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SPECIAL ISSUE: CELEBRATING 20 YEARS OF GEOGRAPHY IN KADUNA STATE UNIVERSITY - ADVANCES AND FRONTIERS IN GEOGRAPHY

Comparative Performance of Sentinel-1 SAR and Sentinel-2 MSI Imagery for Mapping Urban Infrastructure Footprints

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ABSTRACT

The choice of remote sensing data is critical for accurate urban mapping, particularly in regions with frequent cloud cover. This study evaluates and compares the capacity of Synthetic Aperture Radar (SAR) from Sentinel-1A and multispectral optical imagery from Sentinel-2 for mapping urban infrastructure footprints in Osogbo, Nigeria. Using the Google Earth Engine platform, we performed a supervised classification for the year 2023 on both datasets using a Random Forest classifier. Identical training and validation data were used for both classifications to ensure a robust comparison. The results demonstrated a stark contrast in performance. The classification based on Sentinel-2 optical imagery achieved an exceptionally high overall accuracy of 99.93% (Kappa = 0.999), effectively distinguishing between roads, buildings, vegetation, water, and bare ground. In contrast, the Sentinel-1A SAR-based classification achieved a moderate overall accuracy of 67.24% (Kappa = 0.568). The error matrix for the SAR classification revealed significant mixed classification, particularly between roads and buildings, and between certain urban features and vegetation. The study concludes that while Sentinel-1A offers all-weather capability, its utility for detailed urban infrastructure classification is limited when used independently due to its reliance on backscatter and texture, which lack the rich spectral information of optical sensors. For precise urban footprint mapping in studies of medium-sized cities, Sentinel-2 is vastly superior. However, the complementary all-weather capability of Sentinel-1A suggests that a synergistic multi-sensor fusion approach would be the most effective strategy for continuous urban monitoring in tropical regions.

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1 Introduction

Nigeria, as a developing nation, faces intense pressure on its urban infrastructure due to rapid and often unplanned urban growth. The United Nations (2019) projects that the African urban population will double in 2050, triggering more stress on existing infrastructure systems of cities, particularly in medium-sized cities, of which Osogbo is an example. Informal settlements have had urbanisation that surpasses that of critical infrastructure development that has caused inefficiencies and inequalities in service delivery to a great extent. The predicaments are not peculiar to Nigeria but rather belong to a wider tendency that involves urban centres in the Global South in which urbanization is taking place at a speed that is far faster than governments' planning and execution of sustainable infrastructure systems (Cohen, 2006).

Sustainable urban planning and management are based on accurate and timely mapping of urban infrastructure. An essential tool in this regard has turned out to be remote sensing, which can be divided into the optical and microwave (Radar) categories of satellite sensors. Reflected solar radiation in different spectral bands, recorded by optical sensors such as Landsat and Sentinel-2, enables the detailed classification of land cover based on its spectral signature (Herold et al., 2003). The biggest weakness of optical imagery is, however, that the cloud cover and weather conditions can pose a major setback, especially in areas such as Nigeria, where it is mostly tropical.

Synthetic Aperture Radar (SAR) systems, such as Sentinel-1A, actively transmit pulses of microwaves, and the signal reflected is observed. This will enable them to penetrate clouds and capture data during the day and night, which is available as a reliable data source even when there is bad weather (Brunner et al., 2010). SAR data is surface geometry, roughness, and moisture sensitive and therefore useful in a variety of applications. But it has not been used as extensively in the detailed classification of land cover in urban areas, as optical images, because it is not multispectral and thus cannot make easy differentiation between materials such as asphalt, concrete, and plants.

Although some studies have investigated SAR application in urban mapping, including many studies where optical data are also used (Ban et al., 2015; Nwaezeigwe, 2018), there is a lack of direct and controlled comparisons specifically on the footprint of urban infrastructure (roads and buildings) in medium-sized cities in Africa. These cities often have heterogeneous urban landscapes and limited resources, making choosing the most effective and efficient mapping technology a practical concern for local planners.

This study addresses this gap by conducting a

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systematic comparative analysis of Sentinel-1A (SAR) and Sentinel-2 (optical) imagery for the specific task of urban infrastructure footprint classification. The primary objective is to evaluate and compare the accuracy and effectiveness of these two widely available and free data sources in mapping roads and buildings in Osogbo, Nigeria. The findings will provide clear guidance to researchers and urban practitioners on the strengths and limitations of each dataset for urban applications in similar contexts.

