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IDENTIFYING INFORMAL SETTLEMENTS IN SATELLITE IMAGES FOR SUSTAINABLE URBAN PLANNING: A SYSTEMATIC REVIEW OF METHODS AVAILABLE

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Abstract:

The current urbanization trend, along with a shortage of affordable housing, has led to the proliferation of informal settlements in most cities in the global south. The variance in spectral, spatial image resolution, texture, colours, and complex physical shapes of informal urban settlements has made it difficult to provide accurate evidence for urban planners to achieve sustainable urban planning. In this article, the PRISMA methodology was used to thoroughly investigate various techniques used to classify informal settlements from satellite imagery between 2010 and 2021, as well as identify the methods' strengths and weaknesses, along with image indicators used in generating adequate information for sustainable urban planning. According to the study, the dominant models and approaches used to identify or detect informal settlements in satellite imagery for urban planning purposes are remote sensing, GIS, and artificial intelligence (machine learning) applications, as well as quantitative indicators. It was also revealed that without an integrated methodology, the proposed approaches used in different studies could not accurately detect and classify informal settlements. This is due to similarities in the texture of buildings of both formal and informal settlements, as well as variations in image spectral and spatial resolutions, as reported in previous studies.

Keywords:

Informal Settlements, Detection, Extract, Satellite Images, And Indicators

Introduction

The exponential growth in the urban global population has led to the spread of unplanned settlements (informal settlements) that have neglected zoning, land use plans, and service allocation. The key causes for this trend according to Kakembo and van Niekerk (2014) are the urbanisation of poverty and lack of affordable housing in urban areas. Additionally, Hofmann, Taubenböck, and Werthmann (2015) that informal settlements (IFSs) were a product of informal urbanization on marginal land in urban areas.

Currently, IFSs are homes to both social and economic vulnerable people on the earth's surface. In developing countries, the inadequate information on the identification of existing and potential IFSs within cities remains a core concern to policymakers and urban planners (Ibrahim, Titheridge, Cheng, & Haworth, 2019) towards achieving sustainable development of city planning (Bhangale, Rathod, Rajgor, Rami, & Kurte, 2016). Several studies have attempted to identify and quantify the expansion of IFSs using varieties of methods and satellite images. Some studies have used convolutional neural networks (CNNs), remote sensing, machine learning, deep convolutional neural networks (DCNN), and artificial neural networks (ANN) (Bhangale et al., 2016; Gadiraju, Vatsavai, Kaza, Wibbels, & Krishna, 2018; Mboga, Persello, Bergado, & Stein, 2017; Persello & Stein, 2017; Ravi Prabhu, Parvathavarthini, & Alaguraja, 2021). While several other studies used the spatial fusion, textural segmentation of remotely sensed images, agent-based, contourlet assisted deep learning, image-based classification, object-based change detection, and predictSLUMS models (Ansari, Malhotra, & Buddhiraju, 2020; Hofmann & Bekkarnayeva, 2017; Ibrahim et al., 2019) to identify, extract, quantify, monitor, and predict the expansion of IFSs in several regions. Similarly, this same researcher and others like Jain (2007), Kuffer, Barros, and Sliuzas (2014), Kamalipour and Dovey (2019), Gram-Hansen et al. (2019), Stark (2018), Tingzon et al. (2020) have additionally used remotely sensed data sets such as IKONOS, QuickBird, Worldview-2, OpenStreetMap, Sentinel, and Landsat imageries, to identify IFSs.in different regions.

The absence of a coherent definition of IFSs' regional differences, theory locations (Barros & Sobreira, 2008), as well as the variation of spectral and spatial image resolution has challenged the general mapping rules for identification and prediction of IFSs development (Hofmann et al., 2015) from satellite images. Other impediments are similarities of settlements texture, roof colour, structural size, and the dynamic physical shapes of the settlements (Busgeeth, Brits, & Whisken, 2008).

Additionally, Hofmann et al. (2015) established that a lack of theory and a high degree of heterogeneity in appearance through different systems for IFS detection have made semi-automatic spatial identification of IFSs in satellite images a difficult task for monitoring informal urban development. This situation has generated challenges for urban administrators and planners in separating the physiognomy of formal settlements from that of IFSs. Thus, it is important to identify appropriate tools and methods for identifying IFSs from remotely sensed images for effective urban planning.

