

Faculté des bioingénieurs

Assessing the potential of sub-metric resolution airborne data in the identification and characterization of urban impervious surfaces in Louvain-la-Neuve

Author: Lakshmi RAJEEV KUMAR
Supervisors: Professor Pierre DEFOURNY (UCLouvain)
Dr. Julien RADOUX (UCLouvain)
Jury Dr. Sophie BONTEMPS (UCLouvain)
Dr. Merle MURU (University of Tartu)
Year: 2023-2024
Course: Master SAIV – MSc Erasmus+ GEM: Geo-information Science
and Earth Observation for Environmental Modelling and
Management

Acknowledgements

In the completion of this master's thesis, I am deeply grateful to all those who have been a crucial part of my studies and life.

First and foremost, I sincerely thank my supervisors, Professor Pierre Defourny and Dr. Julien Radoux, for their invaluable assistance and guidance throughout my thesis work. Their expertise and support have been instrumental in shaping this research.

My sincere thanks go to the European Union and the Erasmus Mundus program for granting me the opportunity to pursue an exceptional level of education at both the Catholic University of Louvain and the University of Tartu.

I am also thankful to all the teachers and colleagues at both universities for giving me so much expert knowledge and experience.

I owe immense gratitude to my family and friends for their unwavering mental support and motivation during the challenging times of my thesis journey. Your encouragement has been a pillar of strength for me.

Lastly, I thank my jury members, Dr. Sophie Botemps and Dr. Merle Muru, for their time and effort in reviewing my work.

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List of Acronyms

AEIDLMRS	Automatic Extraction of urban Impervious surfaces based on Deep Learning and Multi-source Remote Sensing data
ALOS-PALSAR	Advanced Land Observing Satellite- Phased Array L-band SAR
ASM	Angular Second Moment
CART	Classification and Regression Tree
CHRIS/Proba	Compact High Resolution Imaging Spectrometer on board the Project for On-board
CNN	Convolutional Neural Networks
DBN	Deep Belief Network
DEM	Digital Elevation Model
DOQQ	Digital Orthophoto Quarter Quadrangles
GCLM	Gray-Level Co-Occurrence Matrix
GDAL	Geospatial Data Abstraction Library
GEE	Google Earth Engine
GIS	Geographic Information System
IF	Impervious Surface Fraction
ISA	Impervious Surface Area
LARS	Least Angular Regression
LIDAR	Light Detection and Ranging
LSMA	Linear Spectral Mixing Analysis
LULC	Land Use Land Cover
MESMA	Multiple Endmember Spectral Mixture Analysis
MLP	Multi-Layer Perceptron
MNF	Minimum Noise Fraction
MRS	Multi-Resolution Segmentation
NDVI	Normalized Difference Vegetation Index
OBIA	Object-Based Image Analysis
OTB	Orfeo Toolbox
PICC	Projet Informatique de Cartographie Continue
POHA	Pixel And Object-Based Hybrid Analysis
PSI	Pixel Shape Index
QGIS	Quantum Geographic Information System

RF	Random Forest
RGB	Red, Green Blue
RSI	Remote Sensing Images
SAR	Synthetic-Aperture Radar
SESMA	Simple Endmember Spectral Mixture Analysis
SFS	Structural Feature Set
SMA	Spectral Mixing Analysis
SPOT	Satellite Pour l'Observation De La Terre
SR	Super Resolution
SRTM	Shuttle Radar Topographic Mission
SVM	Support Vector Machines
VHR	Very High-Resolution
VRT	Virtual Raster
WMS	Web Map Service

Chapter 1. Introduction

Urbanization has led to the increase and spread of impervious surfaces, which include roads, rooftops, and sidewalks. These impervious surfaces do not allow water to penetrate the ground, leading to increased surface runoff, higher flood risks, urban heat islands, and a reduction in biodiversity. Accurate mapping and identification of such surfaces are crucial for urban planning and management. However, the complex nature of urban landscapes and the diversity of materials used in construction present significant challenges for remote sensing and image classification techniques.

In the past, impervious surface mapping relied on medium-resolution satellite imagery and manual digitization methods, which are time-consuming and often require more spatial detail for urban areas. With advancements in remote sensing technologies, very high-resolution (VHR) airborne imagery and Light Detection and Ranging (LIDAR) data have emerged as valuable resources for detailed urban surface analysis. These datasets provide high spatial resolution and accurate height information, enabling more precise identification and characterization of impervious surfaces.

This study assesses the potential of sub-metric resolution airborne data combined with LIDAR-derived height data masking in identifying and characterizing urban impervious surfaces in Louvain-la-Neuve, Belgium. Louvain-la-Neuve, a university town with a compact, mixed-use urban model, presents a diverse range of impervious and semi-pervious surfaces, making it an ideal case study for this research.

Specifically, this study aims to extract texture features like Haralick and Structural Feature Set (SFS) from VHR imagery and evaluate their effectiveness in classifying impervious surfaces. By leveraging the Orfeo Toolbox (OTB) for feature extraction and employing a Random Forest (RF) classifier, this research seeks to improve the accuracy of impervious surface mapping and map with more details than just pervious – impervious surfaces. The study involves the development of a training/validation dataset through fieldwork and other supplementary datasets.

The study tries to understand which texture features could be employed in classifying different pervious, semi-impervious, and impervious surfaces and to find if these features could perform well.

Chapter 2. State of Art

This chapter gives the state of the art on which the study is based. It gives insights into previous research on characterizing the imperviousness of surfaces using remote sensing and photogrammetry. The chapter also compares the methods and results obtained.

2.1. Impervious Surfaces

Impervious surfaces can be defined as material surfaces that do not allow water to penetrate them (Arnold & Gibbons, 1996). The European Commission defines impervious surfaces as regions where the natural soil has been partially or wholly covered by non-natural substances, resulting in the permanent impairment of the soil's natural functions (Schmidt & Barron, 2020). Roads and rooftops are the most common and readily recognizable examples of impervious surfaces, with other types encompassing sidewalks and patios. The impervious surface is recognized as a significant environmental indicator for assessing urban land utilization and water quality (Arnold & Gibbons, 1996). The imperviousness of surfaces has adverse effects on society, the environment, and the economy (Langenkamp & Rienow, 2023).

Impervious surfaces result in higher run-off, which increases the intensity and probability of floods and soil erosion (Schmidt & Barron, 2020). This also contributes to decreased water quality as pollutants such as pesticides, pathogens, nutrients, and sediments flow into the water bodies (Wang & Li, 2019; Yang et al., 2009). Impervious surfaces such as roads and buildings also increase the urban heat island effect by inducing higher surface temperatures. Additionally, such artificial surfaces result in a loss of biodiversity and induce land fragmentation (Fokaides et al., 2016).

2.2. Relevance of Impervious Surface Mapping

A clear understanding of impervious surfaces is needed for various research fields, including hydrology, urban climate, and urban spread (Schmidt & Barron, 2020). The traditional method of impervious surface measurement involves the usage of planimetric data like that of roads or buildings, digitized and characterized manually in 2D, which is time-consuming and only suitable for smaller areas (Sanborn, 2023). Geographic Information System (GIS) has become a valuable tool for mapping and studying the spatial distribution of impervious surfaces. Additionally, in the past years, the extensive use of remote sensing data has brought improvements in mapping impervious urban surfaces (Schmidt & Barron, 2020; Yang et al., 2009).

Mapping impervious surfaces is considered a challenge due to the complex nature of various urban landscapes and the spectral properties of the various land cover types (Yang et al., 2009). Impervious surfaces have diverse appearances in Synthetic-Aperture Radar (SAR) and optical images. This difference is due to several reasons, such as the diversity in materials used for construction, the shadows cast by tall buildings, and the various spatial, spectral, and polarimetric signatures (Attarchi & Rahnama, 2019).

2.3. Methodologies Adopted over the Years

In recent years, researchers have used diverse types of remote sensing methods and airborne datasets to map impervious surfaces. The general process for impervious surface detection comprises selecting data sources, preprocessing the data, extracting features, performing classification, and finally, creating thematic maps (Wang & Li, 2019).

2.3.1. Image Classification

The process of extracting diverse features from Remote Sensing Images (RSIs) is associated with choosing appropriate resource data and algorithms. Image classification methods are categorized into four groups based on the scale of pixel processing: subpixel-based techniques, pixel-based techniques, object-based techniques, and deep learning-based techniques (Wang & Li, 2019).

Pixel-Based Methods

In previous decades, pixel-based methods have been the primary approach for image processing (Ye et al., 2023). Pixel-based classification focuses on the spectral and ancillary information within each pixel to assign a class label (Rittl et al., 2013).

Among the studies conducted using the pixel-based analysis, a greater number of researchers used RF classifier, a type of machine learning algorithm. It comprises numerous individual decision trees functioning as an ensemble. Each tree within the random forest produces a class prediction, and the class with the most votes is adopted as the model's final prediction (Tony Yiu, 2019). RF classification is known for its high accuracies, robust results and low sensitivity to overfitting, and is more capable of handling high dimensional multicollinear data (Langenkamp & Rienow, 2023; Zhang et al., 2013). It is also less affected by noise and feature selection compared to other widely used methods like support vector machines (SVM) (Zhang et al., 2013).

In a study conducted in Germany, Langenkamp & Rienow (2023) used True Digital Orthophoto (TDOP) and local land use data for impervious surface mapping with RF classification. They followed a binary supervised classification approach and defined two classes, impervious and non-impervious, with results showing the impervious surfaces and with an overall accuracy of 92.31% and kappa coefficient of 0.8462. Meanwhile, Zhang et al., (2020), in their study, produced a global 30m map using the multi-source, multitemporal RF classifier and inferred that the method yielded the highest accuracy with an overall accuracy of 95.1%.

Similarly, Genyun Sun et al. (2022) used Sentinel-1 and Sentinel-2 images along with the Shuttle Radar Topographic Mission (SRTM) dataset in Google Earth Engine (GEE) to produce a 10 m resolution multitemporal impervious database for the Lancang-Mekong basin covering five countries including Vietnam, Laos, Cambodia, Myanmar, and Thailand. To avoid misclassification by detecting bare rock in the mountains as urban buildings due to similar spectra and backscattering, the slope was calculated using the Digital Elevation Model (DEM). The slopes greater than 15 degrees were labelled non-impervious surface before using the RF classifier. The resulting products had an overall accuracy ranging from 91.45% to 92.44% and a Kappa coefficient in the range of 0.829 to 0.848 (Genyun Sun et al., 2022).

Other machine learning algorithms are also used in pixel-based classification with neural network classification like Multi-Layer Perceptron (MLP) models, a class of feedforward artificial neural networks. A neural network is a versatile classifier that does not rely on fixed parameters, making it adaptable to diverse types and structures of input data. It can handle fuzzy output values and has the capability to estimate complex, non-linear relationships between input data and the desired outputs (Attarchi & Rahnama, 2019). MLP is designed to depict the correlation between the class activation levels assigned to shadow pixels by the initial MLP and the real type of land cover beneath the shadow. The model relies on a set of training pixels affected by shadows, where the land cover type is already known (Chormanski et al., 2008).

Attarchi & Rahnama (2019) used Landsat 5 TM Scene and one ALOS-PALSAR (Advanced Land Observing Satellite- Phased Array L-band SAR) full polarimetric image for their study on urban surface impervious surface detection. They used neural network classification to get a binary map result with an overall accuracy of 95.86%. They inferred that in the absence of an optical image at medium-resolution, full polarimetric L-band SAR images can serve as an alternative. The polarimetric bands and their associated texture features prove effective in

detecting impervious surfaces within heterogeneous urban areas characterized by high relief. Chormanski et al. (2008), in their research, employed MLP models to map the proportions of four primary land-cover classes (impervious surfaces, vegetation, bare soil, and water/shade) to improve distributed run-off prediction in the Woluwe river basin. The models utilized both high-resolution (IKONOS images) and medium-resolution ((Landsat ETM+)) satellite data for this mapping task.

Sub-Pixel-Based Methods

Subpixel-based procedures involve the division of mixed pixels into independent attribute units based on proportions derived from spatial information in an original low-resolution image. These procedures leverage decomposition technology to manage mixed pixels effectively (Wang & Li, 2019). Sub-pixel algorithms are predominantly utilized for medium-resolution imagery and less commonly for high-resolution images. Their purpose is to estimate and map impervious surfaces, identifying them as a distinct type of surface material (Weng, 2012).

Yang et al. (2009) and Dams et al. (2013) used high-resolution optical imagery paired with medium-resolution imagery like SAR and Landsat to map impervious surfaces. Yang et al. (2009), in their study, used Classification and Regression Tree (CART) based methodology, which uses high-resolution imagery as training sets for mapping impervious surfaces in medium-resolution imagery. CART is a prognostic model that demonstrates the estimation of outcome variable values based on a set of incomplete variables (Kori & Kakkasageri, 2023). It can manage remote sensing data from various sources and sensors with varying statistical distributions and physical characteristics. The algorithm employs a binary recursive partitioning process, dividing each parent node into two child nodes. This iterative process continues by treating each child node as a potential parent node (Yang et al., 2009). Dams et al. (2013) also employed a soft classification approach to get Impervious surface Fraction (IF) to study the impact of land use change on water balance. They used a linear regression model to derive the IF in medium-resolution image using the high-resolution (IKONOS) IF values.

One other widely used methodology under sub- pixel-based approach is the Spectral Mixing Analysis (SMA) (Weng, 2012). The utilization of SMA allowed for the computation of land cover fractions within a pixel. This process includes the modelling of a composite spectrum by combining distinct spectra representing pure land cover types, known as endmembers (Roberts et al., 1998; Wu & Murray, 2003). It is further classified into Linear Spectral Mixing Analysis (LSMA) and Non-Linear Spectral Mixing Analysis (Wu & Murray, 2003).

The non-linear SMA model proves to be effective in handling diverse landscapes (Wang & Li, 2019). In contrast, linear SMA technique operates under the assumption that a pixel's spectrum is a linear combination of the spectra of its various components called endmembers, with each component's spectral proportions being accurately represented (Deng et al., 2012; Weng, 2012). This process generates a series of maps representing the proportions of each component within the pixel (Deng et al., 2012). Therefore, the linear spectral mixture model has gained significant recognition for effectively analysing urban mixed pixels (Sarkar Chaudhuri et al., 2017).

Wu & Murray (2003) and Sarkar Chaudhuri et al. (2017) in their studies used Landsat 7 Enhanced Thematic Mapper Plus (ETM+) scene and three images of LANDSAT-5, LANDSAT 7 ETM+ and LANDSAT-8 respectively to obtain impervious surface distribution and Impervious Surface Area (ISA) respectively. In both studies, a fully constrained LSMA method was applied to derive the impervious surface distribution and additional vegetation and soil cover in the former study. In the LSMA method, four endmembers were derived, and since the impervious surface could not be a single endmember, it was represented as a fraction by adding the low albedo and high albedo endmembers (Sarkar Chaudhuri et al., 2017; Wu & Murray, 2003). Other data sets were used by the studies such as eight Digital Orthophoto Quarter quadrangles (DOQQs) and Land Use Land Cover (LULC) datasets. In both the studies the impervious surfaces were all considered as one single category without any subgroups. Deng et al. (2012) also did LSMA analysis on Landsat images for extraction of ISA but used five endmembers to obtain the results.

In another study by Demarchi et al. (2012), the potential of a 9 m Super Resolution (SR) enhanced Compact High-Resolution Imaging Spectrometer on board the Project for On-board (CHRIS/Proba) was evaluated using Multiple Endmember Spectral Mixture Analysis (MESMA) approach. The method allows endmembers to vary on a per-pixel basis and resulted in six endmember classes and four landcover classes: vegetation (forest and herbaceous), grey (grey road and grey roof materials), bare soil and red (red roof materials).

Object-Based Methods

The object-oriented method has two main workflow steps: multi-resolution segmentation and knowledge-based classification of the segments (Xiaoxia et al. 2005). It involves utilizing a set of pixels that share characteristics akin to the basic units of analysis using a specified scale parameter (Ye et al., 2023). Segmentation is the process of dividing the image into distinct, non-overlapping regions, ensuring that each region is homogeneous while no two adjacent

regions are homogeneous (Yan et al., 2006). The segments known as image objects, serve as the fundamental processing units (Benz et al., 2004). The Object-Based Image Analysis (OBIA) approach uses not only spectral properties but also considers characteristics such as shape, texture, context, and relationships with neighbours, as well as super- and sub-pixels (Weng, 2012).

The researchers Lichtblau & Oswald (2019), Luo et al. (2018), and Verbeeck & Van Orshoven (2012) applied the object-based model to detect/improve impervious surface mapping using eCognition, a widely used OBIA software. The three papers also used the multi-resolution segmentation (MRS) algorithm embedded in the software. Lichtblau & Oswald (2019) used the OBIA approach to classify roads, buildings, parking lots, and driveways. They developed a rule-based OBIA in the eCognition software workflow for semi-automatic classification of impervious land-use features, whereas Luo et al. (2018) used an object-based post-classification fusion approach to improve the accuracy of impervious surface mapping. They employed a joint classification and two independent classifications, including the fusion for the no-data areas of LIDAR data, the real changed areas between the LIDAR data and high-resolution image resulting from their different acquisition times, and the shadow areas of the high-resolution image. The object maps were created by means of MRS.

Slightly different from the two studies, Verbeeck & Van Orshoven (2012) focus on the use of external geo-information in the segmentation of very high-resolution (VHR) imagery to improve the detection of imperviousness in urban neighbourhoods. The author compared the effect of four segmentation methods and assessed the accuracy of the produced classification and the accuracy of the segmentation separately. Out of the four methods, named pixel-based method, traditional OBIA, boundary suggestion method, and absolute boundary method, the absolute boundary method that used the vectorial boundaries got the highest overall accuracy of 82% and kappa value of 68%. This eCognition methodology was compared to another method by the researchers (Li et al., 2011). The method involves hierarchical segmentation of the imagery by combining multichannel watershed transformation and the dynamics of watershed contours, followed by the object-based classification for impervious surface mapping. The segmentation process includes the use of histogram thresholding for shadow detection and extraction of impervious surfaces in the shadow areas. This watershed-based segmentation method was found to perform better in visual and quantitative (average difference) evaluations.

Deep-Learning Methods

Deep learning is characterized by a neural network featuring a large number of hidden layers, constituting a multi-layer perceptron. This network can conduct sample training and testing through unsupervised learning methods and provides valuable identification features, thereby enhancing classification accuracy (Wang & Li, 2019).

Sun et al. (2019) and Huang et al. (2019) conducted a study employing deep learning methods using LIDAR for impervious surface extraction. Sun et al. (2019) focused on the extraction of urban impervious surfaces using Worldview-2 data with a resolution of 0.46 m along with the LIDAR by using 3D convolutional neural networks (CNNs). It is a type of deep neural network that is commonly used for image and video recognition, natural language processing, and other tasks involving high-dimensional data (Huang et al., 2019; Sun et al., 2019).

In their study, Sun et al. (2019) determined the hyperparameters for the 3D CNN model by analysing training and validation samples, emphasizing the critical role these initial parameters play in the model's ability to extract and classify information accurately. Three land classes were set: impervious surfaces, vegetation, and bare soil, based on V-I-S (vegetation-impervious surface-soil) model. The V-I-S model is a conceptual framework used for urban ecosystem analysis through remote sensing and was introduced as a standardized method to quantify and compare the biophysical composition of urban environments (Ridd, 1995). The authors inferred that the addition of LIDAR data enhanced the impervious surface extraction by providing the height details needed to reduce the misclassification of roads and other surfaces as bare soil and obtained an overall accuracy of 93%. On the other hand, Huang et al. (2019) in their study used a methodology called Automatic extraction of urban impervious surfaces based on deep learning and multi-source remote sensing data (AEIDLMRS). The resolution of the LIDAR data used was 0.5m and the other data sets were resampled to the same higher resolution. In the proposed method, the authors used Minimum Noise Fraction (MNF) fuzzy C-means clustering, CNN, and deep belief network (DBN) in various stages throughout the study to automate the extraction of impervious surface and pervious surface as a binary product. Compared to the other algorithms used in the experiment the AEIDLMRS scored highest average R^2 value (0.95), lower values for average RMSE (6.65%) and MAE (5.12%).

Hybrid Approach

Since there are limitations to both pixel-based and object-based methods, a pixel and object-based hybrid analysis (POHA) was proposed by Zhang et al. (2013) in their study conducted on 2.4 m resolution QuickBird image, which is a multispectral high-resolution satellite imagery. In the study pixel-based analysis generated impervious seed pixels, which served as prior knowledge for the subsequent object-based analysis. The object-based analysis was then applied to produce POHA results using the weighted minimum distance strategy. The authors also used human-computer interaction to generate the final impervious surface map with binary classification.

However, in another study by Yang et al. (2009), a combination of spectral unmixing and object-based classification was used. The study employed linear spectral unmixing, implementing both Simple Endmember Spectral Mixture Analysis (SESMA) and MESMA models. A quantitative comparison was conducted to detect impervious surface information in the presence of tree canopies. Subsequently, hierarchical object-based classification was employed to extract impervious surfaces in both shadow and non-shadow areas. The final impervious surface map was derived by extending the detected impervious surface information through tree canopies based on the object-based classification result. For the hierarchical object-based classification, the authors used the MRS algorithm in eCognition.

Texture Features for Image Classification.

Another technique used in remote sensing for image classification is the application of texture features. Texture, a critical feature utilized by the human visual system, can be defined as the local variation in pixel values, which may repeat in random or regular patterns (Robson Schwartz et al., 2012). These features provide valuable information about the spatial arrangement of tonal variations within a band (Haralick, 1973).

