Deep Learning-Based Assessment of Urban and Vegetation Changes Using High-Resolution Khalifasat Satellite Imagery over Dubai

Maitha A. A. Nuaimi[1], Eman H. Salem[1], Hala F. S. Ibrahim[1], Asma Abdulla A. Al Ali[1], Hussein M. Abdulmuttalib[1], Raja Biswas[2]*, Le Hai Ha[3], Sandip Banerjee[3], and Abhay S Mittal[3]

[1]Dubai Municipality, Government of Dubai, United Arab Emirates (UAE) - maithaali@dm.gov.ae
[2]Research and Development, Skymap Global Pte Ltd, India - raja.biswas@skymapglobal.com
[3]Technical Department, Skymap Global Pte Ltd, Singapore - sandip.banerjee@skymapglobal.com

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ABSTRACT:

Accurate detection and monitoring of urban changes are crucial for sustainable urban planning and management, sustaining economic growth, as well as advancing smart city initiatives. Due to the unprecedented urbanization and rapid population growth in the emirates of Dubai over the last few decades, it is essential to closely monitor and detect changes in urban land cover. While traditional classifiers using low-medium resolution open-source satellite images have shown success in the broad-level classification of land use and land cover concerning urbanization, they are time-consuming, labour-intensive, and limited to minute-level detailed urban change detection. Thus, the present study significantly focuses on precise change detection of various urban classes and associated vegetation cover during 2021-2022 using high-resolution KhalifaSAT images through the application of a deep learning algorithm. The study implemented an advanced machine learning tool (available in the Geo-AI platform, Eofactory) to generate a super-resolution image. Also, after performing various pre-processing of the image, a deep learning-based U2-Net model was implemented for the change detection. The model has efficiently detected changes in different urban features such as newly constructed buildings, rooftop changes, demolished buildings, and building extensions as well as changes in associated vegetation with an overall accuracy of 0.82 and, a kappa coefficient of 0.76.

1. INTRODUCTION

The continuously increasing number of people moving to cities has led to uncontrolled urban growth, posing serious threats such as poverty and environmental degradation. Thus, it is necessary to rely on sustainable urban planning and management (Hafner et al., 2023; Marchesi & Bruzzone, 2009). Sustainable regional development can be achieved based on the analysis of accurate and timely information on the areas of sprawls of settlements, building density, industrialization score, road network indicators, and others (Fyleris et al., 2022; Hafner et al., 2023). In addition, the continuous monitoring, and Spatio-temporal assessment of land use land cover changes associated with urbanization is crucial for decision-making related to sustainable urban development (Wang et al., 2018). Urbanization has surged at an unparalleled pace across numerous regions worldwide. In contrast, the emirate of Dubai has witnessed significant economic growth, experiencing drastic population growth and rapid urbanization over the last few decades, transforming from a small trading port to a global city. The desert areas have transformed into residential, commercial, sports, and tourism projects. Moreover, the offshore environment has been converted into artificial islands such as Palm Jumeirah, Palm Deira, and the World Islands. Developing mini-cities within the city is a significant characteristic of Dubai, several mini-cities such as Dubai Festival City, Sports City, Media City, Healthcare City as well as Internet City have been developed. It is evident that around 25% of the world's construction cranes operate in Dubai, which reflects the scale of recent development in the city (Badouri, 2007; Nassar et al., 2014). Indeed, the unprecedented rate of urbanization in Dubai has attracted the attention of economists, environmentalists, and urban planners. However, there is a lack of information publicly accessible on the expansion of Dubai and limited studies have been carried out for the detection of urban changes concerning the use of high-resolution satellite images leveraging cutting-edge technologies (Fyleris et al., 2022; Hafner et al., 2023). The major reason behind the recent urban development in Dubai could be the policy to diversify the economy through investment in real estate, due to diminishing oil reserves. Which led to a ten-fold increase in the population since 1975 (Nassar et al., 2014). Additionally, Dubai's urban expansion has not been constrained by physical barriers like desert plains or the Gulf Coast, or by issues of land ownership (Nassar et al., 2014). This, makes Dubai, an interesting site for studying urban change detection that might support policymakers for future sustainable urban development projects.