To address these challenges, this work attempts to conduct a systematic literature review on the current methods used to identify IFSs on remotely sensed data in developing countries within the last ten years (2010-2020). The study would also examine the methods' strengths and weaknesses, as well as the spatial indicators, use to identify IFSs from satellite images.

The remainder of the paper is organized as follows: Section 2 addresses the review's method; Section 3 discusses the review's findings based on the documents gathered. The final segment is devoted to discussions of the findings and conclusions on possible methods for detecting IFSs on satellite imagery in the global south.

Methods

This paper systematically reviews relevant literature on the method used to extract and detect IFSs on a given remotely sensed data. The review was conducted using the Preferred Reporting Items for Systematic Review and Meta-Analysis which is known as PRISMA (Moher, Liberati, Tetzlaff, Altman, & Group, 2009). PRISMA was adopted for this study based on its principle of transparent reporting style of a systematic review with a checklist (Moher et al., 2009). The data for the study were sourced from Scopus and Web of Science databases based on their reliability, efficiency, and extensive coverage of contemporary publications (Aghaei Chadegani et al., 2013). The informal settlement, detection, and satellite images were used as keywords in the search engine. To intersect and unite the search terms for systematic literature search, we used Boolean operations such as "OR" and "AND" to search for English articles from journals, and book chapters between 2010 and 2021.

Data collected from Scopus on 15 April 2021 using informal settlements, detection identification, and satellite image as search terms generated 27 documents between 2010 and 2021 from this search queries and limits -TITLE-ABS-KEY (informal AND settlements AND detection OR identification AND satellite AND image). We further generated 200 more documents from Web of Science on the same date using search query - TITLE: (informal AND settlements AND detection OR extraction AND satellite AND image).

Results

A total of 227 documents were generated from both the Scopus and Web of Science databases. Out of the 227 records, 19 were excluded for duplication. The 109 were further screened out from the remaining 208 documents due to their lack of the study's suitable keywords in both titles and keywords of the individual records - IFS, detection, extraction, and remote sensed. Out of 99 records remaining, 56 were discarded based on diversion from the main study subject matter. Among the 43 articles remaining, only 23 records were granted full access due to affiliation issues (Figure 1) and used in this paper. Thus, only 23 were included in this review
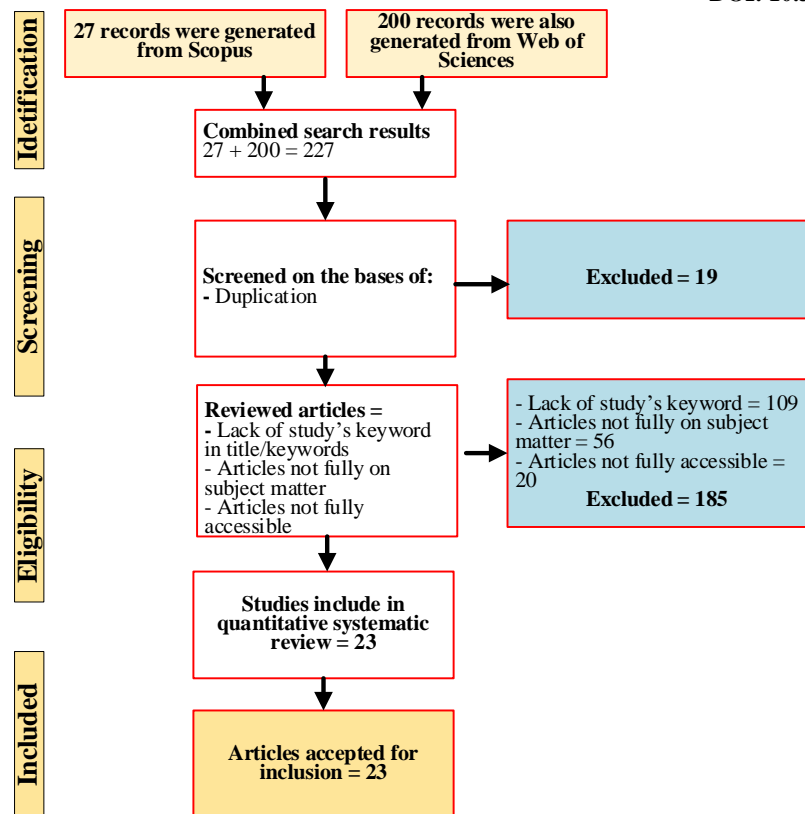
Figure 1: Flow of information in the phases of a systematic review
Source: (Moher et al., 2009)

