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Using Local Knowledge and Remote Sensing in the Identification of Informal Settlements in Riyadh City, Saudi Arabia

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Abstract: Urban planning within Riyadh, the capital of Saudi Arabia, has been impacted by the presence of informal settlements. An understanding of the spatial distribution of these settlements is essential in developing urban policies. This study used remotely sensed imagery to evaluate and characterize informal settlements within the city, both with and without expert knowledge of the study area (defined as expert knowledge, EK). An informal settlement ontology for four study sites within Riyadh City was developed using an analytical hierarchy process (AHP). Local knowledge was translated into a ruleset to identify and map settlement areas using spatial, spectral, textural, and geometric techniques. These were combined with an object-based image analysis (OBIA) approach. The study demonstrated that combining expert knowledge and remotely sensed data can efficiently and accurately identify informal settlements. Two classified images were produced, one with EK, and one without EK, to investigate how a detailed understanding of local conditions could affect the final image classification. Overall accuracy when using EK was 94%, with a kappa coefficient of 89%, while without EK accuracy was 68% (kappa coefficient of 61%). The final OBIA classes included formal and informal settlements, road networks, vacant blocks, shaded areas, and vegetation. This study demonstrated that local expert knowledge and OBIA helpful in urban mapping. It also indicated the value of integrating a local ontological process during digital image classification. This work provided improved techniques for mapping informal settlements in Middle Eastern cities.

Keywords: informal settlements; local expert knowledge; OBIA; AHP; high-resolution imagery

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1. Introduction

1.1. Research Background

The development of informal settlements (also known as unplanned areas) is increasing in many parts of the world. This is due to several factors including rural-to-urban migration, a shortage of affordable housing, rising poverty levels and societal inequality [1,2]. The reasons may vary between locations, but all informal settlements have some common features. They tend to be characterized by high population and housing density, a lack of suitable shelter for many residents, and physically demanding environmental conditions [3]. Marginalization and displacement issues caused by social conflict, natural disasters and climate change are key factors in the rise of these settlements [4]. In the Arabian Peninsula, these developments are mostly due to housing accessibility constraints, rural-to-urban migration (due to a lack of employment opportunities and low wages in rural areas) and a lack of government law enforcement. According to a UN-HABITAT [5] report on the Arabian Gulf area, informal settlements in Saudi Arabia are primarily inhabited by non-Saudi nationals and illegal residents whose allowable stay for work, tourism or religious activities has expired.

Informal settlements are usually found in the center of urban areas or in proximity to these areas [6]. In many cases they are comprised of the older residential parts of the city. They differ from slums because they have evolved in tandem with more recently developed urban areas. They can be distinguished by very old buildings combined with more contemporary structures. This combination of traditional and modern architecture is found in Riyadh city (Figure 1). No previous studies have been undertaken to delineate informal settlements in the city, although research has been conducted in other cities within the Kingdom of Saudi Arabia (KSA) [7,8]. These studies did not, however, use local expert knowledge to identify indicators useful for defining informal settlement characteristics specific to the area of interest. This previous work relied on international studies which examined informal settlements with very different characteristics to those found in the Arabian Peninsula.

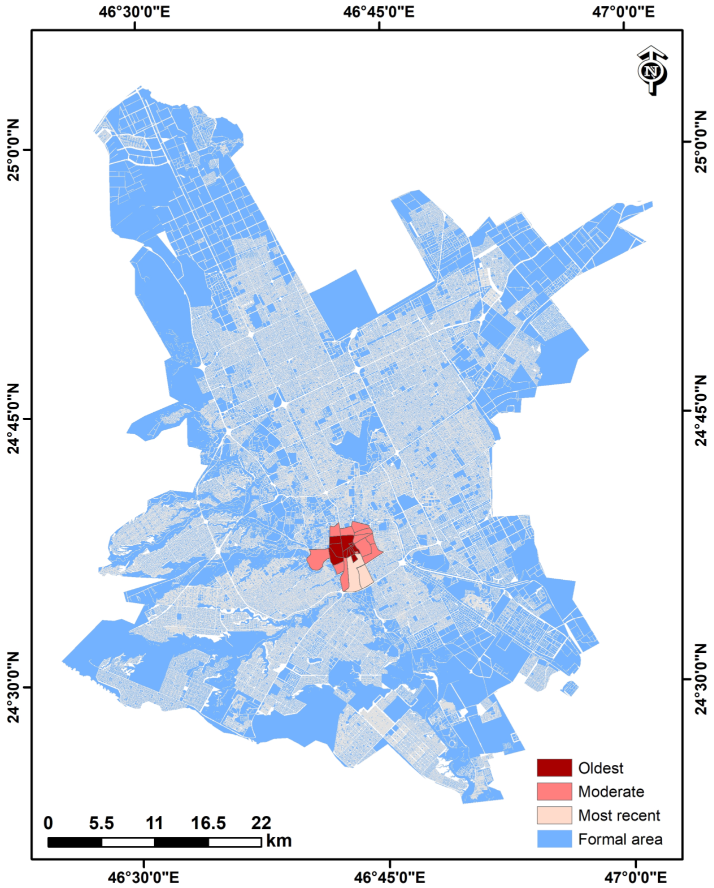


Figure 1. Informal settlement in the neighborhoods of Riyadh city, from oldest (dark red) to most recent (light red) (Source: Riyadh Municipality).

1.2. Literature Review

During the last decade, there has been a global focus on defining the extent of informal settlement development and improving the standard of living of people in these areas. Karimi and Parham [9] investigated settlement growth, evolution, and function. Aljoufie et al. [10] examined at the relationship between urban growth and transportation. This analysis indicated that transportation network expansion had stimulated Jeddah's urban spatial expansion and residential growth. Jehani [11] showed how informal settlement growth continues in the KSA and suggested some methods to improve these urban environments. El Menshawy and Shafik [12] discussed affordable housing as a solution to problems associated with informal settlements. More recently, Breengy and Yusof [7] reviewed informal settlement areas within Saudi Arabia and found that, in general, living conditions in these settlements were substandard and were commonly associated with social problems, literacy issues, unemployment and urban decay. Accessibility issues during emergencies were common and the areas also had high crime and suicide rates and environmental problems [13].Informal settlements are present in several Arab cities, including Cairo, Alexandria (Egypt), Dubai (United Arab Emirates) Sana'a (Yemen), and Oman (Jordan) [3]. Due to policies implemented by the government, Saudi Arabia has not suffered from the slum and shanty town issues that have occurred in other developing countries [3].

Several theories have been proposed regarding informal settlements' morphological development. Population census data are commonly used in mapping, with a quantitative index developed to assist in informal settlement area recognition [14]. In most countries, census data for inhabited areas are normally collected once a decade. However, a drawback of this timeframe is that due to the dynamic nature of these populations, the data are often out of date. An associated issue is that information related to slum location or concentration may also not be available, as data from these areas are often not collected for formal statistical studies [14,15].

The use of advanced geospatial methods and remotely sensed data to map informal settlements has challenges [16]. Many pixel-level classification approaches have extracted data from high-resolution satellite imagery. This includes the use of a discrete wavelet frame transform (DWFT) [17], grey level co-occurrence matrix (GLCM) [13,18], and local binary patterns (LBP) [19]. Many are of limited value, and the ability to classify imagery often requires adding extra steps to improve accuracy. Mahabir et al. [16] noted that the reflective surfaces of different objects (in both urban areas and over barren land) may produce similar spectral responses. Mudau and Mhangara [20] also experienced this issue in research in South Africa. They undertook extensive fieldwork to define the various classes of mixed pixels in bare soil and built-up areas. Arid regions and uncultivated farmland could be mistaken for urban areas due to similar reflectance characteristics in the visible and infrared wavelengths [16,20].

Due to the issues noted above, per-pixel methods were not considered appropriate for analyzing complex urban environments exhibiting high spectral diversity, nor for those areas containing small, clustered objects and those with diverse morphological characteristics [14]. Image segmentation, which dates to the 1970's, is the most commonly used method for generating objects. The close integration of GIS and image processing commenced in about 2000 using objectbased image analysis (OBIA) for analyzing geographic objects [21]. This technique groups pixels into sets or objects. The OBIA method focuses on the characteristics of objects such as their shape, size, texture, context, and relationship with adjacent pixels [22]. The mapping of informal settlements with very-high-resolution (VHR) imagery is commonly achieved nowadays using this method [23,24]. Chang et al. [25] have shown that using OBIA techniques can substantially overcome issues associated with the per-pixel method, and these are capable of more precisely defining a spatially complex urban area by successfully distinguishing between settlement types [20,24,26]. Several researchers, including Ghaffarian and Emtehani [27], Kohli et al. [28] and Jovanović et al. [29], have studied the use and effectiveness of OBIA. They concluded that OBIA produces highly accurate results. OBIA does, however, have some limitations. Grippa et al. [30] showed using a specifically optimized segmentation parameter on a small urban area was ineffective when applied to large urban areas due to pixel diversity. Researchers have highlighted the importance of the transferability of the OBIA; however, inconsistent variable selection can still occur, which may result in inaccurate outcomes [14,16,20]. Extracted textural measures and a defined ruleset may also perform differently between and within study areas. The texture of roofs and other features may resemble those of paved roads and other structures commonly found in urban areas, leading to the misclassification of pixels [16]. In summary, although OBIA does have some limitations, it is a widely used method for mapping urban informal settlements [14,24,31]. Expert knowledge about a given area may be required to correctly apply OBIA indicators [28,32], as well as to define the various elements or objects which can be used to classify differing resolution satellite imagery and allow the correct identification of relevant informal settlement indicators [20,23,33,34].

Many studies have used settlement characteristics to define the features helpful in detecting informal settlements from remotely sensed data, although the level of accuracy of these has varied. Using only the spectral characteristic of the imagery is not regarded as ideal. Kohli et al. [28] developed an ontological framework, the generic slum ontology (GSO), to assist in the developing a formal concept of an informal settlement structure when using remotely sensed data. The GSO methodology identifies and uses three morphological characteristics at differing levels in the built environment: the environs, the settlement, and the object levels. At the environmental level, external or pull factors (e.g., hazards arising from floodplains and marshy conditions) are essential [28,33]. At the settlement level, the texture is the key, while at the object level, the significant components of the ontological framework are building and road attributes. Morphological characteristics of the built environment may also differ because of geographical location [28,35].

