QUANTIFYING THE SEALING OF URBAN LANDSCAPES: A COMPARATIVE ANALYSIS OF MACHINE LEARNING MODELS FOR WATER-IMPERMEABLE SURFACE SEGMENTATION USING AERIAL REMOTE SENSING

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ABSTRACT

Urbanization is transforming landscapes worldwide, leading to increased water-impermeable surfaces such as roads and buildings. These sealed surfaces contribute significantly to flooding and heat island effects in urban areas, exacerbating the impacts of climate change on ecosystems and human health. Accurate assessment of the extent and intensity of sealing is therefore essential for developing effective urban planning strategies. We employ aerial remote sensing data and machine learning techniques to segment land cover into classes according to their water-impermeability. We investigate the performance of various deep learning architectures in detecting types of sealed surfaces in orthorectified aerial images. To validate the results, we compare model predictions against ground truth data derived from onsite recordings. Our results show that the best-performing models achieve overall high accuracies in distinguishing between water-impermeable and permeable surfaces. Our proposed methodology can be applied in urban planning and management, as they can inform strategies to mitigate flooding, heat island effects, and ecosystem degradation. By quantifying the extent and intensity of sealing, policymakers can develop targeted interventions to reduce the environmental impact of urbanization. Furthermore, the approach presented has broad applications in remote sensing based land cover mapping and monitoring, underscoring the potential for machine learning driven assessments to inform evidence based decision-making in urban planning and management.

KEYWORDS _ *Remote Sensing, Machine Learning, Urban Planning, Soil Sealing, Urban Sealing*

INTRODUCTION

The rapid growth of cities worldwide presents both opportunities and challenges. While urbanization drives economic development and social progress, the increasing soil sealing significantly impacts both the environment and society (Scalenghe & Marsan, 2009) (Smith, et al., 2024). The expansion of impervious surfaces, such as roads, buildings, and parking lots, at the expense of green and open spaces, is a global trend with profound environmental consequences. Sealed surfaces alter the natural water cycle by preventing rainwater infiltration, thereby increasing surface runoff. This excess runoff transports pollutants and sediments into water bodies and can overwhelm drainage systems, heightening the risk of urban flooding, particularly during extreme precipitation events (Gatto, Martellozzo, Clo', Ciulla, & Segoni, 2024). Additionally, reduced infiltration limits groundwater recharge, disrupting the balance of hydrological systems and affecting water availability (Li, et al., 2023). Furthermore, impervious surfaces contribute to the urban heat island effect by absorbing and retaining heat, exacerbating temperature differences between urban and rural areas. The loss of vegetation and natural soil, which provide evaporative cooling, further intensifies this phenomenon (Cheela, John, Biswas, & Sarker, 2021).

Understanding the extent and distribution of impervious surfaces is therefore crucial for developing sustainable and resilient urban environments. Accurate mapping and monitoring of these surfaces enable informed decision-making regarding infrastructure development, green space planning, and stormwater management strategies. Effective monitoring is essential for urban planners, environmental scientists, and policymakers to mitigate the adverse effects of urbanization and enhance climate adaptation measures.

To facilitate comprehensive monitoring, advanced remote sensing techniques and artificial intelligence (AI) offer promising solutions. In this study, we present an approach that leverages semantic segmentation and deep learning models to extract relevant information on impervious surfaces and the distribution of vegetation in urban areas from aerial imagery. By employing state-of-the-art deep learning techniques, we aim to improve the accuracy and efficiency of impervious surface detection. Furthermore, we compare multiple deep learning models to assess their performance and suitability for large-scale urban analysis.

STUDY AREA

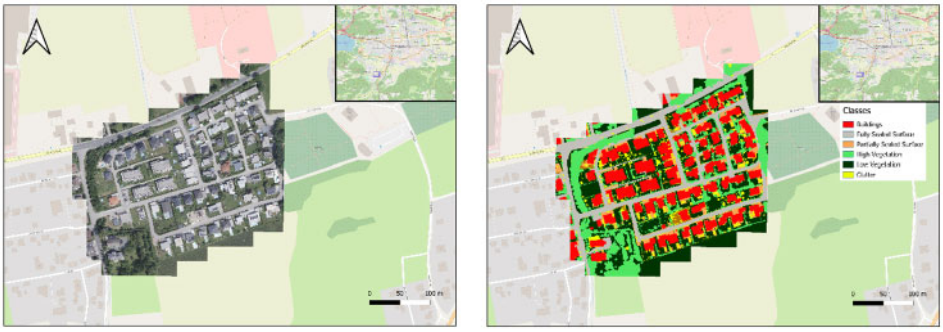

Figure 1: Study area (left) and corresponding segmentation map (right) highlighting open residential development in the Klagenfurt-Viktring district. Map: © OpenStreetMap Contributor

