



# Combining Local Knowledge with Object-Based Machine Learning Techniques for Extracting Informal Settlements from Very High-Resolution Satellite Data

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## Abstract

The classification of informal settlements using very high-resolution (VHR) satellite data and expert knowledge has proven very useful for urban planning. The objective of this work was to improve the accuracy of informal settlement classification within the city of Riyadh, Saudi Arabia. The analysis incorporated the use of expert knowledge (EK). Twenty unique indicators relevant to informal settlements were identified by experts familiar with these areas, and incorporated into the image classification process. Object-based image analysis (OBIA) was then used to extract informal settlement indicators from a VHR image. These indicators were used to classify the image utilising two machine learning (ML) algorithms, random forest (RF) and support vector machine (SVM) methods. A VHR image (e.g., Worldview 3) of the city was employed. A total of 6,000 sample points were randomly generated, with 1800 used for training the VHR image. The classification process was able to clearly distinguish the formal settlement areas from informal areas, road networks, vacant blocks, shaded areas, and vegetation features. The object-based RF technique provided an overall accuracy of 96% (kappa value of 95%), while OB-SVM provided an accuracy of 95% (kappa of 91%). The results demonstrated that object-based ML methods such as RF and SVM, when combined with EK, can effectively and efficiently distinguish informal settlements from other urban features. This technique has the potential to be very useful for mapping informal settlements.

**Keywords** Informal settlements · Local expert survey · Object-based machine learning KSA

## 1 Background

An understanding of the specific characteristics of informal settlements is essential when developing and implementing urban policies designed to benefit marginalized groups within a society. One of the challenges in this process is the absence of a universally-accepted informal settlement definition (Adewunmi et al. 2023). These settlements can generally be distinguished from formal areas by their physiognomy and socioeconomic attributes (e.g., population and

housing density), as well as limited access to social services (Dewan and Yamaguchi 2008; Kuffer et al. 2016). They are typically located in, or near, city centers (Alrasheedi et al. 2023). They differ from slum areas in that they have emerged in tandem with newly built-up areas. They also typically exhibit a mixture of very old and very new buildings. This is particularly true for Riyadh city, the capital of the Kingdom of Saudi Arabia (KSA).

Previous research has demonstrated the value of using medium to high-resolution satellite imagery for mapping urban areas and subsequent use of isolating informal settlements (Mahabir et al. 2018; Li et al. 2022; Cinnamon 2024). The use of very high-resolution (VHR) imagery has become an important part of the decision-making process and has proven to be a valuable data source for researchers and urban planners (Chakraborty et al. 2015; Mahabir et al. 2018, 2020; Cinnamon 2024). Spectral characteristics tend to vary with location (Kuffer et al. 2014; Kohli et al. 2019), so any mapping exercise should consider the geometry and texture of objects (e.g., lacunarity) found within an area

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when using satellite data (Kuffer et al. 2016; Mahabir et al. 2018). Due to its ability to provide detailed properties of real-world features, VHR imagery has commonly been used to identify and map informal settlements in diverse environments (Owen and Wong 2013; Kuffer et al. 2016; Leonita et al. 2018; Maung et al. 2023). It should be noted, however, that the morphological characteristics of the built environment, particularly in regards the type of building materials used, differ according locations (Kohli et al. 2012; Li et al. 2022). A single attribute cannot usually be used to successfully identify an informal settlement area due to its similarity in spectral responses between the formal and informal areas. The same type of building material is commonly used to construct structures found in both areas, especially in the Arabian Peninsula (Alrasheedi et al. 2023) and, as a result, generalization is not possible in the case of informal settlement mapping. Due to these limitations, inclusion of other criteria is highly recommended (Jain 2007; Alrasheedi et al. 2023). For example, incorporation of local knowledge for distinguishing urban features is shown to enhance accuracy of satellite-based mapping (Mandeli 2010), especially identifying informal settlements.

## 1.1 Related works

Mapping informal settlements with VHR imagery is usually conducted with object-based image analysis (OBIA) (Pratomo et al. 2018; Hossain and Chen 2019; Alrasheedi et al. 2023). OBIA has proven useful for extracting spatial and textual features unique to informal settlements. There are, however, some issues with OBIA, including the need for ruleset changes. These changes are related to transferability issues; the level to which an existing ruleset needs to be modified from the original. These are typically based on local knowledge. Grippa et al. (2017), for example, showed that successful use of an optimized segmentation parameter on a small area does not guarantee that it will work well when applied to a large urban area. This appears to be due to the diverse nature of the features being studied (Kuffer et al. 2016; Mahabir et al. 2018; Mudau and Mhangara 2021). Recent work has improved the ability to map informal settlements using satellite images, however the type of indicators to be used with any particular imagery still require contextual “tuning” by local experts to adjust ruleset parameters (Kohli et al. 2016b, 2019; Mudau and Mhangara 2021; Prabhu et al. 2021). Alrasheedi et al. (2023) used local information and OBIA to separate informal from formal settlements. The study noted that some indicators, such as building density and dwelling shape, were ineffective when used in the satellite-based image classification process. Their work concluded that the use of OBIA alone is not sufficient in regards improving classification accuracy, particularly in the Arabian Peninsula, and suggested

that integration of OBIA with the machine learning (ML) method could increase the usefulness of this process for informal settlement mapping.

Many image classification techniques are now available for use in enhancing satellite-based analytical work. One of these methods is ML (Mahabir et al. 2018), recommended due its robustness (Leonita et al. 2018). Three ML methods which are commonly used for extracting information from VHR imagery are Random Forest (RF), Support Vector Machine (SVM) and Deep Learning (DL) (Mahabir et al. 2018; Neupane et al. 2021; Tekouabou et al. 2022). Although ML methods have gained huge popularity to classify homogenous areas (e.g., forest cover), their use in the classification of heterogenous surfaces such as urban features with VHR image are limited. For example, image classification accuracy by ML methods such as RF and SVM algorithms was compared previously but inconsistent and even contradictory results are noted (Maxwell et al. 2018). While both techniques have appeared reliable in some works (Statnikov et al. 2008; Adam et al. 2014; Leonita et al. 2018; Sheykhmousa et al. 2020), a few studies have reported that SVM is superior to RF (Li et al. 2014; Khatami et al. 2016; Raczko and Zaga-jewski 2017; Thanh Noi and Kappas 2017) and vice versa (Belgiu and Drăguț 2016; Adugna et al. 2022). The relative performance of RF and SVM has also been tested on different datasets, including unmanned aerial vehicles (UAVs) (Huang et al. 2015; Guo et al. 2022), multispectral imagery (Duque et al. 2017; Leonita et al. 2018; Schmitt et al. 2018; Prabhu et al. 2021), standard aerial imagery (Kooistra et al. 2014) and VHR imagery (Duque et al. 2017; Mboga et al. 2017). These studies indicated that ML methods can handle complex spatial patterns, and can produce relatively accurate results when compared to per-pixel methods (Mantero et al. 2003; Mountrakis et al. 2011; Wieland et al. 2016; Ajami et al. 2019).

The above studies have provided valuable insights into information extraction from satellite data for classifying informal settlements. However, the effectiveness of ML methods incorporating local knowledge for informal settlement mapping tasks remains relatively unclear (Peng et al. 2023).

