Mapping and Monitoring Informal Settlements Using RS Technologies

Subjects: Remote Sensing

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Research on the detection of informal settlements has increased since 1990s owing to the availability of high- to very-high-spatial-resolution satellite imagery. The achievement of development goals, such as the Sustainable Development Goals, requires access to up-to-date information on informal settlements.

OBIA informal settlements high-spatial-resolution images

1. OBIA Processing Steps

The first step in OBIA is image segmentation. This process partitions the image into meaningful objects used in classification or interpretation. OBIA was introduced around 2000 and implemented using software like Trimble eCognition. The multiresolution segmentation process is the most common image segmentation technique used in informal settlement detection [1]. One of the time-consuming tasks in image segmentation is the determination of the scale parameters that will produce image objects that represent the desired classes [2]. The scale parameter is an essential variable in image segmentation, as it determines the heterogeneity and size of the segmented objects [3]. The higher the scale parameter is, the higher the degree of heterogeneity of the object will be, resulting in larger image objects. Most studies have used a trial-and-error process to determine the scale parameter that would provide the required objects [4][5][6][7]. This supervised segmentation method requires the user to inspect the segmentation results using reference data or local knowledge. The parameters are then fine-tuned until the desired image objects are achieved.

The scale parameter remains a notable problem in the transferability of OBIA classification techniques. The transfer of image segmentation parameters from one sensor to another requires the parameters to be fine-tuned [8]. Reference data such as road or rail data have been used during the segmentation process to improve the boundaries of the resulting image object [7]. Some researchers have employed the Estimation of the Scale Parameter [9] to determine the scale parameter in order to segment informal settlement objects [10][11]. Several studies have used two segmentation levels to detect informal settlements [4][6][7]. This usually involves the segmentation of larger image objects to represent non-built-up versus built-up areas. In contrast, the second level uses higher scale values to create informal and formal land use objects used as sub-objects to distinguish informal settlements from formal settlements. The use of one segmentation level is observed when spectral-based features alone are used for the classification of informal settlements [7].

The availability of image-processing platforms such as Google Earth Engine provides opportunities to implement other segmentation methods, such as Simple Non-Iterative Clustering, which has been successful in segmenting informal settlement image objects from medium-spatial-resolution optical images and SAR [12]. Grid-based segmentation approaches are also used to create images in informal settlement detection [13][14].

Image classification in OBIA is usually performed using rulesets. Expert knowledge is required to generate these rulesets. The most challenging task during the mapping of informal settlements using OBIA is the translation of the characteristics of informal settlements into robust indicators that can be used across the globe during classification [15][16]. A Generic Slum Ontology (GSO) was developed to define generic indicators of informal settlements that can be used globally to detect informal settlements using remotely sensed data [16]. The GSO is based on the built morphology of informal settlements on three spatial levels, i.e., environment, settlement and object. The following subsections evaluate informal settlement indicators and OBIA techniques on these three spatial levels.

2. Detection of Informal Settlements Using Object-Level Indicators

Several studies have investigated using OBIA techniques to detect informal settlements [1][4][8][17]. The rulesets used for detecting informal settlements vary in terms of complexity from one area to another, depending on the ontology of the informal settlements. The object-level indicators tested or used to detect informal settlements include the tone and shape characteristics of dwelling structures [4][11]. The shape characteristics that are used serve to detect informal settlements' size and the simplicity of their roof structures. The dwelling structures in informal settlements are usually smaller [11][15][18] and more irregular in shape [11] than formal structures.

The roofs of dwelling structures in informal settlements can be constructed from a wide range of materials, such as iron, plastic sheets, wooden boards or asbestos [11] and a combination of clothes, wood and straw [19][20]. Image features have been investigated to distinguish the tone and brightness of dwelling structures in formal settlements. Tone measures the intensity of the bands of the image. The use of measurements for the tone of the roofs of dwelling structures in informal settlements using high-spatial-resolution imagery alone is insufficient in detecting informal settlements [2]. This is due to spectral confusion between the dwelling roofs and the surrounding surfaces [2]. The studies investigating the use of shape characteristics of dwelling structures have achieved poor accuracies of around 2–65% [4][11][15].