Among the methods for computing texture features, texture features derived from the Gray-Level Co-occurrence Matrix (GCLM) are notable. Proposed by Haralick in 1973, GCLM is one of the most widely used texture features due to its simplicity and understandable interpretation (Löfstedt et al., 2019).

A study by Kayitakire et al. (2006) evaluated the effectiveness of very high spatial resolution IKONOS-2 imagery in estimating key forest structure variables through texture analysis. The study employed the IKONOS-2 multispectral and panchromatic images (1-meter resolution)

and analysed the relationships between forest variables and texture features using scatterplots and correlation coefficients. The study highlighted that very high spatial resolution imagery, combined with texture analysis, could significantly improve the accuracy of forest structure estimates.

Another similar study was conducted by Beguet et al. (n.d.) to develop an automated method to describe forest structure using VHR Quickbird satellite imagery (spatial resolution of 0.61 to 0.70 meters in the panchromatic channel and 2.44 to 2.88 meters in the multispectral channels). The method combined spectral and Haralick texture features through statistical modelling and uses linear regressions and a stepwise variable selection method derived from Least Angular Regression (LARS) to improve prediction accuracy.

Apart from these studies focused on remote sensing image analysis, one significant application of the Haralick texture feature is found in the study by Loewke (2013), which focused on stem cell identification. In this study, the Haralick texture feature was used in combination with SVM to distinguish and identify the differentiation status of stem cells in time-lapse data. The technique was able to track the ratio of differentiated and undifferentiated cells over time in phase contrast time-lapse data. The study was able to achieve an overall accuracy of 85% for all data types evaluated.

Additionally, in a study conducted by Chaugule & Mali (2014), shape and texture features were extracted to classify paddy varieties using an artificial neural network classifier. The classification using texture features alone achieved an accuracy of around 82.61%.

2.3.2. Others

Apart from the methodologies mentioned above and studies, over the years, researchers have also used other methodologies for the detection and mapping of impervious surfaces. Rodríguez-Cuenca et al. (2014) in their study used five indices to classify impervious surfaces using Satellite Pour l'Observation de la Terre (SPOT), LIDAR, and Digital Terrain Model (DTM) data. The indices were put in the decision tree, and a distinct threshold was established for each decision index, considering the behaviour of each land cover category at each considered index to obtain the results with the legend: non-impervious surface, asphalt, and buildings.

Schmidt & Barron (2020), in their study, utilized the Normalized Difference Vegetation Index (NDVI) from areal imagery of resolution 10 cm paired with vector datasets to map binary

pervious/impervious surfaces. They inferred that misclassification occurred due to the data quality of vector data sets used and that the proposed methodology produced an overall accuracy of 93.1%.

2.4. Overall Synthesis of Literature

The literature review of this master thesis investigates the mapping and analysis of impervious surfaces, emphasizing their environmental impact and methodological challenges. It highlights the necessity for improved classification of surface characteristics, moving beyond a simple binary classification to include semi-impervious surfaces as well. The use of low-resolution satellite imagery is prevalent in existing research, where traditional methodologies such as Spectral Mixing Analysis (SMA) and pixel-based approaches are effective. The review also points to the adoption of object-based and deep learning methodologies for classification. However, it notes that these advanced techniques still predominantly resulted in binary outcomes in most of the studies analysed.

Emerging methodologies, such as hybrid classification approaches that combine multiple techniques, are also noted, yet they remain primarily focused on binary classification. The identification of semi-impervious, impervious, and pervious surfaces using very high-resolution (VHR) aerial imagery remains a significant challenge that needs to be addressed.

The importance of texture features in image analysis is discussed as a potential future direction for VHR image classification. The review underscores the ongoing advancements in remote sensing and machine learning for impervious surface mapping. By leveraging these technologies, including the incorporation of texture features, research can better address the complexities of urban environments, contributing to more sustainable and resilient urban planning and management strategies.

Chapter 3. Objectives

3.1. Background

As discussed in the literature review, most studies have focused on lower resolution satellite imagery, producing binary maps of imperviousness. There has been limited research on using feature extraction for image classification in impervious surface mapping. While most of the research carried out segmentation or object-based approach in mapping, the setback of this methodology, as stated before, is the fact that high-resolution datasets pose computational challenges and the object-based approaches often employ proprietary software, limiting their use, and reducing the spatial resolution or details of the results.

Understanding detailed surface information is crucial for urban planning to mitigate climate change impacts such as flooding and urban heat islands. Indeed, recent practices in urban development and management include semi-impervious surfaces for water management. Along with climate change, the urban heat island effect became a major urban issue that can be mitigated using appropriate materials.

The ambition is to find a method to characterize and classify the surface characteristics using feature and texture extraction from a unique airborne dataset acquired at sub-metric spatial resolution and use it for classification, providing information about various types of surfaces.

3.2. Objectives

This study addresses the existing research gap in sub-metric resolution impervious surface mapping and provides a methodology to better understand impervious surface detection using VHR imagery. In this context, the research question raised in this study is as follows:

What is the potential of sub-metric resolution airborne 3D data in the identification and characterization of urban impervious surfaces with complementary LIDAR-derived height mask?

The specific objectives were as follows:

- Identification of the best processing methods to extract surface characteristics.
- Defining an appropriate typology for the impervious surface mapping.
- Assessment of the mapping performance.

Chapter 4. Materials and Methods

This chapter describes all the materials and methodologies used in this study in detail. It details the study area, the data sets, the sources utilized, and the data processing steps. This chapter details that all aspects of the study are thoroughly documented, allowing for accurate interpretation and potential replication of the research findings.

4.1. Study Area

The study area considered is the university town of Louvain-la-Neuve in Walloon Brabant province in Belgium which has an area of 8.67 km² (Figure 2).

The town emerged in 1968 when the French-speaking university decided to relocate the French speaking section of the University of Louvain from the old town of Louvain (Leuven) to farmland south of Brussels. Inspired by the middle-age urban setting of Louvain, which integrates various functions rather than segregating them, Louvain-la-Neuve adopted a similar urban model.

The design philosophy, influenced by European university towns and early 20th-century British garden cities like Letchworth and Welwyn Garden City, focused on creating multifunctional neighbourhoods at a human scale. Unlike functionalist approaches of the time that segregated uses, Louvain-la-Neuve emphasized compact, mixed-use development around a central pedestrian spine.

Streets are narrow and often shaded to conserve space and shield pedestrians from the elements. Small plots encourage architectural diversity and enable participation from small contractors, while courtyards provide open passages to buildings and green spaces. Buildings are characterized by high-density, low-rise designs with interconnected courtyards and squares, mirroring the communal feel of traditional university towns.

These interconnected courtyards and pedestrian-friendly design influenced the region's surface characteristics. There is an abundance of impervious and semi-impervious surfaces in the urban landscape, and the availability of sub-metric resolution imagery makes it a very fitting choice for the study.

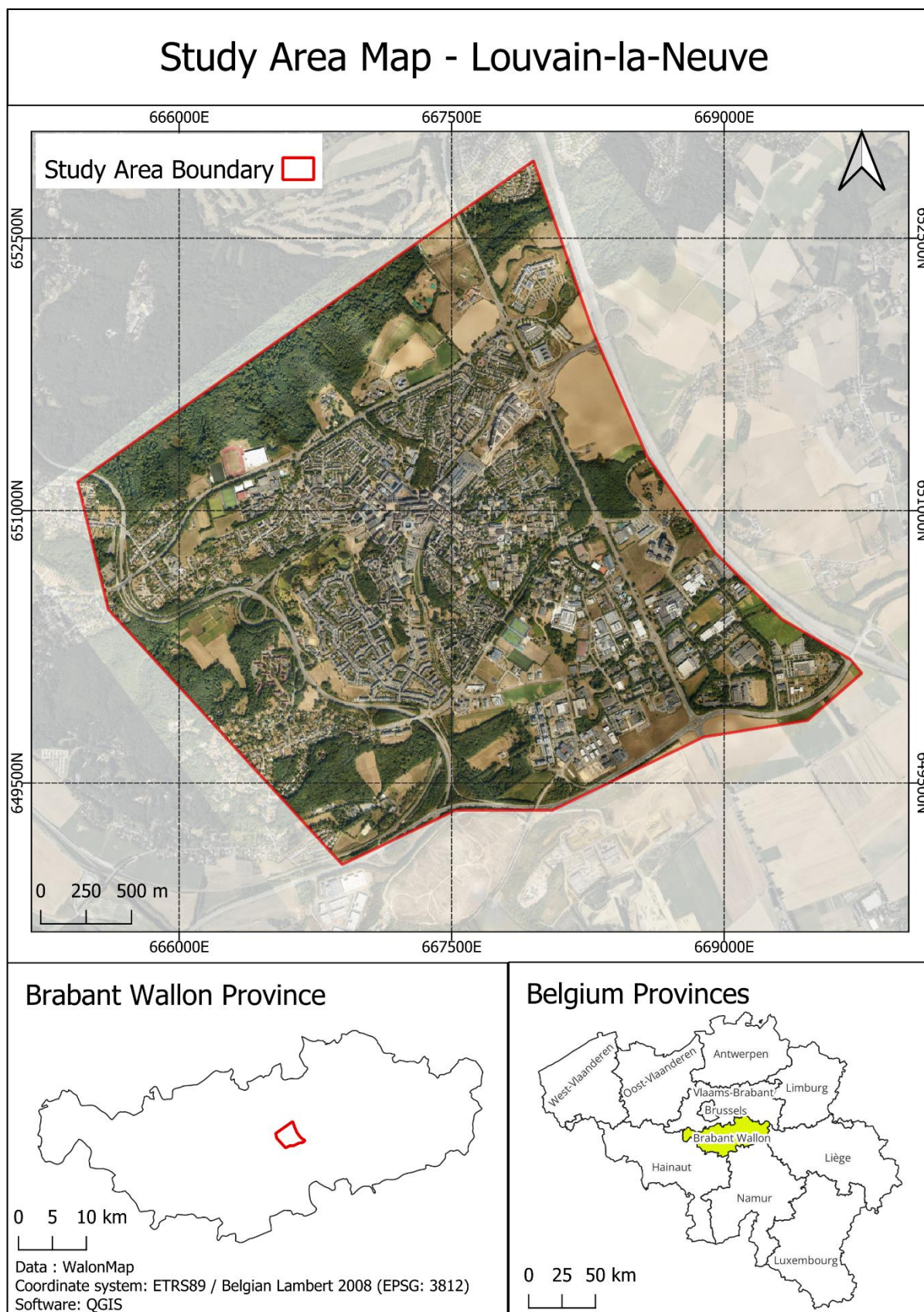


Figure 1. Study area extent and location

4.2. Data Sources

This section details the various datasets used along with their properties, including the spatial resolution, coordinate system, date of acquisition, if available, and their sources.

4.2.1. Aerial Image

The primary dataset used for characterization and classification in this study is an experimental aerial image with a resolution of 4 cm (illustrated in Figure 1. Study area extent and location), acquired by the company Source on August 31, 2022, on request of the UCLouvain geomatics lab. The image was captured using the Sonaca S201 Surveyor aircraft, which flew at an altitude of 636 meters and a speed of 90 knots. The survey had 85% intra-band overlap and 75% inter-band overlap, with a ground sampling distance of 3.36 cm per pixel.

Equipment and Specifications:

Cameras Used:

1. Canon EOS 5DS R
 - Lens: EF85mm f/1.4L IS USM (85mm) at a 62° position
 - Resolution: 8688 x 5792 pixels
 - Pixel Size: 4.24 x 4.24 μm
2. Phase One iXM-RS150F
 - Lens: Rodenstock RS 50mm-Ar (50mm) at a nadir position
 - Resolution: 14204 x 10652 pixels
 - Pixel Size: 3.76 x 3.76 μm

Final image dimensions and specifications used in the study

- Data type - GeoTiff
- 4 Bands - Red, Green, Blue, and Alpha
- Extent - 665004.638,648296.121: 670269.958,653271.201
- Coordinate system - ETRS89 / Belgian Lambert 2008 (EPSG:3812)

4.2.2. LIDAR derived Height Data

The Digital Height Model (DHM) of Wallonia, illustrated using a snapshot in Figure 2., with a resolution of 0.5 meters, was created from LIDAR acquisitions conducted in 2021 -2022. A DHM represents all elements located on the ground surface, such as buildings, bridges, vegetation, and vehicles, within a specified area. This raster data is derived from the calculation

of the difference between the Digital Surface Model (DSM) and the Digital Terrain Model (DTM) (*GeoportailWal*, n.d.).

- Resolution – 50cm
- Coordinate system - ETRS89 / Belgian Lambert 2008 (EPSG:3812)



Figure 2. Height dataset (DHM) derived from LIDAR

4.2.3. PICC Dataset

The Projet Informatique de Cartographie Continue (PICC) serves as the 3D digital cartographic reference for the entire Walloon region as shown in Figure 3. It accurately maps identifiable landscape elements with an x, y, and z coordinate precision of less than 25 cm. Key components of this dataset include:

- Buildings and Structures: Encompassing all architectural and infrastructural elements.
- Equipment: Such as plates, posts, and pylons.
- Railway and Hydrographic Networks: Including all railway lines and water bodies.
- Land Use: Detailed mapping of isolated trees, edges, sports fields, etc.
- Relief Elements: Mapping slopes and other topographical features.
- Roads: Including axes, edges, and sidewalks.

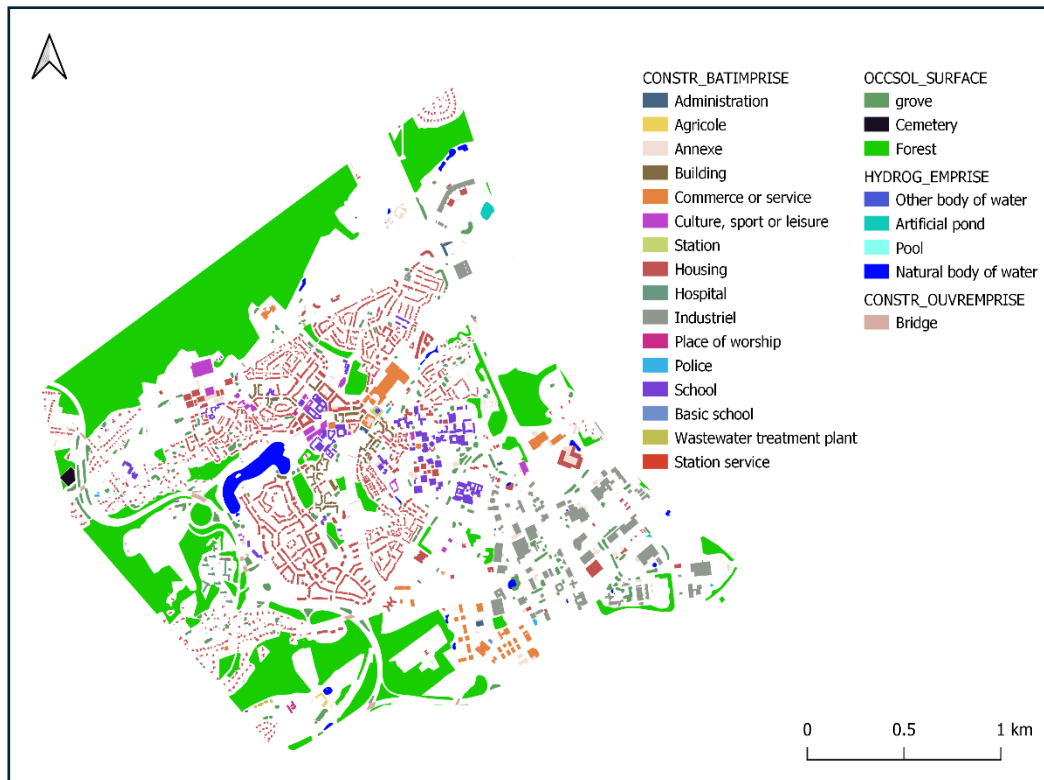


Figure 3. PICC Data for the study area

The PICC is constructed using multiple sources to ensure comprehensive and accurate data representation. The photogrammetric source involves private companies creating 3D vectors from digital photos, verified for completeness and accuracy via statistical sampling and Chi-Square tests. Public contract surveys, also conducted by private companies, undergo accuracy, completeness, and precision tests covering topographic and mobile mapping. Internal sources from the Geometrology Department and contributions from WALTOPO partners follow similar validation procedures. Acceptance criteria mandate less than 5% omissions and errors, ensuring data integration and error correction.

The PICC dataset is used in this study for the training/validation sample generation procedure to aid the fieldwork and visual inspection (*GeoportailWal*, n.d.).

4.2.4. Web Map Service (WMS) Orthophoto Layers

The WMS layers of orthorectified mosaiced imagery of the Wallon region with a resolution of 25cm for the years 2020, 2021, 2022 summer, and spring were used as additional information for the development training validation samples (see Figure 4.). These layers provide comprehensive aerial views, captured vertically and partially orthorectified, aiding in precise and detailed identification of landscape elements (*GeoportailWal*, n.d.).

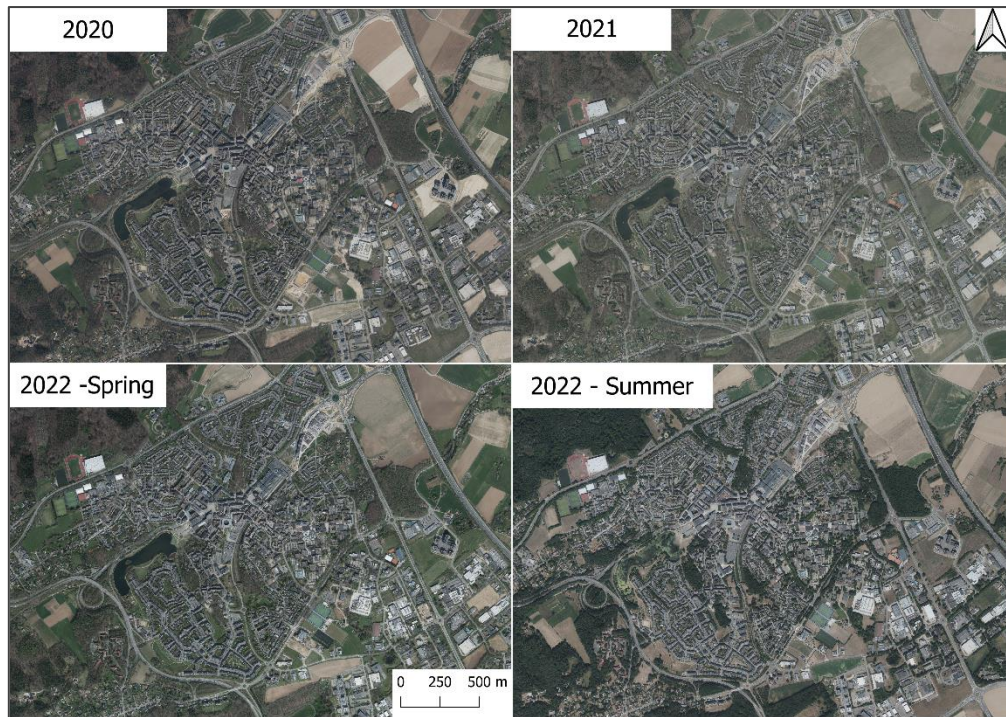


Figure 4. WMS Orthophoto Layers Snapshots for the years 2020,2021,2022 (spring and Summer)

4.2.5. WMS INSPIRE - Land Cover in Wallonia (BE)

This WMS visualisation service (see Figure 5.) enables users to access and view "Land cover" data layers within the Walloon territory of Belgium. Provided by the Public Service of Wallonia (SPW), this service displays geographic data layers related to the "Land cover" theme as specified by the INSPIRE Directive (*GeoportailWal*, n.d.).

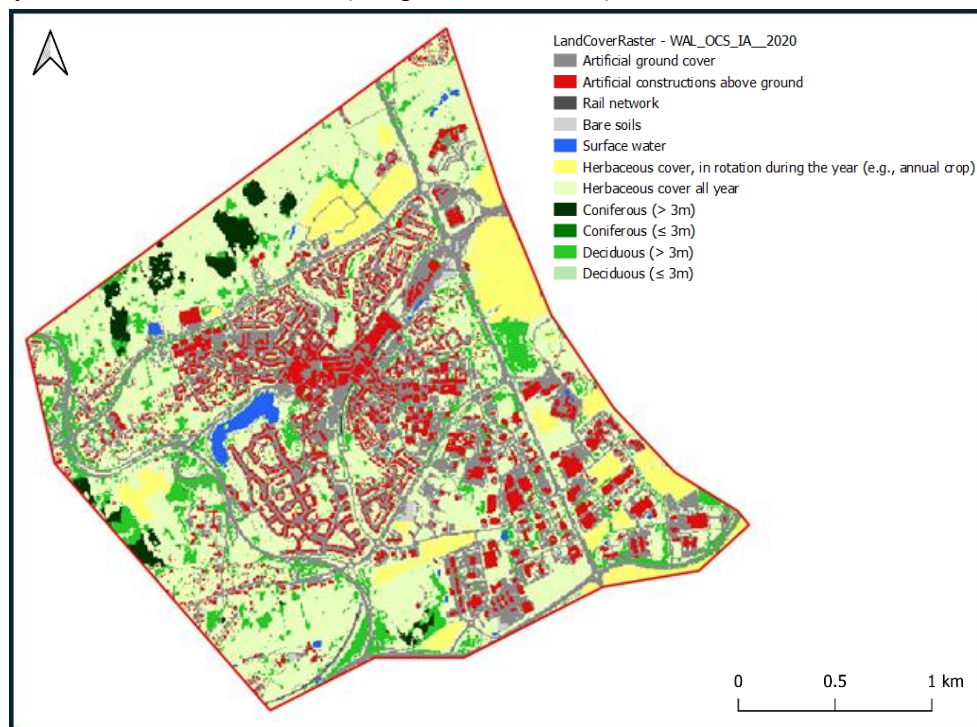


Figure 5. WMS Land cover 2020 snapshot for the study area

4.3. Overview of the Workflow

Figure 6. briefly gives the overall workflow of the study. It indicates the main processing steps, like data collection, feature extraction, layer stacking, and classification. The flowchart indicates the data sets used, and the outputs obtained after each of the processes.