Various studies have recommended defining the indicators for mapping work developing a rigorously defined ontological framework. Kohli et al. [28] proposed the use of six indicators (location, neighborhood characteristics, shape, density, buildings, and access networks) when using OBIA. In a study in the coastal city of Jeddah in KSA, Fallatah et al. [8] showed that the vegetation extent, the lacunarity (the number of gaps within a defined space) of housing structures/vacant land, the road network, and the roofing extent of built-up regions could be used to map informal settlements. They also found that several elements were ineffective in the mapping process, indicating that the definition and characteristics of an informal settlement are specific to the area of study. Building density remains a commonly used informal settlement indicator with the greatest accuracy [28,36,37]. GLCM textural techniques using the shape of the various settlement areas have also been applied with varying degrees of success [14]. In some cases, GLCM textural analysis appears unable to distinguish informal settlements from built-up areas [8,17].

Many studies have relied solely on data-driven approaches to deriving spatial indicators from satellite data and have ignored local knowledge [38,39]. Many of these settlements (including those found in the Arabian Peninsula) are constructed using the same building materials as formal settlements, so local knowledge about specific uses is regarded as an additional and valuable tool. Local knowledge may assist in distinguishing between differing settlement types with very similar spectral characteristics [8].

Several studies have been undertaken on this topic in many diverse locations; however, a completely automated methodology for mapping such settlements using satellite data is not yet available. This study aims to combine OBIA, local knowledge and remote sensing to develop an ontology of informal settlements, focusing on Riyadh, the capital of Saudi Arabia. This study is structured as follows: Section 2 outlines the materials and methods. Section 3 presents the results; and Section 4 discusses the findings. A summary and recommendations for further research are presented in the final section.

2. Materials and Methods

2.1. Study Area

Riyadh is the largest city and capita, of Saudi Arabia. It is located on the Najd Plateau about 600 m above sea level at latitude 24°18″ to 25°11″N, and longitude 46°15″ to 47°19″E (see Figure 2).Like other cities within Saudi Arabia, Riyadh has experienced rapid urbanization since the discovery of large oil deposits in the region in the 1970s [40]. It has also experienced the country's most rapid growth in population numbers, with an estimated eight million people residing in the city in 2020 [41].

Government policies have laid the groundwork for a rapidly expanding urban economy by attracting substantial investment in the education, health, defence and financial sectors. Compared to other cities in Saudi Arabia, Riyadh has a relatively small number of informal settlements. A key reason for the presence of these informal areas is the rapid development and modernization of Riyadh in recent years. This has resulted in people migrating from rural areas to the city for work and an improved lifestyle. The requirement for cheap accommodation to house these workers has also driven this settlement increase [3,42].

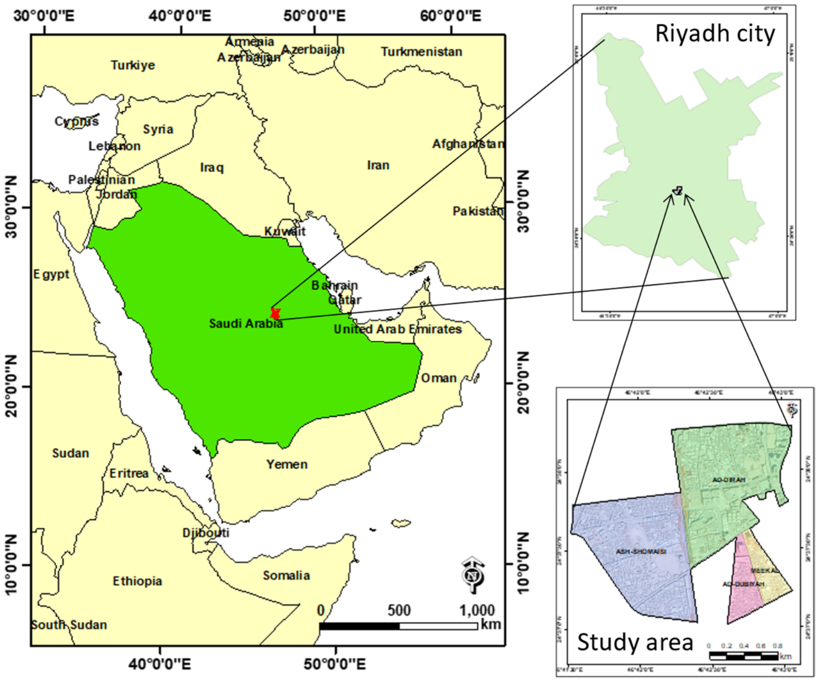
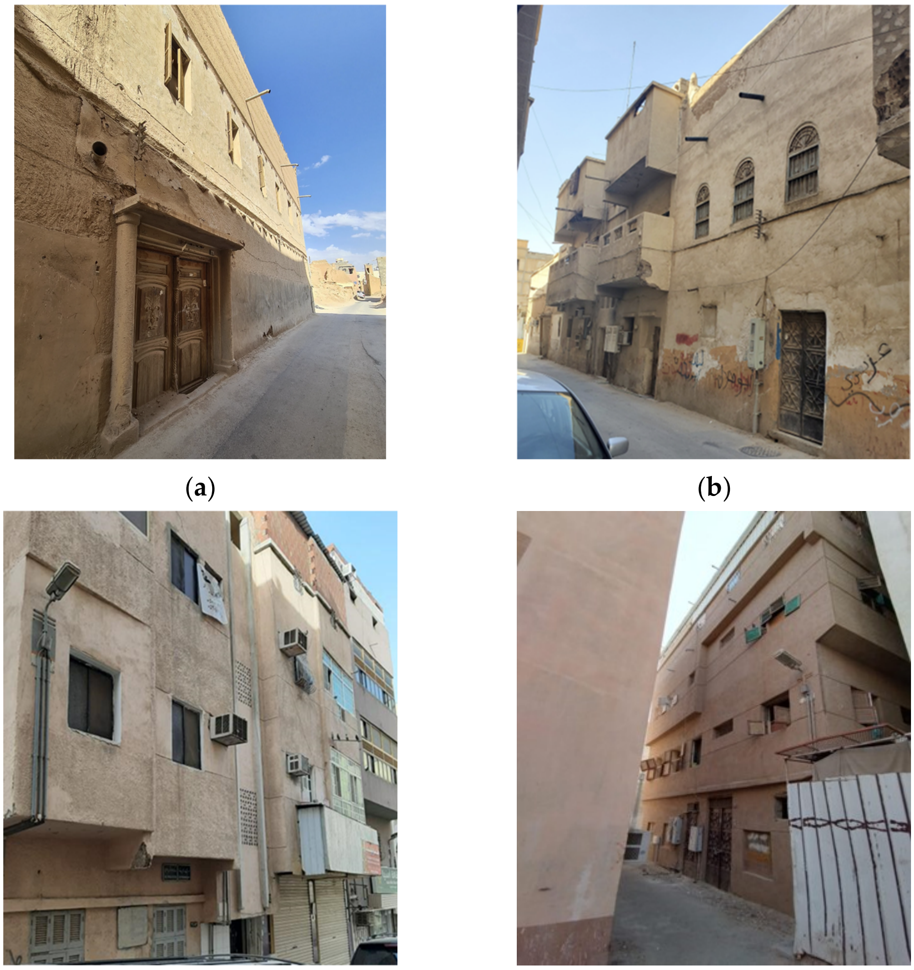


Figure 2. Location of study sites within Riyadh city.

The stated goal of the Riyadh City Centre Development Plan (RCCDP) is to reshape the city center into a national administrative, cultural, historical, and economic hub while at the same time preserving existing urban and cultural heritage. The plan also focuses on retaining current commercial activities, improving road networks, public services, and employment opportunities, diversifying existing housing trends and patterns, working towards a demographic and social balance, increasing the size and number of open areas and improving the overall security of the area [41,43]. Twenty-eight informal settlements within the city were identified by the Riyadh Municipality (Figure 2), with four informal neighborhoods chosen for this study: (a) Al Shomaisi (1.49 km^2), (b) Meekal (0.21 km^2), (c) Al Dirah (0.24 km^2), and (d) Al Dubiya (1.56 km^2). Most of the buildings in the study area are constructed of concrete. Examples of these buildings are shown in Figure 3.

2.2. Data and Image Pre-Processing

WorldView-3 panchromatic and multispectral images with spatial resolutions of 0.31 m and 1.24 m, respectively, were used in this study. These were obtained from the King Abdulaziz City for Science and Technology (KACST), a government organization located in Riyadh City (KSA) (Table 1). Before analysis, radiometric and atmospheric corrections were undertaken using ENVI 5.7 software. Gram-Schmidt (GS) spectral sharpening invented by Laben and Brower in 1998 was used for panchromatic fusion [44]. Fusion of the panchromatic and multispectral images was undertaken to obtain high-resolution multispectral images with a spatial resolution of 0.4 m. The Gram-Schmidt (GS) process is integrated into the sharpening module used by the ENVI software. In maintaining the consistency of the spectral information contained within the images before and after fusion. GS sharpening is a good high-fidelity remote sensing image pan-sharpening approach. The initial pre-processing step was required for the high-resolution images with the results being used to select the optimum spectral bands for the segmentation process. For WorldView-3 imagery, the optimal bands were judged to be bands 2 (450–510 nm), 3 (510–580 nm), 5 (630–690 nm), 7 (770–895 nm), representing blue, green, red, and infrared wavelengths, respectively.



(**a**) (**b**)

(**c**) (**d**)

Figure 3. Building design: (**a**,**b**) old informal dwellings, (**c**,**d**) new informal dwellings. Concrete is used extensively in constructing buildings.

Additionally, an GeoEye-1 image with a panchromatic (0.41 m) and multispectral (1.64 m) bands were obtained from (KACST). The GeoEye-1 data was used as a reference to assess the OBIA classification accuracy. Road network, informal settlements and neighborhood boundary vector data were also obtained from the Riyadh Municipality (RM) in December 2020, December 2021, and March 2022. A local expert knowledge survey was conducted in May 2022 to provide detailed indicator information for the study area. The four study areas were defined as "informal settlements" or "old residential and historical neighborhoods" by the local experts.

