Leverage data fusion from s1-s2 to enable fast and accurate land cover classification

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Abstract
Urban areas face unique challenges in monitoring and managing land cover changes, particularly due to cloud cover that a9ects optical imagery. This study presents an innovative approach to urban land cover classification by fusing `Sentinel-1` Synthetic Aperture Radar (SAR) data with `Sentinel-2` optical data. We aim to develop an automated algorithm capable of providing monthly monitoring of urban land cover changes, enhancing classification accuracy and o9ering critical insights into urban growth and environmental resilience.
Utilizing a combination of 4 images from `Sentinel-1` (VV, VH, VV/VH) and 5 key spectral indices derived from `Sentinel-2` (NDVI, SAVI, BAI, NDWI, and alternative BAI), we created a comprehensive merged dataset of 20 bands. This dataset serves as the foundation for our classification models, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and Neural Networks (NN), which are evaluated for their performance in accurately classifying various urban features.
Additionally, we explore Convolutional Neural Networks (CNN) and the `SAM2` model for advanced classification techniques. Our results demonstrate the potential of SAR and optical data fusion to overcome the limitations of cloud cover, providing a robust framework for automated urban land cover monitoring. This research contributes to a better understanding of urban dynamics and supports e9ective environmental management strategies. Einstein (1905)

Key words: data fusion – machine learning – geospatial

1 Introduction

In recent years, approximately 90% of the world's mapping data has been generated, underscoring the critical importance of leveraging state-of-the-art technologies to create accurate maps that reflect the real challenges facing our planet today. The rapid pace of urbanization has transformed cities, leading to an urgent need for precise tools that can monitor land cover evolution. By comprehensively understanding these changes, we can identify detrimental impacts on the environment while also highlighting effective remediation efforts, ultimately contributing to the development of greener, more sustainable urban landscapes.

However, the utility of optical imagery, particularly from satellites like Sentinel-2, is often compromised by cloud coverage, especially in tropical and coastal regions. This phenomenon results in significant data gaps, which can severely limit the effectiveness of urban monitoring tools. For instance, in Rouen, France, persistent cloud cover restricts the availability of usable optical images to only ten per year, presenting a substantial challenge for consistent urban analysis.

To address these limitations, this study focuses on the exploitation of classification models on fused Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical data. By employing data fusion techniques to mitigate the impacts of cloud coverage, we aim to enable more reliable monthly monitoring of urban land cover changes. The primary objective of this research is to evaluate and compare various machine learning and deep learning models— including Random Forest, Support Vector Machines (SVM), and Convolutional Neural Networks (CNNs)—to identify the most effective methodologies for achieving accurate and robust land cover classification in urban environments.

Diagram 1 show the pipeline of our implementation for testing our method and compare to the *naive* ones.

Why Rouen?

Rouen, a historic city in northern France, presents a diverse urban landscape with a mixture of commercial, residential, and industrial zones, as well as surrounding vegetation and water bodies (the Seine River). Its coastal proximity also makes it a relevant choice for studying urban resilience and environmental dynamics, as it faces potential impacts from coastal erosion and urban expansion.

Urban Dynamics and Environmental Challenges

- Population: Approximately $111,000$ inhabitants in the city center, with a wider metropolitan area exceeding $500,000$ residents.
- Urban Challenges: Urban growth, environmental remediation

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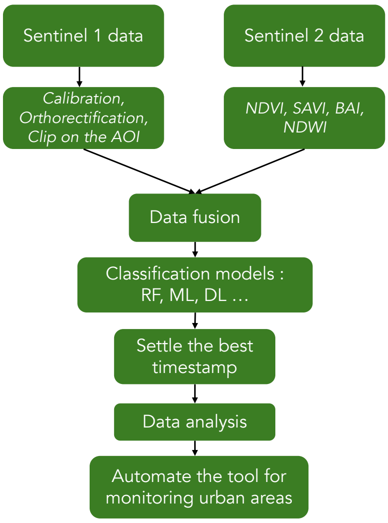

Figure 1. Diagram of algorithm implementaion

e9orts, and flood management due to its proximity to the river and low-lying coastal areas.

- Environmental Focus: Monitoring urban development, green spaces, and remediation strategies aimed at reducing the environmental footprint of urban sprawl.

Application of Data Fusion and Models

For this study, we applied the Sentinel-1 and Sentinel-2 data fusion approach to analyze the land cover changes in Rouen. The various machine learning models (SVM, KNN, RF, NN, CNN, and SAM2) were trained and tested on this region, allowing us to evaluate the accuracy and robustness of each approach in distinguishing between urban features.

