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Article

Mapping Informal Settlements in the Middle East Environment using an Object-Based Machine-Learning Approach

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Abstract: The identification of informal settlements in urban areas is an important step in developing and implementing pro-poor urban policies. Understanding when, where and who lives inside informal settlements is critical to efforts to improve their resilience. This study aims to analyse the capability of machine-learning (ML) methods to map informal areas in Jeddah, Saudi Arabia, using very-high-resolution (VHR) imagery and terrain data. Fourteen indicators of settlement characteristics were derived and mapped using an object-based ML approach and VHR imagery. These indicators were categorised according to three different spatial levels: environ, settlement and object. The most useful indicators for prediction were found to be density and texture measures, (with random forest (RF) relative importance measures of over 25% and 23% respectively). The success of this approach was evaluated using a small, fully independent validation dataset. Informal areas were mapped with an overall accuracy of 91%. Object-based ML as a hybrid approach performed better (8%) than object-based image analysis alone due to its ability to encompass all available geospatial levels.

Keywords: informal settlement indicators; very high resolution (VHR); Urbanisation; Sustainable Development Goals; object-based image analysis (OBIA); machine learning (ML); random forest (RF).

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1. Introduction

Informal settlements and slums have become the predominant form of new housing in the global south. Informal settlements are the product of an urgent need for shelter, a high level of urbanisation and urban growth coupled with a shortage of affordable and suitable land and housing for low-income groups [1,2]. Such settlers are likely to be vulnerable to natural hazards such as fire and flood. The rapid urbanisation process experienced by many countries in the global south over the last few decades has resulted in fundamental challenges in the environment and social structure [3,4]. Planning for informal settlements needs to consider the 2030 Agenda for Sustainable Development, as countries will be required to report progress against the sustainable development goals (SDGs) [2]. This 2030 agenda aims to improve living conditions for the residents of informal settlement by 1) reducing by at least half the proportion of men, women and children living in poverty in all its dimensions, and 2) providing access to adequate, safe and affordable housing together with basic services, an aim that includes the upgrading of slums. While there is growing evidence of a gradual shift in poverty from rural to urban areas, it is clear that improved information is needed on urbanisation, including on the spread of informal settlements [5].

According to UN-HABITAT, the proportion of the urban population living in slums in the global south has declined, although the actual number of slum dwellers has grown considerably and will continue to rise [6]. UN-HABITAT defines a slum household as one lacking any of the following five factors: secure tenure, access to safe water, access to sanitation, a sufficient living area and durability of housing [4]. Durable housing refers to the permanency of the structure – walls, roof and floor; a structure should also be compliant with building codes, well maintained and structurally sound and not located in a hazardous area [5]. Of these factors, only the durability of the housing can potentially be measured using remote sensing techniques [7]. Urban areas typically consist of a mix of land cover features such as water bodies, built-up areas (buildings) and vegetation (gardens, parks and agricultural fields), and this presents a challenge for remote identification and mapping [8]. The heterogeneity of an urban environment is hard to represent with a pixel-based classification approach using only spectral values. Object-based approaches however have the potential to capture this heterogeneity using contextual information for object attribution [9,10].

1.1. Informal Settlement Indicators

Efforts to find effective variables with which to classify satellite images and produce accurate land use land cover (LULC) maps have been an important component of remote sensing studies over the past two decades. A set of well-defined attributes for a systematic approach to the identification and classification of informal settlements was reviewed in [11]. Owen and Wong in [11] proposed 14 indicators using data from Guatemala (see **Table 1**) although mapping these indicators is a challenge especially in countries where key geographical data are missing [12]. Some indicators have been successfully mapped [roofing extent, vegetation, road network and lacunarity of housing structures/vacant land] however, others [texture measure and dwelling size] could not be retrieved [13]. Some of these indicators have been used to map informal settlements and slums [8,10,13] using a slum ontological framework proposed in [14]. In previous work, we adopted this approach, using object-based image analysis (OBIA) to classify informal settlement indicators in a Middle Eastern city [13]. We found that the OBIA approach can map informal settlements indicators at the object level and some indicators at the settlements level. In this paper, we combine both the OBIA and machine learning (ML) approaches in a synergistic way to map informal indicators at the object, settlement and environmental levels (see **Table 1**).

Translating informal settlement indicators into maps of informal settlements is challenging, requiring the integration of local knowledge with an adaptation of these characteristics to define the informal settlements. Past efforts towards automated mapping of informal settlements have focused on multi-spectral satellite remote sensing [11,15]. Here, we adopt the informal settlement ontology of [14], which is useful in terms of understanding the relationship between the image and actual characteristics of the informal settlement. The ontology identifies three spatial levels that refer to the morphology of the built environment: the environ level, the settlement level and the object level. This multi-scale approach considers the variable nature of informal settlements across different contexts by defining a set of indicators at different scales for informal settlements [14] (see **Table 1**). At the object level, building and road characteristics are the major components of the ontological framework; however, at the settlement level, texture measures can be used to represent the contrast between formal and informal settlements. At the environ level, factors that extend beyond the site itself are important, for example, hazards due to the presence of flood plains and marshy conditions [14].

Table 1. Summary of indicators to detect informal settlements (adapted from [11]).

Indicator	Description and expected informal settlement values	Level
Roofing extent of the built-up area	The total area occupied by the building. High density expected.	Object
Dwelling size	Mean dwelling size between <50 m^2 and 380 m^2 classified as informal settlements.	Object
Vegetation extent	Amount of vegetation present. Expected lack of vegetation.	Settlement

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Lacunarity of housing structures	Measures heterogeneity or 'gappiness' of empty spaces (lacunae) between built-up structures. Low value expected.	Settlement
Road segment type and materials	Less road elongation, fewer regular road segments.	Settlement
Texture measures of built-up area	Higher entropy, higher contrast, lower homogeneity in built-up areas.	Settlement
Road accessibility	Road widths are narrower in informal areas and less suitable for vehicular traffic. Roads not easily accessible, a higher proportion of dead-ends (dangles) and fewer intersecting nodes.	Settlement
Consistency of housing orientation	In the computer vision literature, the angles and lengths of line segments exhibit greater angular variability and are shorter.	Settlement
Dwelling shape	The height of dwellings measured by image shadows, or radar/ LIDAR; simplicity of shape (4-sidedness), more 4-sidedness (simple shapes) in informal areas.	Settlement
Dwelling consistency of orientation; dwelling road setback	Precarious house placement, road setbacks lacking.	Settlement
Building density (dwelling separation)	Lower nearest neighbour distance using centroid of dwelling polygons.	Settlement
Proximity to hazards	Hazards include flood zones, hydrologic setbacks, landslide/earthquake, garbage mountains, point source pollution, airports, energy transmission lines and major transportation.	Environ
Geomorphology of terrain	Settlements built in gullies, ravines, steep slopes, unstable soils.	Environ
Proximity to city centre and social services	Network analysis of distance to city services, market area or city centre and healthcare facilities. Greater distances expected overall.	Environ

1.2. Object-Based vs Pixel-Based approaches

The classification of remotely sensed imagery can be divided into two general image analysis approaches: pixel-based classification and object-based classification [16,17]. In pixel-based classification, the spectral pattern for each pixel in the multi-spectral data is used as the basis for categorisation [18]. When extracting informal settlement indicator information from remote sensing data, analysts tend to consider spatial resolution as more critical than spectral resolution [19]. The use of sophisticated commercial software for mapping informal settlements using very-high-resolution (VHR) imagery and ancillary data requires a high level of skill and is considered costly for developing countries. However, the use of conventional methods, such as field surveys, for informal settlement detection can also be time consuming and costly [20]. This paper explores the possibility of implementing a low-cost standardised method for informal settlement mapping. Remote sensing provides a fast, cost-effective and efficient method of mapping spatial distribution and its disturbance dynamics [9]. Since pixel-based approaches are limited to pixel values using VHR imagery [21], object-oriented classification is proposed as an approach to overcome some of these limitations.