The selection of the study area (**Figure 1**) is the result of a thorough assessment of multiple potential target sites within the municipal boundaries of the city of Klagenfurt, Austria, ensuring that the chosen location serves as a representative example of suburban land use and development patterns. Several candidate areas were evaluated based on their spatial composition, diversity of land

cover, and relevance to the research objectives. The final decision is guided by the need to capture a balanced mix of built and green spaces, encompassing residential buildings, private gardens, tree-lined streets, small parks, and open green areas, while also including essential infrastructure elements such as roads, sidewalks, and public service buildings. Given the inherent complexity of urban landscapes, it is challenging to define a single small-scale study area that encapsulates the full spectrum of land cover variations. However, the selected area is highly representative of the larger suburban environment, allowing for meaningful analysis while maintaining methodological feasibility. Its characteristics ensure that key urban greening and soil-sealing dynamics observed here can be extrapolated to similar settings across the municipality, making it a suitable reference for evaluating automated green space monitoring.

DATA PREPROCESSING AND ANNOTATION

The aerial imagery was captured using a high-resolution sensor with a ground sampling distance (GSD) of 5 cm, ensuring detailed spatial resolution. To correct for geometric distortions and maintain spatial accuracy, the raw images underwent orthorectification as part of the preprocessing workflow. Given the large dimensions of the original aerial images (12,500 × 10,000 pixels), a tiling approach was implemented to optimize data processing efficiency. The images are subdivided into smaller tiles of 500 × 500 pixels, each representing a ground area of 25 × 25 meters (625 m²). The study area, depicted in Figure 1, is covered by 139 such tiles, resulting in a total coverage of 86,875 m². The chosen tile size strikes a balance between computational efficiency and the need for spatial context: tiles are large enough to capture the heterogeneity of the suburban environment, encompassing variations in building density, vegetation cover, and infrastructure, while being small enough to allow for rapid processing and targeted analysis. By restricting the evaluation to specific areas of interest, this approach minimizes unnecessary computations and optimizes resource allocation, ensuring an efficient workflow for automated green space monitoring and environmental assessment. The structured dataset facilitates a detailed examination of suburban land cover patterns, supporting applications in urban planning, environmental monitoring, and automated feature extraction.

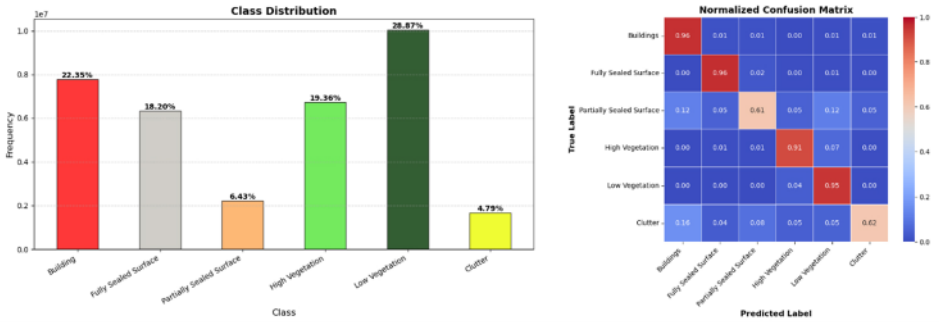

Figure 2: Class distribution across the study area (left) and confusion mask from a single DeepLabV3+ inference (right).

The selected study area is manually labeled to create a ground truth dataset. Labeling is performed at pixel level to accurately delineate different land cover classes. The classification scheme includes six distinct categories (Figure 2): high vegetation (trees and large shrubs), low vegetation (grass, ground cover), buildings, fully sealed surfaces (impermeable materials such as asphalt and concrete), partially sealed surfaces (e.g., permeable pavements and gravel paths), and clutter (objects that do not fit into the other categories, such as vehicles, temporary structures, and construction materials).

The labeling is conducted with a focus on precision, ensuring that each category is well-defined and

distinguishable to maximize segmentation accuracy. Emphasis is placed on distinguishing between fully and partially sealed surfaces, as this differentiation is crucial for assessing soil sealing and permeability in urban environments. To maintain consistency and reduce potential biases, a standardized annotation protocol was established, and multiple annotators cross-validate the labeled dataset.

IMPLEMENTATION AND TRAINING

The annotated dataset is split into training, validation and test sets. To optimize model generalizability and provide an unbiased baseline for comparison of the model performance a test set consisting of 28 randomly chosen images, representing 20% of the study area, is set aside for model comparison.

For every model we employ a k-fold cross-validation strategy with k = 5, to account for noise in the data. This involved randomly splitting the remaining 111 tiles into training (88 tiles) and validation (23 tiles) sets. Model training and evaluation is conducted using OpenMMLabs segmentation framework MMSegmentaion (Contributors, 2020), which provides a modular and extensible platform for deep learning based segmentation tasks. All models are trained with default hyperparameters.

We applied four state-of-the-art deep learning models:

DeepLabV3+: A deep convolutional neural network that utilizes atrous spatial pyramid pooling and an encoder-decoder structure for precise segmentation (Chen, Papandreou, Schroff, & Adam, 2017).