The results of this review are presented in the following sub-sections: summary of included articles with journals used; detection methods, strength, limitations of methods used in the included articles, and IFSs indicators.

Included Articles
Sustainable After identifying and screening documents for inclusion in the report, we identified 23 papers that met the eligibility requirements outlined in Table 1. The papers contained in this collection were drawn from 17 journal publications and five conference proceedings and symposium proceedings between 2010 and 2021 (Table 1).

Table 2 further summarises the methods, strengths, and limitations of the extraction methods used in various journal articles. According to Table 2, the majority of the extraction techniques used in different studies are capable of detecting IFSs from VHR images. However, the difficulty of misclassifying formal settlements for informal settlements is a cause for concern

Table 1: Summary of Included Articles for the Studies

Source/Year	Title	Inclusion criteria	Journals
Ravi Prabhu et al. (2021)	Integration of deep convolutional neural networks and mathematical morphology-based post-classification framework for urban slum mapping	Contains a method of feature extraction	Journal of Applied Remote Sensing
R Prabhu, Parvathavarthini, and Alagu Raja (2021)	Slum Extraction from High-Resolution Satellite Data using Mathematical Morphology based approach	It contains words like extraction and satellite image in the title	Journal of Applied Remote Sensing
Sariturk, Bayram, Duran, and Seker (2020)	Feature Extraction from Satellite Images Using Segnet and Fully Convolutional Networks (FCN)	The title has extraction, satellite image, and method of feature extraction.	International Journal of Engineering and Geosciences
Prathiba, Rastogi, Jain, and Kumar (2020)	Building Footprint Extraction from Very-High-Resolution Satellite Image Using Object-Based Image Analysis (OBIA) Technique	The title contains the needed keywords.	Applications of Geomatics in Civil Engineering
Ansari et al. (2020)	Textural segmentation of remotely sensed images using multiresolution analysis for slum area identification	The title contains the required words like extraction, satellite image, and identification.	European Journal of Remote Sensing
Dahiya, Garg, and Jat (2020)	Automated Extraction of Slum Built-up Areas from Multispectral Imageries	The title contains the necessary words like extraction, satellite image, and slum.	Journal of the Indian Society of Remote Sensing
Rastogi, Bodani, and Sharma (2020)	Automatic building footprint extraction from very high-resolution imagery using deep learning techniques	Contains the important keywords	Geocarto International
Gram-Hansen et al. (2019)	Mapping informal settlements in developing countries	The article title has the necessary keywords like informal	AIES 2019 - Proceedings of the 2019 AAAI/ACM

	using machine learning and low-resolution multi-spectral data	settlement and a method for feature extraction	Conference on AI, Ethics, and Society
Mohammadi, Samadzadegan, and Reinartz (2019)	2D/3D information fusion for building extraction from high-resolution satellite stereo images using kernel graph cuts	It dealt with the subject matter of the study	International Journal of Remote Sensing
Ibrahim et al. (2019)	PredictSLUMS: A new model for identifying and predicting informal settlements and slums in cities from street intersections using machine learning	The subject matter was captured in the study	Computers, Environment and Urban Systems
Park, Fan, John, Ouyang, and Chen (2019)	Spatiotemporal changes of informal settlements: Ger districts in Ulaanbaatar, Mongolia	Content is in line with subject matter	Landscape and Urban Planning
Gadiraju et al. (2018)	Machine learning approaches for slum detection using very high-resolution satellite images	The article title has the necessary keywords like informal settlement and a method for feature extraction	IEEE International Conference on Data Mining Workshops, ICDMW
Hofmann and Bekkarnayeva (2017)	Object-Based Change Detection of Informal Settlements	It dealt with the topic of the study	International Journal of Remote Sensing
Mboga et al. (2017)	Detection of informal settlements from VHR satellite images using convolutional neural networks	The article has all the necessary components of the review article.	2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)
Gevaert, Persello, Sliuzas, and Vosselman (2017)	Informal settlement classification using point-cloud and image-based features from UAV data	Informal settlements, detection, satellite image, and method of feature extraction were discussed in the article	ISPRS Journal of Photogrammetry and Remote Sensing
Persello and Stein (2017)	Deep Fully Convolutional Networks for the Detection of Informal	The method for detecting features on a satellite image was discussed in the article.	IEEE Geoscience and Remote Sensing Letters