2 Materials and Methods

2.1 Study Area

The study was conducted using satellite images of Osogbo, Osun State, Nigeria. Osogbo is the capital of Osun State in southwestern Nigeria. It is strategically located 80 kilometres to the northeast of Ibadan and 200 kilometres to the northeast of Lagos. The geographical context of Osogbo is approximately between latitude 7°46′N and 8°16′N, and longitude 4°34′E and 4°56′E, as shown in Figure 1. Osogbo is located within the region of southwest Nigeria, where there is a concentration of great cultural and economic activities, and thus contributes to the relevance of Osogbo as a case study for such an analysis in Nigeria and medium-sized cities in sub-Saharan Africa. The city's population is estimated at 772,000, owing to a consistent increase in the population (Macrotrends, 2023). Osogbo had a population of 250,951 in 1991 (National Population Commission of Nigeria, 1991) and, with an annual urban growth rate of 3.15%, soared to 772,000 in 2023. This has resulted in a dynamic urban landscape through rural to urban migration and natural increase of population in the city.

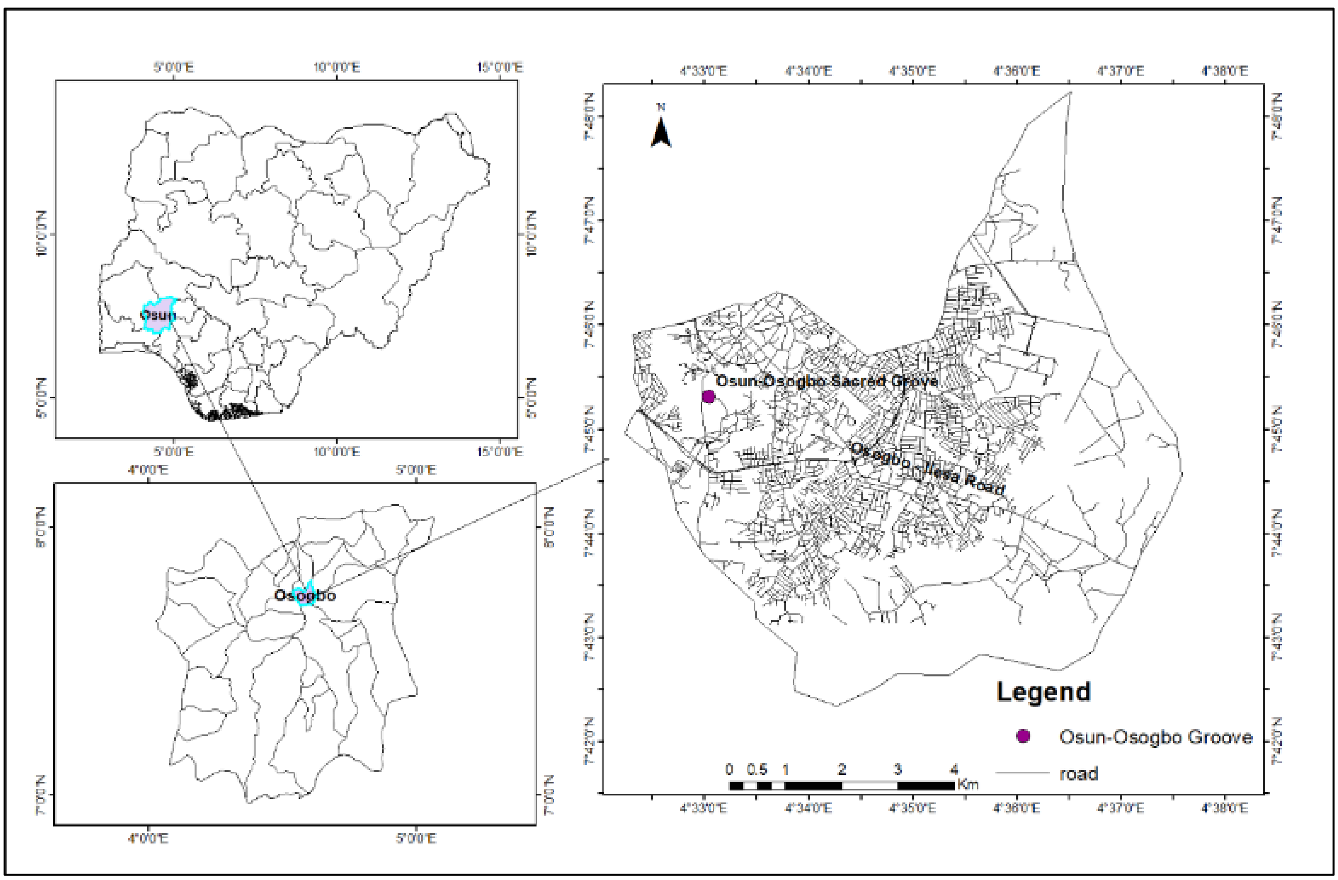

Figure 1: Map of the Study Area

Osogbo features a tropical wet and dry climate (*Aw*) according to the Koppen-Geiger classification. The city experiences warm temperatures year-round, with average highs ranging from 28° in August to 33°C in March. Annual precipitation averages approximately 1,361 mm, with the wet season extending from April to October. Topographically, Osogbo is situated at an average elevation of 328 meters (1,076 feet) above sea level, with elevations ranging between 285 meters (935 feet) and 390 meters (1,280 feet). The terrain is characterized by undulating lowlands interspersed with hills and inselbergs, which are prominent in the region. The city is primarily drained by the Osun River, which flows through Osogbo and continues southward.