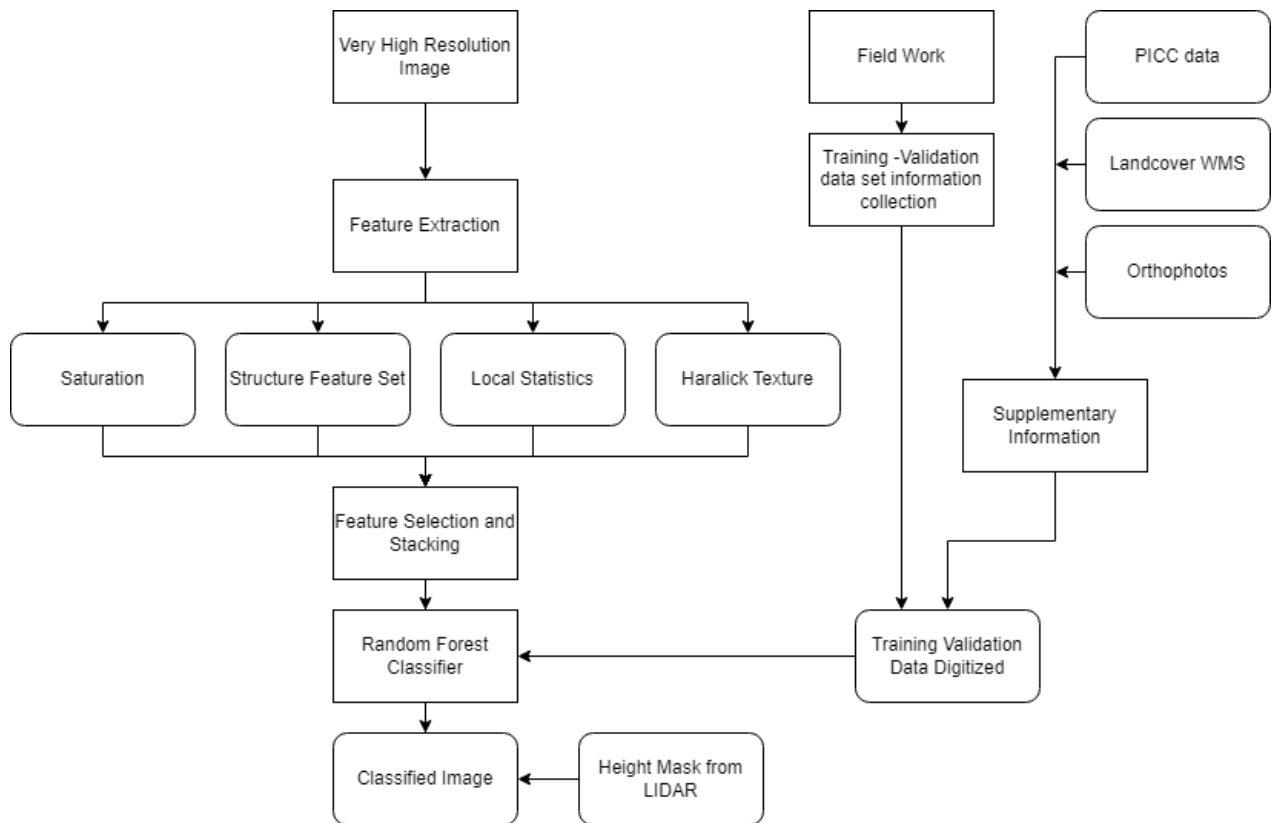


Figure 6. Methodology overview flowchart

4.4. Training/Validation Data Processing

This section details the steps taken in processing and developing the training/validation dataset utilized in this study. The steps involve in situ data collection, development of typology, and data acquisition.

4.4.1. In situ Data Collection

To develop a comprehensive training/validation dataset for the study area, extensive fieldwork was undertaken using the QuantumGIS (QGIS) extension application QField. Initially, 600 random points were generated within the study area using QGIS, and an attempt was made to access each of these points on foot to gather surface observations and photographic evidence. This detailed ground truth information was instrumental in creating a typology comprising 16

distinct classes. Subsequently, these observations were used to label training-validation polygons. Out of the 600 points, 342 were successfully visited, leading to the creation of around 300 polygons, forming the core of the training-validation dataset.

Qfield Application

QField is a leading application for fieldwork developed by OPENGIS.ch, transforming the collection and management of geospatial data. The application helps to collect field data by having an interactive user interface, which is available in QGIS software through the Qfieldcloud extension. The random points generated in QGIS were exported to the Qfield application, and then data on each point were collected, as seen in Figure 7.

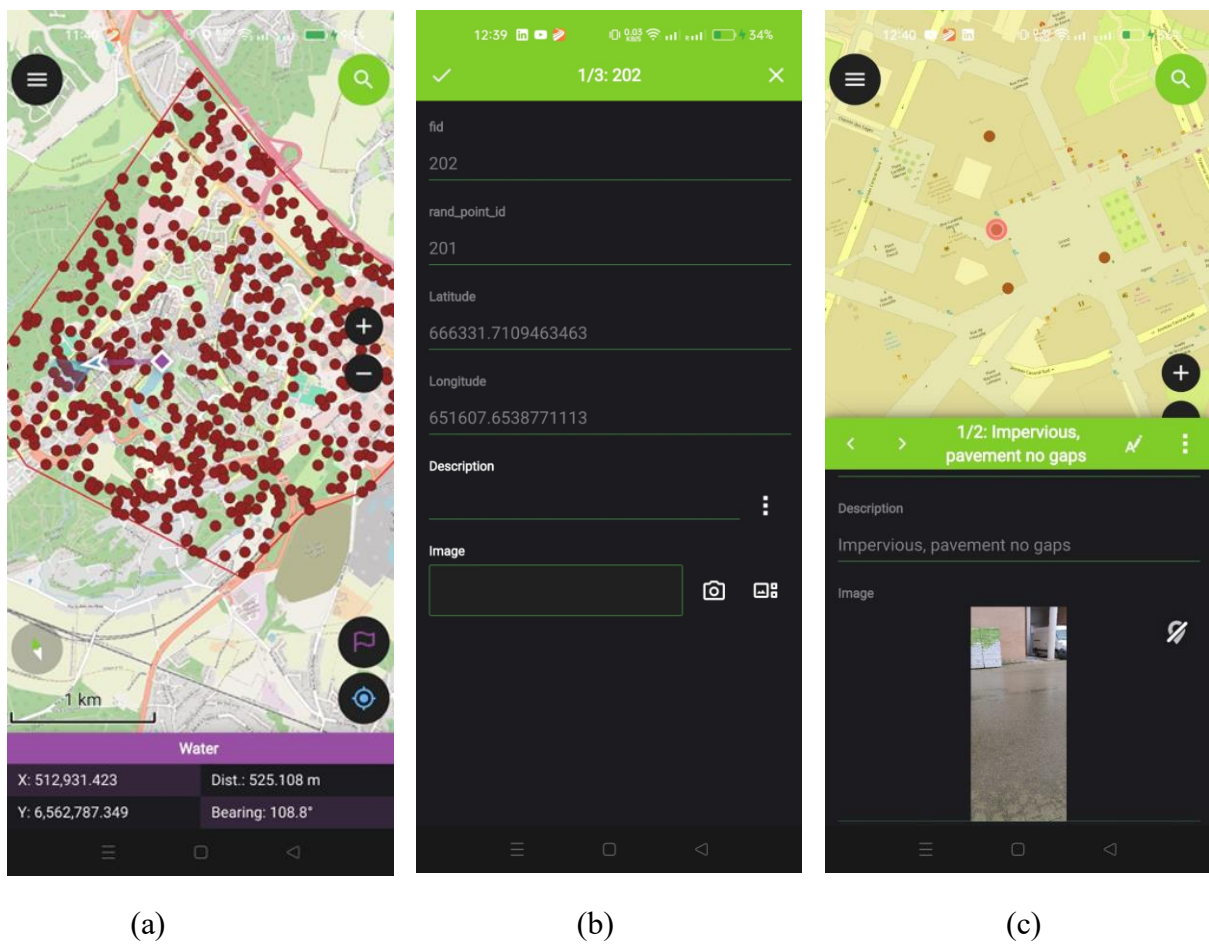


Figure 7. Qfield mobile application interface (a) Navigation, (b) Data point details, and (c) Data collection

4.4.2. Definition of the Surface Typology

This section provides an in-depth overview of the various classes identified and labelled during the field survey. For each type, corresponding images from the fieldwork and snapshots from

the orthophotos are provided to facilitate accurate visualisation. A set of 14 surface types were identified as relevant for the impervious surface mapping. These surface types identified are listed in Table 1.

Table 1. Developed Typology for Training and Validation Dataset

Natural Land Surface Type	Artificial Land Surface Type
Forest	Concrete
Agricultural	Asphalt
Grass	Semi impervious pavement
Water body	Gravel
Bush	Cobbled path
Bare soil	Grass protection
	Metal top
	Vehicles

1. Forest

Forest soils are generally pervious surfaces due to their higher porosity and higher infiltration (Sheil, 2018). These areas are characterized by vegetation, a variety of tree species, and often a layer of understory shrubs. In this study, the



Figure 8. Field image and snapshot from orthophoto - Forest

forest areas are identified by visual recognition based on the field visit information and the orthophotos. Figure 8 gives the image taken during the field visit and the snapshot of the same area in the imagery.

2. Agricultural

Agricultural lands are characterized by cultivated crops, fallow fields and agricultural grasslands. In Belgium, these areas may be seasonally fallow, covered with grass, or intensively farmed with various crops. Like the forests, agricultural lands are also



Figure 9. Field image and snapshot from orthophoto – Agricultural land

considered as areas with higher permeability. The land use information dataset and orthophotos from previous years were used to identify the agricultural areas.

3. Grass

Grasslands in Louvain-la-Neuve are identified by their continuous grassy cover, which is found in parks, lawns, and open fields. These were identified using the ground information taken during fieldwork and the orthophotos. The agricultural



Figure 10. Field image and snapshot from orthophoto – Grass

grasslands are excluded in this category. The grass also allows water to easily drain into the soil and is categorized as a pervious surface.

4. Water body

Water bodies include lakes, ponds, rivers, and residential pools. Waterbodies are collectors of water and are considered as pervious surfaces,



Figure 11. Field image and snapshot from orthophoto – Water body

even when the water body is a residential pool. This data was taken from the PICC dataset, which outlined all the waterbodies in the study area.

5. Bush

Bushes include both high and low shrubs found in various landscapes within the study area. Like trees and grass, bushes also allow water to easily penetrate the soil and are



Figure 12. Field image and snapshot from orthophoto – Bush

considered pervious. High and low bushes are considered into one category of bush in the study.

6. Bare soil

Bare soil is the natural soil that is not covered with any other material. It is considered as pervious in this study as normally soil does allow water to penetrate through them unless after high-intensity rains and they are saturated. Even though compact soil loses its permeability to some extent the study considered all bare soil as pervious. Identification was done through visual inspection during fieldwork and orthophoto analysis.



Figure 13. Field image and snapshot from orthophoto – Soil

9. Concrete

Concrete is an artificial surface and is impervious. Concrete edges in the sidewalks and roads, and concrete stairs were considered in this class using fieldwork information and orthophoto visual verification. Drain caps made of concrete (Figure 10 (b)) were also considered in this class.



Figure 14. Field image and snapshot from orthophoto – (a) Concrete and (b) Concrete drain cap

10. Asphalt roads

Asphalt roads are constructed using asphalt, which is a petroleum product and is impervious in nature. It is visible as black in colour and is identified from the land use dataset and the orthophotos. Roads are generally considered a big part of the



Figure 15. Field image and snapshot from orthophoto – Asphalt Roads

urban land cover and a major constituent of impervious surfaces in urban infrastructure.

11. Semi impervious pavement

The pavements in Louvain-la-Neuve mainly consist of this kind of construction. It is not fully pervious but allows drainage through the gaps between the individual pavers. The construction of such pavements follows a general pattern of a geotextile, then a subbase of crushed rocks or sand, and then the paver blocks (*Pervious Surfaces Overview*, n.d.). All the different types of such pavements were combined in this class into semi-impervious surfaces so that a new

category of surface could be extracted. It was identified by using the fieldwork information mostly and using the orthophotos for visual inspections. The different types of paved surfaces encountered during the field visits and the corresponding snapshot from the image are given in Figure 16.

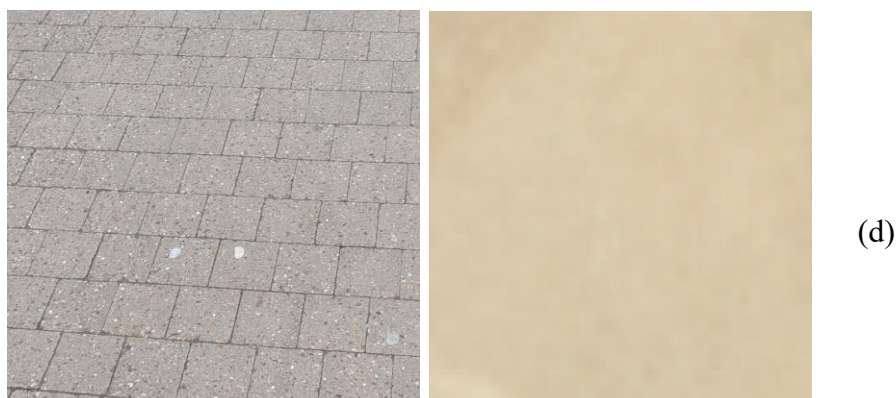


Figure 16. Field images and snapshots from orthophoto – Semi-impervious surfaces of various types (a), (b), (c), and (d)

12. Gravel

Widely found in car parking lots in Louvain-la-Neuve, gravel surfaces are a prevalent attribute in the study area surface typology. The imperviousness of gravel surfaces depends on the compaction it has undergone and could even



Figure 17. Field images and snapshots from orthophoto – Gravel

be classified as impervious along with concrete and asphalt (John Boyle, 2014). However, since we do not know the compaction of the gravel in the study area, it is considered as a semi-impervious surface for a better understanding of the surface characteristics and impact on drainage.

13. Cobbled path

Cobbled paths are surfaces paved with small stones such that some drainage is made possible, along with semi-impervious surfaces. In Louvain-la-Neuve, most built



Figure 18. Field images and snapshots from orthophoto – Cobbled path

areas are surrounded by cobbled bike paths and areas. Cobbled paths are like semi-impervious pavements in drainage action. They were identified using the fieldwork information and orthophotos as no other datasets distinguish the surface type.

14. Grass protection

Another type of surface identified during fieldwork was the in-situ cast concrete systems for grass protection, which are mostly found in parking lots in some areas of Louvain-la-Neuve. These



Figure 19. Field images and snapshots from orthophoto – Grass protection

systems support grass growth

while providing surface strength and drainage. They have similar surface characteristics to semi-impervious surfaces and can have more permeability in some cases. In this study, these surfaces were considered semi-impervious surfaces in general but tried to be classified as separate classes.

15. Metal Tops

Metal drain tops were considered impervious surfaces in this study and were identified and labelled using the orthophoto with manual visual inspection and additional verification using field observations.



Figure 20. Field images and snapshots from orthophoto – Metal drain top

16. Vehicles

Vehicles were also categorized into a separate class to handle their presence on the surface. It will be considered just as vehicles in this study as the surface beneath would be different from place to place and is out of scope for this study.

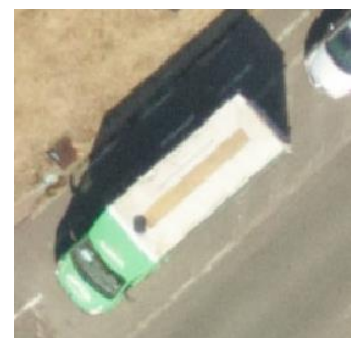


Figure 21. snapshot from orthophoto – Vehicles

Beyond this detailed surface typology established for Louvain-la-Neuve, the various surface classes were consolidated to form four priority categories:

- Pervious (agriculture, forest, grass, water body, bush, bare soil),
- Impervious (asphalt roads, concrete, metal top),
- Semi-impervious (cobbled path, gravel, semi-permeable pavement, grass protection)
- Vehicles.

Some of the other categories, like roofs and solar panels were found during the field data collection but removed from our typology as the study focuses on the ground surface.

4.4.3. Training and Validation Data Acquisition

After identifying the typology for the training validation dataset, the data was manually digitized using the QGIS application. A total of 301 polygons were digitized and then divided into training and validation datasets, with 80 percent allocated randomly to training and 20 percent to validation for each class. The non-uniform size of the polygons corresponding to each surface type results in varying pixel counts, which might impact the classification process. Therefore, to harmonize the training and validation polygons, the centroids of the polygons were buffered to form squares with 20 cm dimensions, as illustrated in Figure 22. This approach ensures that certain classes are not underrepresented or overrepresented in the training and validation datasets.



Figure 22. Training and validation data polygons digitized on the Image

4.5. Feature Computation

The field survey highlights the spatial structure of the most surface types which are captured by the 4cm resolution imagery for classification. Such spatial structure requires the computation of specific features for the classification.

This section details the processing of the imagery and the extraction of various texture features from it. For this purpose, the main tool used is the OTB, which is an open-source toolbox that is useful for feature extraction and classification. The selected features and parameters used are detailed in this section.

For computational easiness, the 4cm resolution image is divided into 35 tiles using the gdalwarp function in the Geospatial Data Abstraction Library (GDAL) library. It is an image mosaicing, warping, and reprojection utility(*Gdal*, n.d.). The features can then be extracted tile by tile.

4.5.1. Haralick Texture Features

Haralick texture features, derived from the Gray Level Co-occurrence Matrix (GLCM), are popular for their simplicity and easy interpretability. The GLCM records the frequency of

various gray level combinations that occur between pixels in a specified direction within the image (5 Orfeo ToolBox Applications, 2018). They have been effectively utilized in various applications such as analysing skin texture, classifying land use and forest types, and in the automatic detection of pollen (Löfstedt et al., 2019). In the OTB toolbox, it can be directly applied to the tiff image file to generate the texture feature layer (parameter details in Appendix I).

In the toolbox, there is the possibility to select between simple, advanced, and higher texture features which will produce sets of 8, 10, and 11 features, respectively. In this study, simple texture features were generated, and the set of 8 features are Energy (texture uniformity), Entropy (measure of randomness of intensity image), Correlation (how correlated a pixel is to its neighbourhood), Inverse Difference Moment (measures the texture homogeneity), Inertia (intensity contrast between a pixel and its neighbourhood), Cluster Shade, Cluster Prominence, Haralick Correlation (5 Orfeo ToolBox Applications, 2018). These features are stored in the results in the same order as separate bands (B1, B2, B3,...B8).

To capture the textures in different directions, textures were extracted in 4 angles: horizontal, vertical, 45 degrees, and 135 degrees. The directions are defined in the parameter keys offset “xoff” and “yoff” in one direction (see Figure 23).

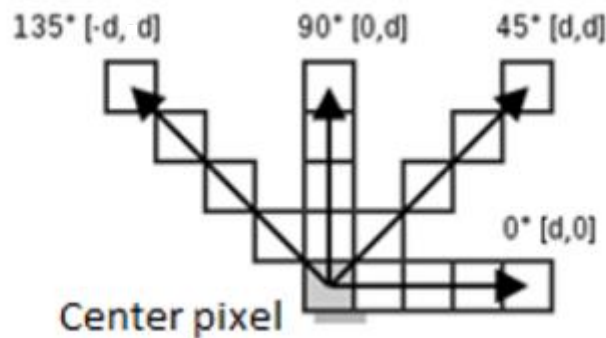


Figure 23. Directions of calculation for Haralick Texture Extraction (5 Orfeo ToolBox Applications, 2018)

For the Haralick extraction in this study, the important parameter specifications are as follows: Channel – 3, which indicates the blue band of the image. It was utilized for all texture feature extraction due to its superior accuracy with GLCM texture features and its higher reflection values for impervious surfaces (Chen et al., 2019; Doma & Amer, 2018).

parameters.xrad and parameters.yrad – 8 which is the radius of the processing neighbourhood, so that it takes 8 pixels to the vertical and horizontal directions.

parameters.xoff and parameters.yoff – Offset for the co-occurrence computation (6,0), (6,6), (0,6), (-6, 6) for the different directions 0, 45, 90, and 135 degrees (with reference to Figure 23.).

Feature Normalisation

To keep the variation in texture in different directions while stacking for the classification, the minimum and maximum values of the eight features among the four directions were calculated using another tool in the OTB toolbox called BandMathX (parameter details in Appendix I). This tool carries out mathematical operations on multi-band images and produces a result in image format. The mathematical computations are executed using the muParserX libraries (*OTB Cookbook*, n.d.).

