Classification of urban environments using state-of-the-art machine learning: a path to sustainability

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Classification of Urban Environments Using State-of-the-Art Machine Learning: A Path to Sustainability †

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Abstract

Urban green infrastructure plays a vital role in the sustainable development of cities. As urban areas expand, green spaces are increasingly affected. The pressure from new developments leads to a reduction in vegetation and raises new public health risks. Addressing this challenge requires effective planning, maintenance, and continuous monitoring. To enhance traditional approaches, remote sensing is becoming a vital tool for city-wide observations. Publicly available large-scale data, combined with machine learning models, can improve our understanding. We explore the potential of Sentinel-2 to classify and extract meaningful features from urban landscapes. Using advanced machine learning techniques, we aim to develop a robust and scalable framework for classifying urban environments. The proposed models will assist in monitoring changes in green spaces across diverse urban settings, enabling timely and informed decisions to foster sustainable urban growth.

Keywords: machine learning; urban green infrastructure; remote sensing; sustainability

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1. Introduction

Urban areas are expanding rapidly, with two-thirds of the world population expected to live in cities by 2050 [1]. Such growth increases pressure on urban green infrastructure, which includes parks, trees, grasslands, and urban forests [2,3]. Limited space in cities restricts new developments and often comes at the cost of green spaces [4]. Green areas play a vital role in alleviating urban stress, which results from environmental pressures like air pollution [5] and the urban heat island effect [6–8], as well as society's exposure to these spaces [9,10]. The degradation of such infrastructure worsens air quality and thermal comfort, ultimately affecting the wellbeing of city residents [6,9,11].

Monitoring changes in urban landscapes requires city-wide observation supported by reliable baseline data [12–14]. Monitoring green infrastructure and its interaction with built-up areas, collectively called urban landscapes, is essential for achieving urban sustainability [15,16]. In this context, urban sustainability refers to the ability of urban systems to maintain ecological integrity, social equity, and resilience over time [17,18]. Traditional ground-based methods have been used to address microclimate changes, including assessing tree health, identifying areas with limited access to green spaces, and planting trees to mitigate impacts [19]. The assessment and deployment of nature-based solutions, such as planting trees and expanding green spaces, depend on a thorough understanding of urban dynamics [10]. However, traditional field surveys are often slow, geographically limited, and lack the temporal resolution needed to track a rapidly changing urban environment. These challenges have increased interest in remote sensing and machine learning techniques to automate land cover classification and analyse green spaces within cities [20–22].

Publicly accessible Earth observation data, such as the European Space Agency's Sentinel-2 satellite data, has significantly enhanced the ability to monitor urban environments [23]. The Sentinel-2 constellation provides high spatial resolution (10–60 m) and a revisit cycle of 5 days, with multispectral bands that detect both natural and anthropogenic features [24,25]. Sentinel-2 is becoming an essential resource for urban classification as it allows for the detection of subtle variations in land cover and vegetation health [26–28]. However, in complex urban areas, classification remains challenging and often overlooks fine-scale urban features [29].

To automate and improve the classification process, state-of-the-art machine learning techniques are increasingly integrated with remote sensing. These include Classification and Regression Trees (CART) [30], Gradient Tree Boosting (GTB) [31], K-Nearest Neighbour (KNN) [32], and Random Forest (RF) [33], as well as deep learning models such as Convolutional Neural Networks (CNNs) [34,35] and transformer-based architectures for spatial–temporal pattern recognition [36]. Among these, RF improves accuracy and robustness by combining multiple trees, making it particularly suitable for noisy and complex urban data. GTB achieves the highest accuracy by sequentially correcting errors, although this approach involves greater complexity and requires parameter tuning [31]. CNNs and other deep learning models show outstanding potential for urban feature extraction by integrating high-resolution street-level imagery; however, they require large, annotated datasets and are more complex to implement for city-wide studies [34–36]. In this study, we focus on the first four decision tree algorithms as a baseline to understand the spatial complexity of urban spaces.

Although the application of machine learning in urban environment monitoring has become widespread, existing studies mainly focus on classification accuracy, with limited integration of socio-environmental indicators (e.g., health vulnerability, exposure to air pollution, accessibility to green spaces). Furthermore, few studies explicitly align their outputs with global sustainability frameworks, such as the United Nations Sustainable Development Goals (UN SDGs). Mapping these SDGs has become increasingly important in environmental research [37,38]. These development goals provide a comprehensive framework that combines environmental, economic, and social aspects to guide global sustainability efforts [16,38,39]. In this study, we specifically focus on SDG 3 (Good Health and Well-being), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action), which are directly relevant to urban resilience but are often underutilised in geospatial analytics [16,37]. These SDGs are closely related to our aim of developing advanced methods for the sustainable classification of urban environments. By utilising these SDG indicators, the research outcomes can be effectively evaluated for their contribution to urban resilience, public health, and climate responsiveness. Ultimately, this approach promotes the development of more inclusive, safe, and sustainable cities.

