other land cover types accurately. Integrating spatial features, such as shape, texture, and context, could enhance the discrimination capabilities of the OBIA approach. Spatial features provide valuable contextual clues that can help distinguish shadows from other classes. The approach however fails to fully capturing the complexity and variability of urban environments.

5.2 Recommendations and future work

In case additional spectral bands are available, it's advisable to explore the computation of different spectral indices to enhance land cover classification and thereby improve the accuracy of extracting built-up areas and buildings. Moreover, if accessible, integrating Digital Surface Models (DSM) into the analysis could lead to more precise identification of buildings and trees. Since buildings and trees are elevated objects, leveraging DSM data can provide additional height information, enhancing land cover classification and significantly improving the extraction of built-up areas. And also If additional ancillary data sources are accessible, integrating them into the developed approach could greatly enhance land cover classification accuracy and subsequently improve the overall results. another crucial step to enhance the developed approach is the conversion of RGB (Red, Green, Blue) bands to HSI (Hue, Saturation, Intensity) color space can offer several advantages in land cover classification. HSI separates the color information (Hue) from brightness (Intensity) and saturation, making it more suitable for analyzing spectral characteristics independently of illumination effects.

References

Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of photogrammetry and remote sensing*, *58*(3-4), 239-258.

Bobáľová, H., Benová, A., & Kožuch, M. (2021). Hierarchical Object-Based Mapping of Urban Land Cover Using Sentinel-2 Data: A Case Study of Six Cities in Central Europe. *PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, *89*, 15-31.

Chen, J., Du, P., Wu, C., Xia, J., & Chanussot, J. (2018). Mapping urban land cover of a large area using multiple sensors multiple features. *Remote Sensing*, *10*(6), 872.

Sertel, E., & Akay, S. S. (2015). High resolution mapping of urban areas using SPOT-5 images and ancillary data. *International Journal of Environment and Geoinformatics*, *2*(2), 63-76.

United Nations. (2022). *Goal 11: Make cities inclusive, safe, resilient and sustainable*. United Nations Sustainable Development; United Nations. https://www.un.org/sustainabledevelopment/cities/

Moskal, L. M., Styers, D. M., & Halabisky, M. (2011). Monitoring urban tree cover using object-based image analysis and public domain remotely sensed data. *Remote Sensing*, *3*(10), 2243-2262.

Salehi, B., Zhang, Y., Zhong, M., & Dey, V. (2012). Object-based classification of urban areas using VHR imagery and height points ancillary data. *Remote Sensing*, *4*(8), 2256-2276.

Kurniawan, A. (2020, May). The use of obia for extraction of land cover and land use in the city of palu. In *IOP Conference Series: Earth and Environmental Science* (Vol. 485, No. 1, p. 012053). IOP Publishing.

Lichtblau, E., & Oswald, C. J. (2019). Classification of impervious land-use features using object-based image analysis and data fusion. *Computers, Environment and Urban Systems*, *75*, 103-116.

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS journal of photogrammetry and remote sensing*, *65*(1), 2-16.

Ma, L., Li, M., Ma, X., Cheng, L., Du, P., & Liu, Y. (2017). A review of supervised object-based land-cover image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *130*, 277-293.

Sertel, E., & Akay, S. S. (2015). High resolution mapping of urban areas using SPOT-5 images and ancillary data. *International Journal of Environment and Geoinformatics*, *2*(2), 63-76.

Phiri, D., & Morgenroth, J. (2017). Developments in Landsat land cover classification methods: A review. *Remote Sensing*, *9*(9), 967.

Labib, S. M., & Harris, A. (2018). The potentials of Sentinel-2 and LandSat-8 data in green infrastructure extraction, using object based image analysis (OBIA) method. *European Journal of Remote Sensing*, *51*(1), 231-240.

Neupane, B., Horanont, T., & Aryal, J. (2021). Deep learning-based semantic segmentation of urban features in satellite images: A review and meta-analysis. *Remote Sensing*, *13*(4), 808.