To reveal complex spatial patterns, Abrahams et al. (2023) noted that OBIA combined with ML may be a paradigm shift in the field of image-based land cover classification. Although OBIA with ML methods have largely been used in homogenous areas such as natural hazards, forests and land use domains (Cooner et al. 2016; Momeni et al. 2016; Phiri and Morgenroth 2017; Liang et al. 2020), study utilising these methods to reveal complex urban patterns are few and far between. A comprehensive review of ML methods by Tekouabou et al. (2022) indicated that incorporating local knowledge into ML methods can be very useful for mapping heterogenous geographic phenomena.

However, studies that have utilized such methods in the urban contexts are mostly drawn from developed countries (Tekouabou et al. 2022; Breuer and Friesen 2023). A universally-accepted definition of an informal settlement is not available (Mudau and Mhangara 2021) and the current literature appears to have overlooked the importance of the unique characteristics of these areas when associated with specific urban settings (Kuffer et al. 2016; Matarira et al. 2022b; Tekouabou et al. 2022; Mudau and Mhangara 2023). Object-based ML techniques using spectral image bands derived from multiple sensors enhance the opportunities for mapping informal settlements on a city scale, which could help to define informal settlement indicators (Mudau and Mhangara 2023). The current study aims to contribute to this space. Primarily, this work intends to combine OBIA and ML methods with local knowledge to characterize spatial patterns of informal settlements. A VHR imagery is used for this purpose and Riyadh city has been considered as the case. Being part of a larger work, a local ontology of informal settlements (LOIS) from satellite data is being developed, which can support urban planners and decision-makers to address increased challenges faced by cities, particularly in the Arabian Peninsula.

## 2 Materials and methods

### 2.1 Description of the study area

Riyadh, the capital (and biggest city) of Kingdom of Saudi Arabia (KSA), is situated on the Najd Plateau (latitude 24°18′–25°11′ N, longitude 46°15′–47°19′ E) at an elevation of 600 m above mean sea level. Like other Saudi Arabian cities, Riyadh experienced rapid urbanization during the 1970's (Hertog 2015) and there are now approximately 8 million people living within the city boundary (Rashid 2018).

Recent government policies have resulted in substantial investments in the defense, education, financial and health sectors. The rapid expansion of the economy, and associated infrastructure modernization resulting from this investment, has been one of the main reasons for the development of informal settlements. People have relocated from other regions into the urban areas seeking greater employment opportunities and a better lifestyle. The ability to access cheaper accommodation in these areas is also driving urban expansion (Khraif et al. 2018).

Four informal settlements (typically older residential neighborhoods) are selected for this study. The selection is based on the advice of local experts. The selected areas were Al Shomaisi (1.49 km<sup>2</sup>), Meekal (0.21 km<sup>2</sup>), Al Dirah (0.24 km<sup>2</sup>) and Al Dubiya (1.56 km<sup>2</sup>). Four neighborhoods along with the study area are shown in Fig. 1.

### 2.2 Data and material

All data was obtained from the King Abdulaziz City for Science and Technology (KACST) and Riyadh Municipality (RM). A Worldview-3 imagery, comprising panchromatic and multi-spectral bands with spatial resolution of 0.31 m and 1.24 m was acquired from KACST. Bands 2 (450–510 nm), 3 (510–580 nm), 5 (630–690 nm), 7 (770–895 nm), representing blue, green, red, and infrared wavelengths, were used. Additionally, a GeoEye-1 image with a panchromatic (0.41 m) and multispectral (1.64 m) bands was also obtained from KACST to be used as reference data. Satellite images were subject to radiometric and atmospheric correction (Alrasheedi et al. 2023).

Road networks, informal settlements, neighborhood boundaries, a digital elevation model (DEM) and a digital surface model (DSM) were acquired from RM. Various specialists with a detailed knowledge of features of local environment were surveyed in regards area-specific indicators. These responses are referred to as expert knowledge (EK) in this work.

### 2.3 Ontological framework

Alrasheedi et al. (2023) developed a LOIS for Riyadh in their original work in Saudi Arabia. The LOIS structure consisted of three levels—object, settlement, and environs—and this overarching framework was used in the current work. Sixteen indicators were defined in the original work using expert knowledge, and an OBIA method was employed. OBIA emphasizes the analysis and classification of objects or segments within an image, rather than individual pixels, so it does not extract spectral information directly from the raw satellite data. Additional indicators have been included in the current work, and used with ML methods (RF and SVM) to improve identification accuracy. Four indicators (e.g., mean green, mean blue, mean infrared, and standard deviation of infrared) have been extracted from the VHR imagery due to some limitations associated with the original sixteen indicators. ML has the ability to work with the full spectrum contained within a VHR image. A summary of the workflow is shown in Figure 2. Information on the additional indicators is shown in Table 1. For details regarding the LOIS structure used, readers are referred to Alrasheedi et al. (2023).

### 2.4 Image analyses

#### 2.4.1 Image segmentation

A multi-resolution technique was used to perform the image segmentation. A scale parameter (SP) and values for weighting of shape and compactness were defined during