The survey data were used to determine all the indicators to be incorporated into the OBIA classification process. This study relied on expert knowledge to identify 16 unique indicators which could be used during the OBIA segmentation process. To choose the best filter to use for defining building border edges, three different edge detection operators were tested (Canny, Gaussian, and Sobel). The Sobel filter provided the best border index extraction and was used for image filtering. Four subset windows (512 $\times$ 512 pixels) were defined from the WorldView-3 image. Each subset represented one neighborhood in the study area. There are three processing steps used in Sobel filtering. The first step uses a kernel size of 3 $\times$ 3 to measure the intensity difference in vertical, horizontal, right, and left directions. This is followed by a gradient realization step to identify edges, with the final step comparing results corresponding to the gradient object at each pixel point in the image [45,46]. This generates the gradient of image intensity at each point while also considering the direction and magnitude of intensity variation. Selection of a suitable image band to extract the specific classes is crucial. Sobel filtering was applied to the selected bands (bands 2, 3, 5 and 7) to identify feature boundaries and define the optimum spectral band for image processing.

Table 1. Characteristics of satellite images, DEM and DSM.

Data	Image Attributes	Band	Spectral Resolution	Ground Sampling Distance (GSD)	Source
WorldView-3	Panchromatic Band	Panchromatic	450–800 nm	0.30 m GSD at nadir 0.34 m at 20° off-nadir	KACST
	MS (multispectral) bands and VNIR (visible near-infrared)	Coastal Blue	400–450 nm	1.24 m at nadir, 1.38 m at 20° off-nadir	
		Blue	450–510 nm		
		Green	510–580 nm		
		Yellow	585–625 nm		
		Red	630–690 nm		
		Red edge	705–745 nm		
		Near-infrared1	770–895 nm		
		Near-infrared2	400–450 nm		
	Acquisition date	8 June 2021			
	Swath width	13.1 km			
	Total cloud cover	0%			
GeoEye-1	Panchromatic	Panchromatic	450–900 nm	0.41 m GSD	KACST
	MS and NIR	blue	450–510 nm	1.64 m GSD	
		green	520–580 nm		
		red	655–690 nm		
		Near-infrared	780–900 nm		
	Acquis. date	17 February 2021			
	Swath width	15.2 km			
	Total cloud cover	0%			
DEM and DSM	Spatial resolution	5 m			KACST
	Coverage	3.5 km^2			

Both digital elevation model (DEM) and Digital Surface Model (DSM) models with a pixel size of 5.0 m were obtained from KACST (Table 1). They were constructed from 34 archive aerial photos captured on 5 February 2020 at a scale of 1:30.000. A nearest-neighbor method was used to resample DEM/DSM to 1.64 m to match with other raster datasets.

2.3. Ontological Framework

Sowa [47] defined the concept of ontology as the vocabulary of classification, taxonomy, relations, and domain axioms. Ontological concepts have previously been used in object recognition work to provide a structure for potential informal settlement identification. A local ontology of informal settlements (LOIS) was adopted for the Riyadh study using the knowledge of local experts and the generic slum ontology (GSO) recommended by Kholi et al. [28]. A flowchart of the process is shown in Figure 4. A local knowledge survey was used to collect specialist information about the areas. Twelve unique indicators were identified as inputs for during the satellite image processing phase. Four main categories were used to build the ontological framework—shape, geometry, texture, and pattern. The conversion of qualitative data indicators into quantitative indicators was achieved using OBIA parameterization. This tested the individual indicators and provided optimum values for each indicator. The resulting classification accuracy was then assessed.

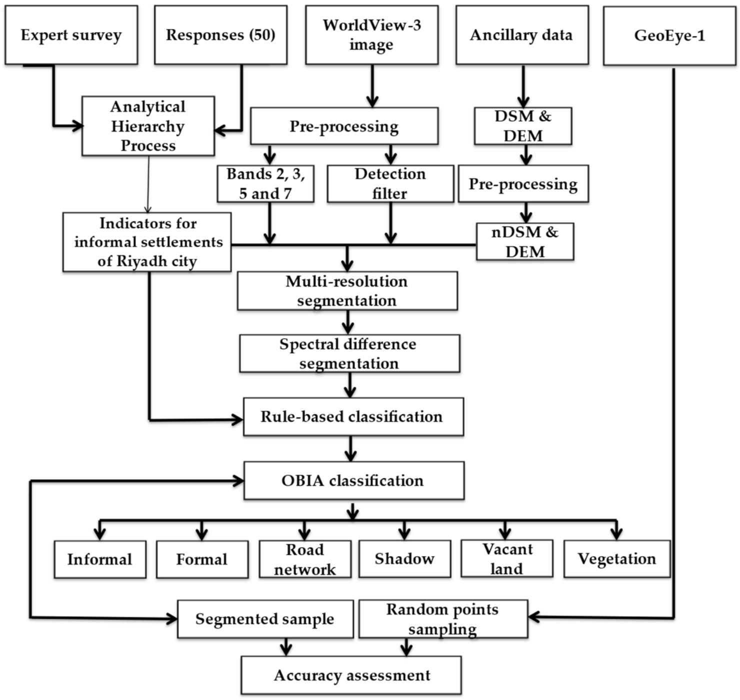


Figure 4. A flowchart for informal settlements identification.

2.4. Expert Survey

This study focused on observable characteristics in very high-resolution (VHR) images. A literature review was carried out to produce an initial list of potential indicators. A semi-structured questionnaire survey was used to refine this list and identify missing indicators. and ensure that the indicators chosen were valid for the study areas. A questionnaire on informal settlements was developed, and ethics approval was obtained in April 2022. The survey comprised of ten questions regarding indicators considered helpful in identifying and mapping informal settlements. The questions were both open-ended and multiple-choice. Fifty experts with knowledge of unplanned and informal urban areas were interviewed. This selection included urban planners, remote sensing experts, geospatial academics, and local administrators. The experts were chosen based on a various criteria, including but not limited to experience, education, and affiliation (education or industry). The sample population included professionals with experience in GIS (geographic information systems), remote sensing, urban science, environmental science, and relevant engineering fields.

The survey was also sent to urban specialists at King Abdulaziz City for Science and Technology in Saudi Arabia (KSA), Riyadh Municipality, The Royal Commission for The Development of Riyadh, King Saud University, and Princess Nora University. The basis for selection included involvement in urban planning and housing, individual specialization areas, and length of experience in the field. The questionnaire listed what was perceived as the most important indicators for each feature of interest, the type of building structure, the period of settlement growth, the most common building size, the approximate percentage of vegetation cover, and the most common roof materials.

The variance inflation factor (VIF) and tolerance statistics were calculated for the indicators to test multicollinearity and uncertainty and to verify that the identified indicators were effective and that the results were statistically significant. This included the production of mean, standard deviation, and percentage values.

A review of previous research noted that not all indicators of informal settlements were relevant for mapping in all situations and that general indicators used in other work could require some modification [14,36,48]. This observation was made using "local condition" knowledge a prime requirement in the current study. The final set of indicators produced was regarded as the most effective at separating informal from formal settlements (Table 2).

Table 2. OBIA parameters and relevant indicators used in segmentation.

Indicators	Description	Definition
NDVI	Normalized difference vegetation index	Measures vegetation
VB	Visible brightness	Measures roads
SD (B)	Standard deviation (Blue) band	Measures how dispersed the data are concerning the to mean brightness of band 2
DSM	Roof	Digital surface model
GCLM texture	Entropy	Measures randomness to detect the texture of an input image
	Contrast	Measures the local variations in the GLCM through the intensity contrast between a pixel and its whole neighbor
	Homogeneity	High value, if GLCM concentrates along the diagonal
	Correlation	Values range between −1 and 1
	Mean	Pixel value is weighted by the frequency of its occurrence in combination with a certain neighboring value
BI	Border index	Percentage of the image border length between the object and the smallest enclosing rectangle
MDS (B)	Mean and standard deviations (blue band)	Digital number values of a blue band and all pixels
Dwelling size	Pixel size (area)	The size of an image object is measured by the number of pixels in the image
Dwelling shape	Shape index	The smoothness of an image object border
Building density	Density	The image object that contains the current candidate pixel/voxel
Housing orientation	Accessibility	The corner of the object that is used as the calculation base for the coordinates
Proximity to hazardous areas (e.g., flooding, landslides)	DEM	Slope

2.5. *Analytical Hierarchy Process (AHP)*

The analytical hierarchy process (AHP) was used to obtain the priority ranking of the typical site and road conditions within the informal settlements [48]. Three criteria were investigated concerning typical site conditions proximity namely the proximity to hazardous industries, distance from social services, and steepness of the land surface (slope). Five criteria were used in assessing typical road conditions: (i) the number of narrow roads, (ii) a large number of crossings with short road segments, (iii) straight roads, (iv) curved roads, and (v) paved roads. Based on indicators from the survey and the VIF and AHP work, a ruleset for OBIA was defined and used to develop a local ontology of informal settlements (LOIS).

2.6. OBIA Segmentation

The Estimation of Scale Parameter (ESP) was used for the multi-resolution image segmentation. The ESP method was developed by Drăguţ et al. [49].The technique allows determining changes in object heterogeneity within a scene, especially to recognize spectral variation within and between objects. The scale parameter (SP) values, shape and compactness parameters were used in this work. An SP of 30 was selected [50]. The weight values of 0.3 and 0.5 were assigned to shape and spectral compactness. Six classes i.e., informal settlements, formal settlements, road networks, shadows, vacant areas and vegetation were defined using the OBIA. These classes were categorized according to the indicators listed in Table 2.

2.7. Indicators

Important indicators of informal settlements were calculated such as the size of homes, road segments and materials, vegetation, roofing, the spatial distribution of housing structures, vacant land, and built-up area texture measurements were calculated (see Table 2). These were mapped with a high degree of accuracy as they were spectrally distinct from other features such as vegetation and contained areas similar in size to those of formal settlements. Built-up areas normally have less spectral reflectance than vacant land and house buildings, so these areas were mapped using only the brightness value. Spectral indices' performance tends to be impacted by the spectrum reflectance of surface features (which can vary across regions) and by variations in topography.

The DSM provided the height and area information for the image objects. The data represented above-ground features and reduced the impact of topography on image processing (Figure 5). DSM data were also used to enhance segmentation accuracy by calculating the roof area of the dwellings. These data accurately identified the shape of the built-up regions in both informal and formal settlement and enabled the calculation of dwelling size according to pixel. The building extraction step was used, as there were significant height and shape differences existed between the buildings and other objects in the DSM. A threshold-based approach was then used with the building extraction data, as building size was one of the indicators used for settlement identification in the LOIS. Based on local experts, the maximum dwelling size within an informal settlement was set at $\leq$280 m^2. Road network buffering was also used in the accessibility model. The slope was extracted and reclassified using the DEM. Considering the slope of the land was essential to calculate the impact of risks from natural hazards such as flooding and landslides in the AHP.