Osogbo urban area has a blend of traditional and modern elements. The Osun Osogbo Sacred Grove is part of UNESCO World Heritage and is integral to the city's cultural identity. Osun Osogbo festival is one of the biggest art festivals in Nigeria, with over 235, 518 tourist visits in 2014 (Orga, 2016).

By contrast, Osogbo is a unique and compelling case to study the urban infrastructure footprints as it juxtaposes the ancient cultural heritage with the modern urban development. The city economy is diversified with a blend of traditional crafts, small-scale industries, agriculture, and commerce. The economic diversity has an impact on the nature of infrastructure that is needed to support the population and where it must be located. Osogbo's urban infrastructure is complex, with the presence of educational and healthcare institutions as well. The incidence of Osogbo's urbanization and growth in its population provides a perfect study area to investigate urban infrastructure footprint, especially due to rapid urbanization and population growth. Furthermore, the land use within Osogbo is diverse and includes densely populated urban centres as well as less developed peri-urban areas with which to investigate various types of urban infrastructure. This diversity can therefore help in understanding the different urban needs and challenges taking place in various urban zones.

2.2 Data Collection

The data used for this comparative analysis included Sentinel-1A SAR and Sentinel-2 MSI, as shown in *Table 1*.

Table 1: Remote sensing datasets used for comparing SAR and optical imagery in mapping urban infrastructure in Osogbo, Nigeria

Sensor	Data Product	Acquisition Date(s)	Number of Images	Spatial Resolution	Polarization / Bands Used	Data Source
Sentinel-1A SAR	GRD, Interferometric Wide (IW) swath mode	15 January 2023; 27 January 2023	2 scenes	10 m	VV and VH polarization	Copernicus Open Access Hub via Google Earth Engine
Sentinel-2 MSI	Level-2A (Bottom-of-Atmosphere reflectance)	18 January 2023	1 scene	10 m (B2, B3, B4, B8); 20 m (B11, B12)	Visible, NIR, and SWIR bands	Google Earth Engine (ESA Sentinel-2 archive)

This study adopted a minimal-image, seasonally consistent approach to enable a robust comparison of Synthetic Aperture Radar (SAR) and optical imagery for urban infrastructure mapping in Osogbo, Nigeria. Images were deliberately selected from the dry season (January 2023) to minimize vegetation cover, atmospheric interference, and surface moisture variability, all of which can obscure built-up features and confound sensor comparison. Sentinel-1A and Sentinel-2 acquisitions were temporally matched within a narrow window (±3 days) to ensure that observed differences in urban feature detection are attributable primarily to intrinsic sensor characteristics such as wavelength, polarization, and spectral response rather than temporal land-cover changes. The limited number of images enhances interpretability and reproducibility while remaining sufficient for evaluating the relative strengths and limitations of SAR and optical data in urban infrastructure mapping. To ensure a fair comparison, primary data (Ground Control Points) and secondary data (training and validation shapefiles) were kept identical for both classifications.

2.3 Data Preprocessing

Sentinel-2 (Optical): The Level-2A product was used, which incorporates atmospheric correction. The image was cloud-masked and resampled to a 10m resolution for analysis.

Sentinel-1A (SAR): Preprocessing in GEE included radiometric calibration and conversion of backscatter values to decibels (dB). A temporal median composite was created to reduce noise. To enhance the feature space for classification, SAR-derived indices were computed: The Normalized Difference Polarization Index (NDPI) and the VV/VH ratio. Speckle filtering was not explicitly applied before classification; however, the Random Forest (RF) classifier is known for its robustness to noisy and high-dimensional input data, which can help mitigate some of the effects of speckle in SAR imagery. RF has been widely used for land-cover and urban classification using SAR data without prior speckle filtering, demonstrating acceptable classification performance even when speckle noise remains in the input features (Jamali & AbdulRahman, 2019; Balzter et al., 2015; Gašparović & Dobrinić, 2021). Specifically, RF's ensemble decision-tree structure helps reduce the impact of random variations and noise on classification outcomes, and prior studies have successfully applied RF to unfiltered Sentinel-1 data for urban and land-cover mapping tasks, indicating its utility in handling SAR speckle to a degree.

RADAR Imagery Preprocessing

The preprocessing of Sentinel-1A Synthetic Aperture Radar (SAR) data in this study focuses on preparing the imagery for classification and analysis while acknowledging certain implicit preprocessing steps. The

Sentinel-1A Ground Range Detected (GRD) collection in Google Earth Engine (GEE) already includes preliminary but comprehensive terrain correction, which meets the research needs for geometric accuracy. Additionally, the random forest classifier used in this study will inherently compensate for some preprocessing steps, such as speckle filtering. The following are the pre-processing steps used in preparing the Sentinel-1A image for the analysis.