In recent years, methods for mapping informal settlements using remote sensing imagery have varied depending on the data source, project aim and resources. For example, OBIA appears to be the most common method for mapping informal settlements [8,10,12,22]. Although rather labour intensive, visual interpretation is still used for informal settlement and slum identification and produces reliable results in the hands of skilled interpreters. OBIA requires a local ontology framework, such as that in [14], to guide the OBIA parameterisation by defining the different features for classification, as discussed in [8,10,13]. The OBIA approach is knowledge based, typically producing a hierarchical classification and has been the dominant approach over the last decade [12,16]. OBIA approaches have been found to work well for the extraction of objects (e.g., roofs and roads) at the settlement level in cases where the urban morphology is combined with a sufficient resolution image to allow for identification [22,23].

1.3. ML for VHR and Complex Urban Areas

ML approaches are information-driven techniques that enable repetitive learning from large and rich sets of training data [24]. ML has become a common method in remote sensing image processing, with algorithms having high reported accuracies and high computational efficiency when working with large datasets [22,24-26]. For a comprehensive review of ML approaches, see [27-31]. Recent studies have explored the potential of object-based ML in simple systems, such as agricultural monocultures [32]. Previous work has showed that feature selection, segmentation and classifier parameter tuning can have a significant effect on the performance of any ML algorithm [33-35]. Urban structure patterns have not been widely analysed using ML at different scales [36]. Wieland and Pittore in [35], explored the potential of ML algorithms in the context of object-based image analysis and tested the algorithm's performance under varying conditions in order to optimise usage for urban pattern recognition tasks. In addition, the authors concluded that ML algorithms allowed for a high degree of automation and possessed great flexibility regarding transferability of the method to diverse image types. Several studies have used ML for urban land cover/land use mapping, using Landsat data at the pixel level [37,38].

1.4. ML Object-Based Analysis

ML approaches can combine textural, spectral and structural features [22] with the most popular algorithms including object-oriented decision trees (DTs), support vector machines (SVMs) and random forests (RFs) or random trees (RTs) [18]. DTs have been used in environmental risk analysis [39], and offered a higher precision compared with other statistical methods [40]. SVMs are particularly appealing in the remote sensing field as they often produce higher classification accuracy than traditional methods for urban structure pattern recognition within built-up areas and for automatic slum identification from VHR imagery [20,41-44]. However, the precision of the results is strongly influenced by the choice of kernel type and associated parameters [20,32,42]. RFs are one of the most popular ML methods for time-series monitoring of forests at the landsat level but have not been used widely in informal settlement mapping using VHR. Examining both pixel-based and object-based ML classification approaches for DTs, RFs and SVMs, no statistical difference between object-based and pixel-based classifications when the same ML algorithms were noted [16,18,20,36].

While ML has been used widely in remote sensing studies their use in urban area mapping has to date been limited. We evaluated several ML approaches for informal settlement mapping. The spatiotemporal detection and analysis of urban areas using VHR imagery [24,45] and mapping constructed from [31] showed that RFs performed better than SVMs in the urban identification context. RF approach yields a robust ML classifier that is relatively unknown in urban management using remote sensing. The key advantages of RFs include their non-parametric nature, high classification accuracy and capability to determine variable importance of each input variable. Therefore, RFs are a good candidate an algorithm for estimating missing values and possess the flexibility to perform several types of data analysis, including regression, classification, survival

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analysis and unsupervised learning [46]. ML (RF) performance has been tested with different remote sensing dataset types, such as data from unmanned aerial vehicles (UAVs) [24,47], multi-spectral data [48-50], aerial images [51] and high spatial resolution imagery [52]. The availability of ancillary data, such as digital elevation models, is useful to support the prediction process. Combining spectral, spatial and textural data provided better classification accuracy [26]. Whether RFs are used to understand or predict, they are powerful and fast compared with other ML algorithms.

1.5. Hybrid Approach (OBIA-ML)

Using a ML approach allows for the incorporation of geospatial and other ancillary data in addition to the base VHR imagery. While OBIA is effective for object level analysis, it is time consuming and bespoke and clearly not viable for mapping an entire city. Therefore, we need another approach. We propose to combine the robust ability of ML to incorporate many types of geospatial data and the proven utility of OBIA at the object level. ML approaches alone have been applied successfully to the mapping of informal settlements in Latin America [24]. This example used indicators related to the morphology of the urban area. Similarly, [53] was able to classify built-up areas and other land cover classes without distinguishing between formal and informal areas. Kuffer et al. [22] in their review of remote sensing for informal settlement mapping state that OBIA and ML are likely to become the dominant paradigm. This paper takes up this challenge, presenting an OBIA-ML fusion technique for mapping informal settlement indicators. In this paper, we propose an object-based ML paradigm adapted to VHR image information content.

2. Case Study and Data

Jeddah is the most populated city in the west of Saudi Arabia. Urbanization has led to a growing number of informal settlements, which affect the urban and social fabric of the city. The population of Jeddah was estimated in 2009 to be around 3.4 million people (14% of the population of Saudi Arabia) and this number is expected to grow at an annual rate of 2.2% (2010 census), to reach 5.6 million people by 2029 (Jeddah Municipality, 2009a). Over recent decades, the city of Jeddah has witnessed dramatic changes to its urban area [54], and the Jeddah Strategic Plan (2009) indicated that there is a severe shortage of adequate housing for low- and middle-income residents. The continued growth of informal settlements means that today, nearly 1 million residents live in such areas [55]. One third of Jeddah's population living in informal settlements lack essential services and are subject to flood risk and other threats [56]. However, funding for large-scale affordable housing and the expansion of housing finance options for the urban poor have remained limited [57].The major factors leading to population growth in the selected area are natural growth (i.e., the birth rate), illegal immigration from other countries and internal migration from rural areas. **Figure 1** shows the geographic location of Jeddah and the extent of the case study area analysed in this research. **Figure 2** shows the distribution of informal settlements in Jeddah, from the oldest informal settlement around the city centre, shown in green, through red and purple, to the most recently occupied (yellow) settlement. Formal and informal settlements are mainly constructed from the same building materials (brick and concrete) in the Middle East, which makes any differences difficult to detect.