Fundamental aspects of monitoring changes in urban areas include the ongoing classification of urban landscapes and the detection of variations over time and space. Developing machine learning models specifically designed for urban environments will support sustainable development amid rapid urbanisation and offer a comprehensive perspective for urban planners, decision-makers, and other stakeholders. This study presents a methodology that combines Sentinel-2 remote sensing data with machine learning models to classify urban land cover, with a particular focus on green infrastructure. Additionally, our approach integrates machine learning outputs with related SDGs. Overall, this research demonstrates a city-scale, semi-automated classification workflow using publicly available Earth observation data and open-source tools, promoting wider adoption in data-scarce or rapidly growing urban regions.

2. Data and Methodology

2.1. Data

The urban area is a complex and constantly evolving environment. To manage this complexity, datasets with medium to high spatial resolution are essential. The availability of Sentinel-2 satellite observations, with a spatial resolution of 10 m and a revisit time of 6–12 days in Europe and other regions, has made monitoring easier [25]. Sentinel-2 provides multi-spectral, high-resolution optical images of global terrestrial surfaces [28,29]. In this study, Sentinel-2 satellite imagery is utilised to train the machine learning models.

2.2. Methodology

We perform supervised classification of the urban environment using Sentinel-2 imagery and decision tree algorithms to train the models. Based on their performance, we evaluate the model, tune the parameters, and reach a final decision [40]. The process is carried out on the Google Earth Engine (GEE) cloud platform [41]. The overall workflow and example are shown in Figure 1.

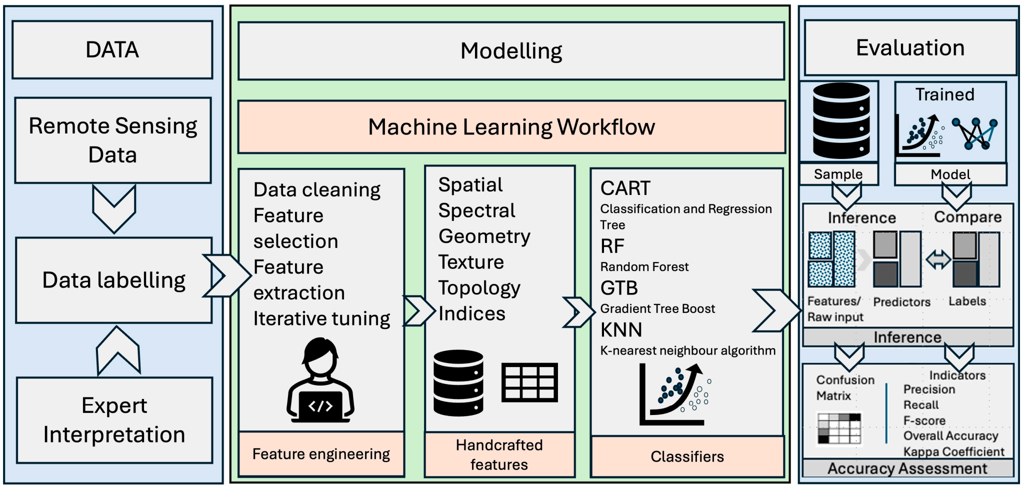

Figure 1. An illustration of a machine learning workflow for remote sensing.

The images are selected prior to processing, based on cloud cover, using those with less than 5% cloud cover. The data are labelled according to our intended categories, with approximately 75–100 features labelled for each. The same labelled data are employed to train all the machine learning models. A confusion matrix was calculated, where correct predictions are on the diagonal, and misclassifications appear in the off-diagonal cells. Using this matrix, the accuracy was assessed with the kappa coefficient, F-test, and overall model accuracy. The kappa coefficient is a chance-corrected metric that measures the agreement between predicted and actual classifications [42]. Values of Kappa close to 1 indicate high agreement, while those near 0 suggest slight or no agreement. We utilised the available Sentinel-2 data on GEE to train the models.