	Settlements in VHR Images		
Bhangale et al. (2016)	Identification of informal settlement using Remote Sensing Images	The article addressed informal settlements, identification, satellite images, and feature extraction methods.	ACM International Conference Proceeding Series
Kohli, Sliuzas, and Stein (2016)	Urban slum detection using texture and spatial metrics derived from satellite imagery	The title of the article includes the requisite keywords, such as informal settlement and a method for feature extraction.	Journal of Spatial Science
Kuffer, Pfeffer, Sliuzas, and Baud (2016)	Extraction of Slum Areas From VHR Imagery Using GLCM Variance	The article discussed the extraction of features from remotely sensed images.	2015 IEEE International Geoscience and Remote Sensing Symposium (Igarss)
Réjichi and Chaabane (2015)	Feature Extraction using PCA for VHR Satellite Image Time series Spatio-temporal classification	The title contains the needed keywords	IEEE Transactions on Geoscience and Remote Sensing
Huang, Liu, and Zhang (2015)	Spatiotemporal Detection and Analysis of Urban Villages in Mega-City Regions of China Using High-Resolution Remotely Sensed Imagery	The article title has the required keywords for the study	Applied Geography
Kit, Lüdeke, and Reckien (2012)	Texture-based identification of urban slums in Hyderabad, India using remote sensing data	The title falls within the context of the review	Procedia-Social and Behavioural Sciences
Asmat and Zamzami (2012)	Automated House Detection and Delineation using Optical Remote Sensing Technology for Informal Human Settlement	The title contains the major keywords	Procedia-Social and Behavioural Sciences

Note: Approved keywords – Detection, extraction, informal settlements, and satellite images.
Source: Authors Review Work (2021)

Table 2: Summary of Other Results

Category	Criteria	Period		
		2010-2013	2014-2017	2018-2021
	Number of publications	2 (8.70%)	9 (39.13%)	12 (52.17%)
Methods	1- Kernel-based deep convolutional neural networks (DK-DCNN) (Prabhu et al., 2021b)	0 (0.00%)	0 (0.00%)	1 (100%)
	2- Multi Shape-Multi Size-Morphological Profile (MSh-MSi-MP) (Prabhu et al., 2021a)	0 (0.00%)	0 (0.00%)	1 (100%)
	3- Fully Convolutional Networks (FCN) and SegNet (Sariturk et al., 2020)	0 (0.00%)	0 (0.00%)	1 (100%)
	4- Object-Based Image Analysis (OBIA) (Prathiba et al., 2020)	0 (0.00%)	0 (0.00%)	1 (100%)
	5- Texture-based segmentation (multiresolution method) (Ansari et al., 2020)	0 (0.00%)	0 (0.00%)	1 (100%)
	6- MATLAB (using multispectral satellite images) (Dahiya et al., 2020)	0 (0.00%)	0 (0.00%)	1 (100%)
	7- UNet-AP (CNN) (Rastogi et al., 2020)	0 (0.00%)	0 (0.00%)	1 (100%)
	8- Machine learning (cost-efficient and cost-prohibitive methods) (Gram-Hansen et al., 2019)	0 (0.00%)	0 (0.00%)	1 (100%)
	9- 2D and 3D information fusión (kernel graph cuts KGC) (Mohammadi et al., 2019)	0 (0.00%)	0 (0.00%)	1 (100%)
	10- PredictSLUMS (spatial statistics and Artificial Neural Networks - ANN) (Ibrahim et al., 2019)	0 (0.00%)	0 (0.00%)	1 (100%)
	11- Semi-structured interviews and OBIA image analysis (Park et al., 2019)	0 (0.00%)	0 (0.00%)	1 (100%)
	12- Machine learning (pixel-based and patch-based approaches or CNN) (Gadiraju et al., 2018)	0 (0.00%)	0 (0.00%)	1 (100%)
	13- Object-based using remote sensing (Hofmann and Bekkarnayeva, 2017)	0 (0.00%)	1 (100%)	0 (0.00%)
	14- Convolutional neural networks (CNNs) (Mboga et al., 2017)	0 (0.00%)	1 (100%)	0 (0.00%)
	15- Integrating 2D radiometric, textural, and segment features, 2.5D topographical features, and	0 (0.00%)	1 (100%)	0 (0.00%)