Pratomo, J., Kuffer, M., Kohli, D., & Martinez, J. (2018). Application of the trajectory error matrix for assessing the temporal transferability of OBIA for slum detection. *European journal of remote sensing*, *51*(1), 838-849.

Chen, G., Weng, Q., Hay, G. J., & He, Y. (2018). Geographic object-based image analysis (GEOBIA): Emerging trends and future opportunities. *GIScience & Remote Sensing*, *55*(2), 159-182.

Truax, D. D. (2004). Comparing spectral and object based approaches for classification and transportation feature extraction from high resolution multispectral imagery.

Anders, N. S., Seijmonsbergen, A. C., & Bouten, W. (2015). Rule set transferability for object-based feature extraction: An example for cirque mapping. *Photogrammetric Engineering & Remote Sensing*, *81*(6), 507-514.

Meyer, M. F., Pfeffer, I., & Jürgens, C. (2019). Automated detection of field monuments in digital terrain models of Westphalia using OBIA. *Geosciences*, *9*(3), 109.

Zaki, A., Buchori, I., Sejati, A. W., & Liu, Y. (2022). An object-based image analysis in QGIS for image classification and assessment of coastal spatial planning. *The Egyptian Journal of Remote Sensing and Space Science*, *25*(2), 349-359.

Gao, Y., Mas, J. F., Niemeyer, I., Marpu, P. R., & Palacio, J. L. (2007, June). Object-based image analysis for mapping land-cover in a forest area. In *Proc. of 5th International Symposium on Spatial Data Quality*.

Hamedianfar, A., & Shafri, H. Z. M. (2015). Detailed intra-urban mapping through transferable OBIA rule sets using WorldView-2 very-high-resolution satellite images. *International Journal of Remote Sensing*, *36*(13), 3380-3396.

Bacha, A. S., Van Der Werff, H., Shafique, M., & Khan, H. (2020). Transferability of object-based image analysis approaches for landslide detection in the Himalaya Mountains of northern Pakistan. *International journal of remote sensing*, *41*(9), 3390-3410.

Bilotta, G., Nocera, R., & Barone, P. M. (2021). Cultural heritage and OBIA. *WSEAS Trans. Environ. Dev*, *17*, 449-465.

Hay, G. J., & Castilla, G. (2006, July). Object-based image analysis: strengths, weaknesses, opportunities and threats (SWOT). In *Proc. 1st Int. Conf. OBIA* (pp. 4-5).

Han, R., Liu, P., Wang, G., Zhang, H., & Wu, X. (2020). Advantage of combining OBIA and classifier ensemble method for very high-resolution satellite imagery classification. *Journal of Sensors*, *2020*, 1-15.

Kavzoglu, T., Yildiz Erdemir, M., & Tonbul, H. (2016). A region-based multi-scale approach for object-based image analysis. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *41*, 241-247.

Hossain, M. D., & Chen, D. (2019). Segmentation for Object-Based Image Analysis (OBIA): A review of algorithms and challenges from remote sensing perspective. *ISPRS Journal of Photogrammetry and Remote Sensing*, *150*, 115-134.

Dronova, I. (2015). Object-based image analysis in wetland research: A review. *Remote Sensing*, *7*(5), 6380-6413.

Ez-zahouani, B., EL Kharki, O., Kanga Idé, S., & Zouiten, M. (2023). Determination of Segmentation Parameters for Object-Based Remote Sensing Image Analysis from Conventional to Recent Approaches: A Review. *International Journal of Geoinformatics*, *19*(1).

Dezso, B., Fekete, I., Gera, D., Giachetta, R., László, I., Benczúr, A., ... & Giachetta, R. (2012). Object-based image analysis in remote sensing applications using various segmentation techniques. In *Annales Universitatis Scientiarum Budapestinensis de Rolando Eotvos Nominatae Sectio Computatorica* (Vol. 37, pp. 103-120).