3. Detection of Informal Settlement Using Settlement-Level Indicators

Settlement-level indicators are physical characteristics of informal settlements that describe the overall shape, form or density of the respective settlement [16]. These indicators include the relative density of building structures and the absence of regular road networks and vegetation. Further indicators are the lacunarity and orientation of built structures [16]. The density of structures in unformal settlements can vary from one settlement to another. In addition, the density of the structures can vary depending on the developmental stage of the informal settlement, i.e., in infancy, consolidation or maturity [20]. Several studies in the literature have been conducted on medium- to high-density informal settlements [4][7][8][17].

The measurement of the GLCM is used to analyze the occurrence of pairs of pixels with specific values and a specific spatial relationship [21]. The GLCM textural measurements are the image features commonly explored, investigated or used for informal settlement detection in areas with medium- to high-density building structures, from high- to very-high-spatial-resolution imagery [5][6][7][14][22]. The window size used during the texture analysis and the spatial relationship analysis can affect the detection of informal settlements [5][6]. The success of these GLCM features in detecting settlements varies from one area to another depending on the morphology of the settlement, the surrounding land use features and the developmental stage of the settlements [6][7]. The integration of GLCM and other features, such as vegetation indices, has been proven to increase the quality of the results [5].

Several studies have attempted to detect informal settlements by analyzing the presence or morphology of land use features. A lack of vegetation is one of the characteristics of informal settlements that have been investigated [1]. This indicator is assessed using vegetation indices such as the Normalized Differential Vegetation Index (NDVI). The NDVI quantifies vegetation cover and has been used to classify land use and land cover features [23]. Informal settlements typically have lower vegetation cover than formal settlements [4][5][7][24]. This indicator is mainly used with other indicators, such as high building density, to detect informal settlements. Even though lack of vegetation could be used as an indicator during informal settlement detection, studies that assess vegetation cover and the biophysical characteristics of informal settlements have not been conducted. Understanding the biophysical characteristics and environmental conditions could help to manage the development of a measure aiming to improve the resilience and health of people living in informal settlements.

The use of lacunarity to detect informal settlements has been investigated in several studies [25][26][27]. Lacunarity is a measure of the deviation of geometric objects which quantifies the spatial heterogeneity of an object [26]. Formal settlements are expected to have higher lacunarity values, whereas informal settlements have lower values [25]. The lacunarity values of informal settlements depend on the developmental stage and density of the settlements [27].

Line detection algorithms such as Canny edge have been used to measure lacunarity in the detection of informal settlements [25][27][28]. In OBIA, lacunarity is also calculated by assessing the relative distance of building structures from vacant land [7]. The effectiveness of lacunarity in detecting informal settlements requires highly accurate informal settlement land use features. The integration of ancillary data available from platforms such as OpenStreetMap can potentially improve the detection of informal settlements.

Informal settlements are characterized by organic and irregular road networks or paths [29]. Only a limited number of studies have integrated the detection of road networks in distinguishing informal from formal settlements [5][30][31]. The geometric characteristics of informal settlement land use features have been investigated using the asymmetry of sub-objects [4][13]. Informal settlements tend to have a lower asymmetry of sub-object values owing to the complex nature of land use features in informal settlements. The asymmetry of sub-objects perform better in detecting informal settlements than the use of the area or density of sub-objects [13]. This may be attributed to the fact that the assessment of the area and density of sub-objects depends on the accuracy of the segmentation results of building structures and land use features in informal settlements [32].

4. Detection of Informal Settlement Using Environment-Level Indicators

The detection of informal settlements using environment-level characteristics has not been thoroughly investigated. Informal settlements are primarily developed on vacant land in undesirable locations close to rivers or services, in low-lying areas or on steep slopes. Areas prone to environmental disasters may also be used for informal settlements [11][16]. Some studies have investigated the location characteristics of informal settlements using ancillary data [33][34][35][36][37]. The integration of location characteristics such as proximity to rivers, roads or railway lines in the OBIA classification process has been proven to enhance the detection of informal settlements [11][38].