	3D geometrical features (Gevaert et al., 2017)			
	16- Deep Fully Convolutional Networks (FCNs) (Persello and Stein, 2017)	0 (0.00%)	1 (100%)	0 (0.00%)
	17- Remote Sensing Images (Histogram Comparison using Bhattacharyya Distance - HCBD, and Hausdorff distance approach based on Citation-KNN (Bhangale et al., 2016)	0 (0.00%)	1 (100%)	0 (0.00%)
	18- Object-oriented image analysis (OOA) (Kohli et al., 2016)	0 (0.00%)	1 (100%)	0 (0.00%)
	19- Gray-level co-occurrence matrix (GLCM) variance (Kuffer et al., 2016b)	0 (0.00%)	1 (100%)	0 (0.00%)
	20- Principle Component Analysis (PCA) (Réjichi and Chaabane, 2015)	0 (0.00%)	1 (100%)	0 (0.00%)
	21- Multi-index scene model and two popular scene models (Huang et al., 2015).	0 (0.00%)	1 (100%)	0 (0.00%)
	22- Lacunarity-based pattern algorithm (Kit et al., 2012)	1 (100%)	0 (0.00%)	0 (0.00%)
	23- Automated house detection technique (spatial-based using tree counting approach) (Asmat and Zamzami, 2012)	1 (100%)	0 (0.00%)	0 (0.00%)
VHR images	1. WorldView-2 (1.84 m)	0 (0.00%)	2 (33.33%)	4 (66.67%)
	2. Wordview 3 (0.4 m)	0 (0.00%)	1 (100%)	0 (0.00%)
	3. Inria Aerial Image (3 m)	0 (0.00%)	0 (0.00%)	1 (100%)
	4. Cartosat-2 series (1 m)	0 (0.00%)	0 (0.00%)	2 (100%)
	5. QuickBird (0.61 m)	2 (25%)	5 (62.50%)	1 (12.50%)
	6. GeoEye-1 (0:5 m)	0 (0.00%)	1 (50%)	1 (50%)
	7. OpenStreetMap	0 (0.00%)	0 (0.00%)	1 (100%)
	8. Ikonos-2 (1 m)	0 (0.00%)	1 (100%)	0 (0.00%)
	9. Unmanned Aerial Vehicle	0 (0.00%)	1 (100%)	0 (0.00%)
	10. Google Earth	0 (0.00%)	1 (100%)	0 (0.00%)
	11. OrbView (1 m)	0 (0.00%)	2 (100%)	0 (0.00%)
	12. Resourcesat. (5.8 m)	0 (0.00%)	1 (100%)	0 (0.00%)
	13. SPOT-5 (5 m)	1 (100%)	0 (0.00%)	0 (0.00%)
LR images	1. Sentinel-2 (10 m)	0 (0.00%)	0 (0.00%)	1 (100%)
	2. Landsat 7 (15 m)	0 (0.00%)	0 (0.00%	2 (100%)

Note: VHR: very high-resolution image; LR: low-resolution image
Source: Author's Review Work

Table 2 indicates that 8.70%, 39.13%a, and 52.17% were inclusive publications recorded for IFS identification in 2010-2013, 2014-2017, and 2018-2021 respectively. Out of 23 publications recoded, 2, 9, and 12 detection methods were used in 2010-2013, 2014-2017, and 2018-2021 respectively. Likewise, VHR images were deeply used by most studies were about 62.50% of the studies used Quickbird between 2014 and 2017, followed by Worldview-2 image which dominated between 2018 and 2021 with about 66.67%. This indicates that VHR images are the most often used images for detecting IFSs. Perhaps due to the image's abundance of detail about the earth's surface (Galeon, 2008). However, only two articles between 2018 and 2021 used LR images (Sentinel-2 and Landsat-7).