The expression that takes all the bands from images in 4 different directions, gets the maximum among them and creates an image is as follows:

exp “max(im1b1; im2b1;im3b1;im4b1)”

4.5.2. SFS Texture Features

To reduce the dimensionality and extract features from the direction-lines histogram, several statistical measures are utilized. Six specific statistical measures have been proposed for this purpose, collectively referred to as the Structural Feature Set (SFS) (parameter details in Appendix I). The features are named:

SFS' Length (B0) - the maximum value in the direction-lines histogram. It indicates the longest line segment detected from the central pixel across all 20 directions.

SFS' Width (B1) - the minimum value in the direction-lines histogram, representing the shortest line segment detected.

SFS' PSI (Pixel Shape Index) (B2) - the mean or sum of the direction-lines histogram.

SFS' W-Mean (weighted -mean) (B3) - measure that calculates the average length of lines radiating from a central pixel, adjusting for how consistent the colour or intensity is along each line.

SFS' Ratio (B4) - describes the shape contour around the central pixel.

SFS' Standard Deviation (SFS' SD) (B5) - measure that shows how much the lengths of direction lines vary around a central pixel. It helps differentiate between narrow, elongated objects like roads and broader, square objects like buildings or grassy areas, even if they have similar average lengths (X. Huang et al., 2007).

Some of the important parameters used in this step are as follows:

Channel – 3 indicates the blue band in the imagery

parameters.spethre – 20 to keep the level of detail as the spectral value difference was between 15- 30 for the bands.

Parameters.spathre – 20 so that 20 pixels from the centre pixel was considered amounting to around 80 cm radius in real world.

4.5.3. Local Statistics Features

This tool computes four local statistical features on a pixel over a specified neighbourhood (parameter details in Appendix I). The 4 statistical features are Mean (B0), Variance (B1), Skewness (B2), and Kurtosis (B3).

The parameter used in this step is as follows:

Radius – 5, which is around 20 cm radius around the central pixel.

4.5.4. Saturation

One other feature that was calculated was the saturation of the image. It helps in discriminating the different surface types based on their colour intensity or purity of the colours. Saturation describes the level of purity or intensity of a specific hue. It is calculated using the Red Green Blue (RGB) values (*Math of Colors - RGB to HSL Transformation*, n.d.) in the BandmathX tool.

Initially, the luminosity of the image is found by using the formula:

$$L = \frac{1}{2} (Max(RGB) + Min(RGB))$$

Where the RGB values must be between 0 and 1. So, for that, the values of R, G, and B bands are divided by 255 to obtain their fractional values. After luminosity is calculated, the saturation can be computed using the formula:

$$\text{If } L < 1 \quad S = \frac{(Max(RGB) - Min(RGB))}{(1 - |2L - 1|)}$$

If $L = 1$

$S = 0$

These formulas in bandmathX equations will be as follows:

$\exp \left((1 / 2) * (\max(\text{im1b1}, \text{im2b1}, \text{im3b1}) + \min(\text{im1b1}, \text{im2b1}, \text{im3b1})) \right)$ for luminosity and

$\exp \left((\text{im4b1} < 1 ? (\max(\text{im1b1}, \text{im2b1}, \text{im3b1}) - \min(\text{im1b1}, \text{im2b1}, \text{im3b1})) / (1 - \text{abs}(2 * \text{im4b1} - 1)) : 0) \right)$ for saturation.

4.6. Feature Selection

To select the best features that would be valuable for classification and to reduce the redundancy of the feature sets used, the Mahalanobis distances of the features were calculated, and the redundant features were removed.

Mahalanobis distance is one of the well-known and commonly used distance criteria. It was introduced by P. C. Mahalanobis in 1936 and is a non-probabilistic criterion. The formula for the computation of Mahalanobis distance is as follows:

$$D_M = \sqrt{(\mu_1 - \mu_2)^T \Sigma^{-1} (\mu_1 - \mu_2)}$$

where,

D_M : Mahalanobis Distance

μ_1 : Mean vector of first distribution

μ_2 : Mean vector of the second distribution

Σ^{-1} : Inverse of mean covariance matrix

$(\mu_1 - \mu_2)^T$: Transpose of the difference vector

A representative smaller area tile of the image was taken, and a corresponding vector sample file was created, taking 5 categories that show the different textures in the image and labelled them. It is then used to extract the raster values for the feature layer. For each category, the mean and variance of these raster values were computed. These statistics were then used to calculate the Mahalanobis distance between categories. This was done for all the layers so that a comparison between the layers could also be made and a heatmap plotted, as seen in Figure 24.

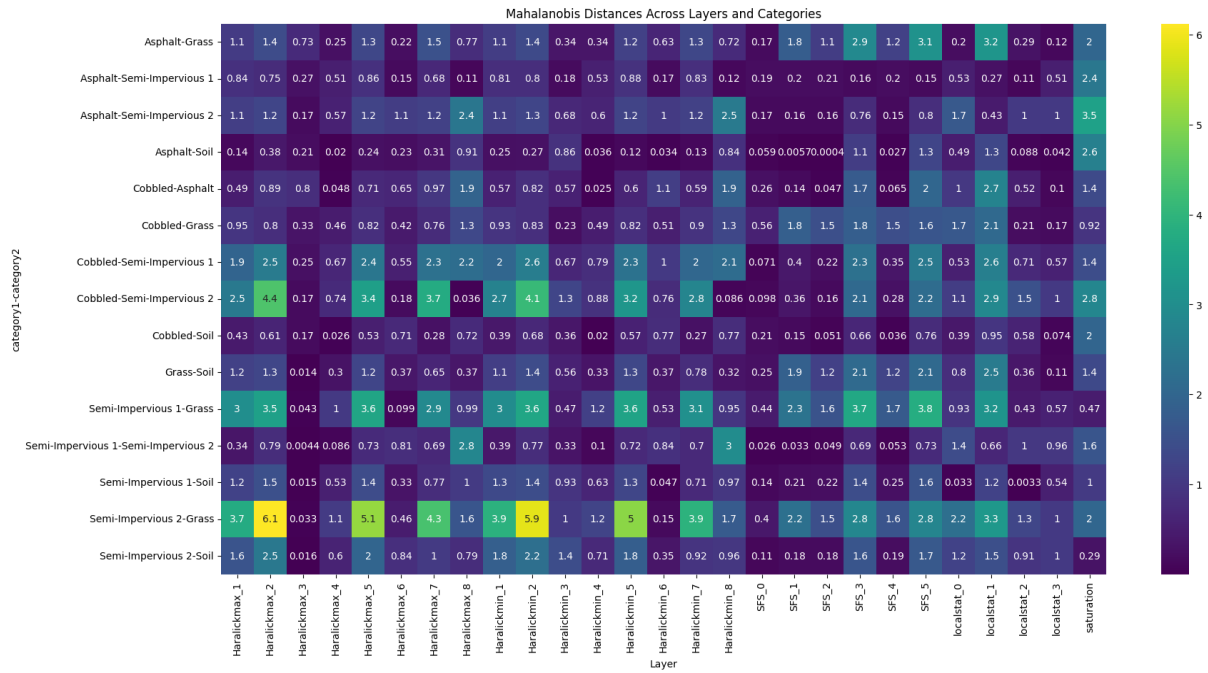


Figure 24. Mahalanobis distance distribution for different feature layers

A threshold of value 3 was decided to keep enough features while reducing their redundancy and filtering out the layers below this threshold. With this threshold, the 12 layers selected were as follows:

Haralick texture maximum and minimum: Energy (B1), Entropy (B2), Inertia (B5) and Cluster Prominence (B7)

SFS features: SFS'W-Mean (B3) and SD (B5)

Local statistics feature: Variance (B1)

Saturation

4.7. Classification

Once the relevant features were identified, the feature layers were extracted tile by tile, mosaiced, and stacked using the gdalbuildvrt function from the GDAL library. This function is

useful for stacking multiple layers without losing the properties of each layer and for mosaicing. It creates a virtual dataset based on the input set of datasets (*Gdal*, n.d.).

Image Classifier definition

The newly created VRT is then used in the `TrainImageClassifier` function in the OTB toolbox (parameter details in Appendix I). The function allows the user to input the training vector data and specify the classifier to use. The function will generate a model to classify the image using RF classifier and store it as a .model or .txt extension (5 Orfeo ToolBox Applications, 2018).

Classification

The classification is carried out on the VRT of feature layers using the model generated in the previous step using the function `ImageClassifier` (parameter details in Appendix I). The function takes in the input image and the model and uses it to classify the image. There is the possibility of providing a masking layer as well before classification (5 Orfeo ToolBox Applications, 2018).

As a post-classification step, a height mask layer derived from LIDAR data was applied to exclude all classes above 2 meters in height, focusing solely on ground surface categories and excluding buildings and other tall structures. The threshold couldn't be set lower than 2 meters because the data displayed too much noise below this height, making it difficult to accurately differentiate between ground-level features. The classes were also consolidated into the four broader categories. This consolidation simplifies the classification process.

4.8. Accuracy Assessment

Accuracy assessment was carried out using the validation dataset generated from the field study. The majority class in the validation polygon was taken as the predicted class, and then the confusion matrix, as well as various scores such as overall accuracy, F1-score, recall, and precision, were computed.

Accuracy measures the overall correctness of a model by calculating the proportion of true positive and true negative predictions out of the total number of samples. It is a straightforward metric indicating the model's general performance across the entire dataset. Precision indicates the accuracy of the positive predictions made by the model. It represents the percentage of true positive predictions among all the positive predictions, calculated by dividing the number of true positives by the sum of true positives and false positives. Recall, also known as sensitivity or the true positive rate, measures how effectively the model identifies actual positive cases. It

is calculated as the ratio of true positives to the total number of actual positive cases, which includes both true positives and false negatives. F1 Score combines precision and recall into a single metric by calculating their harmonic mean. This score is particularly valuable when a balance between precision and recall is needed, as it mitigates the impact of any extreme values in either metric (Walker, n.d.).

These were computed for grouped and ungrouped classes to understand how the feature layers performed and by grouping the categories post-classification makes it easier for characterization.

Chapter 5. Results

This chapter details the various results obtained from the analysis and the classification processes with corresponding images to explain the results. The chapter will first explain the results of all the feature layers generated for the study and then go into more detail about the feature layers selected for classification with more zoomed-in images for better understanding.

5.1. Feature Analysis

All the Haralick extraction results for a zoomed-in image piece shown in Figure 25 are visualised to see the variations in each feature and its distribution. The different bands represent the different features in the extraction. Figure 26 and Figure 27 give the visual



Figure 25. Original image piece snapshot to explain the results of feature layers



Figure 26. Haralick maximum values for a zoomed-in image piece inside the study area.

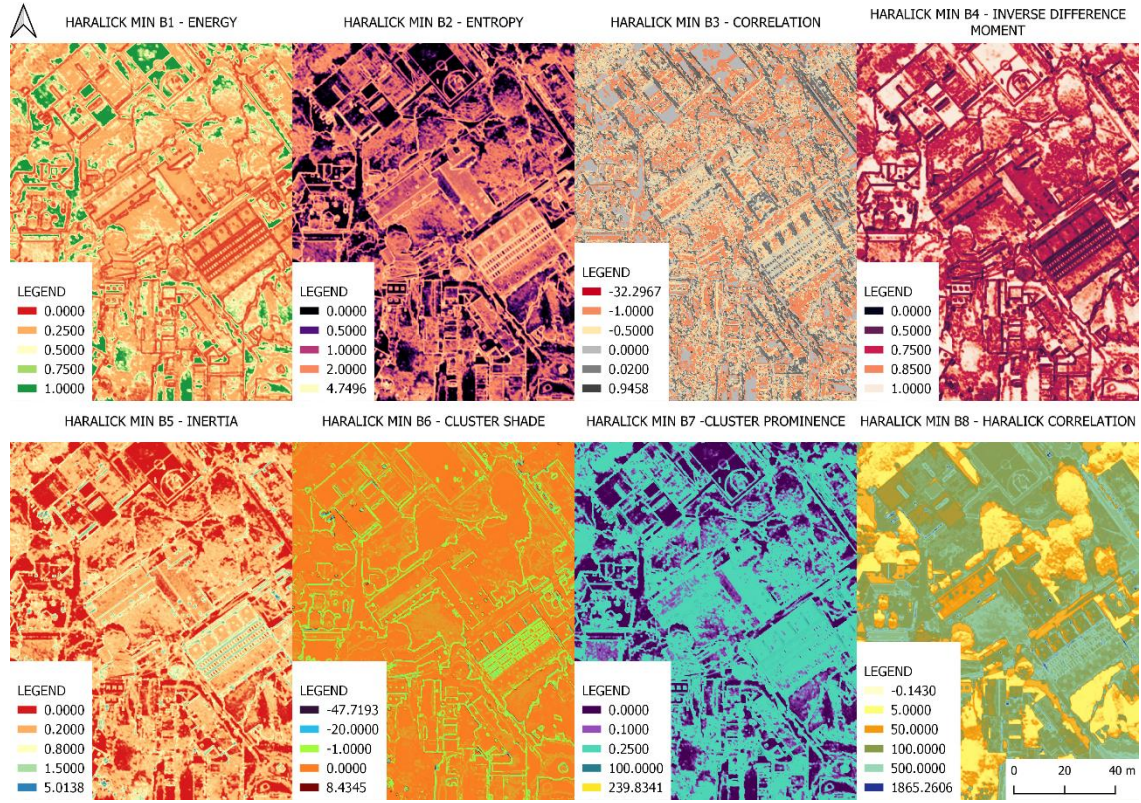


Figure 27. Haralick minimum values for a zoomed-in image piece inside the study area.

minimum, edges present lower values, depicting the value variation for the two extremes indicating the homogeneity of surfaces.

Entropy values range from 0 to 5.27 for maximum and 0 to 4.74 for minimum, with higher values indicating regions with more randomness and complexity in the texture, as seen in the Figures 26 and 27.

The correlation values range from -1.56 to 54.69 for maximum, indicating strong linear dependency between pixel pairs in certain areas, and -32.29 to 0.94 for minimum, suggesting weaker linear dependencies, indicating more random textures in those areas.

The maximum inverse difference moment and minimum inverse difference moment values range from 0 to 1, indicating regions with more uniform and less variable textures but in different areas for the two extremes.

Inertia or contrast values range from 0 to 13.69 for the maximum, suggesting areas with strong variations in local intensity patterns and the values 0 to 5.01 show regions with less variation.

The cluster shade and cluster prominence measure the skewness of the matrix and are considered an indicator of uniformity. The values range from -20.27 to 49.33 and 0 to 628.24, show the regions with higher asymmetry and the values -47.71 to 8.43 and 0 to 239.83 for

minimum values indicate the regions with lesser asymmetry compared to the other areas. When the cluster prominence value is low, the GLCM matrix exhibits a peak around the mean value (X. Yang et al., 2012).

Haralick's correlation is also a measure of the correlation, with values ranging from -0.2 to 4569.41 for maximum and -0.14 to 1865.26 for minimum.

The next set of features generated were the six different SFS features, which are presented in Figure 28 and the results are as follows:

SFS' Length: This map shows the maximum length of direction lines radiating from each central pixel. Higher values are represented by the colour blue, indicating they might be longer.

SFS' Width: This shows the minimum length of direction lines. It highlights smaller or narrower features around the central pixel. Narrower structures should have higher values, shown by lighter colours.

SFS' PSI (Pixel Shape Index): This shows the mean or sum of the lengths of direction lines around each central pixel. It gives an overall measure of the structure. Areas with more complex structures will have higher values, indicated by the blue colour in the value range of 33 and 36.

SFS' W-Mean (Weighted Mean): It calculates the average length of lines from the central pixel, adjusting for the consistency of colour or intensity. Stable and homogeneous areas should have higher values, but most of the areas in the image are blue, which indicates they are not stable areas.

SFS' Ratio: This describes the shape contour around each central pixel by comparing the shortest and longest direction lines. More circular shapes will have higher values and are represented by the colour green in Figure 28.

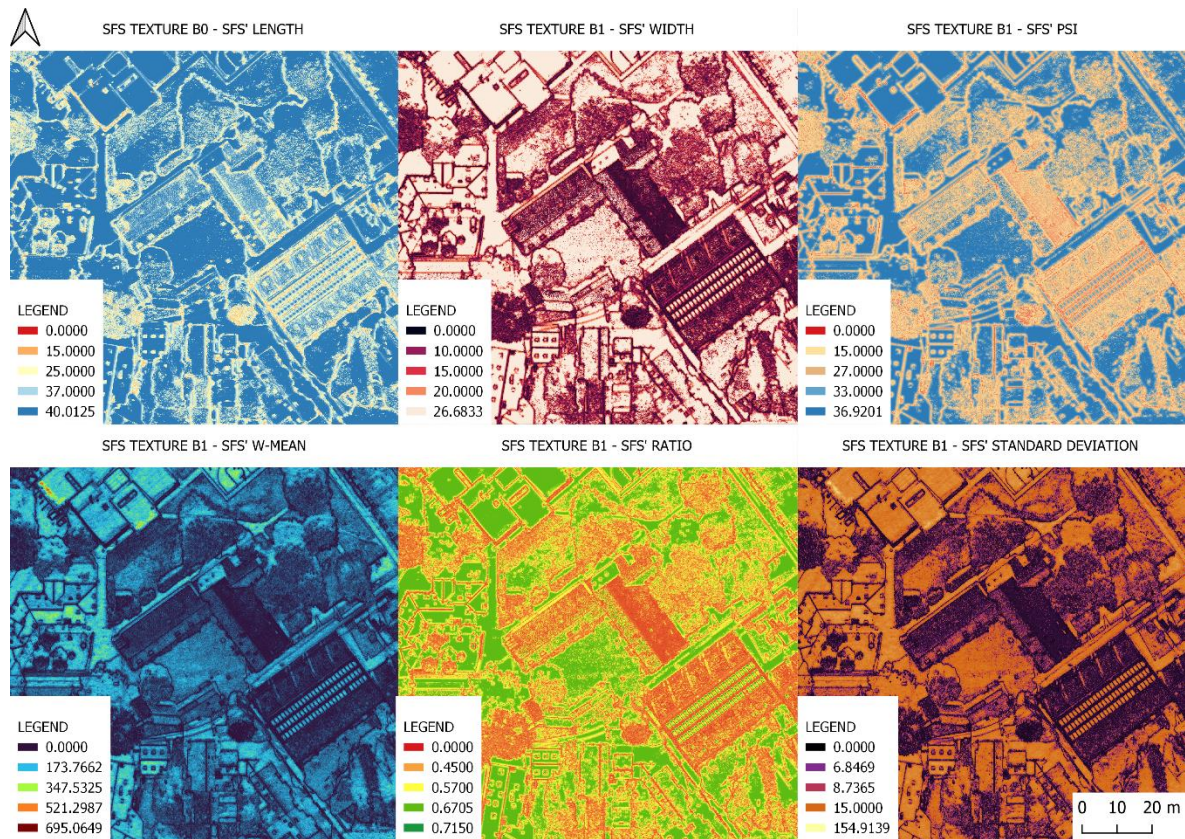


Figure 28. SFS texture values for a zoomed-in image piece inside the study area.

SFS' SD: This represents the variability in the lengths of direction lines around each central pixel. Areas with high structural variability will have higher values, as indicated by the colour orange in the Figure.

The four statistical moments called the local statistics were also computed over the image visualised for the image piece, as shown in Figure 29.

Mean: Depicts the mean for the pixels in the 5-pixel (around 44 cm) neighbourhood and represents some of the artificial surfaces with higher values.

Variance: This measures the spread or dispersion of the data around the mean, with the feature selection step, this layer was taken for classification purposes. The result shows a bit of patterned view in the some of the surface types like cobbled (further detailed in Figure 32).

Skewness: Indicate the asymmetry of the data. Corresponding Figure 28 predominantly shows yellow colours, indicating that most areas have skewness values close to zero, with a few regions exhibiting significant positive or negative skewness. Skewness can also affect the perceived lightness and glossiness such that areas with positive skewness appear darker and glossier than ones with lower skewness(Motoyoshi et al., 2007).

Kurtosis: Measures the peak or tail of the data that gives outliers and extreme values. In the results it was hard to distinguish classes using this feature as seen by the values in Figure 29.



Figure 29. Local Statistics values for a zoomed-in image piece inside the study area.

Saturation

It measures the amount of white colour mixed with the colour. Here in Figure 30, lower saturation values represented by red-orange colour are computed for artificial surfaces.

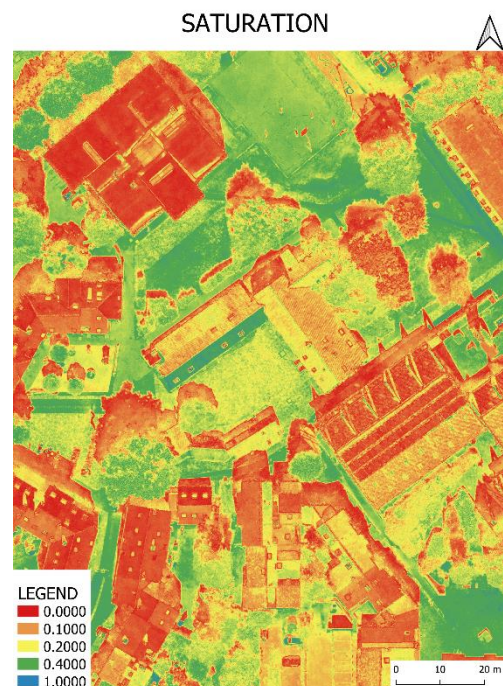


Figure 30. Saturation values for a zoomed-in image piece inside the study area.