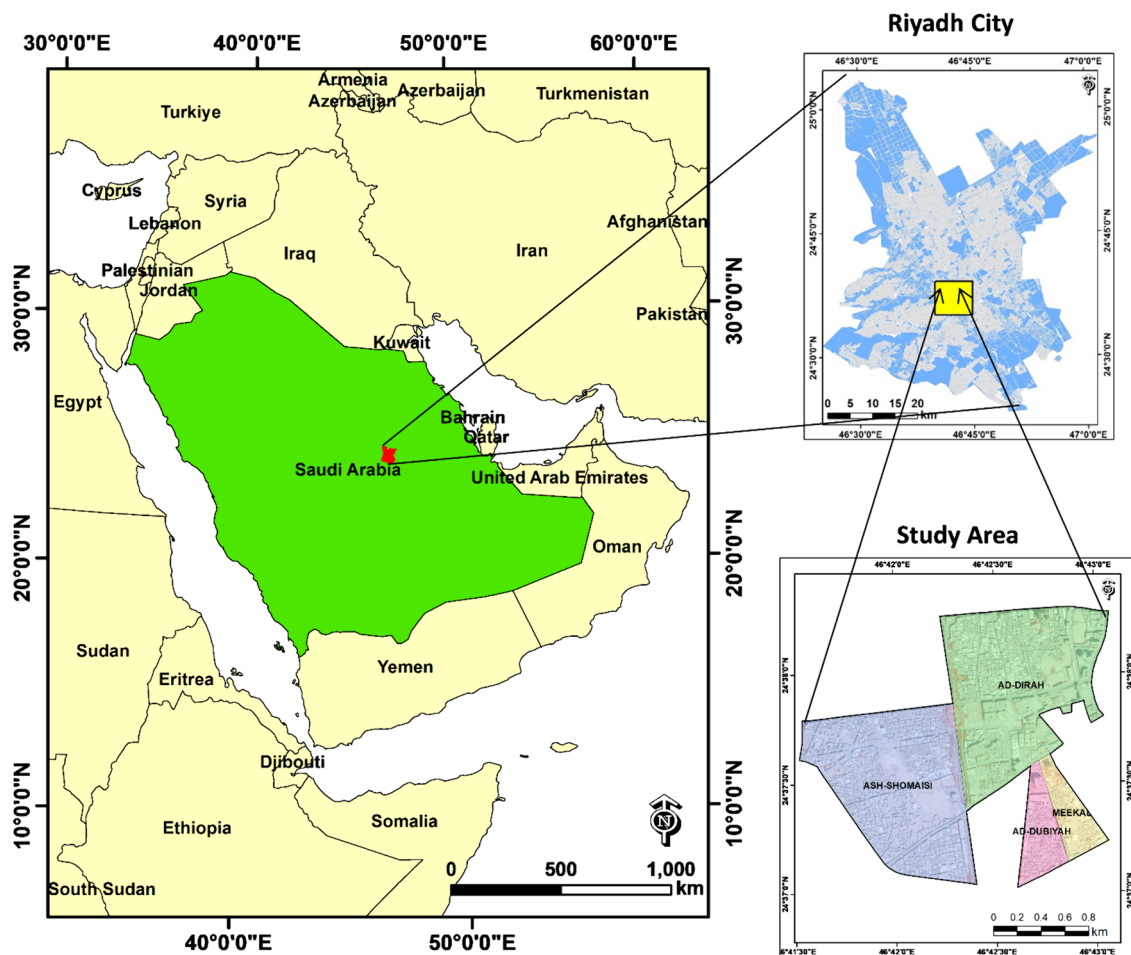


Fig. 1 Location of the four neighbourhoods in the study area

image processing to prevent object overlap. An SP of 30 was selected. The weight values of 0.3 and 0.5 were assigned to shape and spectral compactness (Alrasheedi et al. 2023).

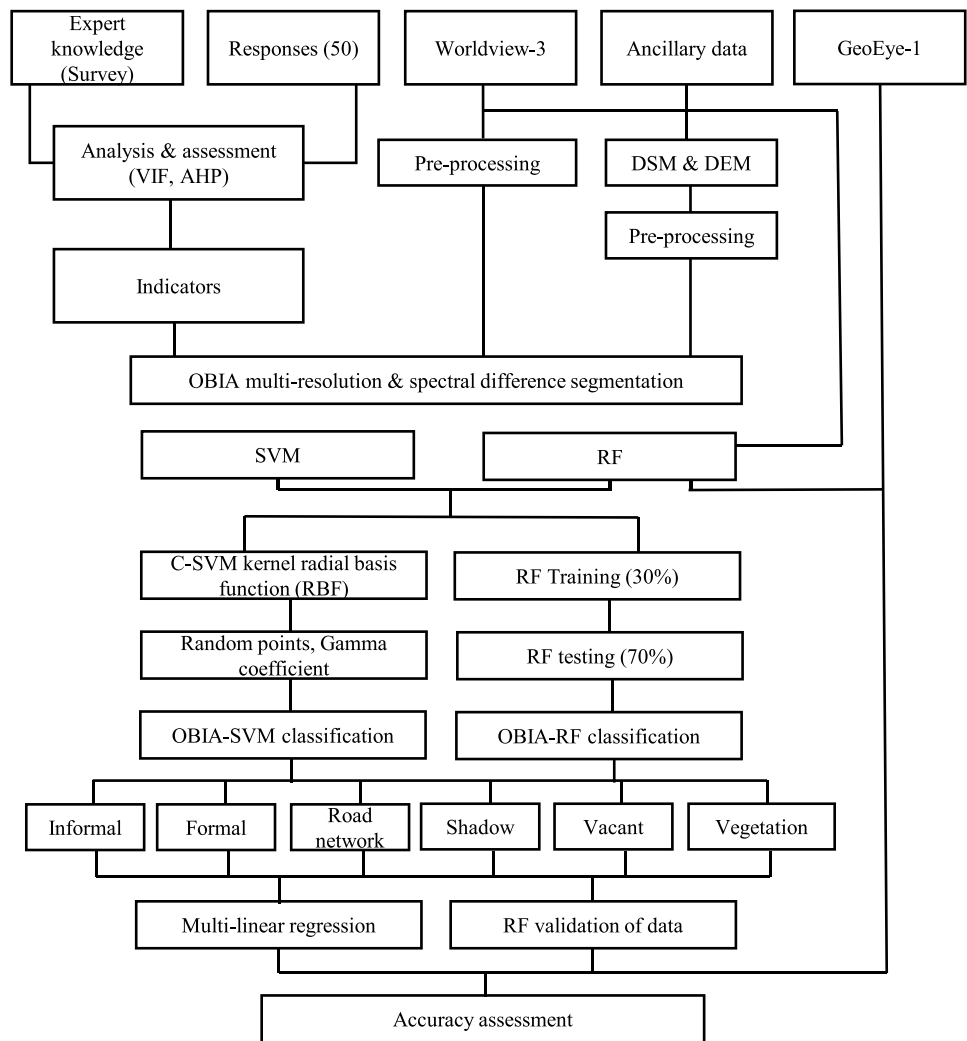
#### 2.4.2 OBIA-RF classification

Use of an ML is typically a multi-step process. It starts with OBIA segmentation of an image, which involves the grouping of pixels with similar spectral and spatial characteristics to form objects (Alrasheedi et al. 2023). These objects were defined as indicators and then used to classify the VHR image using the two ML algorithms, i.e., RF and SVM. Spectral information, shape, texture, and contextual relationships was included in the classification process. ML classifiers were trained using random samples derived from the informal settlements and combined with indicators extracted via OBIA. These classifiers were then generalized to categorize unidentified pixels, based on their spectral values. These steps were applied to both image classification schemes.

Leonita et al. (2018) noted that most ML studies incorporate many training samples in the processing stage to increase classification accuracy, and that these samples need to be randomly selected. In the present work, point samples were generated using a random point generator tool. The points were then visually interpreted and classified to reduce any possible uncertainty associated with spatial autocorrelation. Studies have shown that nonparametric ML algorithms (e.g., SVM and RF) require a large number of training samples than parametric models, to achieve optimal results (Morshed et al. 2022).

A total of 6000 points were randomly generated. These points were then used to classify VHR image using OBIA-RF and OBIA-SVM methods. Each point was converted to a training area (a polygon) with a radius of 2 m (Corcoran 2013). Converting points to polygons using the RF approach involves matching the spatial attributes of the input data with the RF specifications to create classifications which are easier to interpret. Training and testing samples were randomly chosen from reference polygons. 30% samples were used for training and the remaining 70% were

**Fig. 2** Flowchart, showing informal settlements identification process



**Table 1** Four additional indicators used in this work

Indicator	Description	Definition
M (B)	Mean blue band	Mean brightness (band 2)
M (G)	Mean green band	Mean brightness (band 3)
M (IR)	Mean infrared band	Mean brightness (band 7)
SD (IR)	Standard deviation infrared band	Dispersion of data in relation to mean brightness (band 7)

used for testing (Feng et al. 2015; Matarira et al. 2022a). The twenty indicators that had been segmented in OBIA were combined with the RF classifier for training and testing to obtain the relative importance of the indicators. A bootstrap-aggregation method (bagging) was used to split each tree during the training phase (Ghimire et al. 2012). Ten iterative trials were carried out for each model to test any potential variance in accuracy that may have resulted from random samples (Leonita et al. 2018). Two-thirds of the training

samples (in-bag samples) were used to create decision trees during bootstrap-aggregating process. The remaining of the training data, or "out-of-bag" (OOB) samples, were used to perform accuracy. The OOB estimate of error rate, a valid indicator of classification accuracy, is used to assess the effectiveness of an RF model (Zhong et al. 2014). The majority of the trees that contribute to highest classification accuracy influence the final output (Breiman 2001). Two important parameters, ntree (the number of trees) and mtry (the degree of randomness), were used to determine the effectiveness of the RF process. This enabled an accurate assessment of ntree to be considered (Feng et al. 2015).