A GeoEye-1 image was used in this research for informal settlement mapping. This was acquired on 8 January 2010 and has a resolution of 0.5 m panchromatic and 2 m multi-spectral. From among the more than 50 scattered informal settlements in Jeddah (see **Figure 2**), a case study area was selected based on density, history, geographic distribution and susceptibility to flooding, representing the variation in the characteristics of the local informal settlements. The case study area contains a mixture of vegetation and residential and commercial buildings, with the informal settlement section located mainly to the east. It is approximately 70 km^2 in area.

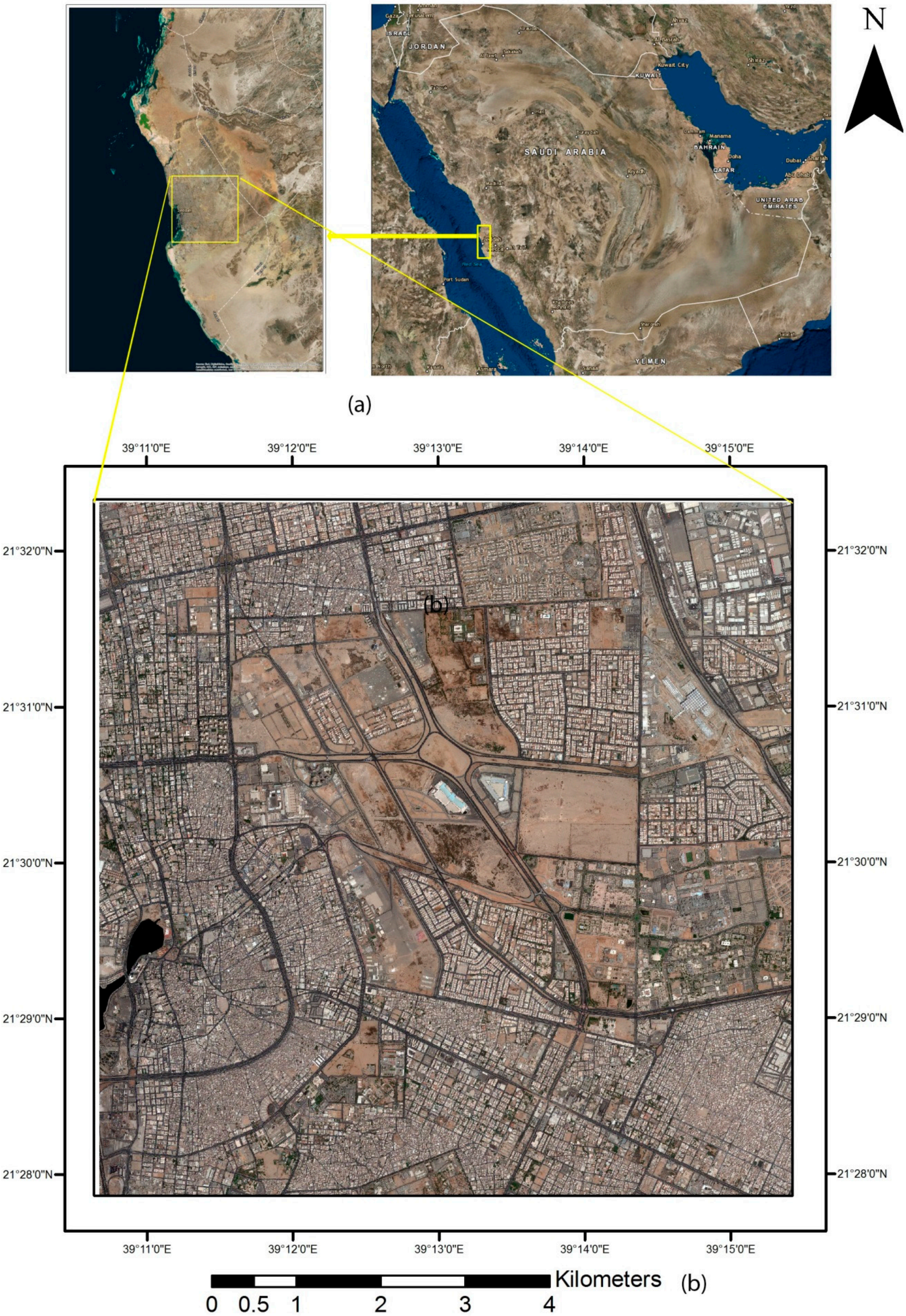

Figure 1. (a) Geographic location of Jeddah, Saudi Arabia and neighbouring countries. (b) Jeddah's location on the Red Sea. The yellow rectangle shows the extent of the case study area analysed in this research (source: Google Earth).

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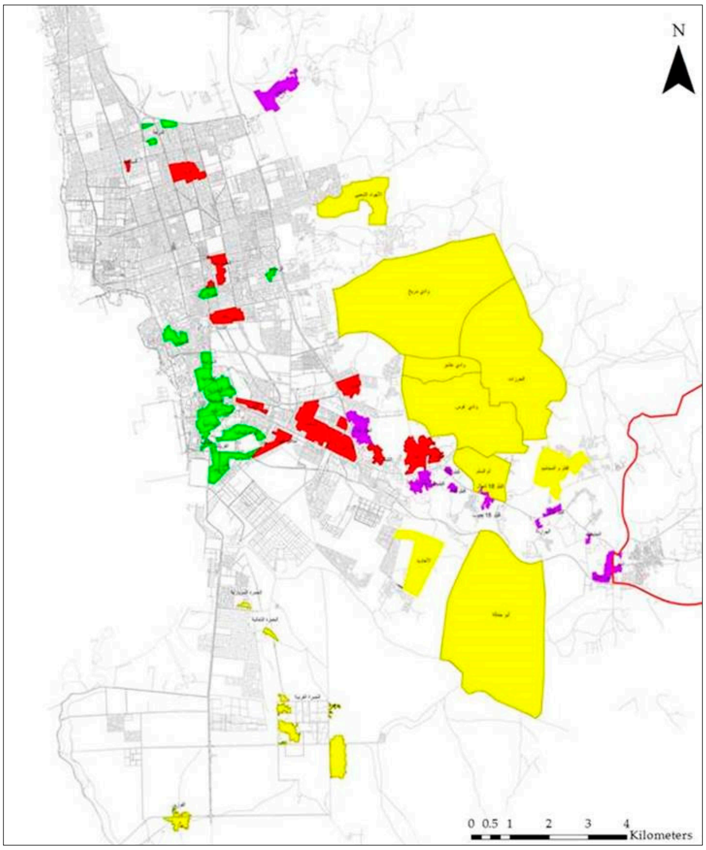

Figure 2. The distribution of informal settlements in Jeddah, from the oldest informal settlement around the city centre (shown in green), through red and purple, to the most recently occupied (yellow) (source: Jeddah Municipality).

3. Method

This research presents an object-based ML approach for mapping informal settlement indicators. Specifically, it adopts the ontological classes proposed in [14] and evaluates the utility of object-based ML in the Middle Eastern environment. The paper explores how the ML technique can be used synergistically with the OBIA paradigm to map informal settlement indicators, using Jeddah as a case study. In this section, the segmentation process is presented, and the informal settlement indicators used to distinguish between formal and informal areas in the case study area are detailed. In this research, object-based mapping approaches were implemented in eCognition Developer 9.0 and RF within the R programming environment.