Data Selection and Filtering

To ensure the selection of high-quality SAR data, the preprocessing begins by filtering the Sentinel-1A GRD collection based on specific criteria such as Date (filterDate -'2023-01-01', '2023-12-31') to ensure the data collected was relevant to the study. The dataset is limited to images acquired within the study area boundaries, covering the entire year of 2023. Only images captured in Interferometric Wide (IW) swath mode are considered, as this mode provides high-resolution data suitable for land cover analysis. The preprocessing also selects images with dual-polarization (VV and VH), which enhances the ability to distinguish different land cover types. To maintain consistency, only ascending orbit passes were included. This ensures that all images have a similar acquisition geometry, reducing variations caused by differences in viewing angles.

Radiometric Calibration and Conversion to Decibels

After filtering, the SAR backscatter values were calibrated and converted into decibels (dB) units, a standard transformation for SAR analysis. This step involves applying a logarithmic transformation (log10) to the VV and VH bands, followed by scaling the values by a factor of 10. The transformation enhances the interpretability of backscatter intensities, making it easier to differentiate land cover types. To reduce noise and enhance the stability of the dataset, a temporal median composite was applied across the selected images. This process mitigates short-term variations caused by atmospheric effects, sensor noise, and minor land surface changes, producing a more reliable dataset for classification.

Computation of SAR-Derived Indices

In addition to the VV and VH backscatter bands, two SAR-derived indices were computed to improve classification accuracy. The Normalized Difference Polarization Index (NDPI) was calculated using the difference between VV and VH backscatter values. This index enhances the differentiation between vegetation and built-up surfaces. Additionally, the VV/VH ratio was computed to provide further insight into land cover characteristics. These indices are then added as additional bands to the dataset, thereby enriching the feature space for classification.

Final Pre-processed Dataset

The final processed SAR dataset consists of four bands:
VV_dB: VV polarization in decibels
VH_dB: VH polarization in decibels
NDPI: Normalized Difference Polarization Index
Ratio: VV/VH ratio
By integrating these preprocessing steps, the Sentinel-1A SAR imagery is prepared for classification, ensuring a balance between computational efficiency and data accuracy.

2.4 Image Classification and Accuracy Assessment

Supervised classification was performed using a Random Forest (RF) classifier in Google Earth Engine. For Sentinel-2, the input features included spectral bands (Visible, NIR, SWIR) and derived indices (NDVI, NDBI). Training samples were extracted from a vector "FeatureCollection" labeled by landcover, with 31,997 building points, 2,207 road points, 10 waterway points, 136 natural vegetation points, and 76 bare ground points. Samples were drawn at 10 m resolution, and the RF classifier was trained with 500 decision trees, using default GEE settings. For Sentinel-1A, the input features were the VV and VH bands in dB, along with the computed NDPI and Ratio indices.

The classification scheme comprised five classes: Roads, Buildings, Vegetation, Water Bodies, and Bare Ground. An identical set of training samples was used to train the RF classifier for both images. The classification output was then validated against an independent set of ground truth points. Error matrices were generated for both the Sentinel-2 and Sentinel-1A classifications to compute overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient.

The analysis of the extracted urban footprints required an accuracy assessment, which will validate the extracted urban infrastructure footprints. This is enabled through GEE generation of confusion matrices for optical and radar-based classifications. Depending on ground truth data acquired from both imagery and field surveys, one can compute metrics such as overall accuracy by comparing these classifications. These metrics give a quantitative measure of whether the classifications are a true representation of reality. GEE's platform provides and compares large datasets, enabling an efficient validation of large datasets that highlight the robust accuracy assessment of optical and RADAR imagery in urban footprint processing.

Figure 2 shows the workflow, which represents how the data collected was manipulated to achieve the study objectives. The objectives of analysing and validating urban infrastructure footprints were accomplished as seen in the workflow using GEE as a comprehensive and efficient platform. Its ability to deal with large datasets, perform complex spatial analysis, and combine datasets makes it a very useful tool in urban infrastructure studies.

