Mapping Urban Slum Settlements Using Very High-Resolution Imagery and Land Boundary Data

Trecia Kay-Ann Williams, Tao Wei, and Xiaolin Zhu

Abstract—**Accurate mapping of slums is crucial for urban planning and management. This article proposes a machine learning, hierarchical object-based method to map slum settlements using very high-resolution (VHR) imagery and land boundary data to support slum upgrading. The proposed method is tested in Kingston Metropolitan Area, Jamaica. First, the VHR imagery is classified into major land cover classes (i.e., the initial land cover map). Second, the VHR imagery and land boundary layer are used to obtain homogenous neighborhoods (HNs). Third, the initial land cover map is used to derive multiple context, spectral, and texture image features according to the local physical characteristics of slum settlements. Fourth, a machine-learning classifier, classification and regression trees, is used to classify HNs into slum and nonslum settlements using only the effective image features. Finally, reference data collected manually are used to assess the accuracy of the classification. In the training site, an overall accuracy of 0.935 is achieved. The effective image indicators for slum mapping include the building layout, building density, building roof characteristics, and distance from buildings to gullies. The classifier and those features selected from the training site are further used to map slums in two validating sites to assess the transferability of our approach. Overall accuracy of the two validating sites reached 0.928 and 0.929, respectively, suggesting that the features and classification model obtained from one site has the potential to be transferred to other areas in Jamaica and possibly other developing Caribbean countries with similar situation and data availability.**

Index Terms—**Classification and regression trees (CART), Jamaica, object-oriented classification, slum settlements, very high-resolution (VHR) image.**

I. Introduction

URBAN living is typically associated with higher levels of literacy and education, better health, and easier access to social services [1]. While offering opportunities, urbanization also brings about problems, such as deterioration of physical, economic, and social living conditions [2]. The problems associated with urbanization can be worse, especially for developing countries, such as those in the Caribbean, compared with more developed countries that are more equipped with resources to deal with the effects of urbanization. With limited resources and places to live, urban slum settlement is one of the global problems associated with urbanization [3]. The number of inhabitants of slum settlements is expected to grow to 889 million by 2020 [4]. Plans, policies, and resources are needed to alleviate this urban problem. Effective planning decisions for slum upgrading require timely and comprehensive mapping of slum settlements [5], [6].

Traditional methods of mapping slum settlements are based on census data and participatory approaches. Census data can be used to create a quantitative index in enumeration districts to identify slums [7], map urban poverty [8], and identify slum settlement spatial patterns [9]. In developing countries, the interval between consecutive census collections are typically long. For example, Jamaica's housing and population census is collected every ten years [10]. In this case, such long lag data are impossible to provide timely and updated information for slum mapping. Another problem with the census-based approach is that the quantitative data are collected in enumeration districts. The heterogeneity and diversity existing within these districts are normally averaged out at district scale [11], [12]. The participatory approach georeferences the collected information (e.g., household conditions, infrastructure, service provisions, physical characteristics) to produce a map of the slum settlements [13], [14]. Although the participatory approach can offer comprehensive and multidimensional data (socio-economic, physical, and legal conditions of the target slums) [15], such details can be subjective, costly, and time-consuming to collect, which makes it ineffective to map slums in developing countries, for example Jamaica [16] and Indonesia [17].

As an alternative to traditional fieldwork approaches, remote sensing provides mapping methods that offer timely spatial data covering extensive urban areas and, thus, are cost-effective [17]. Given the increased availability of high-resolution images (HRI), remote-sensing-based approaches to slum mapping have increased in recent years. Optical systems are more widely used (e.g., [18]–[20]). Radar systems have been increasingly used in slum mapping (e.g., [21] and [22]). Given the higher spatial resolution of recent sensors, physical characteristics of slums are analyzed to identify slum and nonslum settlements

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[18]. Incorporating the major slum dimensions, that is, the socio-economic, legal, and physical aspects, would aid in better understanding slum formation, dynamics, and growth [3]. However, for the purposes of slum mapping, previous studies achieved satisfactory classification results by only using slum's physical characteristics [3], [17].

Without a universal slum definition [3] and varying physical characteristics, slums remain a diverse and complex phenomenon across continents, within countries, and within cities [24]. Parameter settings of similar morphological indicators for mapping [25] as well as context [26] of target slums are almost always needed. Attempts have been made to gain knowledge of global understanding of slum morphology [24] and ontology [27]; however, there are limited data in the most urbanized areas of the developing world, Latin America, and the Caribbean [28]. These highly important cities have been widely ignored for studying slums by the literature. Few studies have started the mapping process by researching the physical slum characteristics in the area of interest then converting the characteristics to image-based features [29], [30]. Knowledge of target slum settlements is essential to prevent misinterpretations of slum physical characteristics that can lead to misclassifications.

Various image analysis features have been used to describe the physical characteristics of slum settlements. Size, density, and layout pattern of the urban morphology [29], [31], [25], [19], composition and configuration of the landscape patches [32], texture and spectral layers [20], [29], vegetation patch compactness, connected road ratio, profile convexity [29], and other contextual features [18], [26] are some of the features used in previous studies. Similarly, there are numerous image analysis methods, such as visual interpretation, object-based image analysis (OBIA) [33], texture-based approaches [34], and machine learning (ML) [35], that have been applied to slum mapping. ML has shown better slum classification accuracy, and the OBIA method is most popular [23] and useful for morphology analysis of slums at varying analysis scales and developing contextual classification features [18], [26], [36].

Using OBIA, the image is segmented into homogeneous spatial units (or objects) based on similar spectral, texture, and/or spatial properties of neighboring pixels [37], and the information may be extracted at varying hierarchal levels (object and/or areal level) [19]. ML classifiers can handle a large pool of image features to capture the multidimensional aspects of the physical characteristics of slums [29]. Commencing with the physical characteristics and then developing corresponding image-based features allows the interpreter to develop systematic rulesets through cognitive network language (CNL) [38] and train ML classifiers [29] to analyze and classify the image objects as a human would interpret the real world. Combining OBIA at varying hierarchal levels with ML facilitates the utilization of the pros of each method to map slums and is a needed approach for improved slum mapping [23], [17], though limited research is available on this approach.