3.1. Classification

The classification process was performed as shown in **Figure 3** in a sequence from top to bottom and was repeated until all objects were classified. These steps formed a ruleset that are applied later to the case study. The process of mapping informal settlements indicators via OBIA starts by grouping the pixels in the image into coherent groups to form segments. Then, informal settlements indicators were created and associated with each segment. After that, ML (RF) was used to carry out analysis and subsequent classification. Finally, the accuracy assessment was performed to check the utility of mapping informal settlements using object based ML approach.

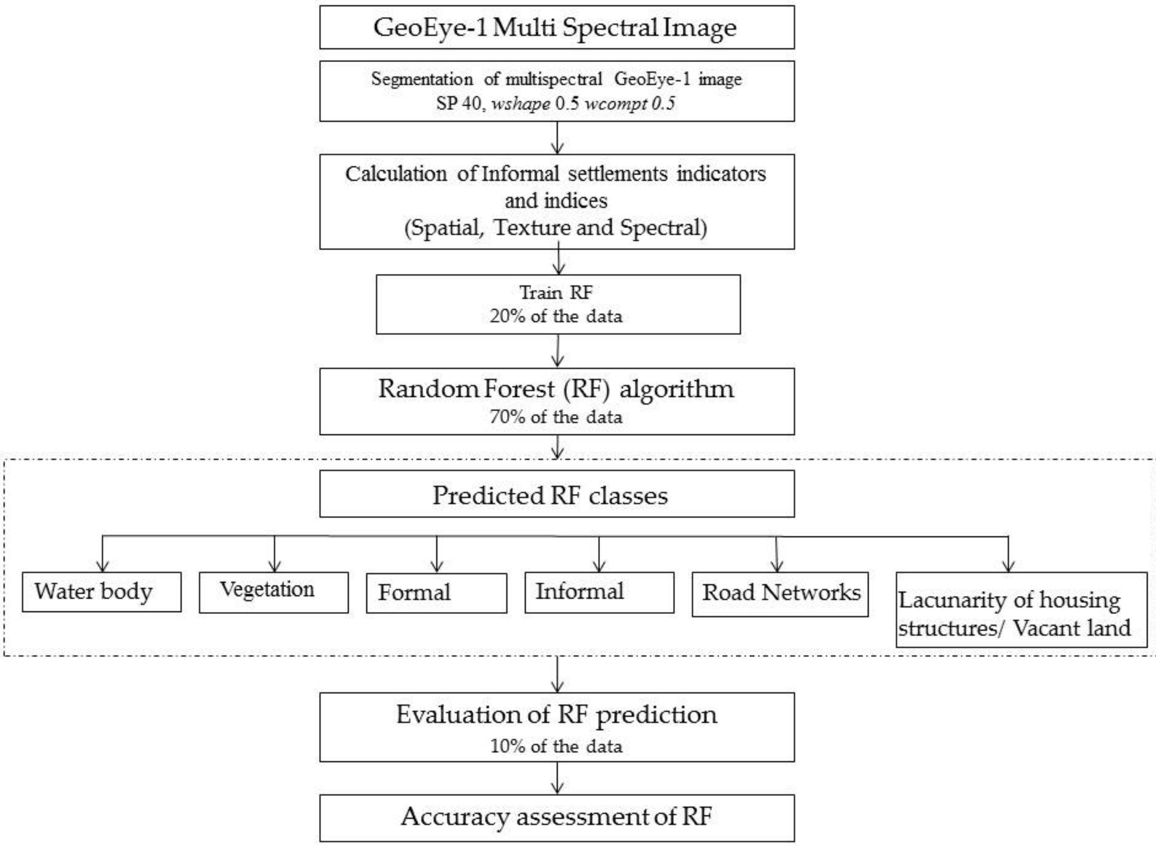

Figure 3. Flow chart of **object-based ML** (RF) ruleset structure for evaluating informal settlements indicators in Jeddah.

Table 2 shows the parameters used to derive each of the informal settlement indicators at the object, settlement and environ levels. Some indicators required only a single parameter, such as vegetation extent, while others required a set of composite parameters, such as road networks. Please note, the dwelling consistency indicator at the environ level was not assessed in this research.

Table 2. Informal settlement indicators and parameters used for object-based ML classification in the Middle East environment.

Informal settlements/ variable	Parameters	Description	Equation/tool
Roofing extent of built-up area	Built up area index (BAI)	BAI is used to measure Built-up area.	BAI = (B1-B4)/(B1+B4)
Dwelling size	Area	The numbers of pixels forming an image object. Mean dwelling size between <50 m2 and 380 m2 classified as informal settlements.	Object feature in eCognition
vegetation	Normalised Difference Vegetation Index(NDVI)	NDVI is used to measure vegetation.	NDVI = (B4 – B3)/(B4 + B3)
Lacunarity of housing structures	Visible brightness (VB)	The mean intensity of all image bands for an image object.	VB = (B1 + B2 + B3)/3

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Road segment type and materials	Normalised difference water index (NDWI)	NDWI An index developed to measure tarred road from other classes.	NDWI = (B2 – B4)/(B2 + B4)
Texture measures	Grey level co-occurrence matrix (GLCM)	GLCM entropy GLCM homogeneity GLCM contrast GLCM correlation GLCM mean.	Object feature in eCognition
Road accessibility	Accessibility	Road network and Junction network were used. Road width too narrow for vehicular traffic in informal areas. Roads not easily accessible, a higher proportion of dead-ends (dangles) and fewer intersecting nodes.	Spatial analysis in ArcGIS
Consistency of housing orientation	Asymmetry	This indicates simplicity of shape. In the computer vision literature, the angles and lengths of line segments exhibit greater angular variability and shorter lengths in informal settlements.	Object feature in eCognition
Dwelling shape	shape	The relative length of an image object, compared to a regular polygon.	Object feature in eCognition
Building density (dwelling separation)	density	Lower nearest neighbour distance using centroid of dwelling polygons. Density is calculated based on the image object that contains the current candidate pixel. This allows for smoothing of the border of the image object without taking neighbour image objects into account.	Object feature in eCognition
Proximity to hazards	Digital elevation model (DEM)	Hazards include flood zones, hydrologic setbacks, garbage mountains, point source pollution, airports, energy transmission lines, major transportation corridors; debris flows, rock and block falls, mass movements.	Spatial analysis in ArcGIS
Geomorphology of terrain	Digital elevation model (DEM)	Settlements built on relatively flat surface.	Object feature in eCognition
Proximity to city centre and social services	ProxToCent	Network analysis of distance to city services, market area or city centre and healthcare facilities. Greater distances expected.	Spatial analysis in ArcGIS

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Table 3 shows GeoEye-1 multi-spectral imagery and the indices supporting object-based ML classification at all of the proposed levels. The performance and significance of informal settlement indicators are presented in section 3 and discussed in section 4.

Table 3. Informal settlement indicators and parameters used for object-based ML classification.