Mahalanobis Distance and Feature Results

The Mahalanobis distances between certain pairs of categories were notably high, with values exceeding 3, which is considered excellent given that a Mahalanobis distance greater than 2 is typically regarded as indicating good separation (Mclachlan, n.d.). For instance, the pairings of semi-impervious pavement and cobble yielded high Mahalanobis distances across several texture layers, indicating strong differentiation between these categories. Additionally, the pair of asphalt and semi-impervious pavement achieved a high value of 3.5 for the saturation layer, demonstrating significant separation. Semi-impervious pavements also showed good separation from the vegetation category of grass, further validating the effectiveness of these categories in the classification process. The layers chosen according to this result is illustrated using a more detailed and zoomed-in figures (Figure 31 and Figure 32).

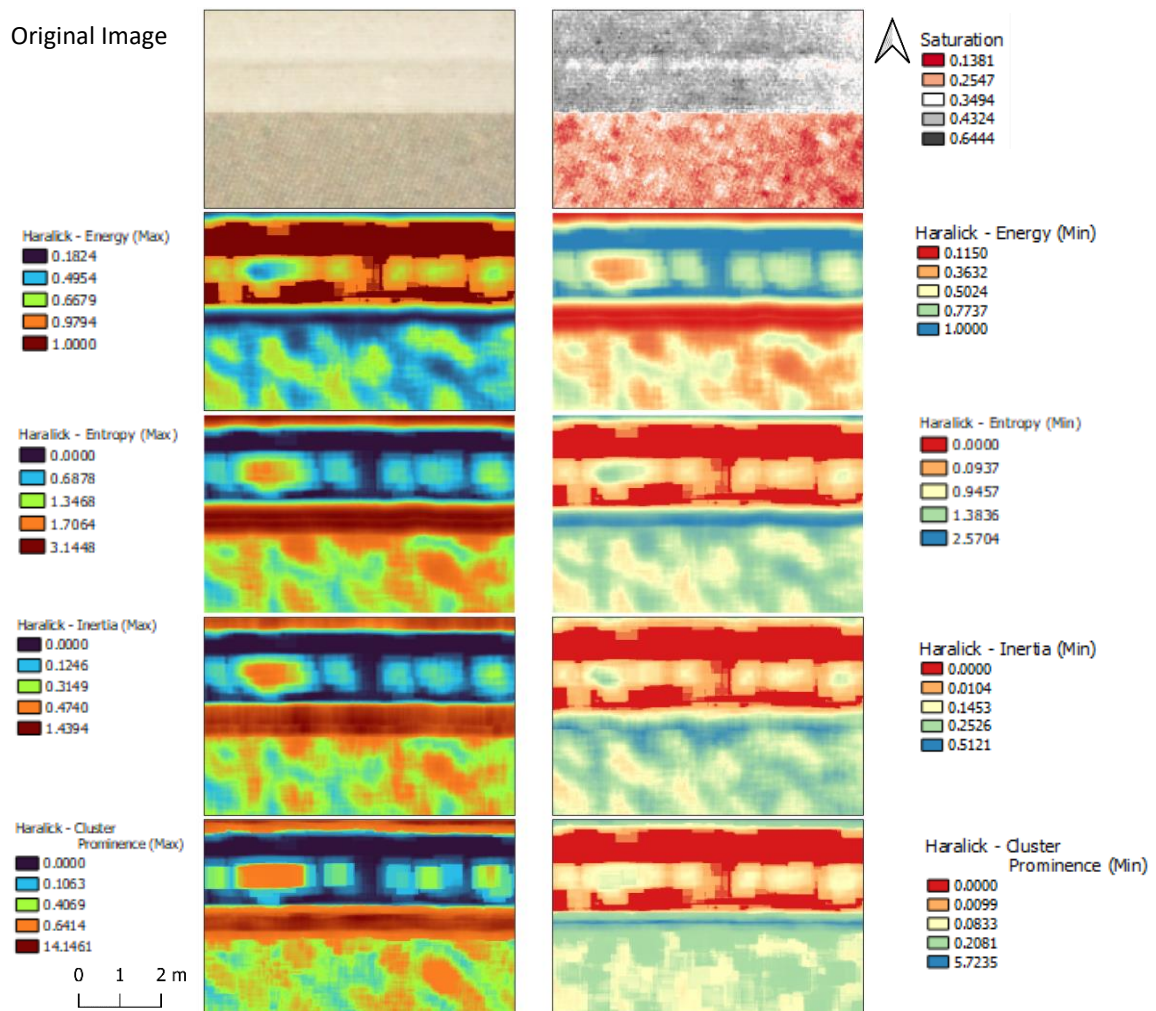


Figure 31. Further zoomed-in snapshot to illustrate feature value variation, Haralick (max-min) and Saturation

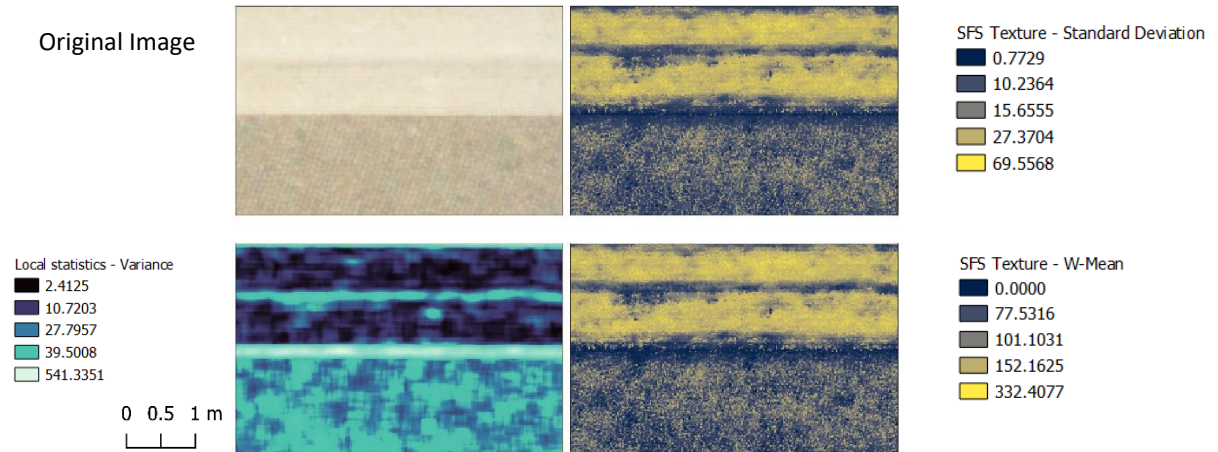


Figure 32. Further zoomed-in snapshot to illustrate feature value variation of SFS texture and Local statistics

The detailed images in Figures 31 and 32 indicate the clear pattern of texture features and other feature layers of the selected layers after Mahalanobis distance computation and comparison. The image area taken is of semi-impervious pavement (with a brighter shade in the original image) and cobbled area (with a darker, more textured look). The edges are again ambiguous, but the features themselves show texture through value variation in Haralick min/max layers and show distinguishing features in other layers as well. Saturation values are also very prominent and different for these two categories. Even with this layer selection, it can be observed from the zoomed-in imagery that there is still high similarity between the layers, which could indicate that this combination of features are still not the best distinguishing ones for these categories.

5.2. Classification Results

This section details the results obtained from the classification procedure using 14 classes and the consolidated 4 classes, as explained in the methodology chapter.

5.2.1. Visualisation Type 1: 14 Classes

The classification results of the stacked VRT using the pre-processed training dataset and the image classifier from the OTB are depicted in Figures 33, 34, and 35. These figures showcase 14 classes labelled by the RF classifier, with corresponding image snapshots for comparison. A comprehensive view of the entire study area is provided in Appendix II.

In Figure 33, a zoomed-in comparison highlights some misclassifications: grass areas are often misidentified as bare soil or even vehicles. However, impervious pavement roads are generally well classified; for instance, pathways through dried grass are somewhat distinctly identified.

There is a noted challenge with asphalt areas, which are sometimes classified as water bodies due to their similar reflective properties.

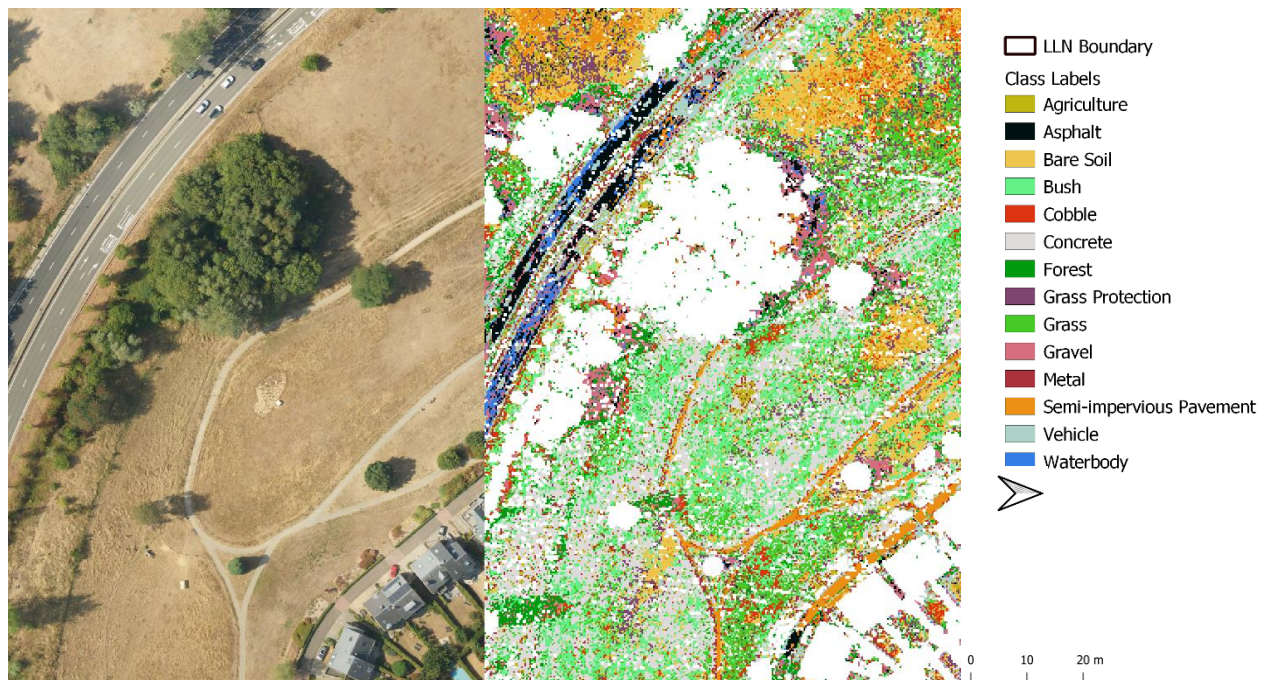


Figure 33. Zoomed-in snapshot and corresponding image for comparing classification result of 14 classes - The Gardens of Moulinsart, in Bruyères district

Figure 34 also demonstrates that impervious pavement is classified accurately to some extent. However, shadowed regions pose a challenge, leading to ambiguous classifications. Here, vehicles are also classified reasonably well.



Figure 34. Zoomed-in snapshot and corresponding image for comparing classification result of 14 classes- near Monument to the memory of Doctor Michel deslescaille

Similarly, in Figure 35, semi-impervious areas are well classified except in shadowed regions, where misclassification into asphalt and other categories occurs.

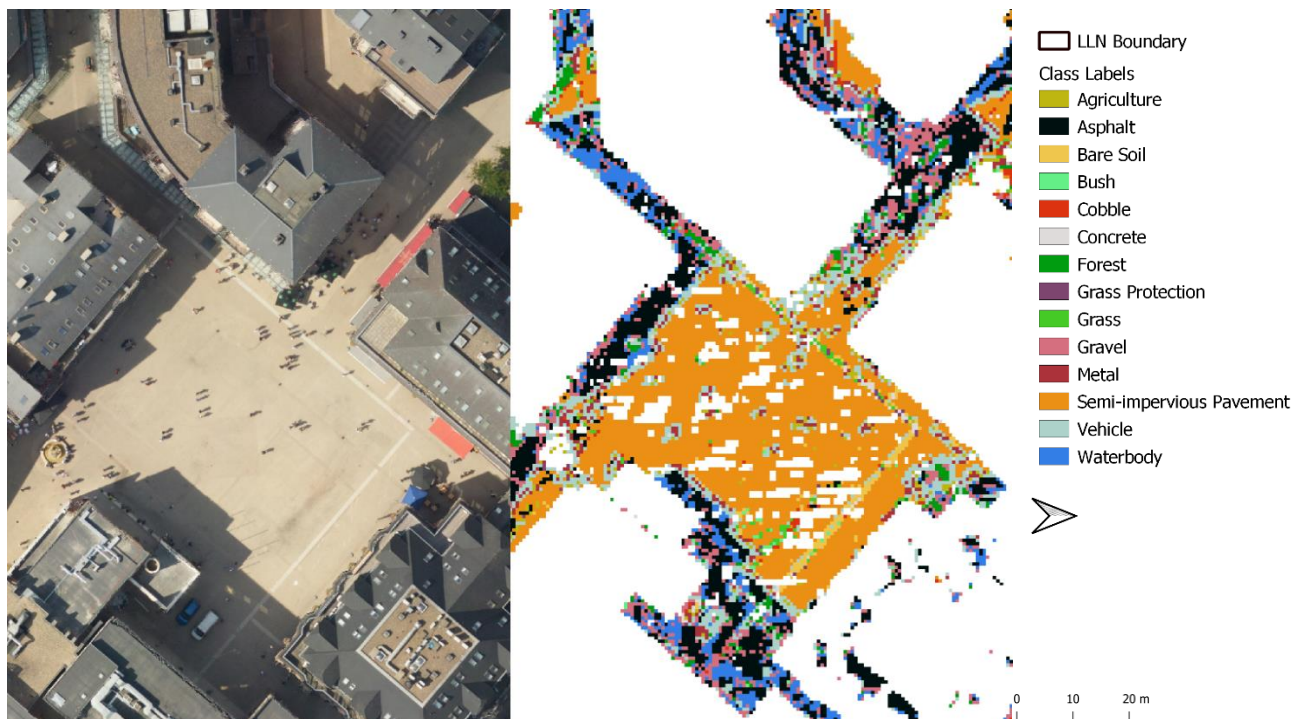


Figure 35. Zoomed-in snapshot and corresponding image for comparing classification result of 14 classes- University Square

Further zoomed-in snapshots in Figure 36 offer a more detailed view of five different areas within the study region. The edges show complex classification issues, with the cobbled areas in the image (a) struggling to be correctly identified using texture layers alone. Notably, the metal drain cap in image set (b) is well classified, distinguishing it from semi-impervious pavement and cobbles. However, bright concrete areas are often misclassified as vehicles due to the higher reflections from vehicles. The classification of semi-impervious pavements varies, with some areas showing homogeneity (image set (c)), while others, like image set (d), mix with bare soil due to similar appearances. Asphalt roads are frequently misclassified with other classes, particularly water bodies, due to their similar colour and texture (image set (e)).

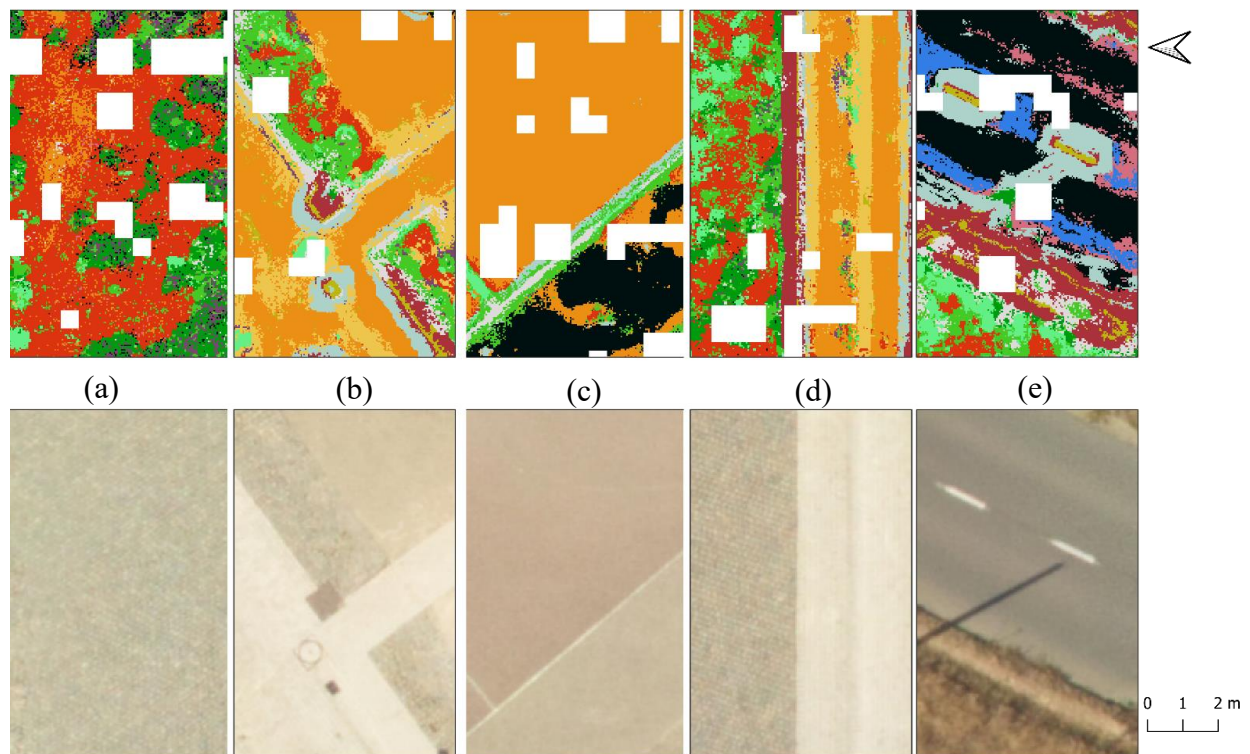


Figure 36. Further zoomed-in snapshots illustrating various surface types classified (a) Cobbled, (b) semi-impervious, cobble with metal and concrete areas, (c) basketball court, (d) cobble and semi-impervious edge, and (e) asphalt road and edges

Some of the above-mentioned visual results were indeed evident in the accuracy assessment but missed many details due to the absence of a good validation dataset.

The corresponding confusion matrix was calculated based on the validation data developed. It is presented in Figure 37. The overall accuracy for the classification was 0.23, which is a very low value. This low accuracy value could be due to validation dataset not being the best one.

The confusion matrix indicates that the classification failed to identify the agriculture surface type given in the colour red and classified them into the cobbled class. At the same time, cobble

only has one correct instance of classification. Out of all the classes, asphalt and semi-impervious pavement were the best predicted classes, shown in green in the Figure 37. Overall, the classification model displayed a high level of confusion and misclassification.

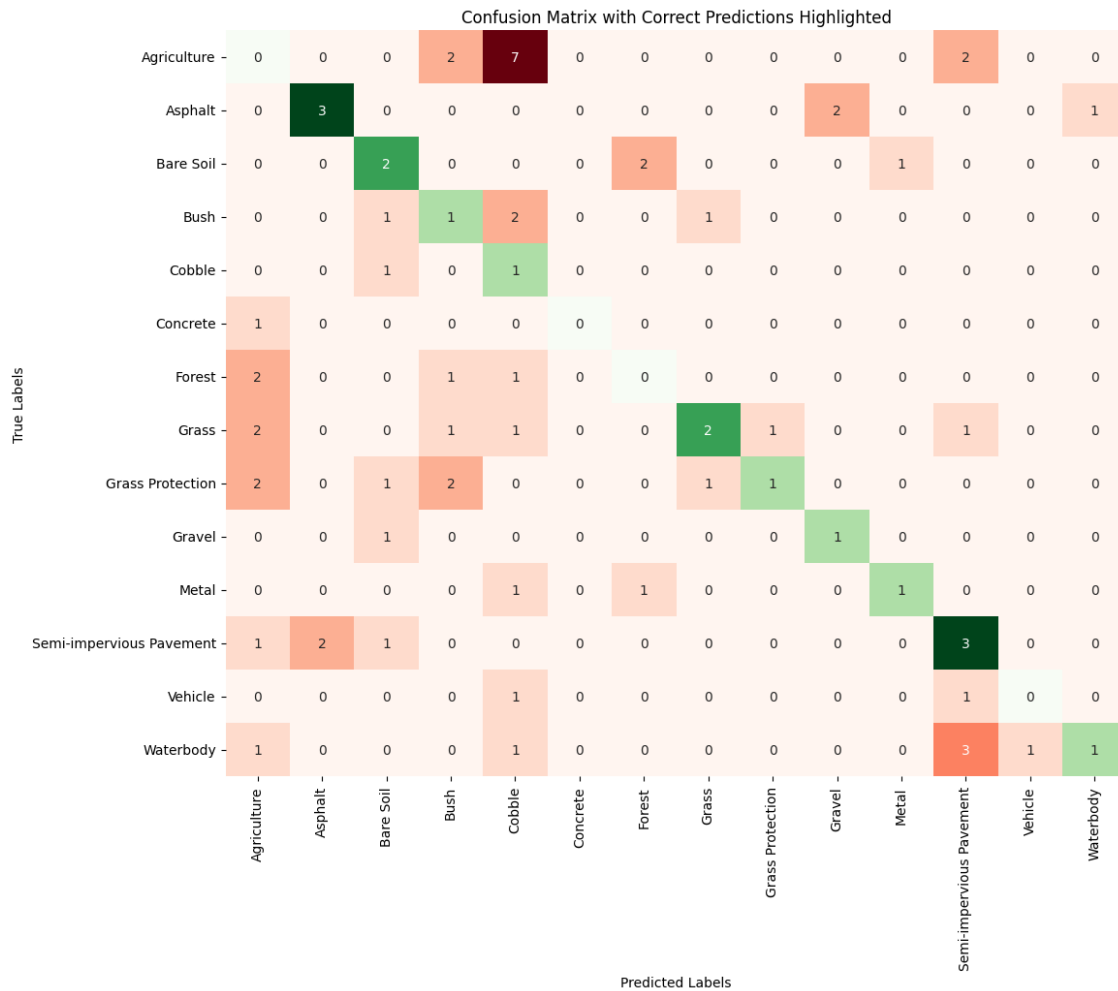


Figure 37. Confusion matrix for 14 class classification visual

The precision, recall, and F1 scores were also computed and given in Table 2. The classification model demonstrates varying levels of performance across different classes. It performs moderately well for the "Asphalt" class, achieving a precision of 0.6, recall of 0.5, and an F1-score of 0.55, indicating a relatively balanced ability to identify and predict this class correctly. However, the model struggles significantly with several other classes, including "Agriculture," "Concrete," "Forest," and "Vehicle," where it failed to make any correct predictions, resulting in precision, recall, and F1-scores of 0 for these categories. This highlights a critical issue, suggesting possible shortcomings in data representation and few other peculiarities including the fact that large chunk of forest was masked by the height mask which led to 0 values for the classification metrics. Another factor is that "Agriculture" is also usually characterized with

temporal information in Belgium which could be the reason it was misclassified into other categories. Additionally, the "Cobble" class showed a particularly low precision of 0.07 despite a higher recall of 0.5, suggesting a tendency to label other instances as "Cobble" incorrectly. For "Bare Soil" and "Gravel," the model showed some ability to make correct predictions.