**2.4.2.1 OBIA-SVM classification** Support vector machines (SVM) algorithm, originally developed by Cortes and Vapnik (1995), is one of the most extensively used ML techniques for pattern recognition. This method was used in this work due to its strengths (Mountrakis et al. 2011; Tekouabou et al. 2022). Classification-SVM (C-SVM) and radial basis function (RBF) were used for image classification. A

kernel function width ( $\gamma$ ) was also used as it produces dot products in higher-dimensional feature space. This process used the same training samples that were employed in the OBIA-RF scheme. A kernel of  $512 \times 512$  pixels of  $C$  and  $\gamma$  with default values of 1 and 3 was applied during the classification process to optimize accuracy. A kernel function was employed to convert non-linear variables into a linear equation in a higher-dimensional feature space. The relative importance of each indicator was then defined by calculating regression for the input indicators and training samples.

**2.4.2.2 Accuracy assessment** The accuracy of the classified images obtained using the OBIA-RF and OBIA-SVM methods, was evaluated using a GeoEye-1 image as a reference image. A total of 6000 samples were chosen at random. The samples were determined based on the class types associated with the image and used as reference to evaluate the accuracy of the informal settlements classification (Alrasheedi et al. 2023). A comparison was then undertaken between the results of classification and the sampling to determine the final accuracy. 2000 points were randomly chosen to use as

reference points. Overall accuracy (OA), kappa coefficient, and F1-score (another accuracy measure) were produced.

## 3 Results

### 3.1 Segmentation and classification

The segmentation method, involving multi-resolution and spectral difference techniques, successfully identified all possible classes. Formal and informal settlements were noted in areas along road network and where vegetation was present (Fig. 3a). The presence of shadow and vacant areas was noticeable within the informal settlements in the image, with shadows observed near narrow streets and around small buildings. Vegetation was distinguished from other classes within the formal settlement boundaries (Fig. 3b). Figures 4–5 show the formal and informal settlements maps derived from OBIA-RF and OBIA-SVM.

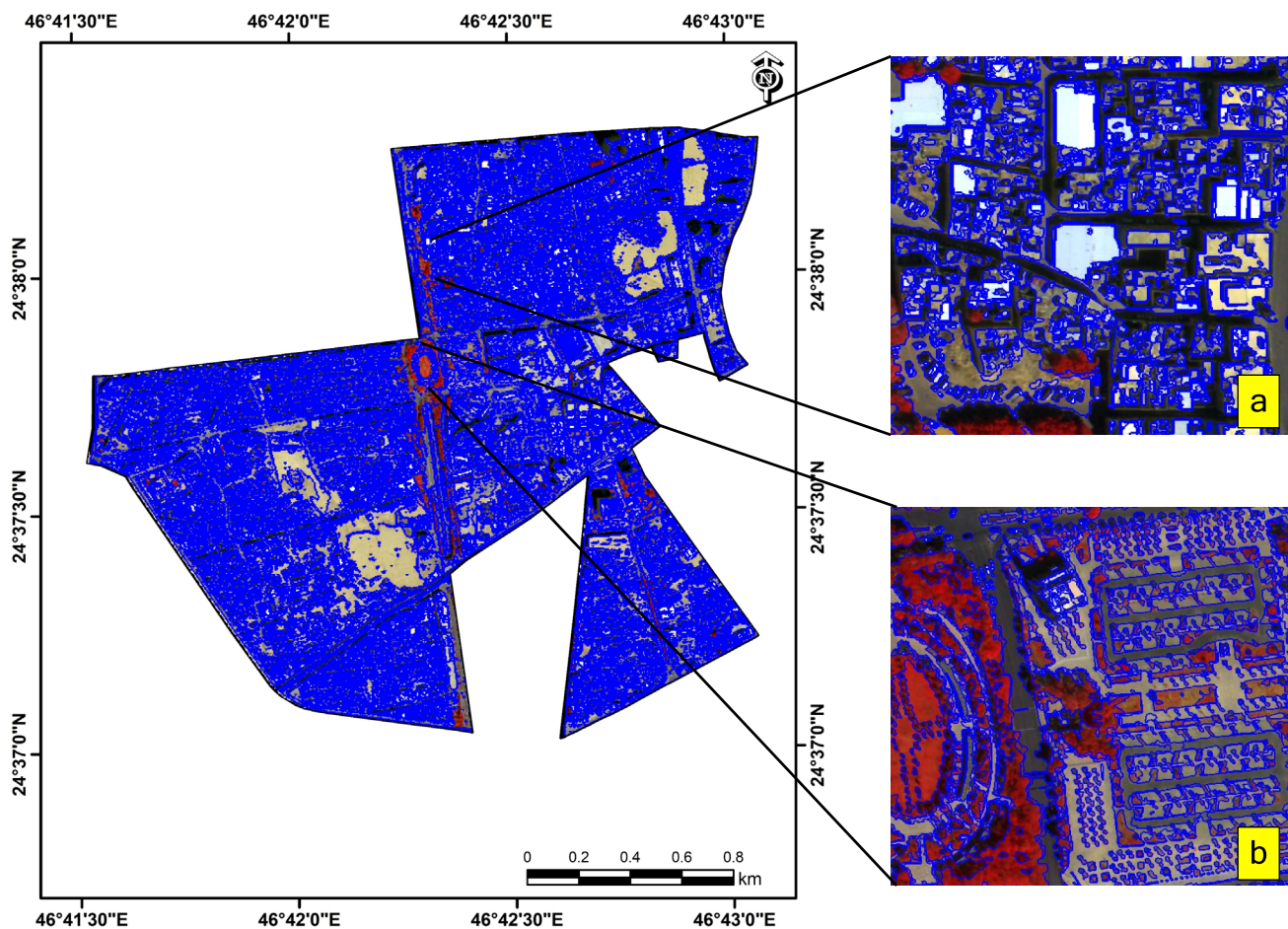
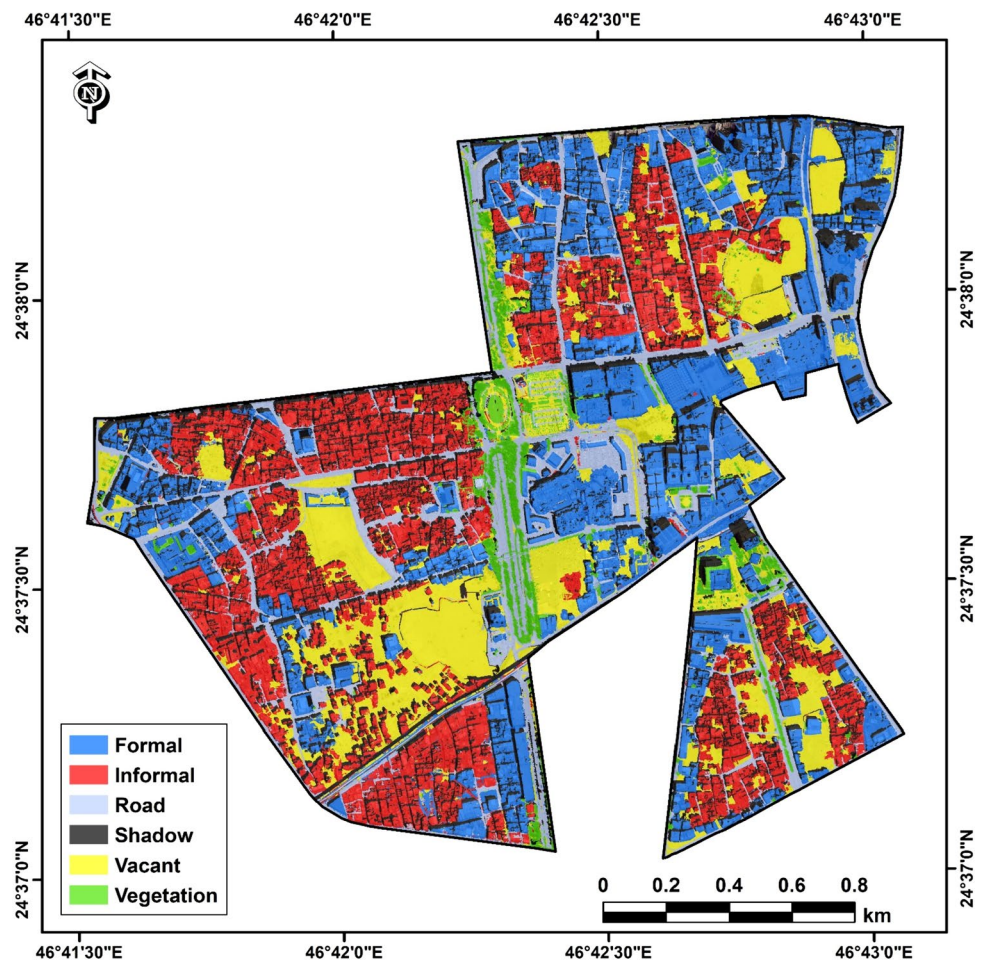