Indicators for Detecting Informal Settlements:
Irrespective of the methods used, indicators for detecting IFS in remotely sensed data are essential parameters for increasing the detection precision. Most significantly, Image-based feature indicators are used in many ways to detect IFSs. They can be used in a selective or large range, or also as a single indicator (Kuffer et al., 2016). However, the report of the Expert Group Meeting on slum identification in 2008 identified IFSs indicators using qualitative and quantitative criteria (Sliuzas et al., 2008). According to Sliuzas et al. (2008) and Hofmann et al. (2015), qualitative indicators include building materials such as roofing sheets; hazardous high-density construction patterns; proximity to public utilities, natural and technical risks; and the structure, scale, and condition of the road network. While quantitative indicators apply to spatial metrics; building heights, land cover distribution, and characteristic scales (relative size of housing units, road networks, and plot ratio). Figure 2 shows the indicators used by the 23 authors included in this work.
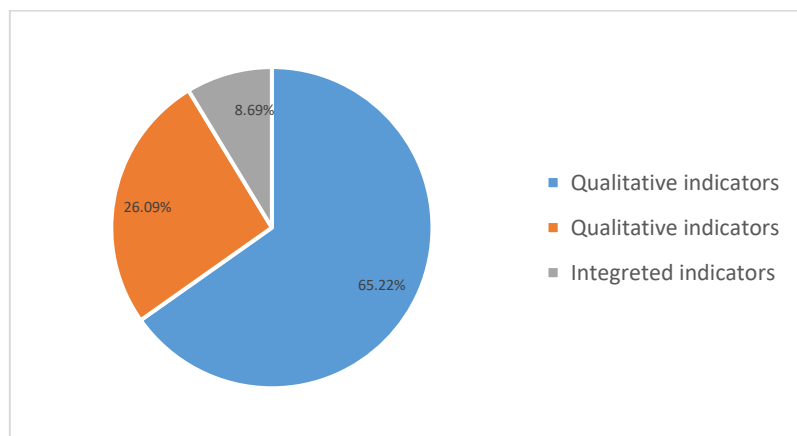

Figure 2: Quantitative, Qualitative, and Integrated Indicators used in the Included
Source: Author's Review Work (2021)

In Figure 1, 65.22% (Dahiya et al., 2020; Gadiraju et al., 2018; Hofmann & Bekkarnayeva, 2017; Park et al., 2019) of the included publication used quantitative indicators (texture, colours, shadow, and non-building áreas, etc); 26.09% (Ibrahim et al., 2019; Kohli et al., 2016; Rastogi et al., 2020) used qualitative (building density, building materials, etc), and 8.69% (Asmat & Zamzami, 2012; Mohammadi et al., 2019) integrated the two indicators to identify IFSs features in the remotely sensed image between 2010 and 2021. This shows that quantitative indicators were mostly used to classify IFSs in satellite images.

Discussions

Detecting and extracting features from remotely sensed data is critical for monitoring and managing urban growth as well as forecasting temperatures, ocean salinity. and identifying objects on the surface (Camps-Valls, 2009) for sustainable urban planning. Previous studies have used automated house detection techniques, lacunarity-based patterns, Object-oriented image analysis, texture-based applications, and remote sensing methods (Asmat & Zamzami, 2012; Bhangale et al., 2016; Gadiraju et al., 2018; Kit et al., 2012; Kohli et al., 2016). Others include machine learning models with VHR images to detect and generate more information on the development of IFSs for sustainable urban planning. In addition, the bulk of the included records used quantitative indicators to detect IFSs in satellite images.