Over the years, various data sources and methods have been employed to investigate landscape changes. For example, demographic changes can be analysed through different socioeconomic, and statistical parameters. However, collecting this data and their analysis are time-consuming, and are not useful to focus on the spatial aspect of change. In contrast, the advent of Remote Sensing technology created a pathway to conduct urban change analysis on a global as well as regional scale. This technology has proven to be a cost-effective, time-saving alternative as compared to other conventional survey-oriented methods (Patino & Duque, 2013). In the last four decades, there has been a continuous advancement in sensor technologies, image processing, as well as in analytical tools. The spatial, spectral, and temporal resolution of the data, as well as the coverage of the sensor, have been enhanced with time. However, there have been operational trade-offs between these parameters that can constrain the limitation of the applicability of utilizing this data to study urban change. Medium-high resolution multispectral satellite images such as Landsat, Liss III, and Sentinel 2 have been extensively used for mapping and detecting urban areas and other land cover types due to their availability of near-global coverage at no cost (Nassar et al., 2014, Elmahdy et al., 2018). However, the advancement of modern satellite technology provided images with high spatial, and temporal resolution such as KhalifaSAT, IKONOS, Quick-Bird, and Worldview, etc., are capable of providing detailed landscape characterization with unprecedented accuracy as compared to the medium-and low-resolution images. Most of these satellites acquire images from optical sensors, supporting adequate detailed texture and colour information, which allows us to monitor urbanization with better accuracy (Wu et al., 2021; Zhou et al., 2022). Several studies have been carried out to evaluate the efficacy of using high-resolution optical images for landcover studies, concerning urbanization and change detection especially in local-level small urban areas (Zhou et al., 2022; Hafner et al., 2023). Doxani et al., (2008), highlighted the potentiality of using Quick-Bird and IKONOS images for the detection of urban changes in Thessalonoki. Additionally, high-resolution aerial images have also been used for urban change detection (Fyleris et al., 2022). However, the process of aerial image collection and data preparation is expensive and time-consuming.

The former traditional methods of change detection relied on direct observation of two images to generate a change map based on visual interpretation (Wang et al., 2018). The results of these techniques are highly reliable but time-consuming, and labour-intensive (Goswami et al., 2022). The process of change detection can be grouped under two different categories such as (i) supervised, and (ii) unsupervised methods. The supervised methods are resistant to several external factors such as illumination variation, changes in atmospheric conditions, and poor sensor calibration during the data acquisition time (Hafner et al., 2023). However, unsupervised methods may be degraded by these external factors. The supervised method uses a training set generated from terrestrial reference data; however, unsupervised methods compare pixels directly without using any reference data (Gomroki et al., 2023). For the detection of urban land use changes, various pixel-based unsupervised methods including image differencing, image rationing, image registration, and change vector analysis have been rapidly used in many studies (Bruzzone & Prieto, 2000). While, implementation of these methods is constrained due to the difficulties of choosing proper threshold values, and selecting appropriate bands to identify the changes. Moreover, different medium to high-resolution satellite images ie., LANDSAT, Sentinel 1, 2, MODIS have been widely explored for the vegetation change assessment and urbanization through the implementation of various traditional supervised classifiers such as Maximum Likelihood Classifier (MLC), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), and Random Forest (Gomroki et al., 2023; Zhou et al., 2022; Wang et al., 2018). However, the detection of vegetation within complex urban areas (detecting, rooftop change, demolition status, etc.,) was found to be difficult based on the use of traditional image classification approaches.

In recent years, deep learning has become one of the efficient methods to process and analyze Earth Observation (EO) data. The vigorous development of deep learning techniques has started a new era in the field of urban change detection. Many studies have focused on the integration of deep learning and high-resolution remote sensing images to extract high-level features from images for change detection purposes (Gomroki et al., 2023). The widely used deep learning methods for change detection can be categorized into five groups: Convolutional Neural Networks (CNN), Autoencoders (AEs) or stack Autoencoders (SAEs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and Deep Belief Networks (DBNs) (Khelifi & Mignotte, 2020). The earlier studies have mostly concentrated on AEs and CNNs methods for the change detection of multispectral data (Gomroki et al., 2023). A large number of studies have considered CNNs for change detection purposes especially in urban land cover or land use, vegetation, building construction, etc due to their advantages of producing results with high accuracy, high performance, ability to extract robust features, and end-to-end training. However, these methods pose a limitation of requiring a time-consuming and high amount of training data (Cao et al., 2017; Wang et al. 2020). Also, studies found AE networks, as a simple and efficient model that employs end-to-end training to extract deep features effectively (Gomroki et al., 2023). In addition, the U-Net model, designed with a CNN architecture, is used for change detection of land use, land cover, forests, as well as urban areas (Gomroki et al., 2023; Wang et al., 2018). However, the U2-Net model, with its unique deep architecture featuring a nested U-structure, allows the capture of contextual information from various scales within an image, which has led to the significant detection of salient objects (Qin et al., 2020).