Fig. 3 Multi-resolution segmentation of worldview-3 image: **a** informal, and **b** formal settlements

**Fig. 4** Informal and formal settlements in Riyadh, obtained from OBIA-RF algorithm



### 3.2 Informal settlements mapping

A total of twenty indicators were used to map the informal settlements from the VHR image. An assessment of the importance of these indicators and their relative contribution to the final classification is shown in Fig. 6. Their contribution to the three ontological levels (e.g., object, settlement and environ levels) was also assessed.

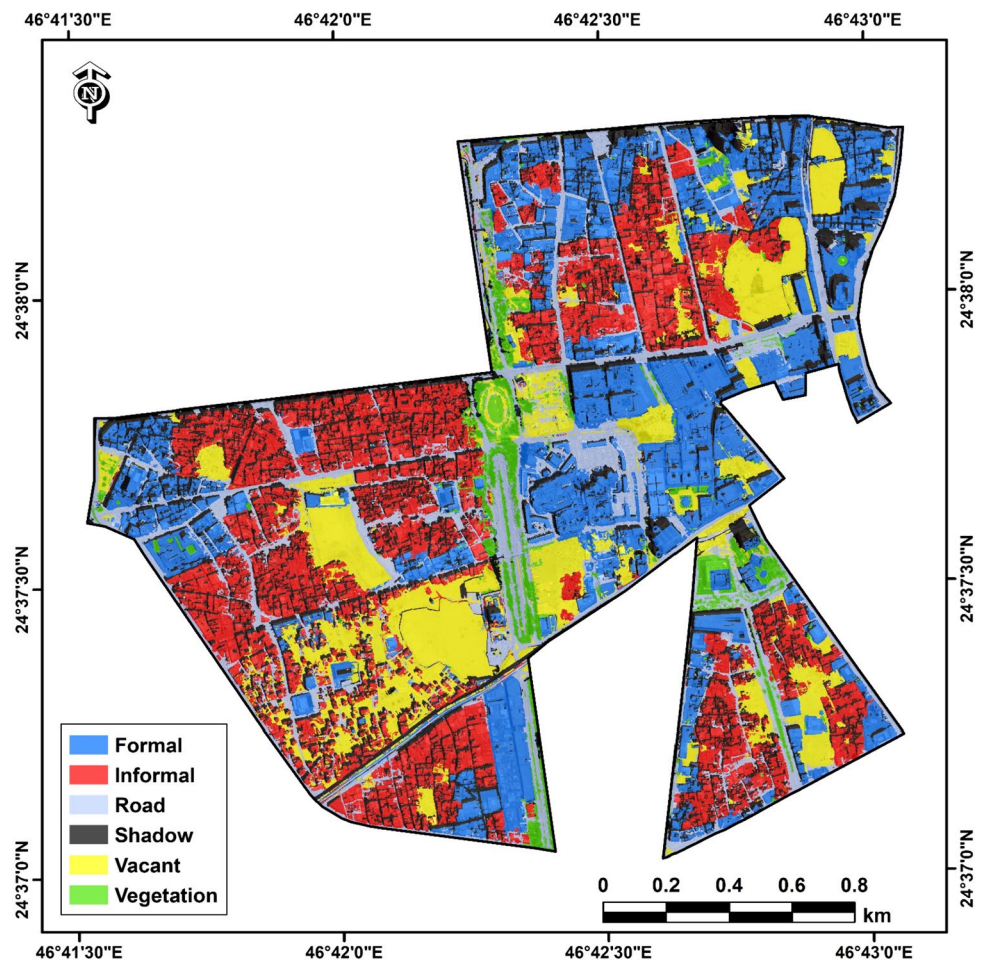
At the object level, dwelling size, and digital surface model (DSM) were used to determine object and roof characteristics. Dwelling size was a strong indicator and rated third in the relative importance in OBIA-RF (68%) but the same parameter rated seventh in OBIA-SVM (58%) (Fig. 6). The relative importance of DSM was minimal in both OBIA-RF (36%) and OBIA-SVM (32%) schemes.

At the settlement level, border index and NDVI were the most important indicators contributing to the OBIA-RF classification scheme. In contrast, the Gray-Level Co-Occurrence Matrix (GLCM) homogeneity and dwelling shape were the two important indicators for the OBIA-SVM method, contributing 77% and 72%, respectively. GLCM homogeneity ranked foremost among the GLCM textural

features due to its ability to capture areal characteristics and distinguish between homogeneous and heterogeneous built-up covers (Fig. 6). Building density ranked as the fourth most important indicator in both OBIA-RF (68%) and OBIA-SVM (64%). Accessibility in terms of road network ranked as the eighth most important indicator in both OBIA-RF and OBIA-SVM (Fig. 6). GLCM entropy was an important input parameter for both ML methods (e.g., RF and SVM), with values of 60% and 55%, respectively. This confirms that GLCM entropy is best for extracting the roofs of buildings. GLCM mean, GLCM contrast and GLCM correlation showed the least impact on image classification. GLCM contrast and homogeneity, on the other hand, were inversely correlated, with homogeneity decreasing as contrast increased. Four indicators related to VHR spectral bands were also tested at the settlement level. Analysis indicated that using the standard deviation of the blue and infrared bands provided a better result than using the mean of these bands. The mean green band ranked lowest in terms of relative importance (Fig. 6).