The grey-level cooccurrence matrix (GLCM) developed by Haralick et al. [13] was used in this study to extract texture of roof and building. Five separate textural measures were applied: (i) GLCM entropy, (ii) GLCM homogeneity, (iii) GLCM contrast, (iv) GLCM correlation and (v) GLCM mean. The roofs of buildings were extracted from band 5 of WorldView-3 image using the GLCM entropy measure.

GLCM contrast, GLCM correlation and GLCMmean measures were used to extract the lacunarity of housing structures and to enhance the texture of the built-up areas. This allowed for better identification of the differing settlement types. The shape, size and brightness of the built-up areas, shadows, and the standard deviation of the blue band values were examined to obtain the mean difference. Differences in visible brightness (VB) and pixel size was also used to classify areas of shadow and vacancy in the study area. Vegetation was extracted from the red and infrared bands of the imagery using the normalized difference vegetation index (NDVI) [51].

2.8. Accuracy Assessment

The classified image and segmented sampling image e.g., GeoEye-1 were used to compute classification accuracy. A total of 600 samples were randomly selected for use as reference data. The sampling segments were defined using the class types identified within the image and used in the segmentation and classification work [52]. A comparsion between the classification result and the sampled segments was then undertaken to define the classification accuracy. Using the methodology of Matarira et al. [15], 1750 random points were selected as the reference data in the GeoEye-1 image. The results were used to compare OBIA classification using EK with the alternative OBIA classification which did not use EK-identified indicators. A confusion matrix was constructed. The producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA) and kappa coefficients (kappa) were calculated. The classification accuracy between the OBIA classification implemented using EK and the alternative implemented without using EK was assesed.

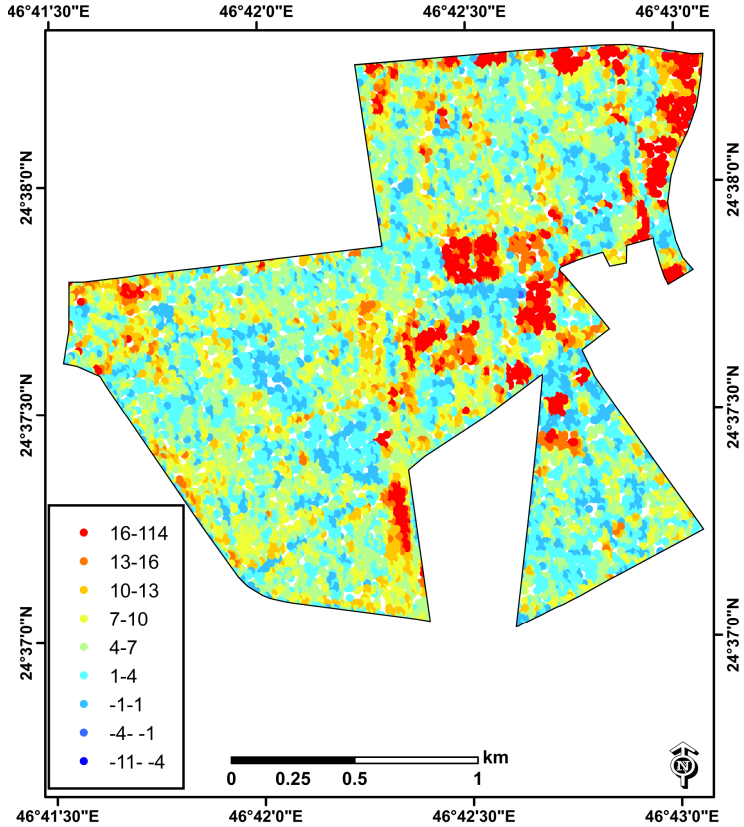


Figure 5. DSM data is used to segment buildings,' roofs, and dwelling sizes.

3. Results

3.1. Survey Assessment

The experts consulted for this survey had 3–10 years of relevant experience. In total, 80% worked directly in the urban planning and housing sector, and the remainder worked in academia. Of these, 80% specialized in geoscience (GIS and remote sensing) technology, while 20% worked in cadastral, civil, and urban planning. Responses were generally based on the background of the individual and the level of knowledge of the specific subject area. The survey results indicated that 82% of the informal settlement-type structures in Riyadh City were unplanned and 18% were planned. Overall, 76% of informal settlement growth in Riyadh city had occurred over a long period, while 24% had appeared very quickly. Regarding the most common size of buildings found in the informal settlements, 40% of the experts indicated an area of $\leq$100 m^2, 52% indicated an area of $\leq$280 m^2 and 8% indicated an area of >280 m^2. The study selected the most common response, which was $\leq$280 m^2. Regarding the percent of vegetation cover, 82% considered a vegetation cover of <20% to be most common for informal settlements, while 18% indicated between 20% and 40% vegetation cover. The most common roof material used in the informal settlements was concrete (suggested by 92% of respondents), while 8% indicated a mud-based material. A summary defining the selected indicators is shown in Table 3. This also shows the results of the statistical analysis of the survey data. The tolerance numbers are generally between 60% and 70%. This is regarded as satisfactory.

Table 3. Survey results, including variance inflation factor (VIF).

Indicators	Number of Experts (n = 50)	Tolerance	VIF
Structure of the informal settlement (planned area)	11		
Structure of the informal settlement (unplanned area)	39		
Timeline—gradual over a long period	39	0.616	1.622
>20% vegetation	41	0.773	1.293
Roof material (concrete/mud)	46	0.523	1.913
Steep slope	4	0.378	2.646
Proximity to social services	32	0.726	1.377
Proximity to hazardous industries	14	0.480	2.082
Narrow road	24	0.622	1.607
Curved road	4	0.613	1.630
Straight road	6	0.684	1.463
Paved road	2	0.727	1.376
Short segments with abundant crossroads and paths	10	0.587	1.705
Building size $\leq$280 m^2	48	0.521	1.918

3.2. AHP Assessment

3.2.1. Typical Site Conditions

The results of the AHP processing for typical site conditions are shown in Tables 4 and 5. Table 4 displays the comparison matrix of indicators, while Table 5 shows the results of the normalized matrix based on Table 4. The final row of Table 5 represents the priority vector weight of each site condition across all responses. This indicates that proximity to social services is the most important criterion for a site indicator, with a weighting of 64.34%. The next most important criterion is proximity to hazardous industries, weighting 28.28%. The least important criterion appears to be slope steepness, weighting 7.38%. The study area does not have any hazardous industries located nearby, apart from some workshops and stores. It is also located flat area with gentle slopes to the northwest. A consistency test of the indicators produced satisfactory results. The lambda max was 3.097, the consistency index CI was 4.85, and the consistency ratio CR was 8%. A good result for testing pairwise matrix criteria numbers is the consistency ratio, which must be less than 10%. A CR of 5% was achieved in this study.

Table 4. Pairwise matrix of indicators used for typical informal settlement site conditions.

Criteria	Proximity to Hazardous Industries	Proximity to Social Services	Steep Slope
Proximity to hazardous industry	1.00	0.33	5.00
Proximity to social services	3.00	1.00	7.00
Steep slope	0.20	0.14	1.00
Total	4.20	1.48	13.00

Table 5. Normalized matrix of priority criteria of typical informal settlement site conditions.

Normalized Matrix	Proximity to Hazardous Industries	Proximity to Social Services	Steep Slope	Sum	Priority Criteria
Proximity to hazardous industry	0.238	0.226	0.385	0.849	28.28%
Proximity to social services	0.714	0.677	0.538	1.930	64.34%
Steep slope	0.048	0.097	0.077	0.221	7.38%
Total	1.000	1.000	1.000	3.000	100.0%

3.2.2. Road Conditions

A typical-road-conditions AHP is shown in Tables 6 and 7. Table 6 displays the comparison matrix of indicators used for typical road conditions, while Table 7 shows the results of the normalized matrix (based on Table 6). The last row represents the priority criteria weight of each road network condition across all responses. This shows that the narrowness of roads is the most important indicator of road conditions, with a weighting of 50.93%. This means that the study sites have a network of narrow roads. Most roads are less than 12 m wide, particularly between the buildings. The next most important criterion indicates that the area also has a lot of crossings (a weighting of 22.03%). These features would impact the ease of vehicle movement, particularly in emergencies. The straight roads, curved roads and paved roads indicators came in as third, fourth, and fifth in importance, with values of 13.69%, 8.90% and 4.46%, respectively. The lambda max = 5.23, the consistency index CI = 5.84, and the consistency ratio CR = 5%.

Table 6. Comparison matrix of indicators used for typical road conditions.

Criteria	Narrow Roads	A Lot of Crossings with Short Segments	Straight Roads	Curved Roads	Paved Roads
Narrow roads	1.00	3.00	5.00	6.00	7.00
Crossings with short segments	0.33	1.00	2.00	3.00	5.00
Straight roads	0.20	0.50	1.00	2.00	4.00
Curved roads	0.17	0.33	0.50	1.00	3.00
Paved roads	0.14	0.20	0.25	0.33	1.00
Total	1.84	5.03	8.75	12.33	20.00

Table 7. Normalized matrix of priority criteria of typical informal settlement road conditions.

Normalized Matrix	Narrow Roads	A Lot of Crossings with Short Segments	Straight Roads	Curved Roads	Paved Roads	Sum	Priority Criteria
Narrow roads	0.543	0.596	0.571	0.486	0.350	2.547	50.93%
A lot of crossings with short segments	0.181	0.199	0.229	0.243	0.250	1.101	22.03%
Straight roads	0.109	0.099	0.114	0.162	0.200	0.684	13.69%
Curved roads	0.090	0.066	0.057	0.081	0.150	0.445	8.90%
Paved roads	0.078	0.040	0.029	0.027	0.050	0.223	4.46%
Total	1.000	1.000	1.000	1.000	1.000	5.000	100.0%

The AHP results indicate that using of slope as a criterion (mentioned by some local experts) is not an effective indicator. The result of the site proximity analysis indicates that the slope has a low percentage weighting (7.38%). The study area is on the elevated Najd Plateau, with a gently sloping land surface.

3.3. Local Ontology

An ontological framework (LOIS) was developed using the local expert knowledge survey results, descriptive analysis and the AHP. This was used to investigate the relationships between all identified indicators. Three levels were recognized: object, settlement, and environment. The final indicators are summarized in Table 8.

Table 8. OBIA ruleset used for local ontology (LOIS).