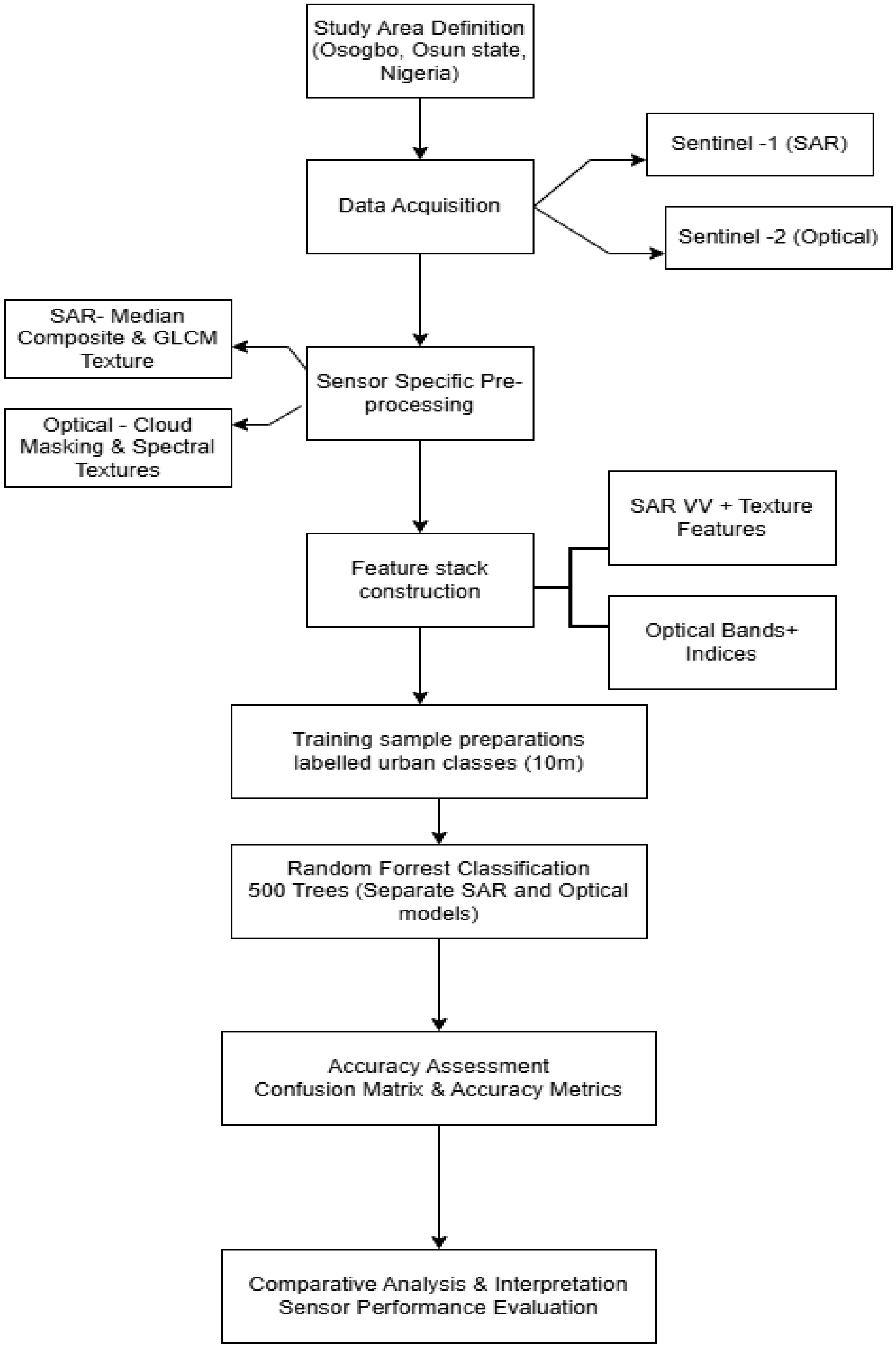

Figure 2: Methodology Workflow

3 Results and Discussion

3.1 Classification Accuracy

Figures 3a and b show Sentinel-1 and Sentinel-2 images, while Figures 4 a and b show a classified image of Sentinel-1 and Sentinel-2.