Existing methods using HRI to map urban slum settlements have two limitations. First, most studies do not analyze how the mapped boundaries of slum settlements can support slum upgrading projects. Actually, it was not until recently in [17] the results of slum mapping using ML were analyzed to support slum upgrading. Some of the main purposes of slum mapping is to delineate slum boundaries, store the mapped settlements and their attributes in a slum geodatabase [39], [40] and to support slum upgrading [16] and slum policy development [16], [41]. The mapping unit (i.e., homogeneous unit in OBIA at the areal scale) used in existing methods does not match the need of slum upgrading projects. Studies have used building blocks derived from a street network or arbitrary image segmentation for the extraction of homogeneous units [20]. However, building blocks from street networks are often larger than slum settlements, and the result of uncontrolled image segmentation do not follow boundaries that are propolicy development for slum upgrading projects. A land boundary layer that has attributes of land registration and valuation information provides key information needed in slum upgrading projects at various stages, such as the policy framework (land registration and ownership), technical and environmental options (parcel of lands occupied by slum settlements, identification of marginal lands, land readjustment/consolidation), and economic analysis (land value and market) [4], [40]. A land boundary layer can control the segmentation process to create slum boundaries that are conducive to practical slum upgrading, that is, the mapping spatial unit would follow actual land boundaries; hence, the boundaries of mapped slum settlements would be delineated along land boundary lines. In addition, a recently critical review of slum mapping also suggests that the integration of remote sensing data and other geospatial data can improve slum mapping [42]. Therefore, this article will explore the effectiveness of integrating land boundary data into the slum mapping process.

The second limitation is that existing studies mainly use traditional image features but ignore contextual features that take advantage of unique or local slum characteristics not represented by traditional image features. Traditional image features include spectral and textural features. For example, textural features from gray-level co-occurrence matrix (GLCM) developed by Haralick *et al.* [34] have been combined with spectral bands to separate slum settlements from nonslum settlements [19], [25], [31]. However, besides these traditional image features, slum and nonslum settlements have difference in terms of physical context features, which capture the landscape arrangement and association between objects in a settlement and between settlements and their environment [27]. For example, slum settlements may be along major roads in the form of linear developments or are closer to hazardous locations than nonslums. Caribbean countries are typically left out of slum mapping research [23], and therefore local knowledge of slum characteristics in this region is of importance to the global need for information on slum formation, upgrading, and monitoring. These additional context features can assist in identifying slum settlements from high and very high-resolution (VHR) images, especially for those slum settlements with diverse physical characteristics and have never been mapped using high and VHR images and therefore traditional features may not be sufficient. It is for this reason that in [27], the study emphasized the development of local ontology of slums using local physical characteristics from expert interviews or field surveys for local slum mapping. Unfortunately, only a few studies attempted to use local context features (for e.g., [26], [29], and [43]), and/or the selection of context features were limited due to the data availability. Therefore, this article will explore the use of context features related to the definition of the target slum settlements and using a cognitive approach in an ML classifier for slum mapping in the Caribbean region.

To address abovementioned limitations, this article presents an approach based on ML and hierarchical OBIA to map urban slum settlements using land boundary data and multiple features derived from VHR images. This proposed approach was tested in the Kingston Metropolitan Area (KMA), Jamaica, where there is limited knowledge on slum settlements, slum settlements have never been mapped using remote sensing approaches, and land boundary data are readily available. The results of this article may be transferred to other regions of the KMA and be used to support the development of effective and sustainable plans, policies, and decisions on slum upgrading in the metropolitan area.

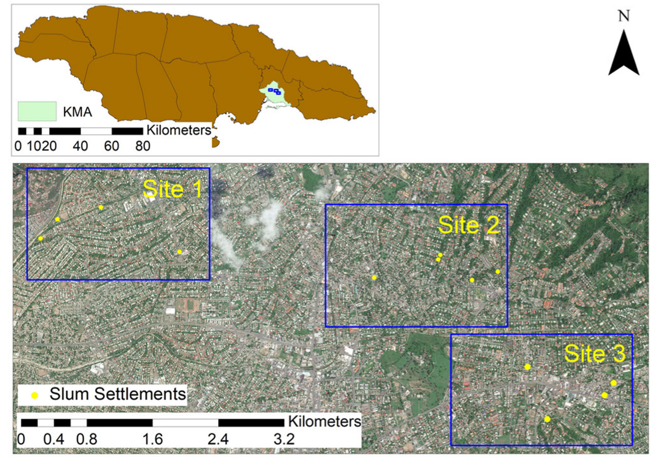


Fig. 1. Location map of study sites 1, 2, and 3: The three rectangles represent the three sites analyzed in this article. Yellow points are the location of slum settlements surveyed in 2008 and 2017.

II. Study Area and Data

KMA is comprised the parish of Kingston and a section of St. Andrew, Jamaica (18˚N and 77˚W). The population of the KMA is 584 627 representing 88% of the total population of Kingston and St. Andrew (UN-Habitat, 2016). KMA spans approximately 181 Sq. km and is relatively flat. It is the center for manufacturing, commerce, government, finance, entertainment, and the main transport terminus for the country.

Jamaica is one of the countries involved in the United Nations' Participatory Slum Upgrading program. The program is aimed at meeting the Millennium Development Goals and Vision 2030 to create sustainable urban centers, including urban renewal and upgrading by 2030 [44] and develop a national policy on slum settlements [41]. The earliest phase of the program resulted in a rapid assessment of the slum settlements in the country. In most Jamaican slum settlements, there are dumps and burning for garbage disposal and poor or nonexistent physical infrastructure (for example, lack of proper sewage disposal facilities). In 2008, there were approximately 754 slum settlements recorded in Jamaica. Twenty percent of Jamaica's population resides in slum settlements, 35% of these settlements are in urban areas, and 66% of settlements have been in existence for more than 20 years. Kingston and St. Andrew have the largest number of slum settlements in Jamaica [16].