Table 2. Classification Metrics for 14 Class Classification Visualisation

Class	Precision	Recall	F1-Score
Agriculture	0	0	0
Asphalt	0.6	0.5	0.55
Bare Soil	0.29	0.4	0.33
Bush	0.14	0.2	0.17
Cobble	0.07	0.5	0.12
Concrete	0	0	0
Forest	0	0	0
Grass	0.5	0.25	0.33
Grass Protection	0.5	0.14	0.22
Gravel	0.33	0.5	0.4
Metal	0.5	0.33	0.4
Semi-impervious Pavement	0.3	0.43	0.35
Vehicle	0	0	0
Water body	0.5	0.14	0.22

5.2.2. Visualisation Type 2: 4 Classes

To have a better visualisation of the classes, the results were reclassified into 4 categories as defined in section 4.3.2, which are pervious, impervious, semi-impervious, and vehicles. The revisualisation of the same areas that were shown in the previous section gives a better understanding of the classification errors in some classes as well as improved results from an overall viewpoint.

Figure 38 highlights the misclassification issues previously discussed, especially in areas with grass. Here, the grass is often mistaken for impervious surfaces, likely because the imagery was captured during summer when the grass appears dry and lacks the vibrant green colour that helps distinguish it from other classes. Additionally, the dry grass texture differs significantly from the typical appearance, contributing to the misclassification.

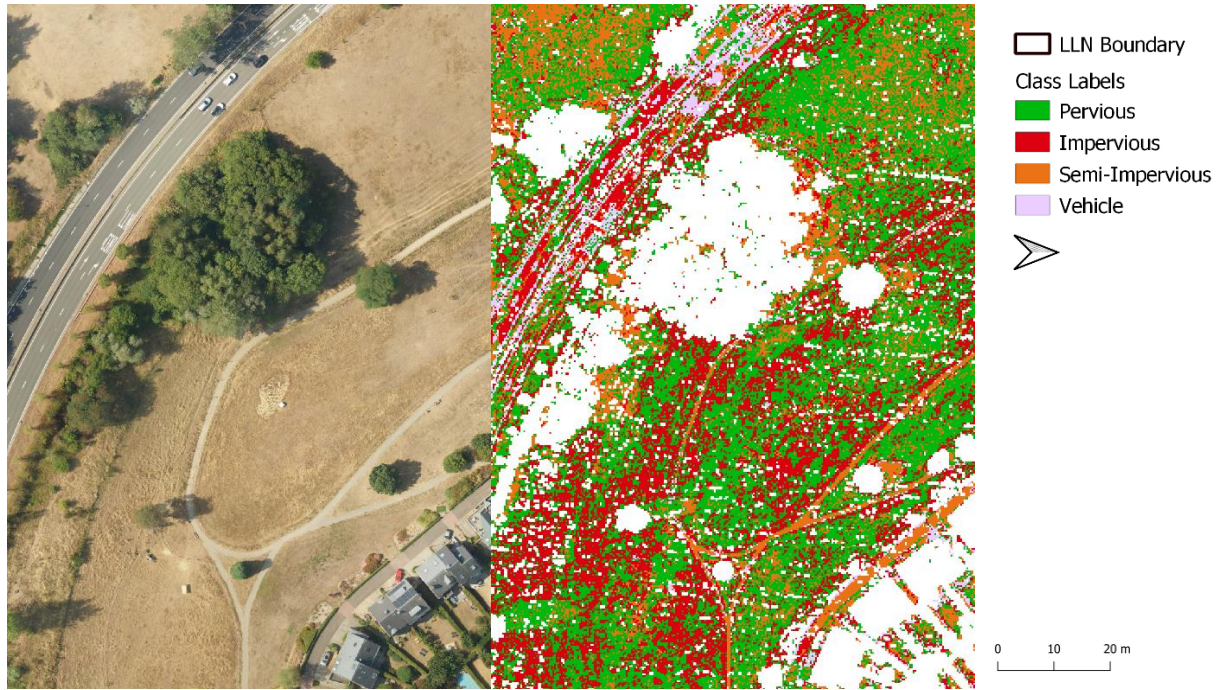


Figure 38. Zoomed-in snapshot and corresponding image for comparing classification result of 14 classes - The Gardens of Moulinsart, in Bruyères district

Figure 39 also gives a clear view of the categories, and we can see that the vehicles are classified as vehicles, but the white markings on roads are also classified as vehicles. This misclassification could be due to the similarity in reflection to that of white vehicles in the training data.



Figure 39. Zoomed-in snapshot and corresponding image for comparing classification result of 14 classes- near Monument to the memory of Doctor Michel deslescaille

Figure 40 serves as a good example of how the classifier handled people in the imagery. In most cases, the classifier categorized all the people and dark areas as impervious surfaces. Despite this, the rest of the area in Figure 40 demonstrates a relatively accurate classification, showcasing one of the better-classified regions in the study. This shows that the classifier can distinguish between semi-impervious and other types of surfaces.

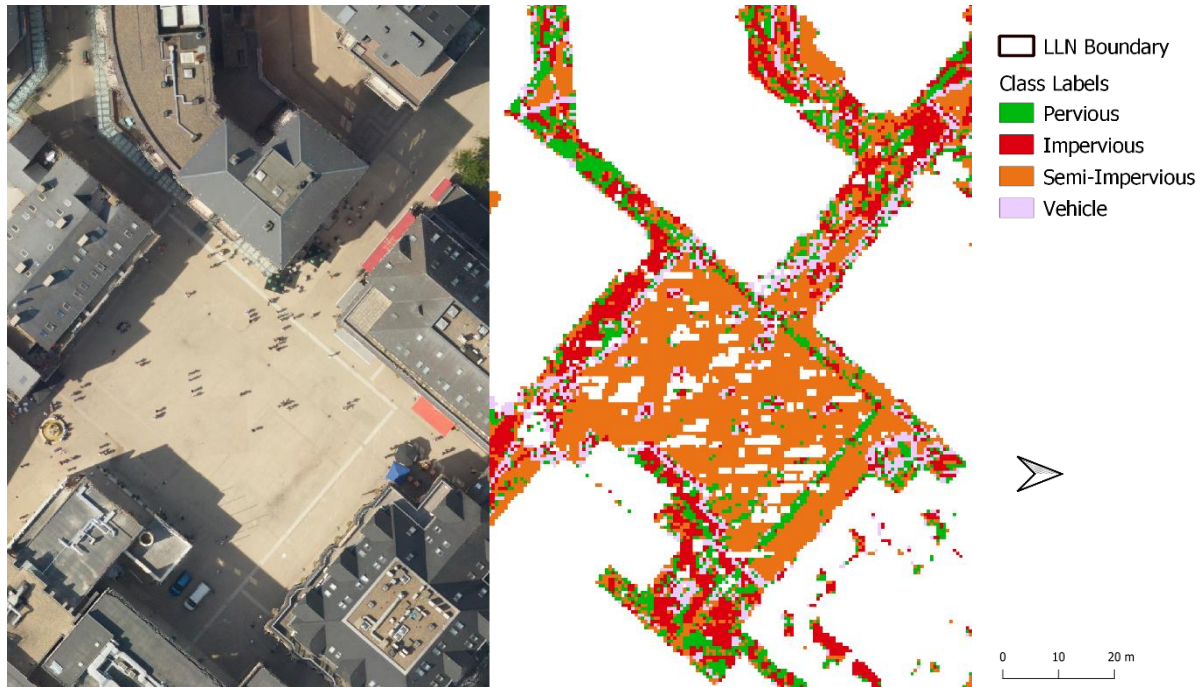


Figure 40. Zoomed-in snapshot and corresponding image for comparing classification result of 14 classes- University Square

Like the previous section, the zoomed-in images in Figure 41 illustrate the classification into four categories. These snapshots clearly show that edges often exhibit variable and complicated classifications, while the interior areas display more homogeneous and accurate classifications. Notably, in image set (d), a particular surface type not documented in the training/validation data was classified as semi-impervious. This suggests that the surface shares properties with other semi-impervious surfaces identified in this study.

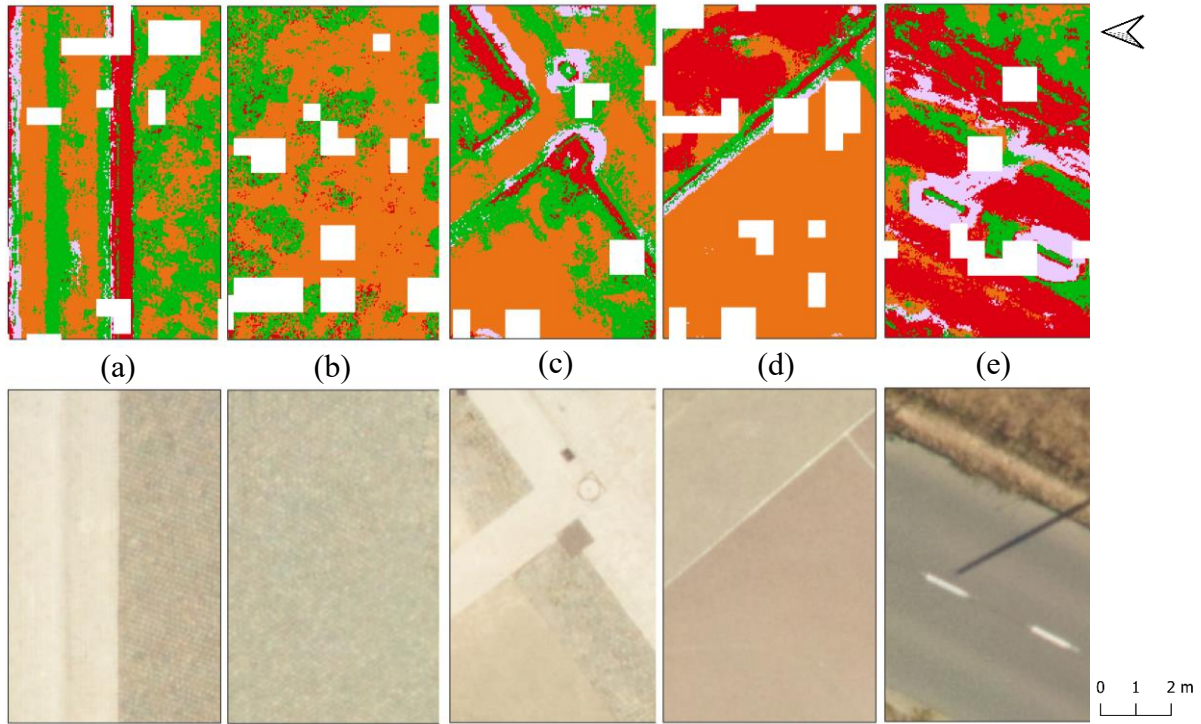


Figure 41. Further zoomed-in snapshots illustrating various surface types classified (a) Cobbled, (b) semi-impervious, cobble with metal and concrete areas, (c) basketball court, (d) cobble and semi-impervious edge, and (e) asphalt road and edges

The confusion matrix for consolidated classes (Figure 42) reveals that the classifier struggled particularly with differentiating between pervious and impervious surfaces. Pervious surfaces were often misclassified into impervious with 12 instances shown in red and semi-impervious with 8 instances. Notably, the semi-impervious surfaces were frequently confused with pervious surfaces, as shown by the high number of misclassified instances. Vehicles, although present, were also sometimes misclassified as pervious surfaces, but this could also be because of a need for more samples in the validation dataset. Overall, the confusion matrix highlights substantial misclassification issues, suggesting that the classifier needs a high level of clarity and needs further refinement to improve accuracy in distinguishing between these surface types. The overall accuracy was 0.43, better than individual classes but still a low value for classification. The increase in accuracy could be attributed to the consolidation, which helped to reduce the complexity of the classification.

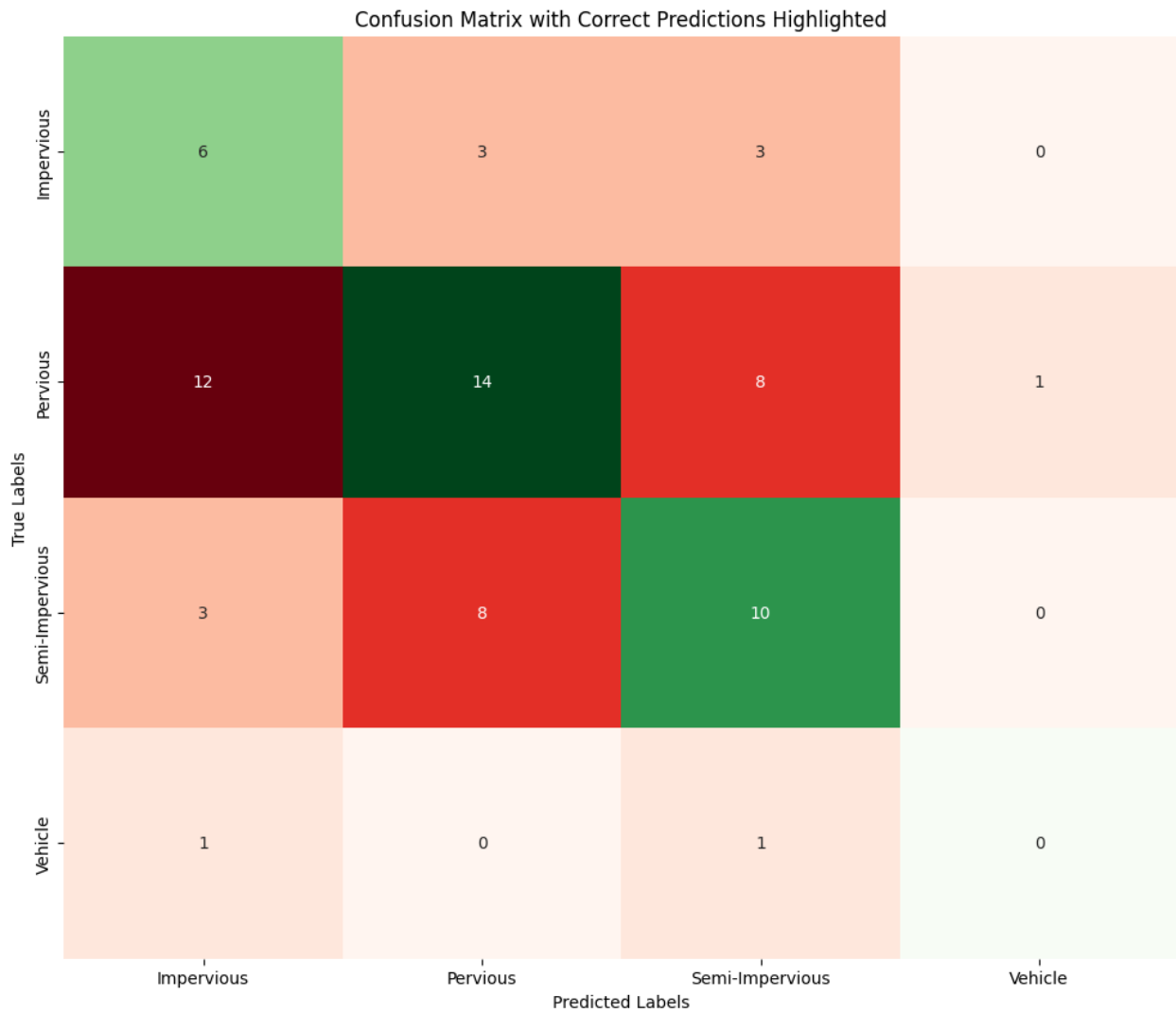


Figure 42. Confusion matrix for 4 class classification visual

Table 3 indicates that the model's performance varies significantly across different classes. The model struggles particularly with identifying vehicles, as indicated by a precision, recall, and F1-score of 0. This suggests that the model needs sufficient validation data for Vehicles.

The relatively higher precision and recall for the pervious and semi-impervious classes indicate that the model is more effective in these categories, though there is still considerable room for improvement. The impervious class shows lower precision but higher recall, suggesting that while the model is better at identifying most of the impervious instances, it also misclassifies other instances as impervious which confirms the visual inspection of image results as well.

Table 3. Classification Metrics for 4 Class Classification Visualisation

Grouped Class	Precision	Recall	F1-Score
Pervious	0.56	0.4	0.47
Impervious	0.27	0.5	0.35
Semi-Impervious	0.45	0.48	0.47
Vehicle	0	0	0

The overall accuracy assessment indicates that the model's performance might be better than what the metrics indicate. The visual interpretation of the classified images suggests that the model may have done a better job than what the numbers show. This difference could be due to a lack of proper validation data. Some classes had fewer data points compared to others after the height mask application post classification. If the validation data is not comprehensive or accurate, it can give a misleading picture of the model's actual performance.

5.3. Proportion of Classes in the Study Area

To gain a clearer understanding of the distribution of each class within the study area, pie charts were created, excluding the area that was masked by the height mask. Pie charts were also plotted with the initial 600 datapoints mapped for training/validation dataset which did not take the height mask into account. These charts visually represent the proportions of the four main classes, as well as the distribution of these classes within the broader categories. This visualisation helps to easily compare the relative sizes and presence of each class across the study area. The individual class proportions for the whole area are given in Appendix III.

5.3.1. Distribution of Classes Across the Entire Study Area

The pie chart in Figure 43 shows the distribution of area by class within the study area in Louvain-la-Neuve. The largest proportion, at 34%, is represented by pervious surfaces, shown in green. This category includes natural surfaces like grass, forest, and bare soil, which are beneficial for the environment as they help mitigate urban heat islands and allow water infiltration. The category included some of the best classified classes like the grass, water body and bare soil.

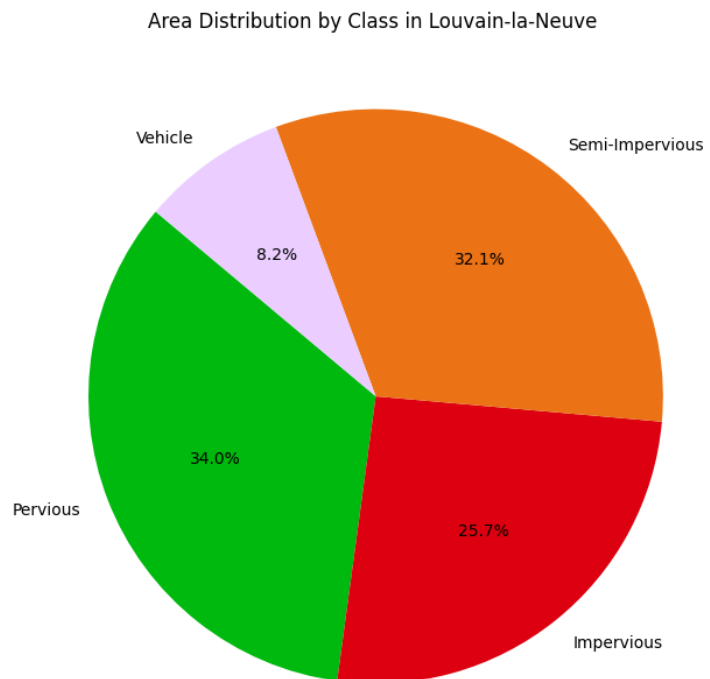


Figure 43. Pie chart representing the proportion of area for each class

The second largest category is semi-impervious surfaces, making up 32.1% of the area. This indicates a positive aspect of urban development, as these surfaces allow varying amounts of water infiltration, reducing the impact of completely sealed surfaces. This category includes classes that were well classified like the semi-impervious pavement, gravel and grass-protection.

Impervious surfaces, such as roads (class that had high classification accuracy) and concrete structures, account for 25.7% of the total area. This reflects the extent of urban infrastructure in the region, which is necessary for transportation and development.