Level	LOIS	Indicators	Local Expert Index for Riyadh	OBIA
Object Level	Accessibility	Shape	Irregular	Varies according to the straightness of the road
		Type	Paved/unpaved roads	>6 m—many paths with short segments
		width	Narrow road	
	Buildings	Building size	>280 m^2	Geometry—asymmetry
		Material type	Roof material concrete	Spectral mean value
Settlements	Shape	Pattern	Irregular shape, elongated shape along linear features	Geometry—buffer around the roads
	Density	Texture	Roof coverage	Texture—entropy
			Amount of vegetation ≥20%	Texture—contrast, homogeneity, correlation, mean of built-up area
			Vacant	
Environs	Neighbourhood	Pattern	Proximity to social services	Geometry—buffer around roads
	Location		Proximity to hazardous industries, steep slopes	

3.4. Segmentation

The multi-resolution and spectral difference segmentation process could satisfactorily identify formal and informal settlements and non-built-up areas. Vacant blocks, such as graveyards, were differentiated from other features within the built-up areas (Figure 6). There were locations where both formal and informal settlements formed part of a road network; this was observed mainly at the settlement boundaries. The shadow class was also clearly recognisable in the image. Areas affected by shadows were seen primarily in built-up areas, near road networks and with objects associated with small buildings. The shadows made these features difficult to distinguish in the imagery.

3.5. OBIA-Extracted Indicators

The results of edge detection filtering are shown in Figure 7. A Sobel filter derive the buildings border index from the WorldView-3 imagery. This was then converted into a vector format to extract the building borders. Three edge detection filters, namely Sobel, Canny, and Gaussian, were assessed to determine efficiency in detecting the border index. The assessment identified the Sobel filter (Figure 7b) as providing the best border definition. Figure 8 shows the results of using Sobel filtering on the WorldView-3 imagery. Band 5 spectral reflectance in WorldView-3 imagery appears best for extracting the border index.

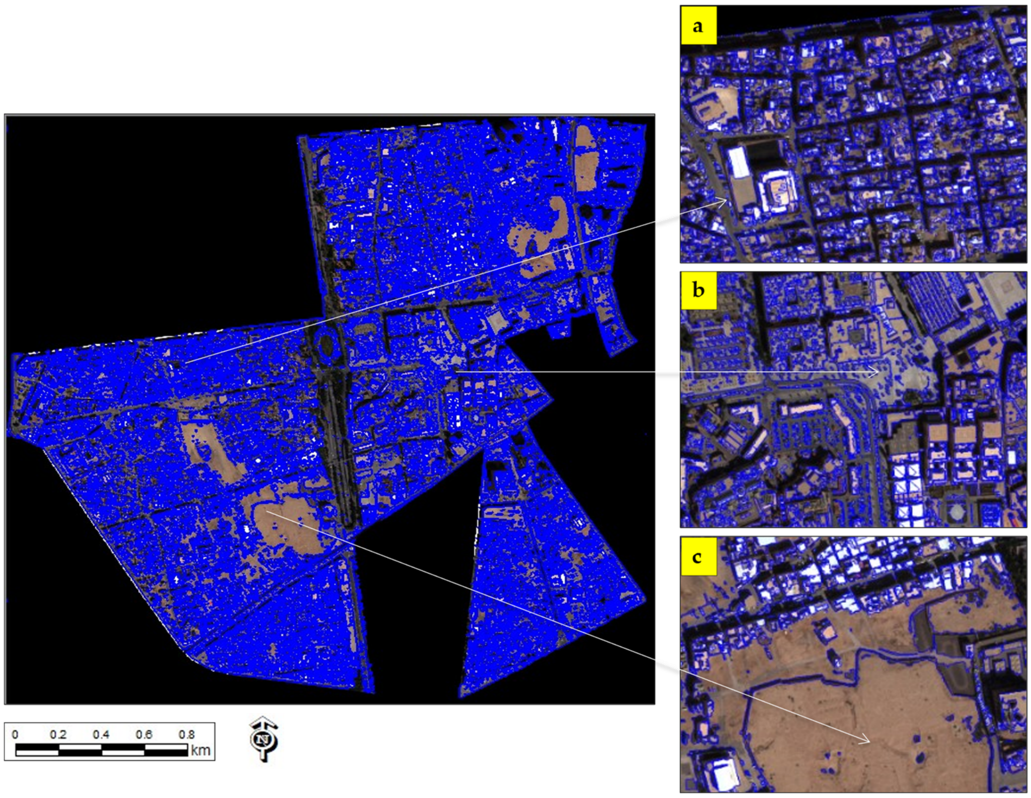


Figure 6. Multi-resolution segmentation of the WorldView-3 imagery using the parameters SP = 30, Wshape = 0.3, and Wcompt = 0.5: (**a**) informal, (**b**) formal, and (**c**) vacant segments.

Five textural measurement results are shown in Figure 9. The GLCM processing clearly defines the built-up areas. It also distinguishes between the formal and informal settlements based on roof type, lacunarity and building size. However, vehicle roofs may also be mistaken for the roofs of buildings (Figure 9a,d). These incorrectly identified features were manually removed where required. The GLCM contrast and GLCM correlation produced the lowest class separation distance of informal and formal settlements. GLCM homogeneity, GCLM entropy and GCLM correlation provided the best separation distance of the two classes, with values of <0.05, <7.9 and >0.81, respectively. The GLCM entropy, with a threshold value <7.9, appears to be the optimum separation distance for classifying buildings and roofs. These results indicate that the selected GLCM entropy and GCLM homogeneity measures effectively distinguishing informal from formal settlements. GLCM contrast, GLCM correlation and GLCM mean were the best measures for detecting the lacunarity of housing structures and enhancing the texture of the built-up areas. The separation distance value of accessibility extracted by housing orientation was <0.99, as shown in Table 9. Roof surfaces in the study area were not homogeneous. This was due to differing roofing materials, pervasive shadows within the image, and image illumination effects. An additional issue was that most of the roofs comprised mixed pixels, which automatically caused problems in extracting these roof surface objects. Some manual editing was required to improve the classification [18].

A building size of $\leq$280 m^2 was regarded as the best areal extent for use in identifying informal and formal settlements. Building areas of <8 m^2 and buildings obscured by shadow were also difficult to recognize. This may be due to variations in building density and other factors such as the reflectance characteristics of small rooms within concrete structures covered by tin roofs. This may also be due to technical issues associated with the OBIA method. It was also noted that using of an optimised segmentation parameter on a small area is not effective when applied to relatively large urban areas, which results from pixel diversity.

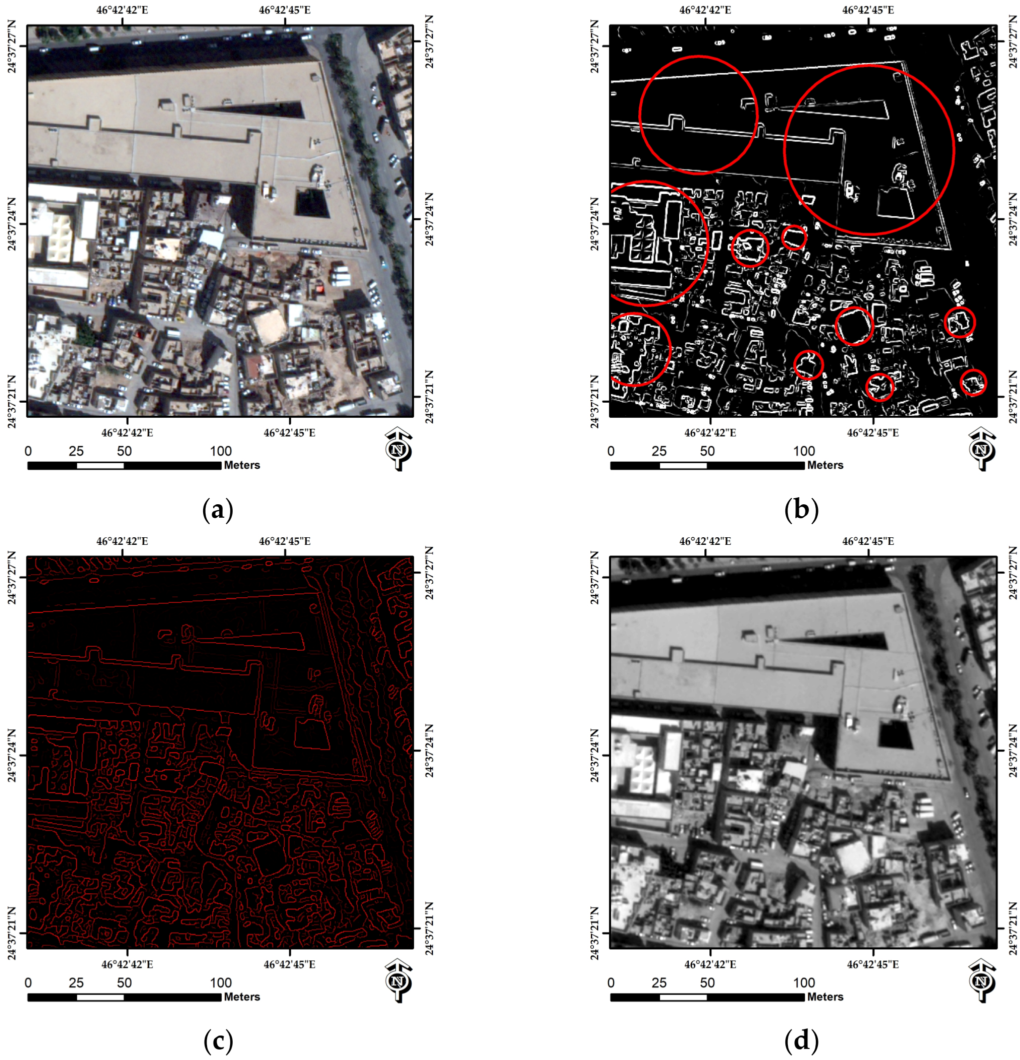


Figure 7. The 512 × 512 pixels were extracted from WorldView-3 imagery to assess the edge detection filters: (**a**) original image subset, (**b**) Sobel, (**c**) Canny, and (**d**) Gaussian.