The report from the participatory approach to slum mapping in Jamaica provided insufficient data for policy development as the policy is still nonexistent in the country. The Squatter Management Unit (SMU) of the Ministry of Housing, Jamaica, is once again attempting to map the slum settlements to populate the national slum geodatabase [39] to develop the long awaited national policy on slum settlements [41]. From expert interviews with representatives from the SMU and the report on the existing slum settlements only point locations of squatter settlements exist, the slum geodatabase remains unpopulated, and not all slums were assessed because of the time, security, and financial constraints to enter each slum. Additionally, there is still a need for comprehensive mapping and analysis using spatial technologies. The SMU requires a method that maps the areal extent/boundaries of slums and provides an alternative to going into possibly unsafe environs. Currently, there is limited spatial information on the present state of slum settlements in the country, and there is a need to integrate imagery in the mapping of slum settlements for the development of policies on slum upgrading [16]. From expert interviews and the study done in [16], a local slum ontology [27] (later described in the methodology) is developed to map slum settlements in the KMA.

Considering the cost, size, and high computational requirements to process VHR images, three pilot sites in KMA are selected in this article to assess the feasibility of the proposed approach for mapping slum settlements. Sites 1, 2, and 3 are 3.02, 3.30, and 2.99 Sq. km, respectively (see Fig. 1). Site 1 is used to train the classifier, determine the most useful features in slum mapping, and, therefore, develop the classification model. Sites 2 and 3 are used to assess the transferability of the classification model to other regions of the KMA. All sites are chosen based on the availability of field-surveyed location of slums. Only 2008 and 2017 field-surveyed points that represent location of slum settlements from the SMU and Jamaica's National Spatial Data Management Division (NSDMD) could be sourced, as the national slum geodatabase remains unpopulated.

2015 VHR World Imagery from Global Mapper with red, green, and blue (RGB) bands and a resolution of 0.5 m covering the three sites are used in this article (see Fig. 1). In the image, the physical characteristics of slum and nonslum settlements can be clearly visualized (see Fig. 2). In addition, the land boundary layer with attributes of registration number and valuation number was sourced at the National Land Agency of Jamaica. The land boundary layer is also used as the thematic layer for road and gully classification (further explained in Table I). Line shape files of gullies and roads were also obtained from Jamaica's NSDMD.

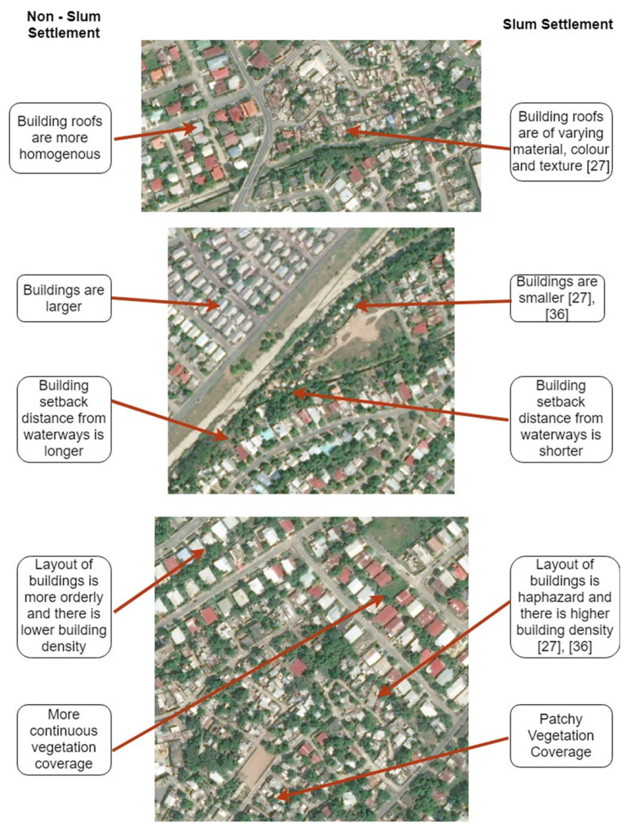


Fig. 2. Physical characteristics of slum and nonslum settlements visualized in VHR imagery.

TABLE I
SUMMARY OF RULESETS FOR LAND COVER CLASSIFICATION

Classification Steps	Ruleset
1. Classify Road, Cloud Cover, Gully	Multiresolution segmentation using thematic layers, land boundary layer and cloud cover Overlap the gully, road, cloud cover thematic layer = gully, road, cloud cover respectively
2. Classify Shadow, Vegetation	Multiresolution segmentation, scale 40, shape 0.3, compactness 0.5
	Mean R < 85 = shadow On shadow Mean B > 39.5 = vegetation On Vegetation Green Ratio (GR) < 0.382 = shadow On shadow Brightness > 82.5 = dull vegetation On dull vegetation GR < 0.365 = unclassified Dull Vegetation = Vegetation
3. Classify Built Up	Multiresolution segmentation, scale 150, shape 0.3, compactness 0.5
	On unclassified Mean GLCM Entropy Blue > 7, Brightness > 153 = built up On unclassified GR < 0.3442 = low GR built up On low GR built up GR > 0.33 = high GR built up On high GR BU Mean GLCM Entropy Blue < 6 = Other On other Red Ratio < 0.3 = built up On unclassified GR > 0.37, RR < 0.3 = built up On unclassified = other On high GR built up, low GR built up = built up

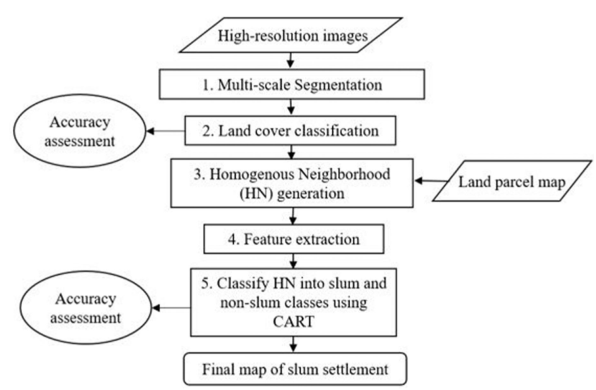


Fig. 3. Flowchart of the proposed method for mapping slum settlements.