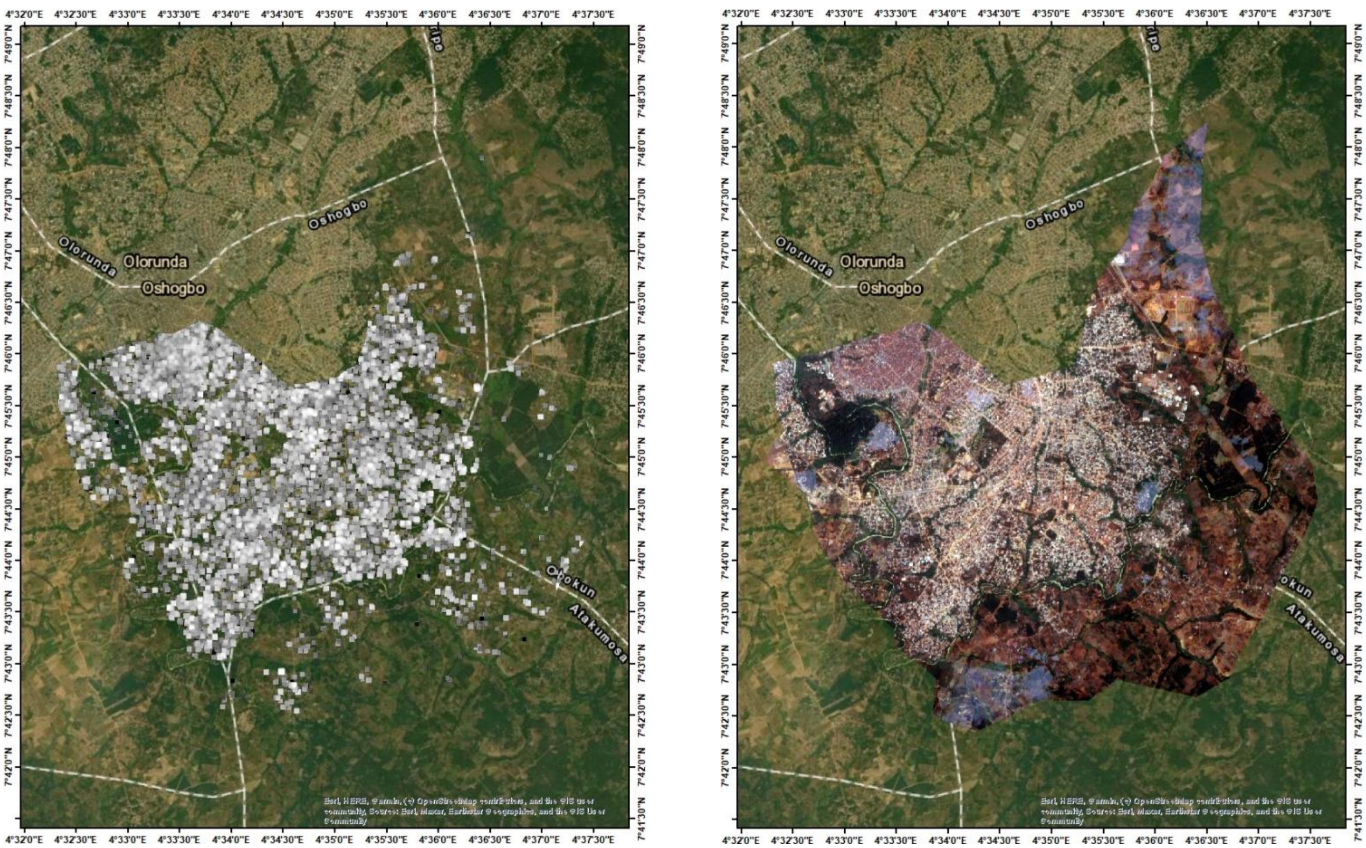

Figure 3: a) VV and VH from Sentinel -1, b) Sentinel-2 Image of the study area

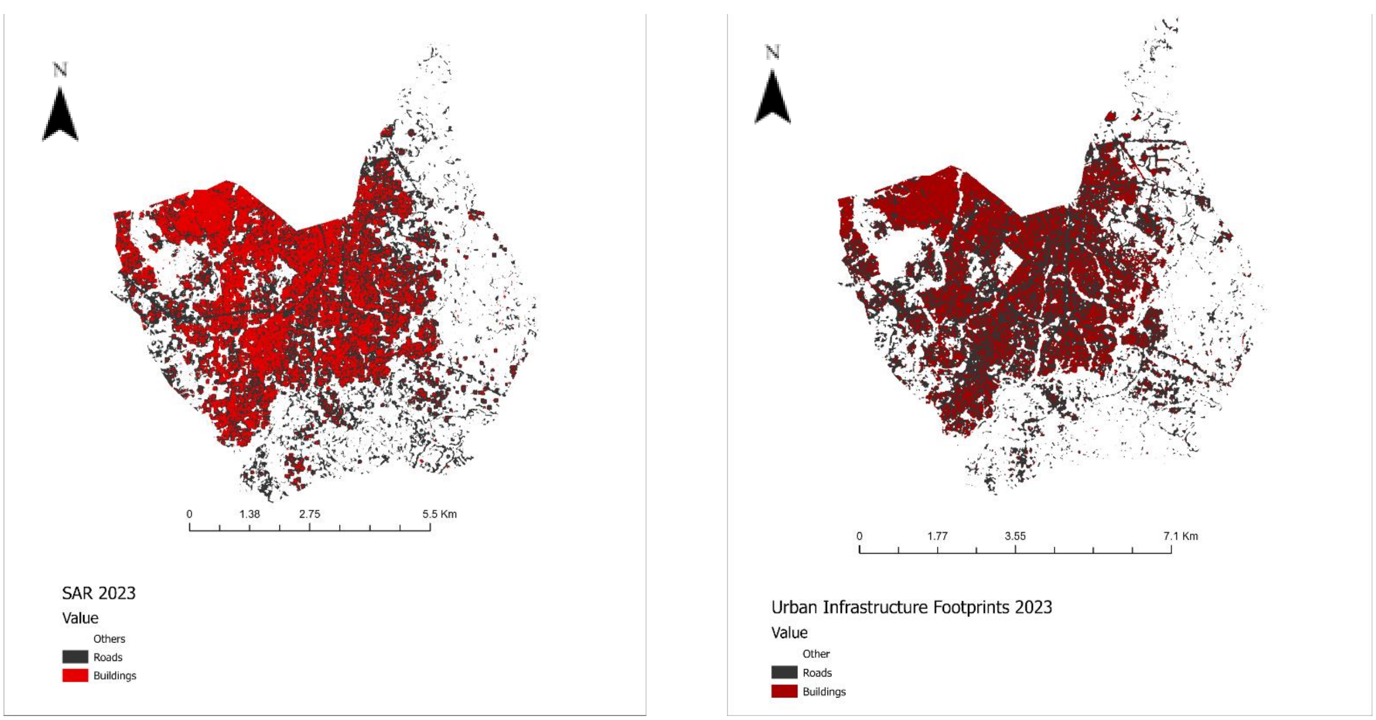

Figure 4: Classification result of a) SAR (sentinel -1) image, and b) Sentinel -2 image