5.3.2. Breakdown of Individual Categories Within Major Groups

The dominance of bush (24.7%), grass (24.6%), and forest (21.5%) in pervious surfaces highlights the significant green coverage, which is crucial for environmental sustainability. These areas are important for urban heat island mitigation, providing shade, and supporting biodiversity. The presence of agricultural land (12.9%) suggests a mixed land use that could support and maintain rural characteristics within the area. Bare soil (11.8%) might indicate areas under development or natural landscapes with less vegetation cover. The smaller percentage of waterbodies (4.5%) could be because the imagery was taken during summer underrepresenting actual waterbodies.

In the semi-impervious category, the majority being cobbled (36.0%) and semi-impervious pavement (34.2%) suggest an abundance of pedestrian pathways, plazas, or other urban features that balance between fully impervious and natural surfaces. Gravel areas (24.1%) are used in driveways, walkways, or construction sites, providing some permeability. Grass protection areas (5.7%) are often used to maintain the aesthetic appeal of grassed areas while allowing for light usage.

The predominance of concrete (53.2%) in impervious surfaces indicates extensive use in infrastructure, which can lead to increased surface runoff and reduced groundwater recharge, or it could be the product of misclassification explained in the previous sections. Asphalt (27.4%) is commonly used in roads and parking areas, contributing to urban heat island effects

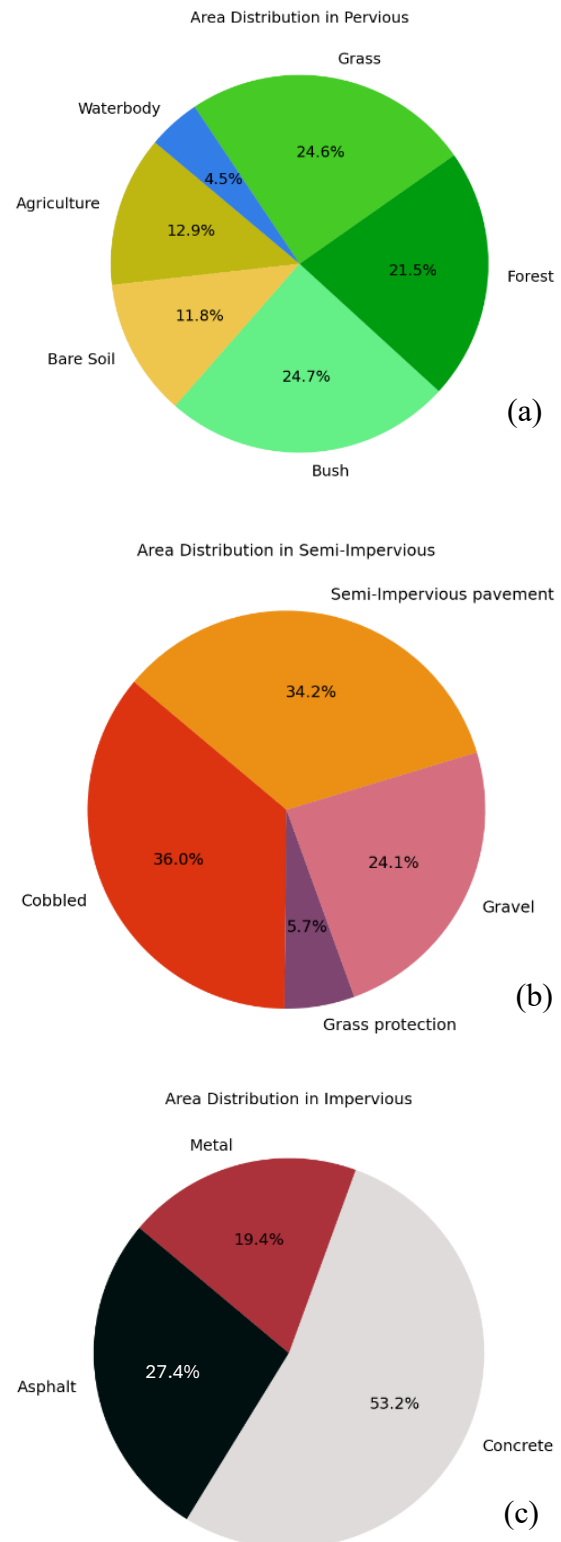


Figure 44. Pie charts representing individual class-wise proportions in (a) Pervious, (b) Semi-Impervious, and (c) Impervious categories

and potentially increasing surface temperatures. The presence of metal surfaces (19.4%) could be associated with the metal drains and drain caps spread around the study area.

The data suggests a well-developed urban area with a substantial proportion of impervious and semi-impervious surfaces. The balance between built-up areas and natural landscapes indicates an effort to maintain green spaces, which are essential for ecological balance and urban liveability.

However, it is important to consider the potential and evident misclassification in several classes.

5.3.3. Proportion of Count of Classes using the Field Survey Points

To gain a clearer understanding of the classification results, the proportion of counts for major surface classes was analysed, as illustrated in Figure 45. This analysis revisited the 600 points generated during the field survey, which contributed to the creation of the training and validation dataset. At these specific locations, the actual surface types were meticulously counted.

The pie chart illustrates the proportion of counts by class, revealing that a significant 61.5% of the surveyed points were pervious

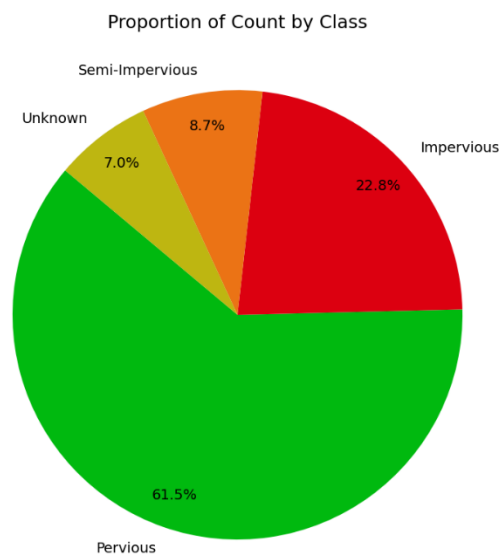


Figure 45. Proportion of Major Classes within the 600 Random Points Generated

surfaces. In contrast, impervious surfaces constituted 22.8% of the points, while semi-impervious surfaces accounted for only 8.7%. Additionally, 7.0% of the points were labelled as 'Unknown' due to inaccessibility (Private Property) and indistinguishability in the imagery.

This distribution highlights the predominance of pervious surfaces in the study area, with a notably smaller fraction representing semi-impervious types. Unfortunately, edge surface types like concrete were not adequately captured by the randomly selected points (Appendix III), indicating that the field survey points might underrepresent certain classes in the overall surface distribution. This field survey results, and the classification output in section.5.2 indicate that the semi-impervious surfaces might have been overrepresented in the classification compared

to the impervious surfaces. This comparison provides a valuable real-world context to the study, offering a clearer understanding of the actual distribution of surface types across the area.

Chapter 6. Discussion

The study presented a comprehensive approach to classify urban impervious surfaces using high-resolution sub-metric airborne imagery supplemented by LIDAR-derived height masks for visualisation. While the classification algorithm's performance metrics - precision, recall, F-score, and overall accuracy values provide insights into its strengths and limitations, the accuracy assessment may only partially capture the true performance due to some limitations in the evaluation process.

6.1. Performance of Classification and Challenges in Distinguishing Surface Types

The study's performance analysis using both 14-class and 4-class schemes highlights significant variability in the accuracy of identifying different urban surface types. The overall accuracy drastically changed from 0.23 to 0.43 for 14 class and 4 class results.

The results indicate that the model faced challenges in accurately classifying certain surface types in the VHR image. Specifically, even with the intra-class spectral and textural variability highlighting the heterogeneity within similar land cover types. This issue, as noted in a previous study by Langenkamp & Rienow (2023) suggests that the training data may not have sufficiently captured this heterogeneity, leading to classification errors.

Moreover, the confusion between bare soil and semi-impervious surfaces in the visual assessment can be attributed to their spectral similarity and lack of texture. The model particularly struggled with classes like concrete and agriculture, which are critical for mapping impervious surfaces. A potential reason for the misclassification could be that the imagery was captured during the summer, when grass and agricultural areas appear similar in the images. Additionally, concrete surfaces, due to their bright appearance, may have also been misclassified. The performance metrics for these classes were notably poor, often computed to zero, underscoring the difficulty in distinguishing these categories from the available information and the lack of training/validation data. To improve the accuracy of the modelling, one effective approach could be to incorporate temporally varying images, allowing for better differentiation of surface types across different seasons.

Shadows can significantly affect the accuracy of land cover classification, often leading to misclassification. This issue is particularly pronounced in high-resolution images, where shadows can obscure critical details, making it challenging to distinguish between different land cover types. The study by Langenkamp & Rienow (2023) highlighted that the RF classifier struggled in areas with high spectral variability and shading. Specifically, shadows caused

confusion between impervious surfaces and other similar classes, leading to notable misclassifications.

Grouping the classes into four significant categories provided some improvement in broader classification. However, the model still faced challenges with the vehicle class, which was often confused with concrete due to their spectral similarities.

6.2. Impact of Training and Validation Data

A significant limitation identified in the study was the lack of comprehensive training and validation datasets. This shortfall likely contributed to the low overall accuracy of the classifications, particularly in more complex surface types in mixed urban areas. The absence of such data can obscure the true extent of classification errors, as observed in the misclassification of pervious and impervious surfaces in this study.

Despite conducting extensive fieldwork, manually developing and labelling classes, and addressing issues such as height masking and unusable data points, the resulting classification accuracy was still insufficient. This highlights the critical need for more comprehensive datasets that accurately represent the diverse surface types and conditions found in urban environments.

To enhance future models, it is crucial to develop comprehensive datasets that thoroughly represent the various surface types and conditions present in urban areas. This enhancement requires significant effort in creating and validating detailed and extensive datasets, which, despite being resource-intensive, is vital for improving model accuracy and ensuring reliable applications in urban planning and environmental management.

6.3. Influence of Texture Features on Classification

The texture features, such as those derived from the Haralick and SFS methods, played a significant role in the classification process, with varying degrees of success. These features provided additional layers of information regarding the spatial arrangement and textural characteristics of different surface types, which were intended to enhance the classification accuracy.

These texture features were moderately effective in capturing the uniformity and complexity of surface textures. For instance, surfaces like semi-impervious pavements and cobbled surfaces, which often exhibit unique textural patterns, were better identified when these features were included in the classification model.

Even though there was good distinction between some classes using these texture features, there was still overlap of properties between the features as seen from the Mahalanobis results. This could be solved by refining the selection of features and adjusting the parameters within these feature sets to enhance the classification accuracy.

6.4. Improving Classification Accuracy: Smoothing and Reducing Salt-and-Pepper Effect

Applying smoothing techniques and reducing the salt-and-pepper effect in the generated classification images could potentially enhance the accuracy and quality of the results. The presence of salt-and-pepper noise often leads to misclassified individual pixels, which can distort the true representation of different surface types in the study area. This effect is particularly pronounced when dealing with complex urban environments where precise classification is crucial.

The accuracy assessment in this study was conducted using the majority class within validating polygons. While useful, this approach may not fully account for the fine-scale variations and noise present in the classification outputs. By applying smoothing techniques, such as median filtering or Gaussian smoothing, the abrupt variations between pixels can be minimized, resulting in a more coherent and accurate depiction of the surface types.

Smoothing can reduce the impact of noise and improve the delineation of homogeneous regions, thus potentially increasing the accuracy metrics like precision, recall, and F1-score.

6.5. Methodological Insights and Future Directions

The study underscores the potential benefits of using advanced texture features and emphasizes the importance of feature selection to prevent redundancy. One notable challenge identified was the frequent misclassification of categories like asphalt and concrete. This issue may be partly due to the timing of image acquisition, as the data collected during the summer included very bright surfaces that were difficult to differentiate. A different date or time when reflections are less intense, might have produced a better output. This finding highlights the need to consider seasonal variations in image acquisition to better capture the actual feature characteristics of various surfaces.

To address these issues, future research should consider incorporating ancillary data, as recommended by Lichtblau & Oswald (2019). This approach could potentially enhance classification accuracy, especially for distinguishing features with subtle feature differences. For instance, integrating thermal imagery or other complementary datasets could provide

additional layers of information, aiding in the discrimination of materials with similar reflectance properties.

Additionally, expanding the training dataset to include more diverse and representative samples, particularly for underrepresented classes such as vehicles and certain impervious surfaces, is crucial. This expansion would help the model better generalize across different urban textures. Integrating additional data sources, such as road data, could also significantly enhance the accuracy of surface classification. Exploring deep learning approaches could further enhance the model's capacity to capture complex urban features and improve classification accuracy across all categories. These strategies could lead to more robust models, offering better support for applications in urban planning and environmental management.

6.6. Analysis of Class Proportions and Urban Development Implications

The analysis of the classification results revealed detailed insights into the distribution of surface types across the study area. The primary classes - Pervious, Impervious, Semi-Impervious, and Vehicle - were evaluated to understand their spatial distribution and implications for urban development and environmental management.

Among the categories, semi-impervious surfaces, accounting for 32.1% of the total area, include features such as cobbled pathways and semi-impervious pavements, which provide partial permeability. This category's significant share indicates a balanced urban design approach that attempts to mitigate runoff while maintaining functionality. The presence of gravel (24.1%) and grass protection areas (5.7%) further underscores efforts to integrate more environmentally friendly and permeable materials in urban infrastructure, which are crucial for stormwater management and reducing surface runoff.

The distribution of these classes highlights the urban area's development and the presence of green spaces. The significant share of pervious surfaces is a positive indicator of efforts to maintain green infrastructure, which is essential for ecological balance and enhancing urban life. The semi-impervious surfaces also indicate a move towards integrating permeable surfaces into urban planning, which can help mitigate the adverse effects of urbanization on the hydrological cycle.

Additionally, the proportion of counts for various classes obtained from field survey provided further context to the classification results. The results indicated that 61.5% of the surveyed points were pervious surfaces, while impervious and semi-impervious surfaces constituted 22.8%

and 8.7% respectively. However, it's important to note that certain surface types, particularly edge surfaces like concrete, were not adequately captured by the randomly selected points. This underrepresentation suggests that the field survey might not fully reflect the actual distribution of all surface types, particularly impervious surfaces, across the study area.

The field survey results somewhat align with the broader classification output, reinforcing the observed predominance of pervious surfaces within the study area. But also has differences with the semi-impervious surface and impervious surfaces proportions. This could also be because of having many points on buildings and roads. These findings emphasize the importance of using comprehensive data collection methods and considering potential misclassifications when interpreting classification results. Moving forward, urban planners could benefit from integrating more refined field surveys and advanced classification techniques to better capture the diverse surface types within urban landscapes.

Chapter 7. Conclusion

This study has aimed to investigate the application and potential of sub-metric resolution airborne data for the identification and characterization of urban impervious surfaces, with Louvain-la-Neuve, Belgium, serving as the specific case study area. The research aimed to bridge the gap in existing methodologies by employing sub-metric resolution imagery to enhance the accuracy of urban surface mapping. The findings provide critical insights into the complex nature of urban environments and the potential of advanced remote sensing techniques in urban planning and environmental management.

The study adopted a comprehensive methodology, integrating fieldwork, feature extraction, and classification techniques. The urban landscape of the study area, Louvain-la-Neuve, presented a diverse mix of impervious surfaces, such as roads and concrete areas, semi-impervious areas like paved paths, and pervious surfaces, including vegetation and water bodies. This diversity posed significant challenges to achieving accurate classification. The application of Haralick texture features, Local Statistics, and the SFS features derived from the imagery was moderately effective in capturing the unique textural characteristics of these surfaces. Haralick features, including metrics like Energy, Entropy, and Inertia, provided useful data on the uniformity and complexity of surface textures. The SFS features, which examine structural patterns in the imagery, added further insights into the spatial organization of the surfaces, helping to distinguish between different types of urban features. However, these metrics sometimes showed similarities across different surface types, complicating the classification process. In addition to these features, the saturation of the image was also utilized, which proved distinctive for specific categories and provided additional aid in the classification process. The saturation metric, indicating the intensity or purity of colours, helped differentiate between surfaces with similar textures but varying colour properties.

One of the main aspects of this study was the use of the open-source tool OTB for feature extraction and the RF classifier for classification. The OTB facilitated the efficient extraction of multiple texture features from the high-resolution imagery. The RF classifier, known for its robustness and ability to handle complex datasets, was instrumental in categorizing urban surfaces into distinct classes. Despite these advancements, the study encountered challenges in achieving high classification accuracy, particularly in differentiating between similar surface types. Misclassifications were observed in areas where the spectral and textural properties of surfaces overlapped, such as between asphalt roads and water bodies or between bare soil and certain types of vegetation.

The study's findings underscore the importance of high-resolution data in urban surface mapping. The classification achieved through this research is crucial for urban planners and environmental managers, who require accurate data to inform decision-making processes. The identification of impervious surfaces, for instance, is vital for understanding the hydrological impacts of urbanization, such as increased surface runoff and reduced groundwater recharge. Similarly, distinguishing between pervious, semi-impervious, and impervious surfaces is crucial for evaluating urban heat island effects and planning green infrastructure interventions. This differentiation helps urban planners, and policymakers assess the extent to which various surface types contribute to urban warming and stormwater runoff. Moreover, understanding the distribution and characteristics of these surfaces can inform decisions on whether additional investments in semi-impervious surface developments are warranted. These surfaces not only offer a balance between permeability and durability, aiding in water management and reducing heat retention, but they also add aesthetic value to urban landscapes.

The study also highlights the potential and limitations of current remote sensing technologies in urban surface mapping. While the use of VHR imagery offers a somewhat detailed view of urban environments, the findings emphasize the need for developing an extensive training dataset that encompasses a broader range of surface types and conditions that can more effectively manage the variability and complexity of urban surfaces. Integrating additional data sources, such as road data, could also significantly enhance the accuracy of surface classification.

In conclusion, this thesis has made significant findings regarding the use of sub-metric resolution airborne data for urban surface mapping. The application of texture features on sub-metric resolution imagery has shown the potential for more accurate and detailed characterization of urban environments. However, the challenges faced also highlight the need for ongoing research and innovation in this field. Future studies should focus on refining classification methods, developing robust training and validation datasets, exploring new data sources, and expanding the geographical scope of research to enhance the transferability and applicability of these techniques across diverse urban settings. The insights gained from this research have important implications for urban planning and environmental management, underscoring the critical role of sub-metric resolution imagery in supporting sustainable urban development initiatives.