III. METHODOLOGY

This study uses ML and hierarchical OBIA to map slum settlements. The proposed method involves five major steps (see Fig. 3). First, multiscale segmentation was applied to VHR images to obtain homogenous objects. Second, the homogeneous objects are classified into five land cover classes. Third, the land parcel map (land boundary layer) is used to segment the image into parcel objects, which are then combined with texture and spectral features to create homogeneous neighborhoods (HNs), i.e., the areal units of slum and nonslum neighborhood's. Fourth, based on the physical characteristics of slums, image features are extracted for each HN. Finally, classification and regression trees (CART), an ML model, is used to classify all HNs into slum and nonslum classes after training with reference samples of nonslum and slum HNs. Details of each step are provided below.

A. Multiscale Segmentation

It has been shown in [45] that OBIA method can generally provide higher accuracies in land cover mapping using HRI than pixel-based methods. Therefore, the OBIA method was used in this article to map land cover types. The formation of objects of different land cover classes (e.g., buildings, road, and vegetation) in a VHR image depends on scale and shape [46], [47]. Image object boundaries created at a single scale is not able to totally encompass or represent all land surface features. Therefore, multiscale segmentation is implemented in this article to segment the VHR image into objects at varying scales for classification [47]. Scales for segmenting different major land surface objects listed in Fig. 4 are based on experiments in site 1, as no universal optimal scales exist from existing studies [25], [48]. Another option for scale selection is presented in [49]; however, these scales selected by experiments can also segment objects well in the testing sites 2 and 3, which suggest that these scales are appropriate.

Fig. 4. Multiscale segmentation of VHR images to create objects at different levels.

(a) (b)

Fig. 5. (a) Subset of parcel polygons (yellow lines). (b) Its corresponding segmentation of HNs (blue lines) at site 1.

B. Land Cover Classification

The CNL in eCognition provides a graphical environment for users to test, refine, and fine-tune the classification workflow in a rule-based expert system [47]. CNL is used to create rules that define characteristics of objects belonging to a specific class. These characteristics go beyond spectral properties of image objects to include spatial components [38] and context [37]. In this article, rules given in Table I were used to classify the objects from multiscale segmentation into meaningful land cover types, including road, cloud cover, gully, built-up, vegetation, shadow, and other class (i.e., unlabeled class, mainly dirt patches).

C. HNs Generation

HNs are used in this article as the spatial unit to map slums and nonslum settlements. The characteristics for the development of the HNs are synonymous to the concept of homogeneous urban patches described in [50] and [51] and more recently in [20]. As previously explained, one of the main purposes of mapping slum settlements is to support slum upgrading projects and policies by delineating useful slum boundaries in a timely, cost-effective, and safe manner [16]; therefore, this article proposes a mapping unit that satisfies this need by using a land boundary layer to create HNs.

To obtain HNs, the land parcel map [see Fig. 5(a)] is used as a thematic layer in eCognition to segment the VHR imagery. Nonresidential parcels are excluded from the HN creation. Specifically, industrial and commercial parcels are removed based on the context of them having larger and brighter building objects. Recreational parcels are also identified and removed if the area of the vegetation and other classes are larger than a specified threshold. For the HN generation, texture and spectral layers are extracted from segmented objects at scale 150, as shown in Fig. 5.

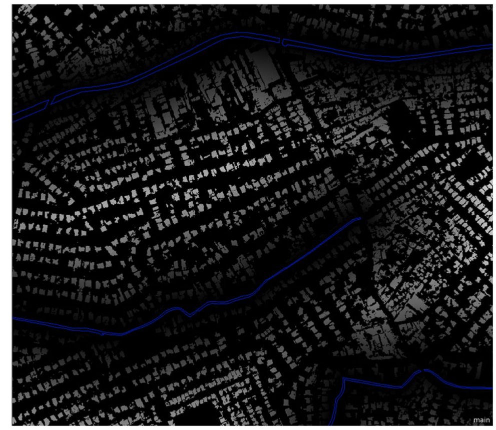


Fig. 6. Subset of distance map at site 1. Darker shade indicates shorter distance to the nearest gully.

Texture layers include GLCM homogeneity, contrast, entropy, and standard deviation. These texture layers along with the spectral layers are used to join land parcels that are homogeneous at a scale of 325 to create the HNs above the parcel level [see Fig. 6(b)]. In this process, texture layers are given a higher weighting than the spectral layers because the characteristics of HNs can be better captured by texture than spectrum. Texture layers have been shown to improve the separation of slum and nonslum HNs when added to spectral layers (see example presented in [20]). Using the land parcels to create the HNs, minimized the boundary problem described in [20], where one neighborhood that appears as an entity would split into small objects because of texture differences within the neighborhood. In addition, the HN boundaries created are policy relevant and practical in slum upgrading projects for land development, since the boundaries of slum HNs represent actual land boundaries. The temporal inconsistency between imagery and land boundary data may not lead to large errors in slum settlement mapping because the HNs are created by combining several neighboring land parcels that have similar spectral and textural characteristics so that any land boundary changes, such as division or integration of parcels, may not affect the HN extraction.

D. Feature Extraction

Local knowledge of slum characteristics is important for accurately mapping slum settlements [27]. From expert interviews and government report [16], knowledge of the local slum characteristics in the study area is acquired. In addition to the report and interviews, from literature review and visual inspection of the location of the reference slum settlements, additional physical characteristics can be interpreted from the VHR images (see Fig. 3). The characteristics are grouped according to spatial levels [19]. To map slums from the VHR image, characteristics in the image that would indicate each physical description

TABLE II
LOCAL SLUM ONTOLOGY

Spatial Level	Physical Description	Indicator	Image Feature
Object Level	Construction material of roof is mixed or old, varying roof colour	Building Roof Characteristics [27]	Spectral Layers Texture Layers
	Houses are smaller	Building Size Characteristics [27]	Area Metrics
	Houses are irregular shaped	Building Shape Characteristics [27]	Shape Metrics
Settlement Level	Less orderliness of houses in the settlement	Layout of Buildings [27], [36]	Aggregation Metrics Diversity Metrics
	More building coverage	Density of Buildings [27]	Building Density Metrics
	Vegetation is patchy because of the haphazard house layout	Continuity of Vegetation	Vegetation Density Metrics Extent of Vegetation Patches
Environment Level	Setback distances of buildings to waterways are shorter	Edge distance from waterways to Building	Distance Map

Note: Physical descriptions of local slum settlements at three spatial levels and their corresponding indicators and image features.