Table 2 shows a comparative accuracy assessment of Sentinel-2 and Sentinel-1A classifications. The comparative analysis revealed a significant disparity in classification performance between the two sensors.

Table 2: Producer's Accuracy Assessment of Sentinel-2 and Sentinel-1A Classifications

Class	Sentinel-1A User's Accuracy (%)	Sentinel-2 User's Accuracy (%)
Roads	46.26	100.00
Buildings	75.36	99.86
Water bodies	49.22	99.86
Vegetation	76.21	100.00
Bare Ground	91.75	99.90
Overall Accuracy	67.24	99.93
Kappa Coefficient	0.568	0.999

The Sentinel-2 classification achieved near-perfect accuracy, demonstrating its high capability for detailed urban land cover mapping. In stark contrast, the Sentinel-1A classification yielded only moderate accuracy, with a Kappa value indicating fair agreement beyond chance.

The effectiveness of SAR imagery in urban classification is influenced by surface characteristics such as roughness, moisture content, and structural properties. These factors can vary significantly with time and seasonal changes, which in turn can affect the radar backscatter and lead to inconsistencies in classification. For example, wet or highly reflective surfaces might be misclassified as water bodies or vegetation. These variations underscore the difficulty in achieving consistent classification results using SAR alone. SAR data's ability to penetrate cloud cover and provide day/night imaging is one of its strengths. However, this advantage is tempered by its difficulty in identifying detailed urban structures. Unlike optical imagery, which can resolve fine structural details, SAR data may struggle with distinguishing between different types of buildings or accurately identifying specific land uses within urban areas. This limitation may reduce the utility of Sentinel-1A for detailed urban land use classification.

In contrast to the limitations of Sentinel-1A, Sentinel-2 offers multispectral optical data that allows for clearer differentiation between urban land cover types. Sentinel-2's ability to capture a broader spectrum of light (including visible, near-infrared, and shortwave infrared bands) enhances its capacity to distinguish between different surfaces. For instance, vegetation can be identified through the Normalized Difference Vegetation Index (NDVI), and built-up areas are more easily delineated using the Normalized Difference Built-Up Index (NDBI) as implemented for the optical image's classification in the study. This higher spectral discrimination allows for a more accurate classification of urban areas, making Sentinel-2 better suited for detailed urban analysis compared to Sentinel-1A.

3.2 *Analysis of Sentinel-1A Classification Errors*

The error matrix for the Sentinel-1A classification provided insight into the sources of error. There was substantial confusion between urban feature classes. For instance:

- A significant number of "Road" pixels were misclassified as "Buildings" (160 out of 428 actual road points).
- "Buildings" were also frequently confused with "Roads" (105 out of 483 actual building points).
- Misclassification also occurred between "Vegetation" and other classes, and "Water Bodies" were often confused with "Vegetation."

This confusion arises because different materials (e.g., concrete buildings and asphalt roads) can produce similar radar backscatter responses based on their surface roughness and orientation relative to the sensor. The lack of distinct spectral signatures, which are readily available in optical imagery, is a fundamental limitation for detailed urban classification using SAR alone.

4 Discussion

The results of this study unequivocally demonstrate the superior performance of Sentinel-2 optical imagery over Sentinel-1A SAR for the specific task of mapping detailed urban infrastructure footprints. The 99.93% accuracy achieved by Sentinel-2 is attributable to its high spatial resolution (10m) and, more importantly, its rich spectral information. Indices like NDVI and NDBI provide powerful means to separate vegetation from built-up areas, while the varying reflectance of materials in the visible and infrared spectrum allows for clear discrimination between roads, buildings, and bare soil.

SAR backscatter intensity is influenced not only by target characteristics but also by environmental conditions and imaging geometry. Variations in soil and vegetation moisture affect the dielectric properties of surfaces, typically increasing backscatter with higher moisture content due to greater reflectivity of microwave radiation. Seasonal timing and weather-related conditions, such as rain or frozen surfaces, can introduce radiometric uncertainty in σ^0 values if not accounted for or masked, thereby impacting the reliability of SAR measurements (Benninga et al., 2019). Additionally, surface roughness and structure strongly modulate backscatter; rougher surfaces tend to scatter energy more diffusely, while smooth surfaces show lower returns, and both spatial variability and temporal changes in roughness can introduce significant errors in derived SAR metrics (Álvarez-Mozos et al., 2009). The imaging incidence angle further alters backscatter; steeper angles generally reduce backscatter intensity, whereas variations in incidence angle across a scene can change how surfaces appear due to geometric effects and local slope differences, affecting interpretation and classification outcomes.