This paper cannot establish the overall proof for feature extraction techniques. However, the paper has indicated that most of the methods employed for feature extraction between 2010 and 2021 were mostly base on artificial intelligence (machine learning models) in conjunction with VHR images. Moreover, Camps-Valls (2009) claims that the current study demonstrates that both traditional and contemporary machine learning (ML) patterns have been successfully extended to remote sensing applications such as sorting, regression, clustering, scripting, and function source separation. The author claimed, however, that ML depends on training data from the observed image scene and hence lacks interpretability.

Despite the strength of ML (Table 3), the study revealed that most of the methods used in the induced articles had issues of misclassifying settlement features. This is due to similarities in buildings and open spaces textures, as well as spatial and spectral differences in the acquired VHR images. Additionally, the included records in Table 3 show that the accuracy and precision of the extraction techniques depend on the spatial and spectral resolution of the input images. (Réjichi & Chaabane, 2015); inputted quantity of training data; and integration of models.

To address these challenges, studies have integrated extraction models to improve the accuracy and precision of knowledge required for monitoring and forecasting the expansion of IFSs for sustainable urban planning by 2030, as specified by Sustainable Development Goal (Sustainable cities and communities:11).

The study has several limitations, which are described in Table 3. The majority of the records included were constrained at the outcome level by differences in the spectral and spatial resolutions of VHR images. However, most of the papers did not specifically state the complexity of misclassification or the standard required training data needed to achieve an extraction model's accuracy. Additionally, most feature extraction techniques are restricted to identifying two-dimensional features. However, between 2018 and 2021, relatively few studies used low-resolution images for feature extraction (Gram-Hansen et al., 2019).

Source/Year	Methods	Strengths	Limitations
Ravi Prabhu et al. (2021)	Kernel-based deep convolutional neural networks (DK-DCNN)	Capable of detecting slums based on VHR imagery	Has inefficiency of misclassifying formal settlements' roofing systems for IFS.
R Prabhu et al. (2021)	Multi Shape-Multi Size-Morphological Profile (MSh-MSi-MP)	It can model urban slum using normal Morphological Description	With the variety of texture of IFSs and the similarity of their shapes and sizes of features, the model faces the issue of incorrect classification of formal for IFS or slums.
Sariturk et al. (2020)	Fully Convolutional Networks (FCN) and SegNet	The FCN was more accurate than SegNet in terms of validity differences.	The accuracy of the method is limited by the dataset used to train the system as well as the number of the trained dataset.
Prathiba et al. (2020)	Object-Based Image Analysis (OBIA)	The model is capable of creating a 3D city model while maintaining a focus on the feature's components.	The model heavily relies on VHR images to determine the footprints of buildings.
Ansari et al. (2020)	Multiresolution method	In terms of class discrimination of features on remotely sensed images, this method outperforms traditional approaches	Low-resolution images limit the method's precision.
Dahiya et al. (2020)	MATLAB (using multispectral satellite images)	The method is capable of extracting features based on their threshold and texture.	There was no separate table for extracting buildings; rather, it extracted all buildings and open spaces as a single entity.
Rastogi et al. (2020)	UNet-AP (CNN)	Highly capable of extracting dense features from VHR images.	For maximum precision, the method is limited to VHR images.

Gram-Hansen et al. (2019)	Machine learning (cost-efficient and cost-prohibitive methods)	The process is capable of extracting IFSs from images with a low resolution.	Although the low-resolution data works well, it falls short of the effectiveness of the CNN trained data on VHR imagery of Kibera's IFSs.
Mohammadi et al. (2019)	2D and 3D information fusion (kernel graph cuts - KGC)	The results show that integrating object-based decision-making with the KGC greatly improves the building extraction process's accuracy and precision.	The model is restricted to VHR images and is confronted with the challenge of identifying indicators for rectangle segment detection.
Ibrahim et al. (2019)	PredictSLUMS: Street intersection data (machine learning).	The model requires limited data to run, Identify, and forecast hotspots in cities that constitute informality.	Due to the model's static structure, it is essential to conduct a time-series study of an area over space and time.
Park et al. (2019)	Semi-structured interviews and applied remote sensing imagery (OBIA image classification)	The method (OBIA) has the potential to use spectral, spatial, temporal, and textual information of IFSs.	The qualitative research was conducted in Ulaanbaatar's Ger district and cannot be generalized.
Gadiraju et al. (2018)	Machine learning (pixel-based and patch-based approaches or CNN)	When combined with the different features used to detect IFSs, the model's accuracy is very high.	The models' high precision is due to their integration with other models, which has a small impact on change analysis.
Hofmann and Bekkarnayeva (2017)	Object-based using remote sensing.	When combined with objects, object-based change detection enables the tracking of thematic differences between objects as well as changes to their property values and possible movement.	When low-resolution images are used, the object-based approach does less well. It also lacks flexibility and portability.