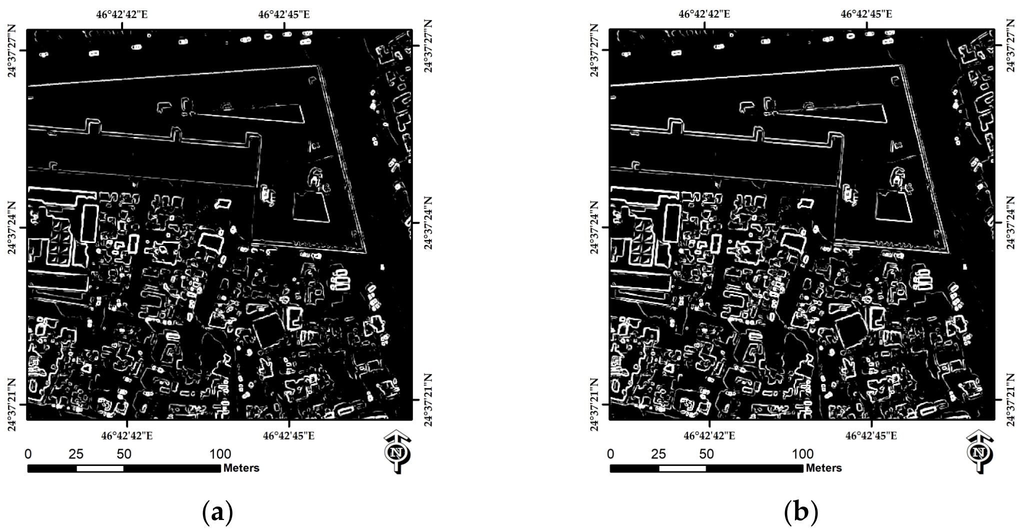
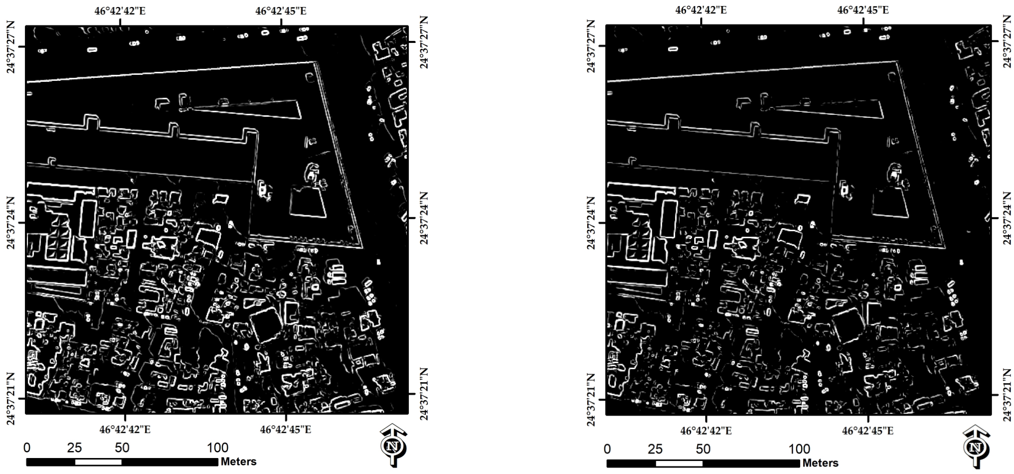


Figure 8. *Cont.*

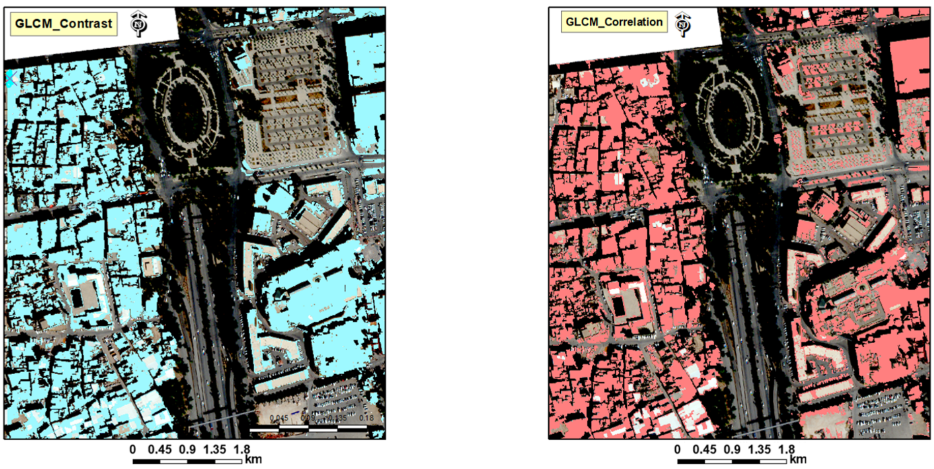


(**c**) (**d**)

Figure 8. Sobel filtering with a 3 × 3 kernel size on four subsets of 512 × 512 pixels of WorldView-3 image bands: (**a**) Band 2, (**b**) Band 3, (**c**) Band 5, and (**d**) Band 7. The spectral reflectance of Band 5 in WorldView-3 is superior to that of Band 3 in extracting a border index.

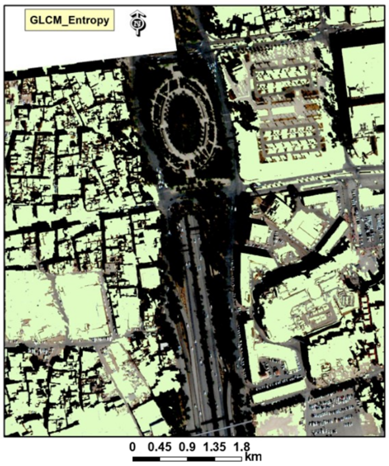
The results of the OBIA classification are shown in Figure 10. The classification of shadow areas was completed using the blue band information. Threshold values ranged from 57 to 76. The DSM was used as an ancillary data source to obtain the height of buildings, especially the smaller buildings impacted by shadows (Figure 10f). A low percentage of vegetation cover was observed in the high-density informal settlements. Most of the vegetation cover is found in the formal settlement areas, where the government and trading entities use many of the buildings. These areas are also used for telecommunication purposes (Figure 10e).

Vacant areas vary in size, with four of the five vacant areas being graveyards. There were also some small vacant areas in the informal settlements used as car parking spaces by the residents (Figure 10d). Vacant areas in the formal settlements were distinguished by shape, although most were generally located in the informal settlements. The results show that graveyards were classified as vacant areas with no vegetation. Graveyards in Islamic countries typically do not contain headstones, so the spectral brightness signature is like vacant land.

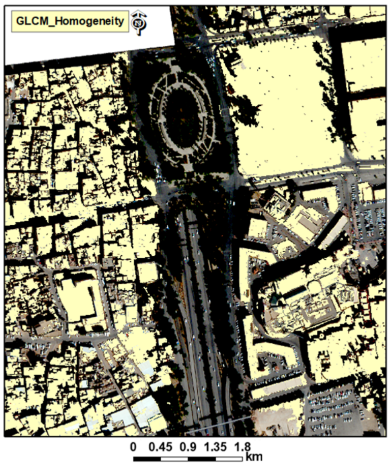


(**a**) (**b**)

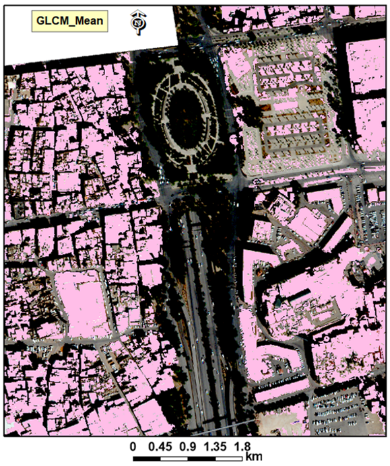
Figure 9. *Cont.*



(**c**)



(**d**)



(**e**)

Figure 9. Five textural measures: (**a**) $GLCM_{contrast}$; (**b**) $GLCM_{correlation}$; (**c**) $GLCM_{entropy}$; (**d**) $GLCM_{homogeneity}$; and (**e**) $GLCM_{mean}$ from the WorldView-3 imagery.

Table 9. OBIA parameter values and indicators used for segmentation.

Indices	Description	Min	Max	Average with Mean
NDVI	Normalized difference vegetation index	0.01	1	0.05
VB	Visible brightness	0	1250	328
SD (B)	Standard Deviation (Blue) Band	32	60	46
DSM	Roof	568	613	590
GCLM texture	Entropy	0	7.9	4
	Contrast	1230	6790	4000
	Homogeneity	0	0.05	0.025
	Correlation	0	0.81	0.4
	Mean	40	126	83
BI	Border index	8	3	11
MDS (B)	Mean and standard deviation of the blue band	37	49	58

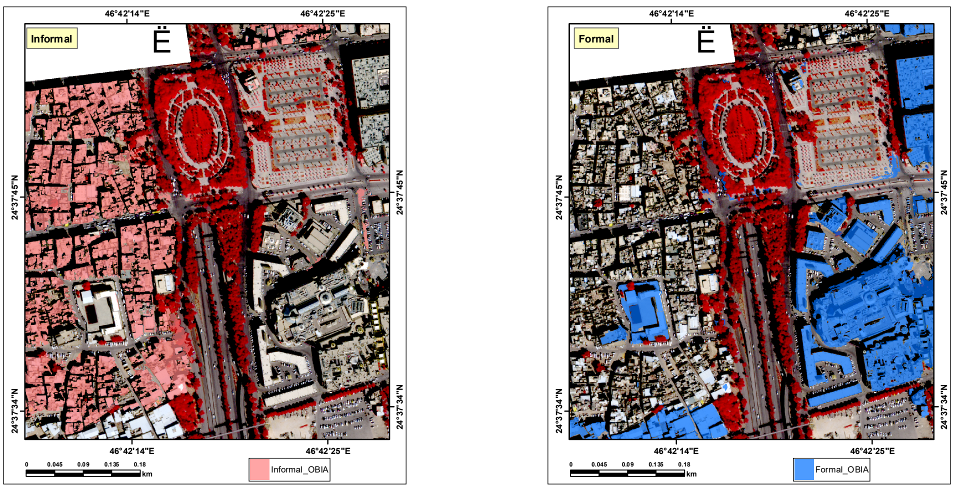
Table 9. *Cont.*

Indices	Description	Min	Max	Average with Mean
Dwelling size	Pixel size (area)	>70 pixel	8	1027
Dwelling shape	Shape index	0	2	1
Building density	Density	0.9	1.3	1.1
Housing orientation	Accessibility	0.48	0.99	0.73
Proximity to hazardous locations (e.g., possible floods, landslides)	DEM	0		200 m