At the environ level, proximity to hazardous locations was regarded as of low importance (-33%) for OBIA-RF

**Fig. 5** Informal and formal settlements in Riyadh, obtained from OBIA-SVM image classification method



and 32% for OBIA-SVM. The topography within these city areas is generally flat, and the probability of a flooding event is essentially the same for both formal and informal settlement locations.

A comparison between the findings of previous work (Alrasheedi et al. 2023) and the current work, indicated that the identification of informal settlements areas improved slightly when using OBIA-RF and OBIA-SVM when compared with using only the OBIA scheme (Fig. 7). There was, however, a slight variation in the total land area produced for the various land covers using the three classification schemes (e.g., OBIA only, OBIA-RF and OBIA-SVM) (Fig. 7). This tends to suggest that the inclusion of new indicators, as well as the use of an ML-based image classification scheme, provides a superior result.

### 3.3 Accuracy assessment

Random points for evaluating land cover classification accuracy are shown in Fig. 8. Results of the accuracy assessment are shown in Tables 2, 3. Overall accuracy for OBIA-RF is high (96% with a kappa value of 95%) compared with

OBIA-SVM (OA is 95% with a kappa value of 91%). In terms of individual class accuracy, OBIA-RF classified four classes (informal, road, shadow, and vacant) as high as shown by the user accuracy metric. OBIA-SVM produced a higher user accuracy value in two classes (formal and vegetation) (Table 2). The results of the F1-score are presented in Table 3. A comparison of the F1 scores indicates that OBIA-RF is more accurate than OBIA-SVM.

Table 4 compares the performance of OBIA image classification with the current work. Overall accuracy of OBIA and OBIA-RF and OBIA-SVM was 94%, 96% and 95%, respectively. A clear improvement in accuracy was noted, with the accuracy of informal areas increasing from 93% (OBIA) to 95% for (OBIA-RF) and 94% for OBIA-SVM. Land cover accuracy for the current ML approaches appears better than for the original OBIA approach (Table 4).



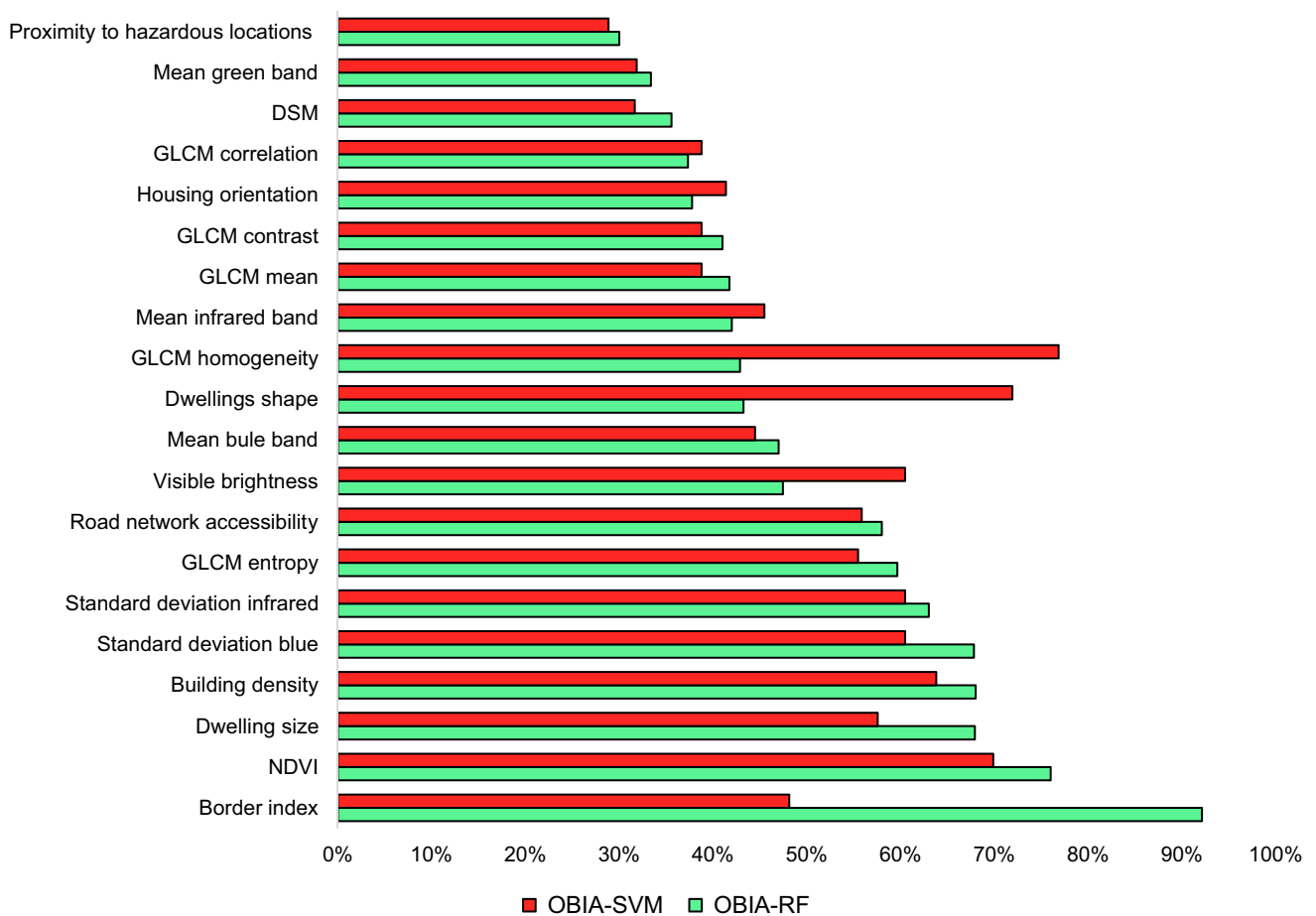
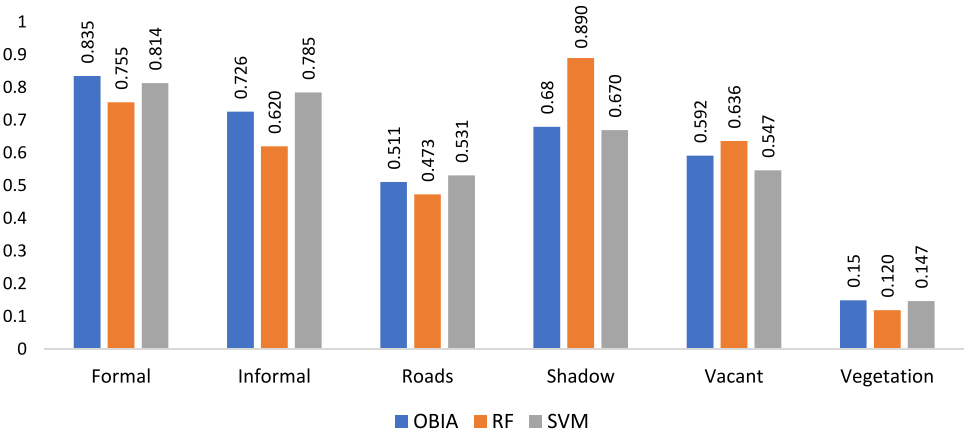