Indices	Description
Multi-spectral bands (RGB and INF)	GeoEye-1 multi-spectral image 4 bands 2 × 2 m spatial resolution.
Border index (BI)	The border index feature describes how jagged an image object is; the more jagged, the higher its border index. This feature is similar to the shape index feature, but the border index feature uses a rectangular approximation instead of a square. The ratio between the border lengths of the image object and the smallest enclosing rectangle.
Standard deviation (SD)	Standard deviation for image bands. Returns the most frequently occurring pixel value per object in the blue band.
Brightness	The mean intensity of all image bands for an image object.
Relative border (RB)	Rel. border to the parent process object (PPO) is the ratio of the border length of an image object shared with PPO to its total border length.
Asymmetry	Asymmetry indicates simplicity of shape.
Roundness	The roundness feature describes how much the shape of an image object is similar to an ellipsoid. It is calculated by the difference of the enclosing ellipsoid and the enclosed ellipsoid. The radius of the largest enclosed ellipsoid is subtracted from the radius of the smallest enclosing ellipsoid.
Compactness	The ratio of the area of a segment to the area of a circle with the same perimeter. Feature value range [0-1].

3.2. Segmentation

Optimisation of segmentation parameters is crucial for analysis transferability from one image to another [58]. The first stage in mapping informal settlement indicators using a ML object-based approach is to generate segments by automatically grouping an image into coherent groups of pixels in order to form segments based on degree of homogeneity [16,53,59,60]. The process of segmentation was implemented using eCognition 9. Indicators of informal settlements were then mapped and assessed, and subsequently, indicators were grouped to provide formal vs informal settlement mapping. To this end, three parameters were optimised to segment objects: scale (SP), shape (W_{shape}) and compactness (W_{compt}). Image object primitives were generated with respect to informal settlement indicators [17] for the selected case study. Values of SP = 40, W_{shape} = 0.5 and W_{compt} = 0.5 were selected through interactive control (see section 4.1). The three parameters values were chosen based on qualitative analysis (visual inspection), after [8,10,13], of the resulting segmentation and the purpose of classification, representing basic land cover features (for example, buildings and the road network). For full details of this method see [13].

3.3. Informal Settlement Indicators

A range of informal settlement indicators were created to facilitate the classification process. Image texture was introduced in [61] as an important source to derive spatial information. Texture features characterise the spatial distribution of intensity values in the image [20]. The grey-level co-occurrence matrix (GLCM) provides additional information for land cover mapping and has been widely used in diverse applications, including urban built-up area extraction [8,10,13,53,62]. The following texture measures were created: $\mathrm{GLCM}_{\mathrm{contrast}}$, $\mathrm{GLCM}_{\mathrm{entropy}}$, $\mathrm{GLCM}_{\mathrm{correlation}}$, $\mathrm{GLCM}_{\mathrm{homogeneity}}$

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and $GLCM_{mean}$ (see Table 2). Additionally, a road accessibility measure map was created using the street network and junction density provided by the Jeddah municipality. Raster layers, representing the level of accessibility, were generated by ArcGIS using a point density function. Geomorphology of terrain (DEM) was divided into three categories based on DEM natural break values in the case study area. In addition, proximity to the city centre was divided into ten categories based on neighbourhoods with an area of 1 km^2. Based on [13], the NDWI index and brightness were used to create road segment types and materials. Road segment types and materials are very typical man-made objects and are significant in urban areas [63]. The built-up area index (BAI) was used to detect the extent to which an area is built up [64].

3.4. Training Data

After the appropriate segmentation parameters were acquired, all informal settlement variables were assigned to each object, such as roofing extent and types, texture measures and the standard deviation of multi-spectral images and shapes in eCognition. Informal settlement indicators and other index variables were combined in order to perform further analysis. Training data were selected using a stratified random distribution to represent each class: such as a road network and built-up area. On the colour composite image, a total of 4,500 samples were selected, representing the variation in image components. The samples were divided into three subsets: 70 % as predictor samples used for the land cover classification, 20% as training data and 10% as validation samples used for accuracy assessment of the classification.

3.5. RF Implementation

The methodological framework consisted of two main steps. In the first step, an object-based algorithm was used to derive the settlement indicators as shown in Figure 3. Then, in the next step RF was applied to evaluate the utility of the informal settlement indicators to distinguish the formal from the informal settlements in Jeddah.

3.6 Accuracy Assessment

In RFs, there is no need for cross-validation or a separate test to obtain an unbiased estimate of the test set error. This is estimated internally, during the run, as follows: each tree is constructed using a different bootstrap sample from the original data. Each tree uses only a portion of the input samples (typically two thirds) for the training, while the remaining, roughly one third (referred to as out-of-bag (OOB)), of the samples are used to validate the accuracy of the prediction [65].

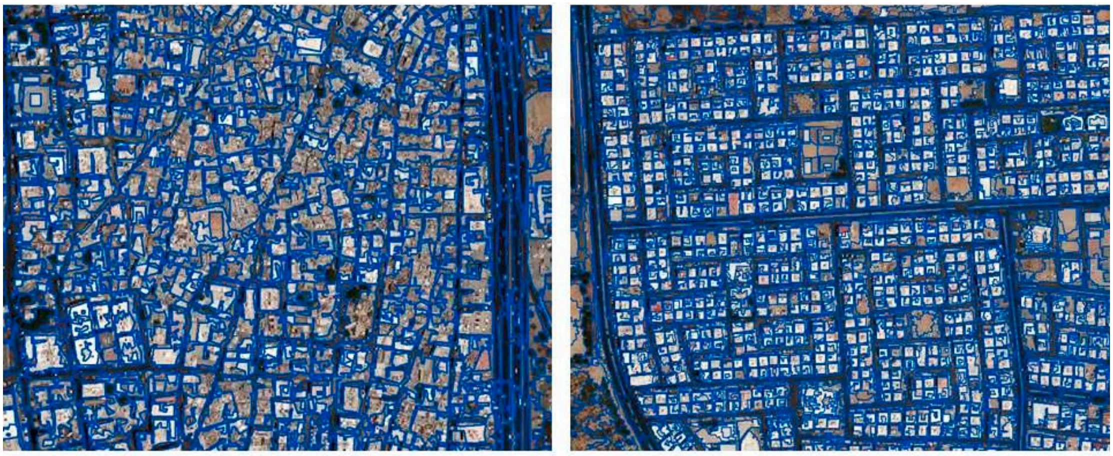
These estimates are made OOB, as explained in [65]. The multiple decision trees of the RF are trained on a bootstrap sample of the original training data. At each node of every decision tree, one of a randomly selected subset of input parameters is chosen as the best split and used for node splitting [66]. Variable selection is significant for interpretation and prediction, especially for multi-dimensional datasets. However, we identified a separate reference dataset (10%) for independent accuracy assessment as a double check for cross-validation (see **Figure 3**). In this paper, a relative importance graph was used to rank the importance of the variables.