We utilize data from both **Sentinel-1** (SAR) and **Sentinel-2** (optical) to overcome challenges like cloud cover in urban land cover classification.
Sentinel-1 provides radar data (VV, VH, and VV/VH ratio) that is resistant to cloud cover, allowing consistent monitoring of urban structures and vegetation.
Sentinel-2 supplies optical data, from which we calculate 4 key spectral indices specifically designed to distinguish urban features:

- **NDVI** (Normalized Difference Vegetation Index): highlights vegetation health
- **SAVI** (Soil Adjusted Vegetation Index): Adjusts for soil influence in areas with sparse vegetation
- **BAI** (Burned Area Index): Detects bare soil and sparse vegetation
- **NDWI** (Normalized Di9erence Water Index): Identifies water bodies and moisture

The use of these indices allows us to highlight specific features that are not visible to the naked eye by combining di9erent spectral bands to extract precise information. For example, the NDVI, which uses the red and near-infrared bands, detects vegetation health by distinguishing areas with dense vegetation cover from those where vegetation is in decline. Similarly, the SAVI, a modified version of NDVI that accounts for exposed soil, is crucial in environments with sparse vegetation. The BAI, using blue and near-infrared bands, detects areas

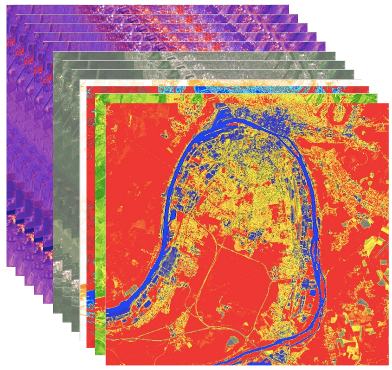

Figure 2. Final merged image with the 20 different selected bands.

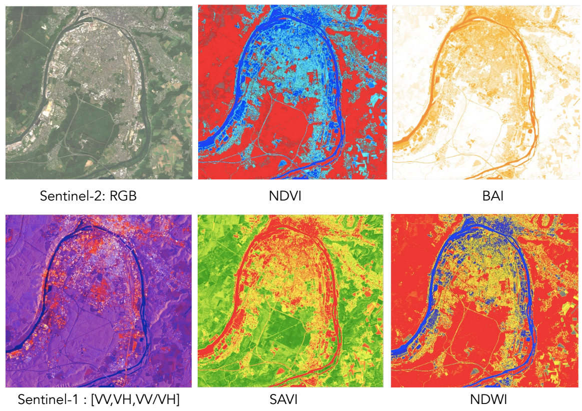

Figure 3. Multispectral Data Visualization of Sentinel-1 and Sentinel-2.

with bare soil or minimal vegetation, often associated with phenomena like fires or erosion. Lastly, the NDWI, which combines the green and near-infrared bands, identifies water bodies or moisture presence, providing key information for assessing hydrology and flood risks.

When combined with Sentinel-1 radar data, which is resistant to cloud cover, these indices enable more accurate and detailed analysis of urban land cover changes. This fusion of data enhances our ability to monitor and predict environmental transformations in cities, improving decision-making for urban planning and disaster mitigation.

The final merged image consists of 20 bands:

- Sentinel-1: 4 images $\times$ 3 bands (VV, VH, VV/VH)
- Sentinel-2: The 5 special indices plus the original B2, B3, B4, B8 bands

All those different bands can be seen in figure 2. Figure 3 show the multispectral data visualization of S1 and S2.

The final merged image consists of 20 bands, formulated as follows:

Merged Image $=$

$$VV_1, VV_2, VV_3, VV_4, VH_1, VH_2, VH_3, VH_4, VV/VH_1, VV/VH_2, VV/V$$

.

This fusion allows us to capture both structural and spectral information, enhancing the precision of our urban land cover classification.

2 Pixel-Based Classification

Land cover classification involves categorizing areas of land into distinct classes based on observed features. This process is crucial for understanding environmental conditions, managing natural resources, and monitoring changes in land use. In this study, we focus on pixel-based classifiers, which analyze each pixel in satellite imagery independently to determine its class based on spectral signatures.

We evaluated several pixel-based classification models, including Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree classifiers. These models utilize the spectral information from merged Sentinel-1 and Sentinel-2 data to classify pixels into categories such as vegetation, water, urban areas, forest, and crops.

To determine the e9ectiveness of each classifier, we computed confusion matrices and overall accuracy metrics.

References

Einstein A., 1905, Annalen der Physik, 322, 891