5. Temporal Analysis of Informal Settlement Extent

Understanding informal settlements can help authorities to better manage the development of informal settlements and urbanization in general. Even though several studies have investigated the detection of informal settlements using satellite images, limited studies have focused on analyzing informal settlement growth [11][13][37][39][40][41][42]. The accuracy of post-classification-based change detection greatly depends on the accuracy of the classification results. In OBIA, the detection process's or ruleset's transferability remains challenging [11]. Machine-learning-based change detection offers a better solution for informal settlement detection [42]. The information assessed in change detection studies has mainly focused on the extent of settlements. The availability of Unmanned Aerial Vehicles (UAV) provides an opportunity to assess building structure growth or changes in informal settlements [43].

6. Informal Settlement Mapping Using UAVs

The use of 3D information for detecting building structures in informal settlements using UAVs, unmanned aerial systems or drones has been an area of interest among researchers in recent years. UAV technology can acquire ultra-high-spatial-resolution images, 3D point clouds, detailed Digital Surface Models and Digital Elevation Models [44]. This technology also provides flexibility in the selection of spatial and revisit times based on the information requirements of the project [45]. The integration of 2D and 3D information heights generated from UAV products has been proven to provide more accurate results than pixel-based classification [46]. The mapping of land use features in informal settlements (including building structures through integrating 2D and 3D information provided by UAV technology) produces the detailed information required to support many applications, including planning for the upgrading of slums [46].

UAV products have also been used to classify roofs according to the roof materials and building heights, providing valuable information that can be used during spatial planning and as an indicator for classifying informal versus formal settlements [47]. The assessment of land use features in informal settlements using UAV image products is limited to smaller geographic areas [48]; for city-wide informal settlement mapping, high-spatial-resolution images are required. In contrast, UAV technology is suitable for the localized assessment of features in informal settlements to support specific projects, such as upgrade projects [49].

The capacity of UAVs to assess the morphology of building structures for determining fire disaster risk in informal settlements has been demonstrated [50]. Point cloud data used to create a 3D model of the building structure have been investigated to support several applications, including informal settlement upgrades [51]. Furthermore, multitemporal UAV products have successfully identified upgraded dwelling structures in informal settlements [43]. It has been shown that using UAV products to detect features in informal settlements provides classification accuracies of 90% or higher [43].

7. Studying the Morphology of Informal Settlements Using Landscape Metrics

The research aiming to distinguish informal settlements from formal settlements using landscape metrics is new. A recent study in China successfully distinguished urban villages from formal areas with higher accuracy in two cities using patch and landscape metrics [52]. The study of the spatial patterns of informal settlement structures using landscape patterns has also received limited attention [36][50]. Study of the spatial patterns of informal settlements can provide information with which to better understand the configurations of settlements and, hence, aid in planning services. Furthermore, integrating spatial patterns with other information types, such as disaster occurrence, can help to identify areas at risk of such events [50].

8. Mapping of Informal Settlement Land Use Features

Understanding the built environments of informal settlements is essential for providing primary and emergency services. Research on the high- to very-high-spatial-resolution extraction of building structures in informal settlements has been an area of interest for many scholars and researchers in the past two decades [53][54]. This was made possible by the launch of satellites such as IKONOS, QuickBird and Worldview. The quantification of building structures provides information required to estimate population size and facilitates the provision of health and other essential services, such as emergency response services (including fire and disaster management). The extraction of building structures from high-spatial-resolution imagery is a complex process owing to the size and heterogeneity of the surrounding land use features, such as roads and open spaces.

Limited studies have investigated the extraction of roads in informal settlements, yet these are essential infrastructure, as they provide transportation and emergency service access. The detection of road features in informal settlements is challenging, as roads in informal settlements have similar physical characteristics compared to other land use features when using high-spatial-resolution satellite imagery [55].

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