Mboga et al. (2017)	Convolutional neural networks (CNNs)	The method produces high accuracy when large training sets, patch size, and a higher number of convolutionary layers are used.	The method's precision is proportional to the number of training sets used, and it is therefore incapable of updating the detection parameter.
Gevaert et al. (2017)	Integrating 2D radiometric, textural, and segment features, 2.5D topographical features, and 3D geometrical features.	The combination of two-dimension and three-dimension features applied to Digital Surface Models (DSM) provides a high classification accuracy of IFS.	When the DSM is propagated into classification, it produces inaccuracies.
Persello and Stein (2017)	Deep Fully Convolutional Networks with dilated kernels (DKs): FCN-DKs.	It can learn detailed features that track long-range pixel connections while retaining a restricted range of network requirements within a short time.	A low-resolution image reduces the model capacity.
Bhangale et al. (2016)	Remote Sensing Images (Histogram Comparison using Bhattacharyya Distance - HCBD, and Hausdorff distance approach based on Citation-KNN	The methods have a high ability to process and identify IFSs between 2 to 13 seconds	The identification of IFSs with high precision and sensitivity is more easily accomplished with VHR images than with low-resolution images.
Kohli et al. (2016)	Generic slum ontology (GSO) - Object-oriented image analysis (OOA)	The models can define and distinguish slum areas by using texture and spatial metrics.	IFSs are easier to identify with high accuracy and sensitivity with VHR images than with lower resolution images.

Kuffer et al. (2016)	Gray-level co-occurrence matrix (GLCM) variance	This technique has a capacity of generating accuracy of 84% to 88% when combined with NDVI in detecting IFSs	The methods are accurate when VHR images are used instead of low-resolution images. However, the detection efficiency is limited by the GLCM and NDVI variance values.
Réjichi and Chaabane (2015)	Principle Component Analysis (PCA)	The model extracts related features using spatial, spectral, and texture features and also enables the development of a spatio-temporal map describing not only land cover classes but also their changes over time.	The proposed approach's outcome is dependent on the precision of the spatial segmentation stage. As a result, optimizing the segmentation phase is critical.
Huang et al. (2015)	Multi-index scene model and two popular scene models - bag-of-visual-words and supervised latent Dirichlet allocation.	The approach is capable of defining and identifying complex urban systems.	The model's ability to extract building heights and measurements is limited by the visual imagery
Kit et al. (2012)	Lacunarity-based pattern algorithm	The method is well-suited for determining the IFS's core. Additionally, it employs uniform metropolitan morphology as opposed to regional characteristics.	A low-resolution image limits the capability of the model.
Asmat and Zamzami (2012)	Automated house detection technique (spatial-based using tree counting approach)	This approach is capable of detecting, segregating, or delineating legal from illegal structures within a 2m distance.	This method's performance is constrained by the spatial and spectral resolution of the input image.

Source: Author's Review Work (2021)

Conclusion

Rapid demographic growth and the associated expansion of IFSs in developing countries is a critical challenge for effective monitoring and planning of urban development. Therefore, it is important to gather the necessary details on the spatial expansion of IFSs to ensure the proper implementation of sustainable urban planning.

We used the PRISMA methodology in this article to systematically investigate methods for identifying or extracting IFSs from remotely sensed images. We found out that majority of techniques used quantitative indicators to identify IFS features in VHR between 2010 and 2021. In addition, several of the models used artificial intelligence (machine learning) in collaboration with VHR remote sensing data and GIS applications.
This paper strongly suggests that future studies of determining IFSs for sustainable urban planning should integrate feature extraction techniques as well as image indicators in both low and VHR images in detecting IFSs for improving results accuracy.

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