TABLE III
LIST OF LANDSCAPE METRICS EXTRACTED FOR SLUM CLASSIFICATION

Slum Conditions	Metric Name	Formula
Land Cover Layout: Slums display disorderlines s in the arrangement	Contagion Index	$CONTAG = \left\{1 + \left[\frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[P_i * \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right] * \left[ln\left(P_i * \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]}{2\,ln(m)}\right] * 100\right\}$
	Aggregatio n index	$AI = \left(\frac{g_i}{max \ \to g_{ij}}\right) * 100$
of land cover objects	Shannon's diversity index	$SHDI = -\sum_{i=1}^{m}(P_i * lnP_i)$
	Simpson's diversity index	$SIDI = 1 - \sum_{i=1}^{m} p_i^2$
	Shannon's evenness index	$SHEI = \frac{-\sum_{i=1}^{m}(P_i * lnP_i)}{lnm}$
	Simpson's evenness Index	$SIEI = \frac{1 - \sum_{i=1}^{m} p_i^2}{1 - \left(\frac{1}{m}\right)}$
Shape: the extracted roof coverage displays complex shapes	Shape Index	$SHAPE = \frac{.25p_{ij}}{\sqrt{a_{ij}}}$
	Landscape Shape Index	$LSI = \frac{.25\sum_{k=1}^{m} e_{ik}^*}{\sqrt{A}}$
	Fractal Dimension Index	$FRAC = \frac{2ln(.25p_{ij})}{lna_{ij}}$
Density: Slum patches will have a higher density than non-slum areas.	Edge density	$ED = \frac{\sum_{k=1}^{m} e_{ik}}{A} * 10{,}000$
	Patch Density	$PD = \frac{n_i}{A} * 10{,}000 * 100$
	Patch Richness Density	$PRD = \frac{m}{A} * 10{,}000 * 100$
Size: The size of building patches in a slum is larger since the buildings are clustered together	Patch Area Mean	$MN = \frac{\sum_{j-1}^{n} x_{ij}}{n_i}$
	Patch Area Standard Deviation	$SD = \sqrt{\frac{\sum_j^n = 1\left[x_{ij} - \left(\frac{\sum_j^n = 1x_{ij}}{n_i}\right)\right]^2}{n_i}}$
	Landscape Division Index	$DIVISION = \left[1 - \sum_{j=1}^{n}\left(\frac{a_{ij}}{A}\right)^2\right]$
	Mean patch radius of gyration	$\mathrm{GYRATE} = \sum_{r=1}^{z}\frac{h_{ijr}}{z}$
	Effective mesh size	$\mathrm{MESH} = \frac{\sum_{j=1}^{n} a_{ij}^2}{A} * \left(\frac{1}{10{,}000}\right)$
	Splitting index	$\mathrm{SPLIT} = \frac{A^2}{\sum_{j=1}^{n} a_{ij}^2}$
	Percentage of Landscape	$\mathrm{PLAND} = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} * 100$

Note: P_i is proportion of the landscape occupied by patch type (class) i, g_{ik} = number of adjacencies (joins) between pixels of patch types (classes) i and k based on the double-count method, m = number of patch types (classes) present in the landscape, including the landscape border if present, g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method, max-g_{ii} = maximum number of like adjacencies (joins) between pixels of patch type (class) i (see below) based on the single-count method, a_{ij} = area (sq. m) of patch ij, A = total landscape area (sq. m), p_{ij} = perimeter (m) of patch ij, $e{*}ik$ = total length (m) of edge in landscape between patch types $*$ (classes) i and k; includes the entire landscape boundary and some or all background edge segments involving class i, e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i, n_i = number of patches in the landscape of patch type (class) i, x_{ij} = patch size, h_{ijr} = distance (m) between cell ijr [located within patch ij] and the centroid of patch ij (the average location), based on cell center-to-cell center distance, z = number of cells in patch ij.

were determined, and corresponding image analysis features are identified to create a local slum ontology (see Table II). All image features in Table II are grouped into three sets: spectral and texture layers, landscape metrics, and distance map. Subsequent sections provide details of these three sets of features.

1) Spectral and Texture Features: Spectral and texture features associated with building roof characteristics are used as the first set of features for slum classification. In each HN, mean values of the red, green, and blue bands are used as the spectral features, and the variables generated from GLCM are used as texture features. The spectral and texture features are derived from the building class described in Section III-B and aggregated to each HN.

2) Landscape Metrics: Landscape metrics are used as the second set of features for slum classification based on building area and shape characteristics, layout of buildings, building density, and continuity of vegetated surface. Landscape metrics are computed for each HN. Table III lists the landscape metrics based on the slum descriptions. All landscape metrics are calculated using the open source software, Fragstats [52].

3) Distance Map: Considering that slums are often situated on marginal lands, such as areas closer to gullies, the distance of each building to the nearest gully is used as a feature to identify slum settlements. A subset of the distance map is shown in Fig. 6.

E. Slum Classification and Transferability of Classification Model

The supervised ML algorithm, CART classifier, is used to classify HNs into slum and nonslum settlements. Given input features and training samples, CART uses the most powerful feature to separate observations. The tree creates more branches using the input features to determine which class each observation belongs to. The branching of the tree continues until a terminating node is reached, that is, a final decision of which class an observation belongs to [35]. Advantage of this method is that we can easily interpret the results and know the important features and their thresholds from the output of the decision tree.

All three sets of features (i.e., spectral and texture features, landscape metrics, and distance map) are inputs of the CART classifier. The texture and spectral features are used solely in the CART classifier, then the landscape metrics only, followed by a combination of all three sets. This is done to analyze the effect of adding context features on traditional image-based features (spectral and texture features) and demonstrate the effect of developing a local slum ontology [27], [30]. To investigate which set of features are more effective for mapping slum settlements, the results using a single set of features was compared with the results using all three sets of features. The CART classifier is trained in site 1 using samples of 41 slum HNs and 141 nonslum HNs. The field-surveyed points (see Fig. 1) are used as a reference to create HN training samples. Since the surveyed location of slums are points, the HNs within the vicinity of the point location were identified as slum HNs if they visually fit the local ontology in Table II. HNs that visually appear to be the opposite of the slum HNs are used as the samples for the nonslum HNs. The trained CART model is then used to classify all HNs in site 1 into slum and nonslum HNs. Inputting all features in the CART model allowed the algorithm to select the most important features to differentiate slum HNs from nonslum HNs in the form of a decision tree [29].