3.6. Accuracy Assessment

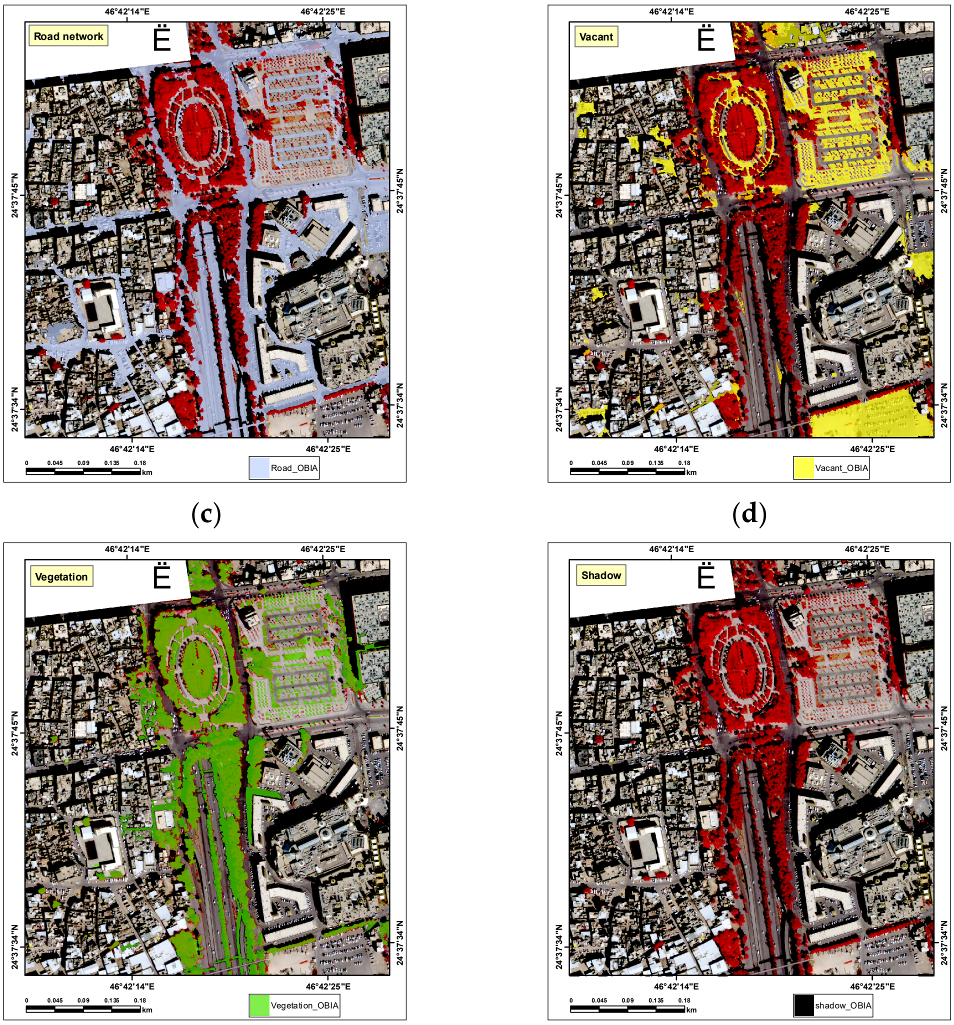
Accuracy assessments of the sampling segmentation process and the random point reference data are shown in Figure 11. The accuracy of the sampling segmentation was calculated for all classes (Table 10). The overall accuracy of the classification using EK is 94%, and the corresponding kappa coefficient is 89%. This indicates that settlement identification is satisfactory. The accuracy of the random point reference data of the imagery classified without using EK is shown in Table 11. The overall accuracy is 68%, and the corresponding kappa coefficient is 61%, indicating that settlement identification is subpar. User accuracy was 53% and 59% for informal and formal classes, respectively, while the highest accuracy was 97% for the vegetation class.

The results of the image classification implemented without using EK are shown in Figure 12 and indicate that all classes are interbanded. Most of the area is covered by formal and shadow classes. The results of the image classification implemented using EK are shown in Figure 13 and indicate that the road network in the informal settlements is characterized by narrow, unpaved roads of irregular shape. Most of the roads are <6 m wide. The shadows cast by tall buildings also impact roads in adjacent areas, categorised as shadowed areas. Paved roads potentially have areas covered by sand, which can appear as vacant land. The classified image process also interprets the graveyards as vacant areas containing no vegetation.



(**a**) (**b**)

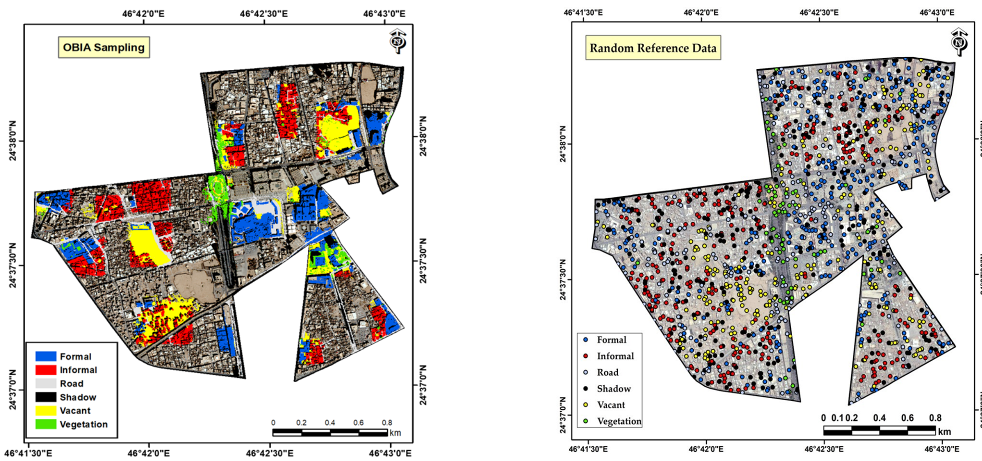
Figure 10. *Cont.*



(c) (d)

(e) (f)

Figure 10. Results of image classification: (**a**) informal settlements; (**b**) formal settlements; (**c**) road network; (**d**) vegetation; (**e**) vacant; and (**f**) shadow.



(a) (b)

Figure 11. (**a**) Sampling segmentation and (**b**) random point reference data generated from OrbView-5 reference image (**b**) were used to assess overall accuracy.

Table 10. Accuracy assessment of image classification with EK included.

Class	Objects	Formal	Informal	Road	Shadow	Vacant	Vegetation	Total	User Accuracy
Formal	36,283	894	9	5	1	4	2	915	0.98
Informal	25,551	23	352	3	1	0.00	0.00	379	0.93
Road	12,207	10	5	86	2	0.00	1	104	0.83
Shadow	9368	6	2	0.00	17	0.00	0.00	25	0.68
Vacant	15,710	8	1	0.00	1	10	0.00	20	0.50
Vegetation	1114	3	0.00	0.00	0.00	0.00	54	57	0.95
Total	100,233	944	369	94.00	22	14	57	1500	0.00
Producer accuracy		0.95	0.95	0.91	0.77	0.71	0.95	0.00	0.94

Overall accuracy = 94%; kappa coefficient = 89%.

Table 11. Accuracy assessment of image classification without EK included.

Class	Object	Formal	Informal	Road	Shadow	Vacant	Vegetation	Total	User Accuracy
Formal	22,491	195	55	28	27	22	6	333	0.59
Informal	17,825	53	102	9	16	9	2	191	0.53
Road	9258	14	14	137	22	12	5	204	0.67
Shadow	11,817	22	16	11	301	2	15	367	0.82
Vacant	12,647	25	27	33	20	204	9	318	0.64
Vegetation	783	0	0	0	2	0	85	87	0.97
Total	74,821	309	214	218	388	249	122	1500	0
Producer accuracy		0.63	0.47	0.92	0.77	0.81	0.69	0	0.68

Overall accuracy = 68%; kappa coefficient = 61%.

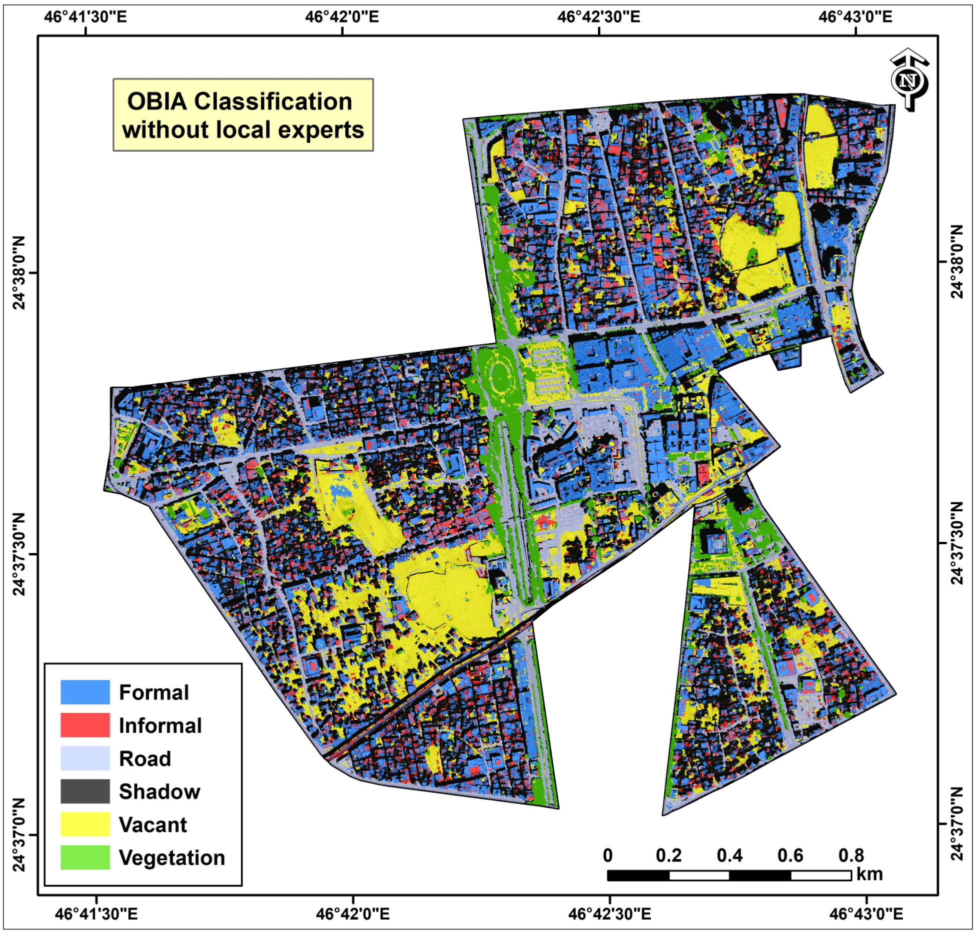


Figure 12. OBIA-based classified image of informal and formal settlements (without EK).