3. Results and Discussion

We have implemented four decision-making algorithms to assess their ability to classify urban environments. Figure 2 shows the four machine learning models tested in the Borough of London, UK. We used five categories: Water body, Grass, Vegetation, Built-up, and Roads. These categories are based on our further research into how green spaces interact with the built environment. Additionally, we distinguish between the contributions of grass (i.e., height less than 1 m) and tall, large-canopy trees. Figure 3 shows the confusion matrices for each model as heat maps, along with an overall accuracy comparison displayed via a bar graph. The diagonal cells in the confusion matrix represent correct predictions, while the off-diagonal cells indicate misclassifications. The CART, GTB, RF, and KNN models have overall accuracies of 83%, 86%, 90%, and 87%, respectively (Table 1). The RF outperforms the other models in overall and class prediction performance. The Kappa coefficients for CART, GTB, RF, and KNN are 0.78, 0.81, 0.86, and 0.83, respectively. All Kappa values suggest that the model predictions are fairly consistent with the true labels. Among the individual classes, "built-up" was predicted well, followed by the "vegetation" and "roads" classes.

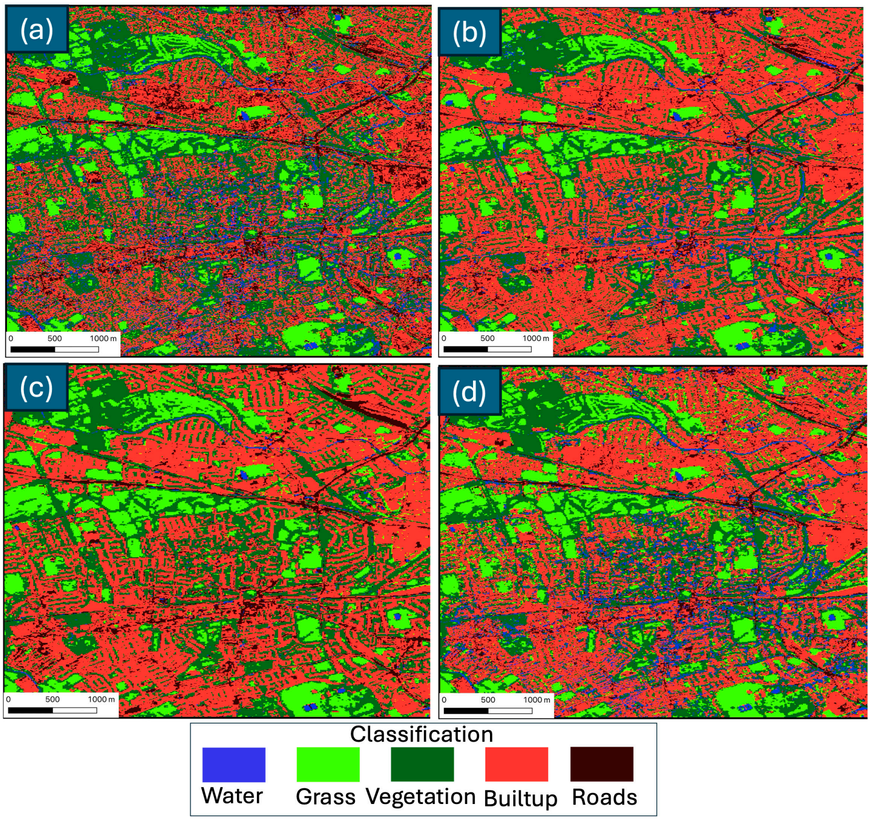

Figure 2. Machine learning model results: (**a**) Classification using CART, (**b**) GTB, (**c**) RF, and (**d**) KNN.

Table 1. Summary of the classification performance of each model.

Model	Accuracy	Macro F1-Score	Weighted F1-Score
CART	0.83	0.823	0.830
GTB	0.86	0.839	0.857
RF	0.90	0.892	0.901
KNN	0.87	0.847	0.868

Further evaluation of each model's performance is needed to identify a suitable and resilient option for different urban environments. However, the training of the models must continue to include urban areas with diverse spectral responses to satellite observations. For example, an urban setting in the Global North may not necessarily share the same features as those in the Global South. Therefore, ongoing adaptation of the models for various types of urban areas should be considered.