Since small isolated slum HNs unlikely exist in reality, a postclassification process, i.e., the majority rule, can further filter out the errors in the slum classification map. To further explain, since the landscape metric feature, edge density (ED), is area dependent, small nonslum HNs can have a high density comparable with slum HNs; therefore, filtering out small isolated slum HNs can improve the classification accuracy.

To test the transferability of the decision tree from site 1 to other regions in the KMA, the classification model is applied to sites 2 and 3. Sites 2 and 3 also contain field-surveyed slum points that can be used to create the HN validation samples to assess the transferability of the classification model to other regions of the KMA.

F. Accuracy Assessment

To assess the accuracy of the slum classification in site 1, the validation samples (i.e., HN polygons) are selected by visually inspecting the VHR imagery, and those samples were not used to train the CART model. The slum HN validation samples for sites 2 and 3 are selected based on the field-surveyed slum locations, that is, the HNs within the vicinity of the point location that visually fit the local slum ontology in Table II are identified as slum HNs. The HNs that visually appear to be the opposite of the slum HNs are used as the validation samples for the nonslum HNs. Accuracy indices, including overall accuracy, kappa coefficient, user's and producer's accuracy derived from

Fig. 7. Land cover classification of site 1.

TABLE IV
ERROR MATRIX AND ACCURACY ASSESSMENT OF THE LAND COVER CLASSIFICATION AT SITE 1

Classification	Ground reference (Objects)				Total	ua
	Other	Shadow	Vegetation	Built-up		
Other	19	0	0	0	19	1.000
Shadow	0	115	1	1	117	0.983
Vegetation	3	19	122	0	144	0.847
Built-up	4	0	1	140	145	0.966
Total	26	124	124	141		
pa	0.731	0.858	0.984	0.993		

Note: Overall accuracy = 0.932; kappa coefficient = 0.902.

the error matrix by the HN samples in eCognition, are used to assess the classification accuracy [47].

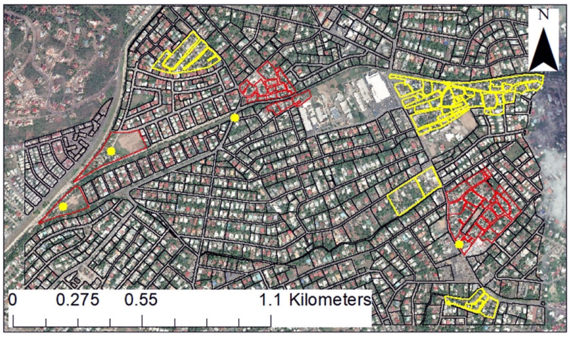
IV. Results and Discussion

A. Land Cover Classification at Site 1

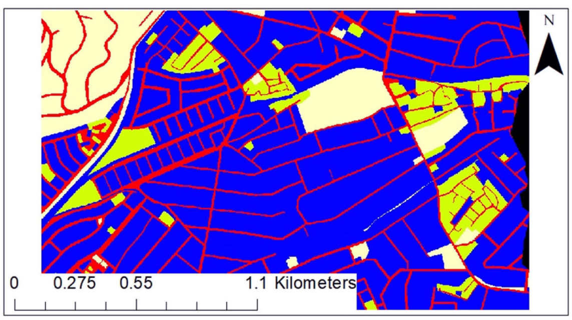
The land cover classification map is shown in Fig. 7. The quantitative accuracy assessment shows an overall accuracy of 0.932 and kappa index of 0.902 for the land cover classification. The user's and producer's accuracy are both higher than 0.96 for the built-up class (see Table IV). The high accuracy in land cover classification suggests that it is reliable to be used for the consequent slum classification. By inspecting the results, some parking lots near the buildings were misclassified as buildings. To avoid the influence of this misclassification on the slum mapping, manual corrections are done. It should be noted that the misclassification of parking lots could be mitigated in future studies if Lidar data or high-resolution digital surface model is available in the country.

B. HN Generation

The generated HNs represent homogeneous morphological neighborhoods of slum and nonslum settlements (see the example in Fig. 5). The chosen scale of 325 has two effects on



(a)



(b)

Fig. 8. (a) Map of all slum settlements at site 1. (b) Classification map using all three set of features.

the segmentation when creating the HNs. The scale resulted in even the smallest slums being sufficiently separated from a nonslum, a limitation outlined in [20] but larger neighborhood's that have similar texture and spectral properties are subdivided into two or more neighborhoods. However, the scale of the segmentation is sufficient for slum classification, as shown in subsequent sections.

When slum upgrading projects are undergoing, a land surveyor is needed for land boundary information. Given that the HNs created are based on parcel boundaries then the land boundaries that are affected by slum settlements can be explicitly determined. The advantage of the slum settlements adhering to the land boundaries is therefore "slum-upgrading friendly." Knowing the parcels affected by slums, the land registration status, the valuation, and registrations numbers are known from the attributes of the land boundary layer. The owners, adjoining owners, land value, and registration status are all prerequisites of any land development and, therefore, any slum upgrading project. In addition, this information can be maintained in the slum geodatabase.