Knight, J. F., Corcoran, J. M., Rampi, L. P., & Pelletier, K. C. (2015). Theory and applications of object-based image analysis and emerging methods in wetland mapping. *Remote Sensing of Wetlands: Applications and Advances*, 175-194.

Wang, P., Chen, P., Yuan, Y., Liu, D., Huang, Z., Hou, X., & Cottrell, G. (2018, March). Understanding convolution for semantic segmentation. In *2018 IEEE winter conference on applications of computer vision (WACV)* (pp. 1451-1460). Ieee.

Tian, T., Li, C., Xu, J., & Ma, J. (2018). Urban area detection in very high resolution remote sensing images using deep convolutional neural networks. *Sensors*, *18*(3), 904.

Salehi, B., Zhang, Y., Zhong, M., & Dey, V. (2012). Object-based classification of urban areas using VHR imagery and height points ancillary data. *Remote Sensing*, *4*(8), 2256-2276.

Kucharczyk, M., Hay, G. J., Ghaffarian, S., & Hugenholtz, C. H. (2020). Geographic object-based image analysis: a primer and future directions. Remote Sensing, 12(12), 2012.

Khadanga, G. (2014). Image Segmentation using OBIA in eCognition. *Grass and Opticks, A Review of the Techniques and Approaches, Geomatrix, IITB*.

Indradjad, A., Nasution, A. S., Gunawan, H., & Widipaminto, A. (2019, June). A comparison of Satellite Image Compression methods in the Wavelet Domain. In *IOP Conference Series: Earth and Environmental Science* (Vol. 280, No. 1, p. 012031). IOP Publishing.

Santos, C., & Rapp, L. (2019). Satellite imagery, very high-resolution and processing-intensive image analysis: Potential risks under the gdpr. *Air and Space Law*, *44*(3).

Ma, X. (2023). High-resolution image compression algorithms in remote sensing imaging. *Displays*, 102462.

Atik, S. O., & Ipbuker, C. (2021). Integrating convolutional neural network and multiresolution segmentation for land cover and land use mapping using satellite imagery. *Applied Sciences*, *11*(12), 5551.

Tian, J., & Chen, D. M. (2007). Optimization in multi-scale segmentation of high-resolution satellite images for artificial feature recognition. *International Journal of Remote Sensing*, *28*(20), 4625-4644.

Ji, L., Zhang, L., & Wylie, B. (2009). Analysis of dynamic thresholds for the normalized difference water index. *Photogrammetric Engineering & Remote Sensing*, *75*(11), 1307-1317.

Bhandari, A. K., Kumar, A., & Singh, G. K. (2012). Feature extraction using Normalized Difference Vegetation Index (NDVI): A case study of Jabalpur city. *Procedia technology*, *6*, 612-621.

Chen, Y., Chen, Q., & Jing, C. (2021). Multi-resolution segmentation parameters optimization and evaluation for VHR remote sensing image based on mean NSQI and discrepancy measure. *Journal of Spatial Science*, *66*(2), 253-278.

Merge objects – ecognition | knowledge base (no date) *eCognition | Knowledge Base*. Available at: https://support.ecognition.com/hc/en-us/articles/360015317080-Merge-Objects (Accessed: 31 January 2024).

Verbeeck, K., Hermy, M., & Van Orshoven, J. (2012). External geo-information in the segmentation of VHR imagery improves the detection of imperviousness in urban neighborhoods. *International Journal of Applied Earth Observation and Geoinformation*, *18*, 428-435.

Gianinetto, M., Rusmini, M., Candiani, G., Via, G. D., Frassy, F., Maianti, P., ... & Dini, L. (2014). Hierarchical classification of complex landscape with VHR pan-sharpened satellite data and OBIA techniques. *European Journal of Remote Sensing*, *47*(1), 229-250.