Fig. 6 Contribution of indicators to OBIA-RF and OBIA-SVM the classification of informal settlements

Fig. 7 Area (km<sup>2</sup>) of land cover categories— a OBIA, b OBIA-RF, and c OBIA-SVM

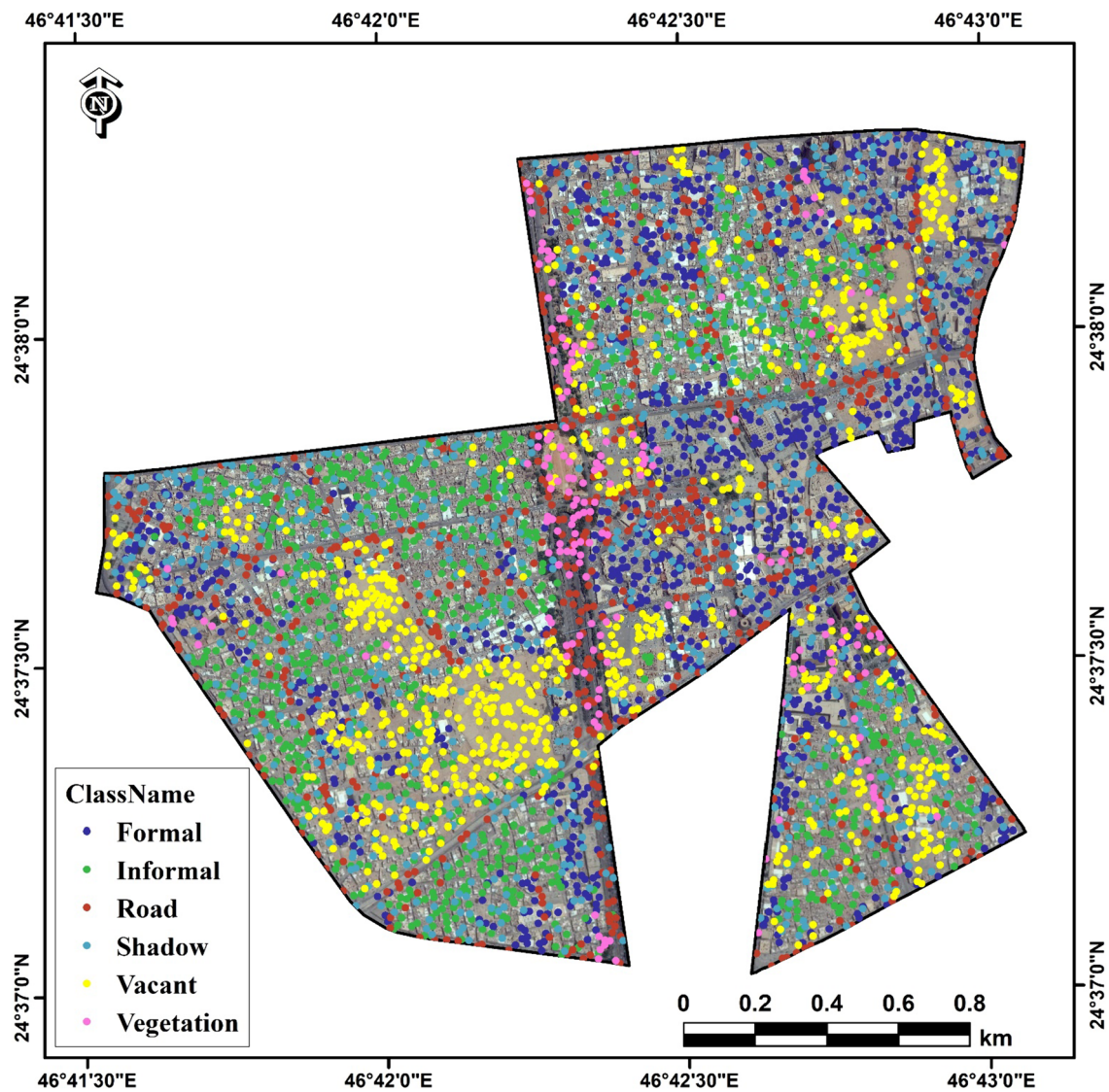


### 4 Discussion

This study aimed to improve the current approach to informal settlement mapping. It used OBIA-RF and OBIA-SVM methods to map areas within Riyadh city, KSA and to report on the classification accuracy obtained. Four

neighborhoods were chosen as case sites. A total of twenty geospatial indicators were used to classify a VHR image.

Both the OBIA-RF and OBIA-SVM classification approaches performed well and produced similar informal settlement mapping outputs (Figs. 4, 5). Spectral band thresholds, textural measurements, and geometric feature indicators have proven to be very useful in the classification



**Fig. 8** Reference samples obtained from GeoEye-1 image for evaluating accuracy of land cover classification

process. This agrees with previous studies which have combined OBIA-RF and OBIA-SVM (Haque et al. 2016; Mugiraneza et al. 2019; Yang et al. 2019). These studies, however, looked at homogeneous land cover such as forest, land use and land cover and wetland areas, as opposed to the heterogeneous land cover found in urban informal settlements. The current work used ML classification methods to extract informal settlements in heterogeneous settings. The results are encouraging and can be tested in similar environments.

The current study has incorporated features such as buildings, roads, vegetation, and shadows into the image classification process and this may have produced a better classification accuracy result. The effects of spectral reflection, however, does pose a significant challenge for the classification process. When using OBIA-RF and OBIA-SVM methods, the results suggest that building density, road

accessibility and dwelling size are the most useful informal indicators to use for mapping informal settlements. This finding agrees with studies that have focused on slum area classification, although without the use of OBIA integration (Duque et al. 2017; Leonita et al. 2018; Lu et al. 2024; Parashar et al. 2024).