C. Slum Classification at Site 1

Fig. 8(a) shows the reference map of slum settlements of site 1, and Fig. 8(b) shows the classification map using the CART

TABLE V
ERROR MATRIX AND ACCURACY ASSESSMENT OF THE SLUM CLASSIFICATION AT SITE 1 USING ALL THREE SETS OF FEATURES

Classification (Objects)	Ground Reference (Objects)		Total	User Accuracy
	Non-Slum Neighbourhood	Slum Neighbourhood		
Non-Slum Neighbourhood	123	8	131	0.939
Slum Neighbourhood	3	34	37	0.919
Total	126	42		
Producer Accuracy	0.976	0.810		

Note: Overall accuracy = 0.935; kappa coefficient = 0.818.

classifier and all the three sets of features (spectral and texture features, landscape metrics, and distance map). In site 1, the reference slum HNs (41 red polygons) in close proximity to the field-surveyed slum location (yellow points) are samples for training. The slums that have similar appearance to the reference HNs, that is, the slum HNs in yellow and without field data, are samples for validation (42 polygons). Using nonfield-surveyed HN for validation still requires field inspection because slum and nonslum can be visually similar; however, the accuracy of the classification model is further tested against field surveyed slum locations when transferred to sites 2 and 3. The overall accuracy of the slum classification at site 1 is 0.934 and kappa coefficient is 0.818 (see Table V), which suggests that the features are useful to achieve acceptable slum classification results in the study area. Nonslum HNs are misclassified because they contain buildings with similar texture and spectral properties to slum HNs. The misclassified nonslum HNs is also attributed to those HNs that contain buildings with roofs of various colors, and during segmentation each roof color would be segmented as individual objects hence increasing the density of buildings in the nonslum neighborhood and resulting in the nonslum HN being misclassified as a slum HN. Nonslum HNs were misclassified using the landscape metrics because of those HNs where the building roof has similar spectral properties to the driveway (or walkway), and, therefore, when segmented, the shape of the roof is more irregular than it actually is resulting in the misclassification. The producer's accuracy of slum settlements is 0.810, indicating some slum settlements are omitted in the classification. In site 1, after applying postclassification rule described in Section III-E the overall accuracy increased to 0.994, kappa coefficient to 0.984, and the user's and producer's accuracy of slum settlements to 1 and 0.976, respectively.

Fig. 9 shows the decision tree from the CART classifier model applied to site 1 using all three sets of features. Only five features are important in the classification process, and these five features are from all the three sets. This implies that the target slum is a diverse phenomenon that can be described by various physical dimensions. The important image features for slum classification in site 1 are ED, aggregation index, texture and spectral properties, distance map, and landscape shape index, suggesting that building roof and shape characteristics, layout

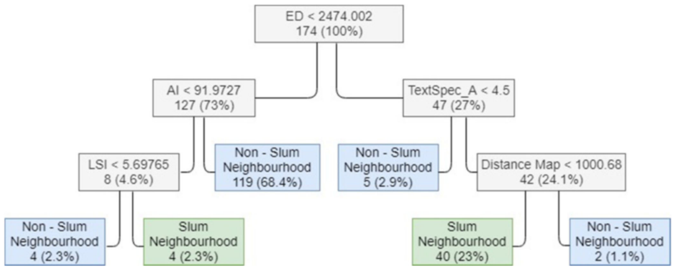


Fig. 9. Threshold of the most important features using all three sets of features: ED = edge density, AI = aggregation index, TextSpec_A = texture and spectral layers aggregated, and LSI = landscape shape index.

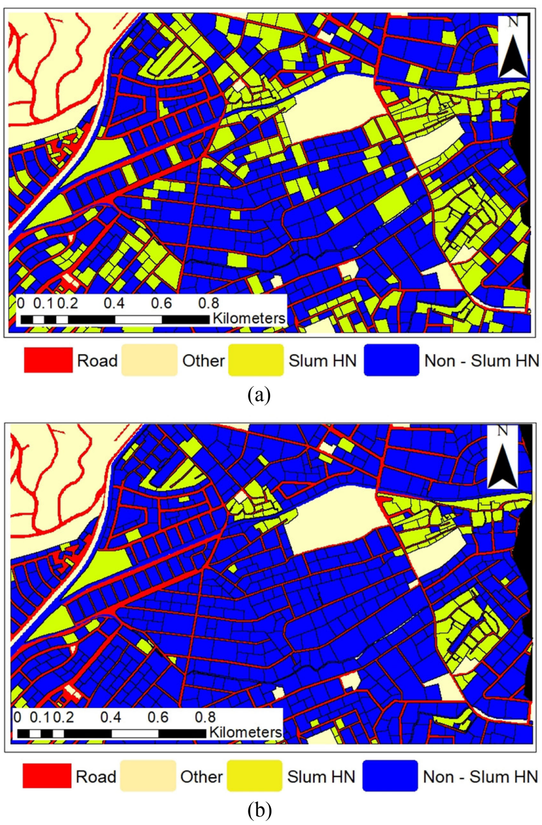


Fig. 10. Slum settlement classification using (a) only spectral and texture features and (b) only landscape features.

of buildings, building density, and distance from building to gullies are useful indicators of slum settlements in the study area.

Fig. 10(a) and (b) shows the slum classification using only spectral and texture features and only landscape features, respectively. Their accuracy assessment is listed in Table VI. Compared with the reference map shown in Fig. 8(a), both classification results have significant errors. In the classification map using only spectral and texture features [see Fig. 10(a)], majority of the slum HNs were accurately classified (producer's accuracy 0.952), indicating that building roof characteristics is a useful indicator of slum neighborhoods. The classification accuracy using the landscape metrics [see Fig. 10(b)] is higher than that of the classification accuracy using the spectral and texture features

TABLE VI
ACCURACY ASSESSMENT OF SLUM SETTLEMENT CLASSIFICATION USING ONLY SPECTRAL AND TEXTURE FEATURES AND ONLY LANDSCAPE METRICS FEATURES

	Overall accuracy	Kappa coefficient	Producer's accuracy of slum	User's accuracy of slum
Using spectral and texture features	0.845	0.649	0.952	0.625
Using landscape features	0.911	0.752	0.762	0.865

TABLE VII
ERROR MATRIX AND ACCURACY ASSESSMENT OF THE LAND COVER CLASSIFICATION AT SITE 2

Classification	Ground Reference (Objects)				Total	User Accuracy
	Other	Shadow	Vegetation	Built-up		
Other	19	0	0	11	30	0.633
Shadow	0	170	6	4	180	0.944
Vegetation	2	0	160	0	162	0.988
Built-up	8	0	0	249	257	0.969
Total	29	170	166	264		
Producer Accuracy	0.655	1	0.964	0.943		

Note: Overall accuracy = 0.951; kappa coefficient = 0.928.