4. Results

This section presents the results of mapping each informal settlement indicator as described in **Table 1**. First, we present the results of the segmentation algorithm (see **Figure 4)**, before considering the mapping accuracy of each indicator and concluding with the findings in terms of the distinction between informal and formal settlements. Second, the results of the object-based ML approach are presented at three spatial levels: object, settlement and environ. **Figure 5** provides the 27 variables with respect to the relative importance to classification as calculated by the RF. **Figure 6** shows the result of the object-based ML approach, with an overall accuracy of 91%. Informal settlement indicators are presented here with respect to the three spatial levels as shown in **Table 2**.

4.1 Segmentation

A set of object primitives were generated with respect to informal settlement indicators for a selected case study. Values of SP = 40, W_{shape} = 0.5 and W_{compt}= 0.5 were selected through iterative and interactive control (see Figure 4). In general, the segmentation worked well, except for some informal areas where the definition of individual buildings failed (centre of Figure 4a): the spectral homogeneity of the tightly grouped buildings at this point proving problematic.



(a) (b)

Figure 4. Multi-resolution segmentation of the GeoEye-1 image (SP = 40, $\boldsymbol{W_{shape}}$ = 0.5, $\boldsymbol{W_{compt}}$ = 0.5). In informal settlements (a), building clusters and the general pattern of buildings are outlined. In formal areas (b), the individual buildings, road network and trees are successfully outlined.

4.2 Informal Settlement Mapping

An informal settlement map was constructed by assigning to each segment the highest ranked agent from the RF model. Generally, the indicators showed high importance in classifying informal settlements using VHR imagery, with the exception of the DEM (see **Figure 5**). The results are presented in three sections according to the three ontological informal settlement spatial levels.

At the object level, both the roofing extent in the built-up areas and the dwelling size indicators featured among the ten most important indicators. The roofing extent was detected using the BAI, and it rated third in importance, with a relative importance of 19.8%. Dwelling size is ranked fourth in relative importance, with a relative importance of 19.7%.

At the settlement level, density and the texture measure $\text{GLCM}_{\text{contrast}}$ were the most significant information sources for distinguishing informal settlements from other classes, with building density (dwelling separation) the most important variable. Of the five texture measures, the $\text{GLCM}_{\text{entropy}}$ was the most successful parameter, rated second in the importance graph, with a relative importance of 19.4%. In contrast, $\text{GLCM}_{\text{correlation}}$ was the least important variable at the settlement level, with a relative importance of 14.3%. Road accessibility occupied tenth place in the full list and seventh place at the settlement level. All parameters at the settlement level contribute to informal settlement mapping, as shown by the red bars in **Figure 5**. The vegetation indicator was detected using the NDVI parameter, which has the seventh most important variable.

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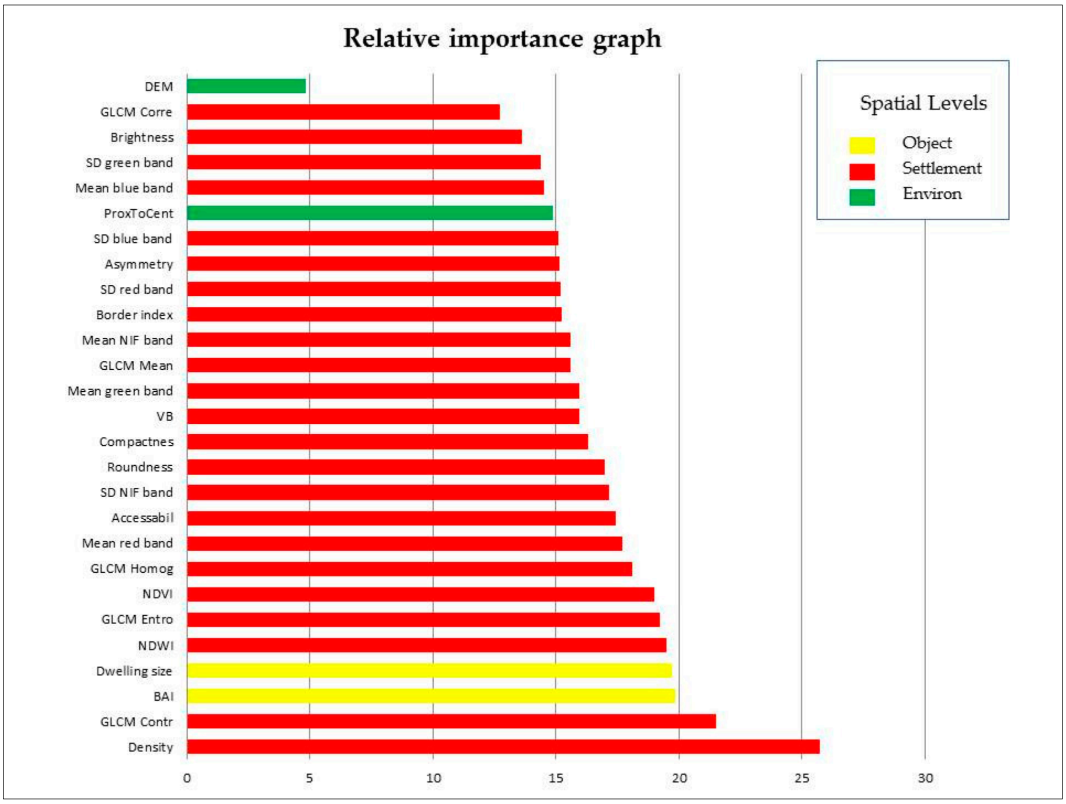


Figure 5. The relative importance for 27 object-based RF classification variables in three different spatial levels. Yellow bars represent object level, red the settlement level and green the environ level.

At the environ level, the geomorphology of terrain (DEM) parameter had the least impact on the classification using RFs and proximity to city centre had the highest impact. The red band represents the highest importance at 17.7%, followed by the SD of NIR bands and roundness with approximately 17%.

Table 4 shows the accuracy assessment estimates for predicted classes using RFs. The overall accuracy of the informal settlement indicators with object-based ML was 91%. In general, the results were very encouraging with all classes returning user and producer accuracies >85%.

Table 4. Accuracy assessment estimates for predicted classes.

Reference/ predicted	Formal	Informal	Road network	Vacant land	Vegetation	Water body	Total	Producer accuracy
Formal	641	10	2	6	0	0	659	97%
Informal	93	651	8	1	0	0	753	86%
Road network	5	6	287	3	1	0	302	95%
Vacant land	8	0	7	167	6	0	188	89%
Vegetation	1	4	2	0	111	0	118	94%
Water body	0	0	0	0	0	1	1	100%
Total	748	671	306	177	118	1	2021	
user accuracy	86%	97%	94%	94%	94%	100%		