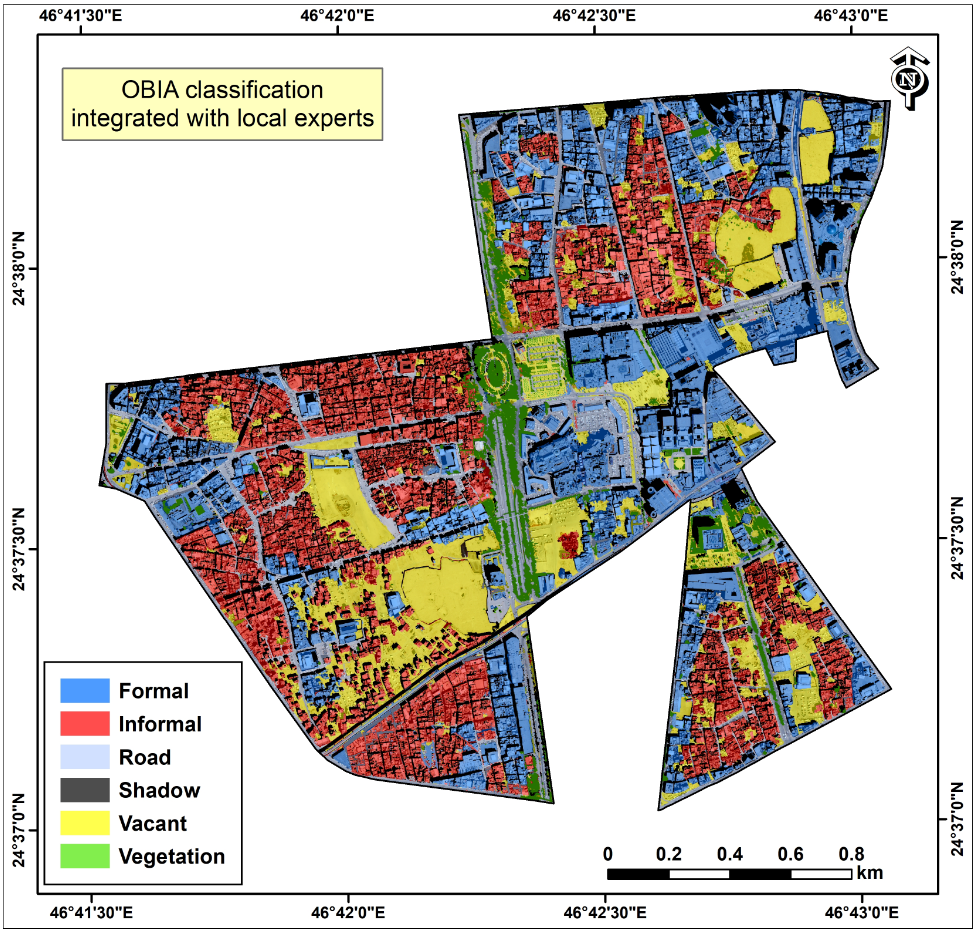


Figure 13. OBIA-based classified image of informal and formal settlements (with EK).

Table 12 displays the areal extent of the differing land cover classes produced by the OBIA classification using EK and without using EK. This indicates that the total formal settlement area using EK was 0.83 km^2, which made up 24% of the total study sites. For informal settlements, the respective values were 0.72 km^2 and 21%. The total formal settlement area without using EK was 0.8 km^2, which made up 24% of the total study sites. For informal settlements, the respective values were 0.26 km^2 and 7%.

Table 12. Area of different land cover classes by OBIA classification.

	With EK		Without EK	
Class	**Area (km^2)**	**Percentage (%)**	**Area (km^2)**	**Percentage (%)**
Formal	0.83	0.24	0.8	0.24
Informal	0.72	0.21	0.26	0.07
Roads	0.51	0.15	0.53	0.15
Shadow	0.68	0.19	1.11	0.32
Vacant	0.59	0.17	0.57	0.16
Vegetation	0.15	0.04	0.22	0.06

4. Discussion

This study aimed to integrate remotely sensed (WorldView-3) imagery and local knowledge to develop an ontology of informal settlements. Using satellite imagery and geospatial techniques is considered very effective in identifying differences between settlement types. Duque et al. [45] noted that it is difficult to recognize informal settlements using just one method, and Schmitt et al. [46] showed that class accuracy is greatly influenced by the particular city structure. In the current project, the information provided by professionals with a detailed knowledge of the study area characteristics proved very useful for extracting unique urban indicators which can be integrated into the OBIA segmentation and classification process (Tables 8 and 9). A comparison of three edge detection techniques indicated that the Sobel filter produced the best result. The choice of filter for segmenting an image is crucial for optimum object detection [53]. The observed efficiency of the Sobel filter in extracting border index data for delineating informal from formal settlements agrees with a study conducted by [54]. The use of AHP-based local knowledge (Tables 5 and 7) and OBIA successfully detected the characteristics of the informal settlement areas and provided a helpful structure for further classification work. The majority of the informal settlements were clearly visible. They are typically residential, are often seen in older areas and are primarily located in the middle and to the south of the city. They are also confined to areas considered suitable for urban redevelopment, as they commonly adjoin urban and commercial areas with a high land value. They can be identified by building density variation and low vegetation cover, have easily accessible social services and often have road networks which are difficult to traverse easily due to the narrowness and irregularity of the streets. In the survey conducted for the project, 82% of the local experts indicated that vegetation coverage in an informal settlement normally makes up less than 20% of the total area (Table 3). This agrees with findings from a study conducted by [6]. It was noted that the characteristics of informal settlements can differ markedly from place to place, even within one city. Other studies have found that such settlements were normally located close to hazardous areas, tended to lack access to basic services, and were close to hills, rivers, and valleys [55,56]. These observations were not confirmed in the current work. The study area is classified as semi-arid flat-lying and is not normally exposed to flood events.

The process of informal settlement characterisation used in this research relied heavily on local knowledge to define indicators considered useful for inclusion in the image classification process (see Table 2). A similar work conducted by Silva et al. [57] noted that the segmentation of an image is influenced by several internal factors such as regional demographics, local experience and skills, and external factors, such as image quality. All these inputs need to be optimized to perform OBIA segmentation successfully. Conversely, some studies have indicated that using of local knowledge and experience is not a significant factor regarding the final classification accuracy [36,58]. The work of Han et al. [59] and Kohli et al. [23] utilised images of differing resolutions and no local expert knowledge input. This affected the ability to extract parameters such as GLCM and the classification process. The current work clearly shows that local expert knowledge is an essential factor in the success of any mapping, and that using of a local ontology enables the integration of this factor during the classification process. The results indicate that using expert knowledge substantially improved the segmentation and classification process and increased the accuracy of informal settlement mapping. In this respect, the current study agrees with the findings of [14,16,60].

The OBIA segmentation process does have several limitations [61]. One issue is that classification accuracy can be limited by the shadowing effect of tall buildings, which causes difficulties in identifying buildings with irregular shapes or patterns. This shading can also affect vehicles and small structures (see Figure 8). The reflectance characteristics of small tin-roofed concrete buildings also returned inconsistent GLCM values. Some studies have noted issues with the reflective surfaces of objects made up of mixed pixels [20,61,62]. The current research shows that this can be overcome by developing a ruleset for OBIA processing allowing for the extraction of parameter values using the relevant indicators. Some manual intervention was required to rectify misclassification issues. Merging adjacent pixels with similar features during the segmentation process minimized pixel-based mixing during classification. The near-infrared (NIR) band in the WorldView-3 imagery also assisted in the identification of mixed pixels within the informal settlement areas.

Textural differences help identify informal area patterns, the roof material type and nominal building size [14], tops of buildings, vacant land and roads (see Table 9). Textural similarity issues, however, may still occur [63]. The delineation of building size, orientation, and pattern variation (regular or irregular) is essential in the identification process [64]. This work indicated that GLCM entropy (extracted from band 5 of the WorldView-3 image) is best for detecting high-density dwellings and the roofs of buildings. GLCM homogeneity and the visible brightness of the image are best for detecting road networks. Previous studies have shown that using of a texture index is ideal in cases that show a clear distinction between roofing type and other classes, particularly vacant land [24]. Informal settlement dwellings tend to be built with materials that produce significant spectral noise. This is a known issue in OBIA processing. Unpaved roads, for example, appeared brighter than roofs, making it difficult to distinguish individual dwellings. Other informal settlement mapping studies have indicated varying levels of accuracy using the OBIA process [65,66]. In this work, the classification accuracy of most classes was high, particularly for formal and informal settlements and vegetation (see Table 10). In contrast, the classification accuracy of vacant and shaded areas was average (see Table 10). Some external factors may have influenced the final mapping quality. The production of mixed pixels by shaded areas in locations containing both high- and low-rise buildings is usually due to the density of buildings in those areas. Some paved road pixels also appeared as vacant areas, a feature most likely related to sand encroaching onto the paved areas from the surrounding desert.

5. Conclusions

This study has used a combination of remotely sensed data and expert knowledge to develop an ontology for informal settlements in Riyadh City. An object-based image classification process was used to detect informal settlements. The classification method produced a map containing six classes: formal and informal settlements, road networks, vacant areas, areas of shadow and vegetated areas. An assessment of conducted on the final product indicated an overall accuracy of 94% and a kappa coefficient of 89%. The results demonstrate the importance of incorporating expert knowledge into informal settlement mapping process when using high-resolution satellite imagery. Some limitations were found during the OBIA processing. This included an inability to access comprehensive demographic data; issues caused by ground shadows; various building size; density issues; and vehicles producing noise in the image.

Further work should focus on the ruleset generated for mapping settlements and look at selecting more significant number of urban indicators unique to the study area. The results could also be improved by using Lidar data to adjust the satellite image resolution and optimize rooftop information extraction. The current research has shown that OBIA, in combination with expert local knowledge regarding the optimal indicators to use, is a useful method for mapping informal settlements in a Middle Eastern city. This method can be easily adapted for use in other areas of the world.

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