Fully Convolutional Network (FCN): A deep learning model for image segmentation that replaces fully connected layers with convolutional layers to achieve pixel-wise classification (Long, Shelhamer, & Darrell, 2014).

Pyramid Scene Parsing Network (PSPNet): A model incorporating a pyramid pooling module to capture multi-scale contextual information (Zhao, Shi, Qi, Wang, & Jia, 2016).

SegFormer: A transformer based segmentation model that combines lightweight convolutions with self-attention mechanisms to enhance spatial feature representation (Xie, et al., 2021).

In all training runs we use data augmentation techniques random cropping, flipping and normalization.

Evaluation and Results

The trained models are assessed using the Intersection over Union (IoU) metric across six distinct land cover classes using RGB (Red-Green-Blue) color channels (Table 1). Additionally, the best-performing model, DeepLabV3+, is further analyzed to compare segmentation performance using RGB vs. RGI (Red-Green-Near Infrared) color inputs (Table 2).

Table 1: Average Intersection over Union [%] per Class on RGB test data set

	DeepLabV3+	FCN	PSPNet	SegFormer
Building	89,68	89,56	89,38	88,47
Fully_Sealed	90,96	91,12	90,98	89,31
Partially_Sealed	48,33	47,19	47,32	43,35
High_Vegetation	80,03	79,40	79,40	78,16
Low_Vegetation	90,81	90,26	90,20	90,33
Clutter	52,13	51,56	50,16	52,82

The average IoU scores for RGB data after the k-fold cross validation for each model and land cover class is presented in Table 1. DeepLabV3+ consistently achieved the highest IoU scores across most classes. FCN performed competitively, particularly excelling in the Fully Sealed category with an average IoU of 91.12%, the highest among all models. All models exhibited strong performance in the Building and Vegetation (High and Low) classes, with all average IoU values exceeding 78%.



Figure 3: K-fold Model performance for individual classes on the RGB test data set

However, segmentation of Partially Sealed Surfaces proved to be challenging, with all models achieving average IoU scores below 50%. Among them, DeepLabV3+ yielded the best result (48.33%), indicating a relatively better ability to distinguish this class. Similarly, the Clutter class exhibited substantial variation across models, with SegFormer obtaining the highest average IoU (52.82%). The results for each individual training run on RGB data are presented in Figure 3.

To further investigate the impact of spectral bands on segmentation performance, the best performing network architecture, DeepLabV3+, is further evaluated using RGI image inputs. The results of the comparison of RGB and RGI are presented in Table 2. For comparison the test set contains RGI images of the same special extent as the RGB test set.

Table 2: Average Intersection over Union [%] per Class for DeeplLabV3+ on RGB versus RGI test data set

	DeepLabV3+ (RGB)	DeepLabV3+ (RGI)
Building	89,68	88,60
Fully_Sealed	90,96	90,44
Partially_Sealed	48,33	45,35
High_Vegetation	80,03	80,14
Low_Vegetation	90,81	90,72
Clutter	52,13	47,91

The results for each individual training run RGB vs. RGI are presented in Figure 4:



Figure 4: K-fold Model performance for individual classes on RGB versus RGI test data set

The results on RGB input outperform those on RGI input across most classes and runs. Notably, average segmentation performance decreased in the Building (-1.08%), Fully Sealed (-0.52%), Partially Sealed (-2.98%), and Clutter (-4.22%) classes when using RGI. These results indicate that the near-infrared channel likely does not enhance performance for these categories and may carry only limited additional information for the land cover classes in question.

However, a slight improvement is observed for the High Vegetation class (+0.11%). The Low Vegetation class exhibited minimal differences between input types (-0.09%).

CONCLUSION

Our results demonstrate that DeepLabV3+ consistently delivers the highest IoU scores across most classes in our dataset, making it the most well-balanced model for our segmentation task. While FCN achieved slightly better performance for Fully Sealed surfaces and SegFormer in Clutter classification, DeepLabV3+ provided strong and reliable results across all categories, highlighting its robustness in urban land cover segmentation.

DeepLabV3+ performs particularly well on distinct and well-defined classes, capturing structural and spectral characteristics with high accuracy. This highlights its effectiveness for remote sensing applications, particularly when working with high-resolution datasets. Additionally, our findings confirm that RGB input consistently outperforming RGI inputs in our setting.

While segmentation of more heterogeneous classes, such as Partially Sealed and Clutter, remains challenging, these categories represent highly variable materials and structures, making them inherently complex to classify. The confusion matrix in Figure 2 shows an almost equal distribution of misclassified pixels over all other classes for both. Future research should focus on enhancing model architectures and dataset diversity to further refine the segmentation of these nuanced classes.

Expanding the dataset to include a broader range of examples within these challenging categories could significantly improve model generalization and accuracy.

Finally, while RGB input has proven to be the superior spectral combination in this study, the potential benefits of RGI and other spectral bands should not be dismissed entirely. More advanced feature extraction techniques and model architectures designed to leverage near-infrared information may further improve segmentation results, particularly for vegetation and complex surface materials.

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