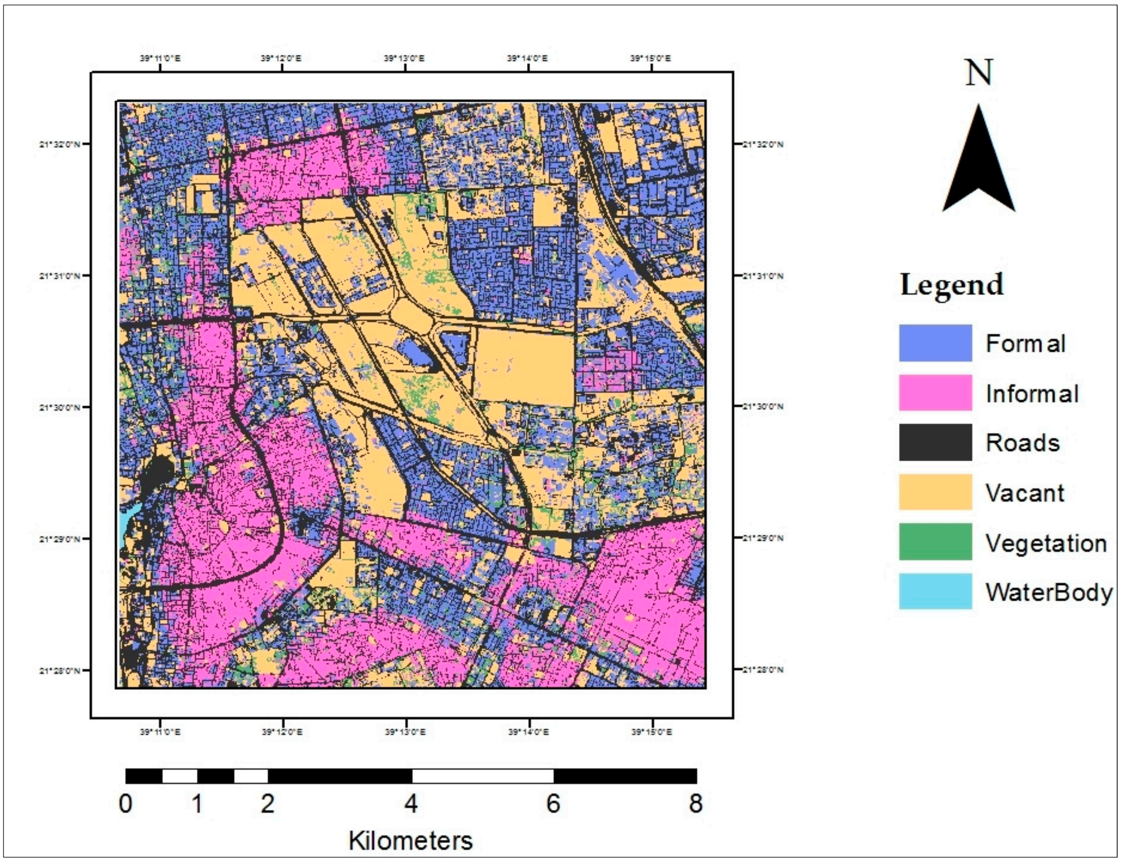


Figure 6. Result of object-based ML approach classification.

5. Discussion

Methods, such as census surveys, have traditionally been used to collect data in urban areas; however, informal settlements are often however outside of census scope. Using remotely sensed data and ancillary information to characterise informal settlements is therefore useful [67]. Past efforts towards automated mapping of informal settlements have focused on the OBIA approach using multi-spectral satellite remote sensing [8,10,13,17,60]. However, the OBIA approach is challenging as it requires the integration of local knowledge and site-specific characteristics [57] to define each informal settlement. This section discusses the performance of the informal settlement indicators using an object-based ML approach and VHR imagery.

5.1 Classification

In this section, we assess the performance of the object-based ML algorithm at each ontological level. Our results for informal settlement mapping were of a high standard, comparable with the OBIA approach implemented by [8,10,13]. The relative variable importance graph (**Figure 5**) shows the importance of each indicator using an object-based ML (RF) to perform the analysis.

At the object level, the roofing extent of the built-up area and the dwelling size were the most important indicators and both ranked in the top four overall. These indicators are cited as the primary indicators to distinguish informal from formal settlements [8]. The roofing extent in a built-up area is represented by the BAI index (see **Table 2**) and occupied third place in the variable importance graph. Dwelling size is another leading indicator used for informal settlement identification [8,11]. Object-based ML is used to map dwelling size to quantify shape-based (shape, size and spacing) characteristics of informal settlements. Although dwelling size in informal settlements varies due to dwelling separation [11]. Such a variation played a major role in this classification. However, the proposed method mapped dwelling size with a high relative importance of 19.7%.

At the settlement level, informal settlement indicators have a relative importance of between 12% and 20%. They have a marked impact on classification accuracy on the large scale [22]. For example, the density and texture measures are the most important variables among the indicators and indices used. As can be expected from an image with many formal and informal settlements, dwelling density was the most important variable in the classification. In this research, five texture descriptors were calculated using GLCM; together, these form a vector that describes the texture of each segment. The texture measure $GLCM_{contr}$ had the second highest importance of all indicators and was the most important at the settlement level, as shown in **Figure 5**. However, the texture measure $GLCM_{corre}$ indicator has the least impact on the classification at the settlement level, with a relative importance of 12.7%. To map informal settlements layout and other land cover classes, the texture measure $GLCM_{Entro}$ has been used [68], based on Haralick's method [61]. The results from texture measures vary because of textural homogeneity [69]; however, the inclusion of texture information seems to be suitable for the classification of bare soil areas [70]. Previous studies have proved the suitability of the texture parameter in cases involving a clear distinction between roofing extent and other classes, especially vacant land [8], as roof building texture is homogeneous. Such spatial information is essential for risk management and is clearly a major source of information using visual interpretation and image processing [71].

The performance of the indicator 'vegetation' was the most successful, with a 94% accuracy using the NDVI index. This relatively simple measure is successful since vegetation is spectrally distinct from other indicators. Giving such high mapping accuracy across the case study, vegetation is likely to be applicable to any Middle Eastern city. Vegetation typically is not present in informal settlements, appearing on the edge of formal areas or where main highways start. However, the parameter can be seen in the formal areas and outside built-up areas as groups of trees. Significant pockets of vegetation are present in the old informal settlement borders and embedded in informal settlements adjacent to the city centre.

Mapping of the lacunarity of housing structures/vacant land was mainly based on the visible brightness parameter. Lacunarity of housing structures/vacant land was different for the older informal settlements compared to the newer areas. In the older areas close to the city centre, vacant land is often found within existing settlements, whereas in newer informal settlements, which are far away from the city centre, such areas are typically adjacent to them rather than embedded within them. Road segments and accessibility are obvious measures for mapping informal settlements. They are the main characteristics of informal settlements in the Middle Eastern city of Jeddah, allowing them to guide the analysis. However, irregular road patterns in the informal settlements have a low reflectance. Therefore, we incorporated the NDWI index to overcome this, as in [72], as it helps to identify objects with a low reflectance.

At the environ level, indicators were less important and ranked lower than both the settlement and object level indicators with a relative importance between 12% and 20%. Today informal settlements usually occur outside the city centre [8,11], but this has not always been the case. This explains the lack of descriptive capability in the proximity indicator. Additionally, the geomorphology of terrain (DEM) had the least effect on the classification, with a relative importance of less than 5%. This is since the terrain is almost flat, which means that the flood hazard is equally distributed into formal and informal settlements. Identifying informal settlements using terrain geomorphology can be very helpful, especially when informal settlements are within river banks or on steep slopes at risk of landslide [10]. In general, only small improvements were associated with the environ level indicators which did not increase the accuracy of the Quazah district case study (5 Km^2). However, when the spatial scale of analysis was increased to a much larger area (70 Km^2) an improvement in accuracy was noted. However, the environ level indicators have increased the classification accuracy at a landscape or city level [22].