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Appendix I – OTB Parameter Tables

HaralickTextureExtraction

Parameter Key	Parameter Name	Parameter Type
in	Input Image	Input image
channel	Selected Channel	Int
step	Computation step	Int
ram	Available RAM (Mb)	Int
parameters	Texture feature parameters	Group
parameters.xrad	X Radius	Int
parameters.yrad	Y Radius	Int
parameters.xoff	X Offset	Int
parameters.yoff	Y Offset	Int
parameters.min	Image Minimum	Float
parameters.max	Image Maximum	Float
parameters.nbbin	Histogram number of bin	Int
texture	Texture Set Selection	Choices
texture simple	Simple Haralick Texture Features	Choice
texture advanced	Advanced Texture Features	Choice
texture higher	Higher Order Texture Features	Choice
out	Output Image	Output image
inxml	Load otb application from xml file	XML input parameters file
outxml	Save otb application to xml file	XML output parameters file

BandMathX

Parameter Key	Parameter Name	Parameter Type
il	Input image-list	Input image list
out	Output Image	Output image

ram	Available RAM (Mb)	Int
exp	Expressions	String
incontext	Import context	Input File name
outcontext	Export context	Output File name
inxml	Load otb application from xml file	XML input parameters file
outxml	Save otb application to xml file	XML output parameters file

SFSTextureExtraction

Parameter Key	Parameter Name	Parameter Type
in	Input Image	Input image
channel	Selected Channel	Int
ram	Available RAM (Mb)	Int
parameters	Texture feature parameters	Group
parameters.spethre	Spectral Threshold	Float
parameters.spathre	Spatial Threshold	Int
parameters.nbdir	Number of Direction	Int
parameters.alpha	Alpha	Float
parameters.maxcons	Ratio Maximum Consideration Number	Int
out	Feature Output Image	Output image
inxml	Load otb application from xml file	XML input parameters file
outxml	Save otb application to xml file	XML output parameters file

LocalStatisticsExtraction

Parameter Key	Parameter Name	Parameter Type
in	Input Image	Input image
channel	Selected Channel	Int

ram	Available RAM (Mb)	Int
radius	Neighborhood radius	Int
out	Feature Output Image	Output image
inxml	Load otb application from xml file	XML input parameters file
outxml	Save otb application to xml file	XML output parameters file

TrainImageClassifier

Parameter Key	Parameter Name	Parameter Type
Io	Input and output data	Group
io.il	Input Image List	Input image list
io.vd	Input Vector Data List	Input vector data list
io.valid	Validation Vector Data List	Input vector data list
io.imstat	Input XML image statistics file	Input File name
io.out	Output model	Output File name
io.confmatout	Output confusion matrix or contingency table	Output File name
cleanup	Temporary files cleaning	Boolean
sample	Training and validation samples parameters	Group
sample.mt	Maximum training sample size per class	Int
sample.mv	Maximum validation sample size per class	Int
sample.bm	Bound sample number by minimum	Int
sample.vtr	Training and validation sample ratio	Float
sample.vfn	Field containing the class integer label for supervision	List
ram	Available RAM (Mb)	Int

elev	Elevation management	Group
elev.dem	DEM directory	Directory
elev.geoid	Geoid File	Input File name
elev.default	Default elevation	Float
classifier	Classifier to use for the training	Choices
classifier libsvm	LibSVM classifier	<i>Choice</i>
classifier boost	Boost classifier	<i>Choice</i>
classifier dt	Decision Tree classifier	<i>Choice</i>
classifier gbt	Gradient Boosted Tree classifier	<i>Choice</i>
classifier ann	Artificial Neural Network classifier	<i>Choice</i>
classifier bayes	Normal Bayes classifier	<i>Choice</i>
classifier rf	Random forests classifier	<i>Choice</i>
classifier knn	KNN classifier	<i>Choice</i>
classifier sharkrf	Shark Random forests classifier	<i>Choice</i>
classifier sharkkm	Shark kmeans classifier	<i>Choice</i>
classifier.libsvm.k	SVM Kernel Type	Choices
classifier.libsvm.k linear	Linear	<i>Choice</i>
classifier.libsvm.k rbf	Gaussian radial basis function	<i>Choice</i>
classifier.libsvm.k poly	Polynomial	<i>Choice</i>
classifier.libsvm.k sigmoid	Sigmoid	<i>Choice</i>
classifier.libsvm.m	SVM Model Type	Choices
classifier.libsvm.m csvc	C support vector classification	<i>Choice</i>
classifier.libsvm.m nusvc	Nu support vector classification	<i>Choice</i>
classifier.libsvm.m oneclass	Distribution estimation (One Class SVM)	<i>Choice</i>
classifier.libsvm.c	Cost parameter C	Float
classifier.libsvm.nu	Cost parameter Nu	Float
classifier.libsvm.opt	Parameters optimization	Boolean
classifier.libsvm.prob	Probability estimation	Boolean
classifier.boost.t	Boost Type	Choices
classifier.boost.t discrete	Discrete AdaBoost	<i>Choice</i>

classifier.boost.t real	Real AdaBoost (technique using confidence-rated predictions and working well with categorical data)	<i>Choice</i>
classifier.boost.t logit	LogitBoost (technique producing good regression fits)	<i>Choice</i>
classifier.boost.t gentle	Gentle AdaBoost (technique setting less weight on outlier data points and, for that reason, being often good with regression data)	<i>Choice</i>
classifier.boost.w	Weak count	Int
classifier.boost.r	Weight Trim Rate	Float
classifier.boost.m	Maximum depth of the tree	Int
classifier.dt.max	Maximum depth of the tree	Int
classifier.dt.min	Minimum number of samples in each node	Int
classifier.dt.ra	Termination criteria for regression tree	Float
classifier.dt.cat	Cluster possible values of a categorical variable into $K \leq \text{cat}$ clusters to find a suboptimal split	Int
classifier.dt.f	K-fold cross-validations	Int
classifier.dt.r	Set Use1seRule flag to false	Boolean
classifier.dt.t	Set TruncatePrunedTree flag to false	Boolean
classifier.gbt.w	Number of boosting algorithm iterations	Int
classifier.gbt.s	Regularization parameter	Float
classifier.gbt.p	Portion of the whole training set used for each algorithm iteration	Float
classifier.gbt.max	Maximum depth of the tree	Int
classifier.ann.t	Train Method Type	Choices
classifier.ann.t back	Back-propagation algorithm	<i>Choice</i>

classifier.ann.t reg	Resilient Back-propagation algorithm	<i>Choice</i>
classifier.ann.sizes	Number of neurons in each intermediate layer	String list
classifier.ann.f	Neuron activation function type	Choices
classifier.ann.f ident	Identity function	<i>Choice</i>
classifier.ann.f sig	Symmetrical Sigmoid function	<i>Choice</i>
classifier.ann.f gau	Gaussian function (Not completely supported)	<i>Choice</i>
classifier.ann.a	Alpha parameter of the activation function	Float
classifier.ann.b	Beta parameter of the activation function	Float
classifier.ann.bpdw	Strength of the weight gradient term in the BACKPROP method	Float
classifier.ann.bpms	Strength of the momentum term (the difference between weights on the 2 previous iterations)	Float
classifier.ann.rdw	Initial value Δ_0 of update-values Δ_{ij} in RPROP method	Float
classifier.ann.rdwm	Update-values lower limit Δ_{min} in RPROP method	Float
classifier.ann.term	Termination criteria	Choices
classifier.ann.term iter	Maximum number of iterations	<i>Choice</i>
classifier.ann.term eps	Epsilon	<i>Choice</i>
classifier.ann.term all	Max. iterations + Epsilon	<i>Choice</i>
classifier.ann.eps	Epsilon value used in the Termination criteria	Float
classifier.ann.iter	Maximum number of iterations used in the Termination criteria	Int
classifier.rf.max	Maximum depth of the tree	Int

classifier.rf.min	Minimum number of samples in each node	Int
classifier.rf.ra	Termination Criteria for regression tree	Float
classifier.rf.cat	Cluster possible values of a categorical variable into $K \leq \text{cat}$ clusters to find a suboptimal split	Int
classifier.rf.var	Size of the randomly selected subset of features at each tree node	Int
classifier.rf.nbtrees	Maximum number of trees in the forest	Int
classifier.rf.acc	Sufficient accuracy (OOB error)	Float
classifier.knn.k	Number of Neighbors	Int
classifier.sharkrf.nbtrees	Maximum number of trees in the forest	Int
classifier.sharkrf.nodesize	Min size of the node for a split	Int
classifier.sharkrf.mtry	Number of features tested at each node	Int
classifier.sharkrf.oobr	Out of bound ratio	Float
classifier.sharkkm.maxiter	Maximum number of iteration for the kmeans algorithm.	Int
classifier.sharkkm.k	The number of class used for the kmeans algorithm.	Int
rand	set user defined seed	Int
inxml	Load otb application from xml file	XML input parameters file
outxml	Save otb application to xml file	

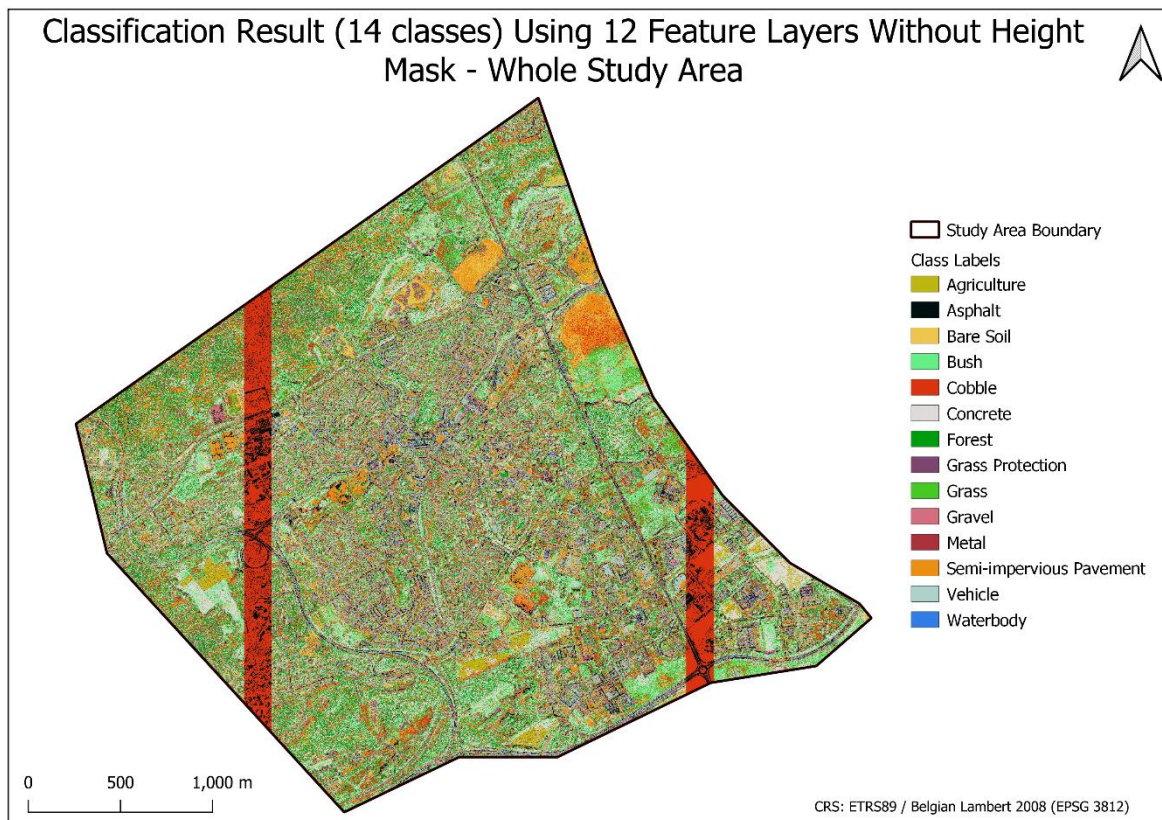
ImageClassifier

Parameter Key	Parameter Name	Parameter Type
in	Input Image	Input image
mask	Input Mask	Input image

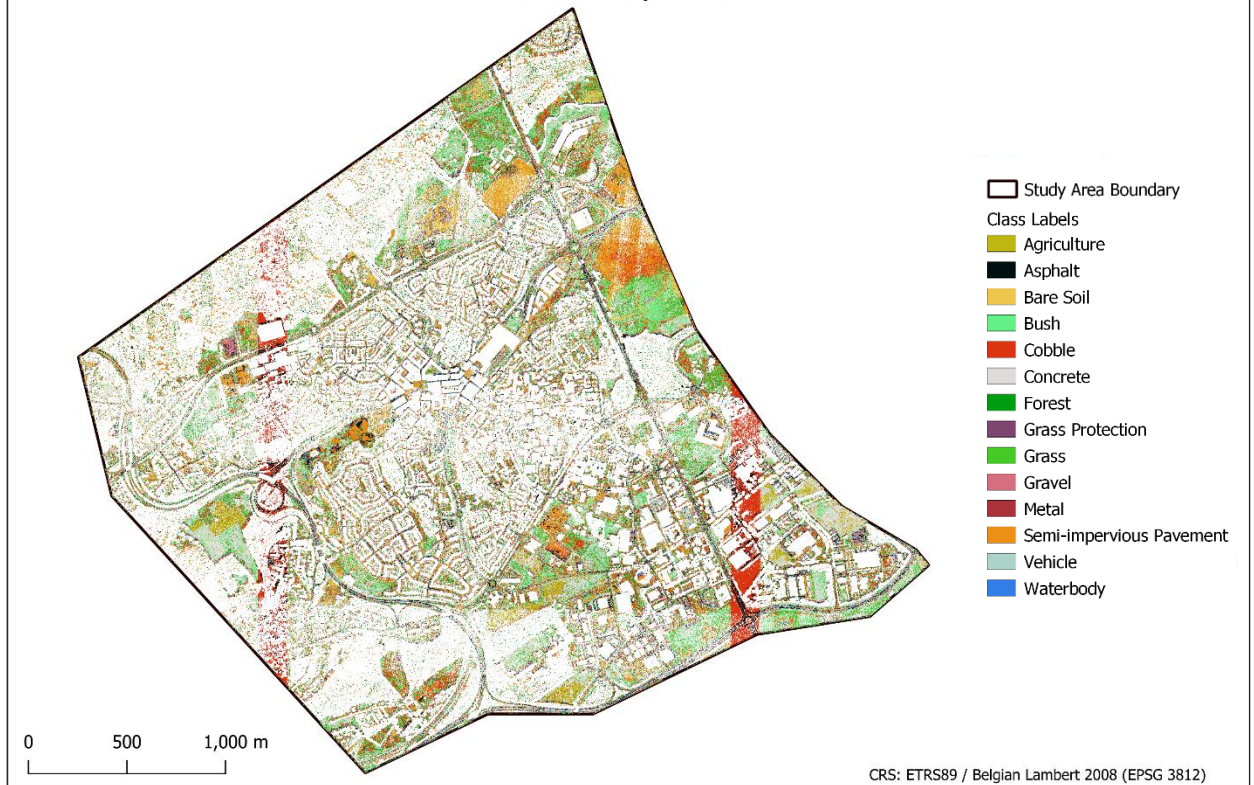
model	Model file	Input File name
imstat	Statistics file	Input File name
nodatalabel	Label mask value	Int
out	Output Image	Output image
confmap	Confidence map	Output image
ram	Available RAM (Mb)	Int
inxml	Load otb application from xml file	XML input parameters file
outxml	Save otb application to xml file	XML output parameters file

Appendix II – Classification Results Additional Images

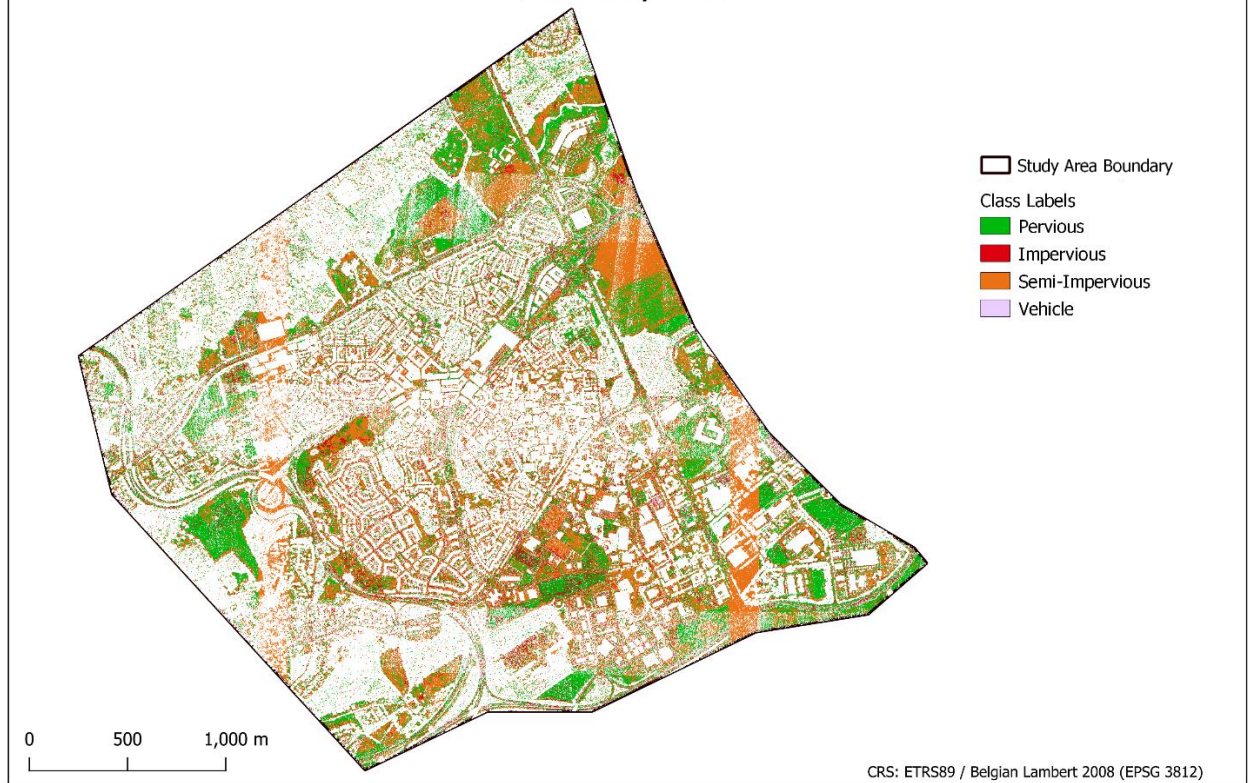
Note: There are missing tiles (tile 19 and 25) that is classified as impervious in the classification.



Classification Result (14 Classes) using 12 Feature Layers with Height Mask - Whole Study Area

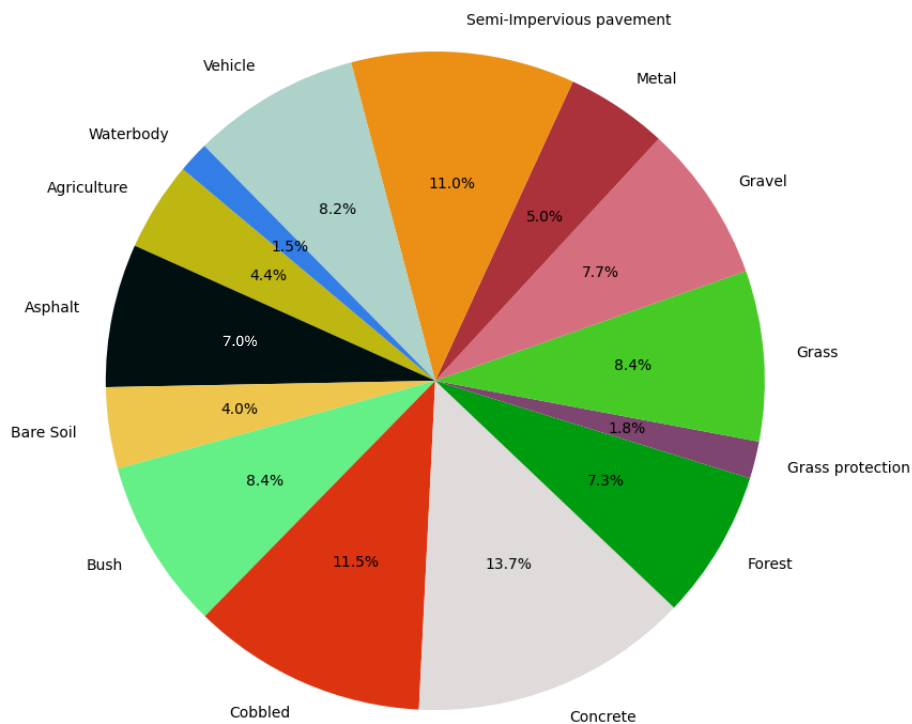


Classification Result (4 Classes) using 12 Feature Layers with Height Mask - Whole Study Area

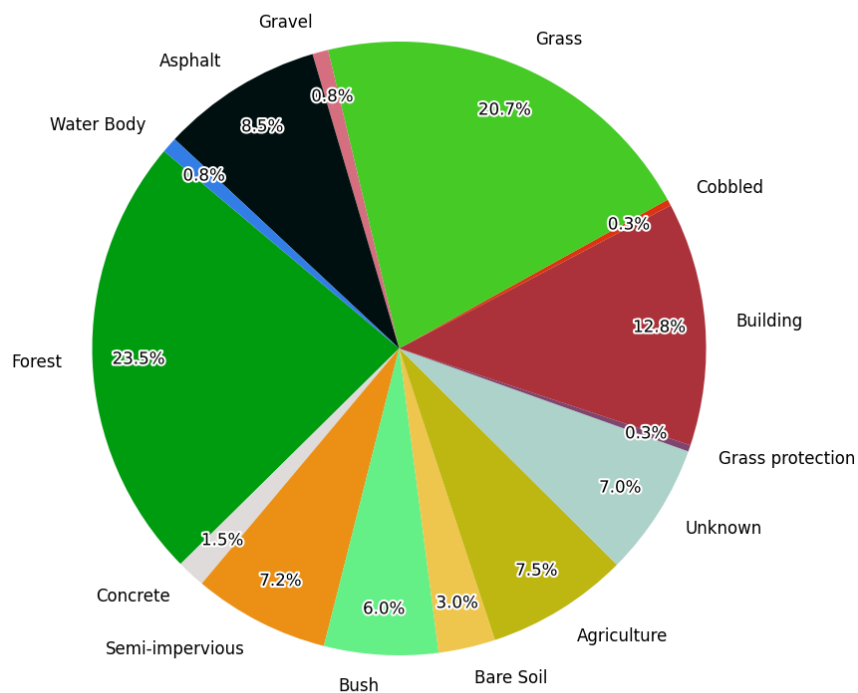


Appendix III – Pie Charts for Individual Classes for Whole Area excluding the Height Masked Pixels and Count Proportions for All Classes

Area Distribution by Category



Proportion of Count - All Categories



Assessing potential of sub-metric resolution airborne data in identification and characterization of urban impervious surface in Louvain-la-Neuve

Lakshmi Rajeev Kumar

Abstract

Urbanization has led to an increase in impervious surfaces such as roads, rooftops, and sidewalks, which prevent water from soaking into the ground. This can result in more surface runoff, higher flood risks, urban heat islands, and a loss of biodiversity. Accurate mapping and identification of these surfaces are essential for urban planning and management. This study explores the potential of using sub-metric resolution airborne data combined with LIDAR-derived height data masking to map and characterize urban impervious surfaces in Louvain-la-Neuve, Belgium.

The research uses advanced texture features, including Haralick texture features and Structural Feature Set (SFS), as well as image saturation, to capture the distinct textures and colours of these surfaces. These features are processed using the Orfeo Toolbox (OTB) and classified with a random forest classifier. Although there were some challenges in distinguishing similar surface types, the study underscores the value of high-resolution data for urban surface mapping. The findings highlight the importance of differentiating between pervious, semi-impervious, and impervious surfaces for urban planning, such as in assessing urban heat island effects and planning green infrastructure.

The thesis concludes that while the use of texture features on sub-metric resolution imagery is promising for detailed urban surface characterization, further research and refinement in classification methods are needed. Future research should aim to develop more extensive training datasets, incorporate additional data sources, and extend the geographical scope of study. These efforts will improve the generalizability and applicability of these techniques across various urban settings. The insights from this research are valuable for urban planning and environmental management, supporting sustainable urban development initiatives.