The modest 67.24% accuracy of the Sentinel-1A classification highlights the inherent challenges of using SAR data for this purpose. SAR backscatter is influenced by factors such as surface roughness, dielectric properties, and sensor geometry, which are not unique to specific urban land cover classes. A smooth concrete roof and an asphalt road can have very similar backscatter characteristics, leading to the high confusion observed between the "Roads" and "Buildings" classes. This finding aligns with studies noting the complexity of urban SAR interpretation (Brunner et al., 2010).

The comparison between Sentinel-2 optical data and Sentinel-1 radar data clearly identifies the fact that radar data is restrictive concerning urban classification at the level of detail. Sentinel-1A possesses cloud-penetrating capabilities and texture-based features, but due to its reliance on backscatter signals, a significant misclassification was observed, achieving only 67.24% overall accuracy. This is relatively good due to the spectral properties of Radar; it is notably lower than the 99.93% accuracy achieved with Sentinel-2. It relates the challenges associated with processing urban features in radar to the ability of spectral indices like NDVI or NDBI, available in optical data, but not in Radar. Sentinel-1 and Sentinel-2 data integration in a multisensory fusion framework may enable such future analyses to exploit the strengths of both datasets (Nagendra et al., 2013). By combining this approach with state-of-the-art machine learning algorithms, the classification accuracy could potentially be increased, and it could give us more reliable insights for urban planning and urban infrastructure management.

The practical implication for urban researchers and planners is clear: for standalone, high-accuracy mapping of urban infrastructure in a single timeframe, Sentinel-2 is the unequivocal choice. However, to dismiss Sentinel-1A would be short-sighted. Its all-weather, day-night capability is its greatest asset. In regions with persistent cloud cover, Sentinel-1A can fill critical data gaps. Therefore, the most robust methodological approach is not to choose one over the other, but to integrate them.

Future work should focus on developing multi-sensor data fusion techniques that leverage the spectral richness of Sentinel-2 and the all-weather reliability of Sentinel-1A. Such an approach would be ideal for time-series analysis, change detection, and continuous monitoring of urban growth in challenging environments, ensuring data continuity even during cloudy seasons

5 Conclusion

This study provides a rigorous empirical comparison of Sentinel-1A SAR and Sentinel-2 optical imagery for urban infrastructure mapping. We conclude that while Sentinel-1A is a powerful tool for all-weather observation, its standalone application for detailed urban footprint classification is hampered by significant spectral confusion, resulting in moderate accuracy. Sentinel-2 optical imagery is dramatically more effective for this task, achieving near-perfect classification results due to its multispectral capabilities. For urban studies requiring high thematic accuracy, Sentinel-2 should be the primary data source; however, the strategic path forward lies in developing integrated methodologies that combine the complementary strengths of both sensors to achieve resilient and continuous urban monitoring.

Sentinel-2 optical imagery outperformed Sentinel-1A SAR in mapping urban infrastructure, achieving 99.93% accuracy due to its high spatial resolution and spectral richness, which allow clear discrimination between buildings, roads, vegetation, and bare soil using indices like NDVI and NDBI. Sentinel-1A achieved only 67.24% accuracy, as its backscatter is influenced by surface roughness, dielectric properties, and imaging geometry, confusing spectrally similar classes. While SAR provides all-weather, day-night imaging and texture-based features, it lacks the spectral discrimination of optical data. These differences highlight that Sentinel-2 is best for detailed urban mapping, whereas Sentinel-1A is suited for complementary applications, suggesting multi-sensor integration to leverage the strengths of both.

As suggested in Nwaezeigwe et al. (2021), leveraging complementary data sources and geospatial techniques enhances the accuracy and applicability of urban studies for planning and environmental management. For instance, integrating texture measures and spectral indices, as demonstrated in this study, improves the delineation of urban-rural boundaries and supports evidence-based policy-making. Moreover, the observed patterns reinforce the importance of preserving urban vegetation for ecological balance and climate regulation, echoing global calls for sustainable urban planning (UN-Habitat, 2020).

Sentinel-1A offers useful information for urban analysis, but also exhibits limiting aspects in terms of discriminability, separately, based on texture, as well as the lack of separability of classes, so it is advisable to apply the latter in conjunction with optical information collected by Sentinel-2. These challenges can be overcome by using a multisensory fusion approach along with advanced machine learning methods in order to increase classification accuracy. In the end, the combined use of Sentinel-1A and Sentinel-2 data will produce better and more accurate urban land cover mapping that is more suitable for the purposes of urban planning and infrastructure management.

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