It is clear that the use of unique, local indicators has a significant positive effect on accuracy when used in large-scale classification projects. This agrees with studies conducted (Matarira et al. 2023; Al Kez et al. 2024; Montes et al. 2024). Textural differences that were noted in the current work appeared to be associated with differences in the GLCM measurement techniques used by Matarira et al. (2023). GLCM entropy is an important indicator for distinguishing between buildings in formal and informal settlements. Identification of building roof types was also

**Table 2** Land cover classification accuracy (%)

Classes	Formal			Informal			Road			Shadow			Vacant			Vegetation			Total			User's accuracy			
	OBIA-RF	OBIA-SVM	OBIA-SVM	OBIA-RF	OBIA-SVM	OBIA-SVM	OBIA-RF	OBIA-SVM	OBIA-SVM	OBIA-RF	OBIA-SVM	OBIA-SVM	OBIA-RF	OBIA-SVM	OBIA-SVM	OBIA-RF	OBIA-SVM	OBIA-SVM	OBIA-RF	OBIA-SVM	OBIA-SVM	OBIA-RF	OBIA-SVM	OBIA-SVM	
Formal	375	906		7	9	3	7	1	2	3	0	2	3	0	2	0	2	397	924		0.94	0.98	0.94	0.98	
Informal	8	19	353	389	2	3	2	1	4	0	2	0	0	2	0	2	0	408	376		0.95	0.94	0.95	0.94	
Road	3	10	4	2	4	87	1	2	2	0	1	1	0	1	1	1	1	310	104		0.97	0.84	0.97	0.84	
Shadow	4	4	2	6	2	0	401	18	2	0	1	0	0	1	0	1	0	415	24		0.97	0.75	0.97	0.75	
Vacant	3	6	1	5	1	0	2	0	345	10	2	0	0	2	0	2	0	358	17		0.96	0.59	0.96	0.59	
Vegetation	5	1	0	1	0	0	1	0	2	0	103	54	0	2	54	54	54	112	55		0.92	0.98	0.92	0.98	
Total	398	946		410	369	93	414	22	357	13	109	57	2000	1500	1500	2000	1500	2000	1500		0.00	0.00	0.00	0.00	
Producer's accuracy	0.94	0.96		0.95	0.96	0.94	0.97	0.82	0.97	0.77	0.94	0.95	0.97	0.77	0.94	0.95	0.95	0.96	0.95		0.96	0.95	0.96	0.95	
Overall accuracy																									
Kappa																									

**Table 3** F1-score of the training and validation of OBIA-ML image classification schemes

Classes	F1-score training		F1-score testing	
	OBIA-RF	OBIA-SVM	OBIA-RF	OBIA-SVM
Formal	0.96	0.94	0.98	0.95
Informal	0.95	0.91	0.98	0.95
Road	0.91	0.92	0.93	0.92
Shadow	0.82	0.78	0.89	0.86
Vacant	0.95	0.9	0.98	0.92
Vegetation	0.93	0.93	0.95	0.96

useful, as noted by Kohli et al. (2016a) and (Kohli et al. 2013), GLCM entropy recorded highest GLCM texture score. This result agrees with Matarira et al. (2022a), who found that GLCM homogeneity recorded the best score in regards all textural features. This may be due to the variability of the features. Incorporation of texture into the ML methods has improved classification accuracy, particularly when applied to the VHR imagery of urban areas. This was also observed by (Owusu et al. 2024). This study has demonstrated that combining OBIA-RF and OBIA-SVM has improved land cover classification accuracy and increased the relative importance of building density, GLCM homogeneity and dwelling shape in the mapping process (Fig. 6).

Incorporating NDVI in the process proved very useful in this work, with NDVI easily extracted from the imagery during the segmentation process. The DSM indicator, however, appeared to be ineffective in distinguishing between informal and formal settlements in both the OBIA-RF and OBIA-SVM approaches. This may be due to the local topography. Although the DSM provides adjacency and homogeneity of building materials of informal settlements, and certain elevation characteristics that distinguish these features from other urban features, narrow roads, low-quality housing structures, and temporary structures may also pose challenges. This result, however, contradicts that noted by Bakula et al. (2016), who found that a DSM was very useful in discriminating between differing urban land cover classes

such as roof of buildings and vacant areas. The current study employed image bands containing both spectral and textural information and was able to produce accurate results. The spectral reflectance of the blue band was particularly useful in characterizing built-up areas and road networks when used with OBIA-RF and OBIA-SVM techniques. This indicates that spectral and textural information can be successfully used for informal settlement mapping.

The accuracy of informal settlement identification when using a combination of OBIA-RF and OBIA-SVM was far better than when using OBIA by itself. ML methods are efficient in discriminating heterogenous land cover types, so incorporation of local knowledge into urban land cover classification work may be a very promising area of further study (Kuffer et al. 2016). Results indicated that combining different input indicators produced better outcomes. Adding additional indicators, such as textural variables, to the original spectral bands can help improve the identification of informal settlements. This also implies that incorporating a greater number of input indicators into the process could improve area identification, an observation that aligns with the findings of Matarira et al. (2023), who suggested that extracting a large number of features from an image may enhance the accuracy of the resulting image classification.

This work also provided evidence that integrating local knowledge with OBIA-based ML methods can reduce human intervention to discriminate urban land cover types, especially discriminating informal settlements. However, it was noted, that there was little difference in the accuracy metrics such as overall accuracy, kappa coefficients, and F1-score of OBIA-RF and OBIA-SVM. This may have stemmed from the distribution of the sample points and suggests that concurrent images are necessary for mapping geographic phenomena such as informal settlements. In the case of a land cover class containing homogenous pixels, either approach can be used to distinguish between formal and informal settlements. In the case of heterogenous pixels, the performance of both methods was relatively low. This warrants further investigation. OBIA-RF appeared to be more effective in the case of a mixed pixel class. This

**Table 4** Comparison of land cover classification accuracy between OBIA OBIA-ML methods

Class	Alrasheedi et al. (2023) OBIA only (%)	OBIA-RF	Difference (%)	OBIA-SVM	Difference (%)
Formal	0.98	0.94	4	0.98	No difference
Informal	0.93	0.95	2	0.94	1
Road	0.83	0.97	14	0.84	1
Shadow	0.68	0.97	29	0.75	7
Vacant	0.50	0.96	44	0.59	9
Vegetation	0.95	0.92	3	0.98	3
Overall accuracy (%)	0.94	0.96	2	0.95	1

observation supports studies by Leonita et al. (2018), Saini et al. (2021), Adugna et al. (2022), Brenning (2023), Dabra and Kumar (2023). Overall, OBIA-RF technique takes less time to train the model, and so is computationally less intensive than the other algorithm (Kuffer et al. 2016; Zaabar et al. 2022; Feng et al. 2023). Conversely, the OBIA-SVM algorithm is sensitive to noise which can influence performance. As emphasized by Farooq and Manocha (2024), there is no clear rule to follow when determining C and  $\gamma$  for C-SVM. The tuning parameter is complex, so defining the range with SVM requires trial and error.

## 5 Conclusion

Two object-based ML classification techniques (e.g., OBIA-RF and an OBIA-SVM) were used to identify informal settlement areas in Riyadh using VHR imagery. Results indicated that these techniques were useful in improving the classification accuracy when local knowledge specific to the study area was incorporated in the process. Accuracy assessments have indicated that OBIA-RF outperformed OBIA-SVM. This work demonstrated the importance of integrating local knowledge into the interpretation and classification of very high-resolution satellite data for mapping informal settlements in an area where building materials and other attributes were alike. Informal settlement areas are increasing in many large cities (including within the Arabian Peninsula) due to climate-related environmental stresses and shocks, so the findings of this work could prove of value to policy makers and urban planners and allow for more informed decision-making.

There has been a general improvement in the extraction of data from remotely sensed images, however limitations still exist. Due to complexities associated with the urban landscape, integrating multisource data could be useful but can be computing intensive. A future study could include medium resolution data such as Landsat to examine the effectiveness of OBIA-based ML methods in isolating informal from formal settlements.

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## Declarations

**Conflict of Interest** The authors declare no conflicts of interest.

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