TABLE VIII
ERROR MATRIX AND ACCURACY ASSESSMENT OF THE LAND COVER CLASSIFICATION AT SITE 3

Classification	Ground Reference (Objects)				Total	User Accuracy
	Other	Shadow	Vegetation	Built-up		
Other	32	0	1	10	43	0.744
Shadow	0	173	6	0	179	0.966
Vegetation	1	6	120	9	136	0.882
Built-up	2	0	0	99	101	0.980
Total	35	179	127	118		
Producer Accuracy	0.914	0.966	0.945	0.839		

Note: Overall accuracy = 0.923; kappa coefficient = 0.891.

[see Fig. 10(a)]. This suggests that the spatial composition and configuration of the building and vegetation is a more useful indicator in slum mapping than the building roof characteristics in the study area. However, using the three sets of features simultaneously in the CART model captures the diversity of the slums best in the study area.

D. Transferability of the Classification Model

The error matrix for accuracy assessment for the land cover classification of sites 2 and 3 is listed in Tables VII and VIII, respectively. The overall accuracy reaches 0.951 and 0.923 and kappa coefficient is 0.928 and 0.891 in sites 2 and 3, respectively. The accuracy results suggest that the CNL developed for land cover classification in site 1 can be transferred to other regions in the KMA. Additionally, given that an RGB imagery is used in this article, an additional near infrared band and digital surface model in future studies may improve classification accuracy.

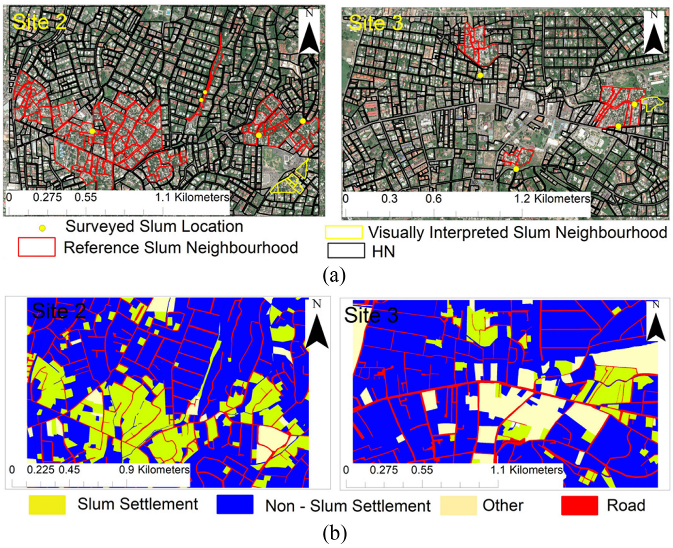


Fig. 11. (a) Reference map of all slum settlement at sites 2 and 3. (b) Classification map using the decision tree at sites 2 and 3.

TABLE IX
ERROR MATRIX AND ACCURACY ASSESSMENT OF THE SLUM CLASSIFICATION AT SITE 2

Classification	Ground Reference (Objects)		Total	User Accuracy
	Non-Slum Neighbourhood	Slum Neighbourhood		
Non-Slum Neighbourhood	122	5	127	0.961
Slum Neighbourhood	8	46	54	0.852
Total	130	51		
Producer Accuracy	0.938	0.902		

Note: Overall accuracy = 0.928; kappa coefficient = 0.827.

The classifier trained using all three sets of features (see Fig. 9) is used to classify the VHR imagery in sites 2 and 3. For site 2, the threshold for ED, a landscape metric feature, is adjusted from 2474.02 to 1500 because the density of the HNs in site 2 is visibly lower than in site 1 and the HNs of site 2 are generally larger than that of site 1. The need for this adjustment agrees with [24], of the variability between slums that can exists within a single city, and, therefore, parameter settings of features is still needed. No parameter adjustment is needed for site 3. Fig. 11 shows classification results of sites 2 and 3. Majority of the HNs are accurately classified in both sites. The overall accuracy and kappa coefficient are 0.928 and 0.827, respectively, for site 2 (see Table IX), and an overall accuracy and kappa coefficient of 0.929 and 0.854, respectively, are achieved for site 3 (see Table X), which are very comparable with that of site 1 (Table V). The high accuracy of the classifier model when transferred to sites 2 and 3 suggest that the model can be used to map slums in other areas of the KMA although minimal parameter adjustment may be necessary.

TABLE X
ERROR MATRIX AND ACCURACY ASSESSMENT OF THE SLUM CLASSIFICATION AT SITE 3

Classification	Ground Reference (Objects)		Total	User Accuracy
	Non-Slum Neighbourhood	Slum Neighbourhood		
Non-Slum Neighbourhood	30	3	33	0.909
Slum Neighbourhood	1	22	23	0.957
Total	31	25		
Producer Accuracy	0.968	0.880		

Note: Overall accuracy = 0.929; kappa coefficient = 0.854.

V. CONCLUSION

Using land boundary layer and VHR imagery to map slum settlements provides useful information for slum upgrading. From a physical understanding of the characteristics of slums from expert interviews and field surveys, a local ontology of slums is developed for the target area, which lends itself to the development of context features. A combination of ML and OBIA methods captures the diversity of slums in the study area, and the results reflect a realistic human interpretation of slum settlements. The mapped slum settlements provide direct land boundary data that are useful for various stages of slum upgrading, that is, policy framework, technical and environmental options, and economic analysis. It is possible that the proposed method could be applied to the entire KMA because of the high transferability of the results, although upscaling to a larger area is not explored in this article due to the computational cost and availability of VHR imagery. It is recommended, however, that the methodology should be implemented in the entire KMA in the future to better test the applicability of the proposed approach.

This article adds insight to the limited slum mapping information in Jamaica and has the potential to be the initiator for timely, extensive, secure, and cost-effective slum mapping using VHR imagery in the country, which is currently lacking. It is the first attempt at slum mapping using VHR imagery in the country and possibly the entire Caribbean. This article can create a focus on slum mapping using remote sensing to a part of the world that is most affected by slum settlements. Additionally, combining other dimensions (socio-economic and legal) of slums may improve the understanding of requirements to upgrade slum settlements.

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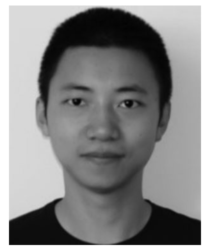

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