5.2 Segmentation

The success of the image segmentation stage is important and has a large impact downstream on subsequent image processing elements [73]. Segmentation parameters were the same values for

OBIA and object-based ML approaches. However, the segmentation process in object-based ML approach was carried out at the object level with one set of values in performing the analysis; there is no need for different segmentation levels such as in [8,10,13,71] since RF is able to ingest all data at one segmentation level. Using the OBIA approach required expert knowledge in order to transfer informal settlement indicators into local knowledge, and each indicator needs significant localised 'tuning' to map informal areas. In contrast, object-based ML did not require tuning or applying different segmentation levels, although the study area contains diversity in the characteristics of informal settlements.

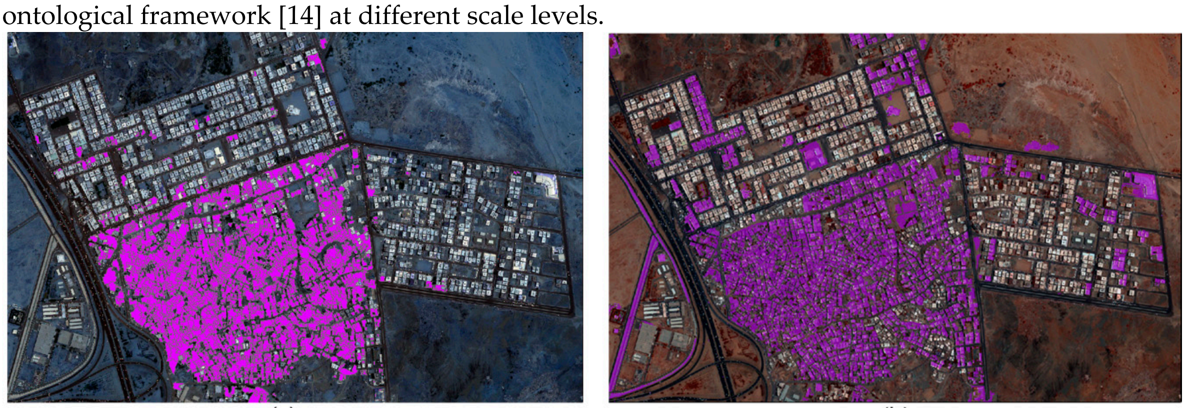
5.3 Comparative Approach: Object-Based ML vs. OBIA

In this section, we assess the performance enhancement gained via our proposed method by comparing the approach presented in this paper to a previous OBIA only approach on the same study area [13]. This is achieved by comparing the results of a previous OBIA based classification of formal and informal settlements for the Quazah district of Jeddah using the same base imagery [13] as shown in **Figure 7**, with the results from this study, as shown in **Table 5** to assess the usefulness of using a hybrid approach.

For the Quazah district case study with 5 Km^2, there was no improvement in the overall accuracy when the object-based ML approach was implemented. However, a marked improvement was noted in the formal settlements identification from 77% to 85% accuracy and road networks from 73% to 95%. Interestingly, these increases in class accuracy are accompanied by decreases in vegetation accuracy from 100% to 60% and vacant land accuracy from 86% to 80%. The OBIA mapping accuracy [13] was then compared with the larger (70 Km^2) city-wide classification performed in this paper (see **Table 5**). At this city-wide scale, the object-based ML approach performed much better, with an overall accuracy of 91% (vs 83% [13]). There was a marked improvement in detecting formal areas using object-based ML, (20%). This improvement contributes to the overall accuracy of the technique. Road segment types and materials in an urban area vary; the road network parameter had the highest improvement at 22% accuracy followed by formal areas with 9% accuracy.

In contrast, there was a slight drop in the accuracy of mapping the vegetation (6%). This could be due to the variation of VHR imagery and implementation of the informal settlement indicators on various spatial levels (object, environment and settlement). However, mapping informal settlements was improved by 1% in the larger case study and 2% in the small case study. This could be for a number of reasons; the complexity of the urban pattern inside informal settlements is a challenge, the spectral similarity between many classes (e.g., roofing extent in the built-up areas and texture measures of the built-up areas) results in classification confusion.

The proposed approach suggests that object-based ML is capable of handling big datasets and was a time-efficient means of enhancing informal settlement mapping accuracy over large areas. The object-based ML approach reported a higher accuracy, as presented in [22], dealing with an ontological framework [14] at different scale levels.



(a) (b)

Figure 7. Panel (a) shows the results of mapping informal settlement using the OBIA approach, while panel (b) presents the final map for the informal settlements using object-based ML.

Table 5. Summary of the accuracy assessment comparison obtained by OBIA approach presented in [13] and OBIA-ML for mapping informal settlements.

compared results	OBIA approach case study 5 Km^2 [13]	OBIA-ML approach case study 5 Km^2	Difference/ improvement	OBIA-ML approach case study 70 Km^2	Difference/ improvement
Formal	77%	85%	8%	97%	20%
Informal	85%	87%	2%	86%	1%
Road network	73%	80%	7%	95%	22%
Vacant land	86%	80%	-6%	95%	9%
Vegetation	100%	60%	-40%	94%	-6%
water body	–	–	–	100%	not comparable
over all accuracy	83%	83%	No differences	91%	8%

5. Conclusion

Mapping informal settlements is crucial for urban risk management. The aim of this study was to analyse the capability of an object-based ML hybrid method to map informal settlements in the Middle East using VHR imagery. This was based on an ontological framework with three different spatial levels. The proposed method of informal settlement mapping, as demonstrated for Jeddah in Saudi Arabia, yields a high level of accuracy. The use of an object-based ML approach for informal settlement mapping proved effective in this challenging Middle Eastern environment, where most of the buildings in formal and informal settlements are constructed from similar building materials. Multi-resolution image segmentation was performed to represent the image components and subsequently, an object-based ML (RF) algorithm was able to classify formal and informal settlements with an overall accuracy of 91%.

The proposed methodological framework was designed to be applicable for the mapping of informal settlement indicators in similar urban contexts in the Middle East. The object-based ML approach using VHR remote sensing imagery does not require parameter optimisation, as the case with OBIA. The hybrid approach attempts to combine the advantages of both the OBIA and ML approaches, to handle the complex built-up environment and variability of VHR imagery.

Parameters at the object and settlement levels have a large impact on classification accuracy while those at the environ level were less important. Incremental improvements in mapping accuracy should therefore be targeting datasets at the object and settlement levels. However, at the case study level in Quazah district, no significant improvement was noted i.e., the two OBIA / object-based ML performed similarly. But, at the city-scale level (70 Km^2) a significant improvement in accuracy were noted by (8%). While previous studies have attempted to map informal settlements using OBIA, the RF algorithm proved to be a useful additional method to map informal settlements particularly at the large area scale.

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