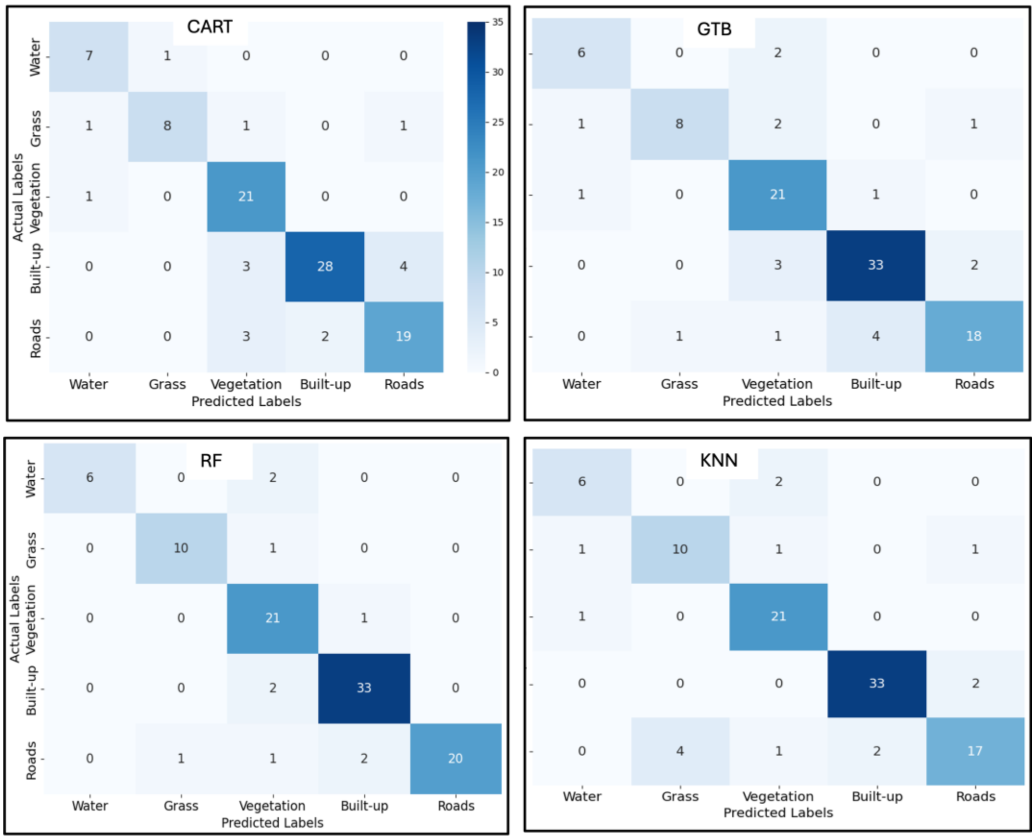

Figure 3. Confusion matrix for the models: CART, GTB, RF, and KNN. The models are displayed as heat maps, illustrating a comparison of the actual and predicted labels. In the heat map, darker colours indicate better class predictions.

Mapping disclosure standards to sustainable development for classifying the urban environment is a vital step in assessing sustainability. Based on the concept of automated urban classification, three related SDGs are chosen: SDG 3 (Good Health and Well-being), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). The reason for selecting these SDGs is that SDG 11 involves increasing urban green spaces to foster sustainable, inclusive cities, achieved through the use of publicly available remote sensing data. SDG 13 is addressed by measuring urban green spaces to support climate action by reducing urban heat and offsetting emissions. SDG 3 is supported by examining the effects of green spaces on residents' physical and mental health, ensuring accessibility for recreation, and pollution reduction. Connecting these research activities to the SDGs is crucial to promote sustainable, informed, and data-driven urban development.

4. Conclusions and Future Developments

Urban green spaces (UGS) are essential for enriching city life by providing numerous environmental, social, and health benefits. Regular monitoring of UGS is crucial to adapt to changes in urban development. We demonstrated the use of multi-spectral satellite remote sensing and advanced machine learning models to classify key urban features. The classification results highlight the effectiveness of combining satellite remote sensing with machine learning for efficiently and accurately identifying features in urban environments. The research showed that, at the borough level, the Random Forest model outperforms the other three models. However, as the spatial scale expands to the city level, performance may decline because large images require significant computational resources. This research, alongside mapping the UN SDGs, makes a substantial contribution to sustainability. Continuous and effective classification of urban areas is crucial for planners, developers, and policymakers. State-of-the-art machine learning, combined with fundamental remote sensing methods, is emerging as an innovative approach to mapping urban environments. In addition to classification based on Sentinel-2 imagery, developing spectral indices and classifying features through these indices are a future area for development. Based on the spectral response of features, complementary results could be obtained to address challenges in urban environment classification. The machine learning models presented in this study require further refinement by incorporating additional remote sensing data. The results also need validation against existing independent terrestrial and aerial surveys. Once refined, the models should be applied to rapidly growing cities in the Global South to demonstrate their capacity to support urbanisation.

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Data Availability Statement: All the data used here are freely accessible datasets from the European Space Agency (ESA) and accessed through GEE.

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Conflicts of Interest: The authors declare that they have no conflicts of interest.

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