Based on the detailed literature review, it has been observed that open-source low to medium-resolution multispectral images have been extensively explored for studying land cover changes in conjunction with urbanization using various traditional classification algorithms (Wang et al., 2018). Many studies have been conducted based on the utilization of machine learning and deep learning methods such as MLC, SVM, KNN, etc., to detect building changes and monitor urbanization. However, despite the enormous importance of exploring changes in the urbanization process in Dubai, limited studies have been carried out using high-resolution satellite images. Also, the use of advanced deep learning algorithms has not been fully explored to detect the detailed and minute level of change detection in urban and associated vegetation over Dubai. Therefore, the novelty of the present study lies in the utilization of high-resolution KhalifaSAT data, and the utilization of the U2-Net deep learning model to detect the changes in complex urban features and vegetation within urban areas with greater accuracy.

2. STUDY AREA

The study area selected for the present work extends between longitude 55°00′00″ to 55°45′00″E and latitude 24°30′00″to 25°36′00″N, which covers the city of Dubai and its surroundings with a total geographical area of around 6300 km^2 (Figure 1). The reason behind the selection of Dubai as our preferred study site due to its rapid developing status. Dubai is the second largest city in the United Arab Emirates (UAE) after Abu Dhabi in terms of population and area, as well as considered to be one of the most rapidly developing cities in the world. The Emirates of Dubai is spread over an approximate area of about 3885 km^2, while the city is covered with an approximate area of about 700 km^2 at an elevation of 5 m.a.s.l. The city is divided into two parts by the Creek of Dubai (which runs south from the Arabian Gulf for 13 km) namely (i) Deira in the northeast, and (ii) Bur Dubai in the south-west. Dubai experiences a warm and sunny climatic condition with an average temperature ranging from 25°C in winter to 37°C in summer (Nassar et al., 2014). Moreover, the Emirates of Dubai is considered a hyper-arid region due to its infrequent average annual rainfall of approximately 8 mm that mostly falls in winter, and late autumn (Nassar et al., 2014). Dubai experiences a monthly mean rainfall between 0.6 to 18.8 mm, mostly during winter (Elmahdy et al., 2018). Dubai has been categorized into three major geomorphic regions such as (i) the eastern mountains, (ii) a dune field, and (iii) the western regions with coastal belt and inland sabkhas (Elmahdy et al. 2018) (Figure 1).

Pacione (2005) stated that, based on the observation and analysis of some historians, the origin of the Emirates of Dubai dates back to around 1833 when 800 people settled in the creek area of Dubai. In the early period, fishing and pearling were the major sources of the economy. Additionally, Dubai served as a transit point for overland trading convoys traveling from Iraq to the Sultanate of Oman and as a strategic seaport facilitating trade between Asia, Africa, and the Gulf region. However, population growth accelerated in the 1970s after the discovery of large oil reserves, which attracted a large labour force primarily from overseas countries. Gradually, the government initiated many infrastructure and industrial projects, such as Dubai International Airport, Port Rashid, the dry docks, and an aluminum smelter, utilizing the revenues from oil reserves. These developments initiated the process of urbanization, which is a major focus of the present investigation.

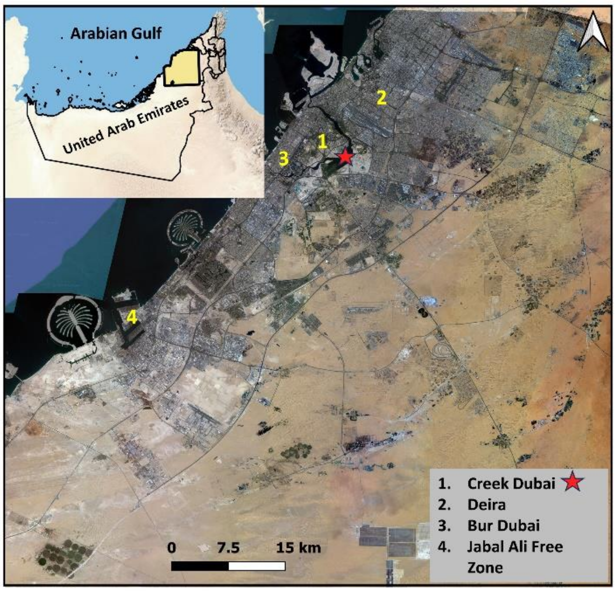

Figure 1. Map of the study area (Data source: Khalifasat, Dubai Municipality; Basemap, ESRI Physical)

3. DATA AND METHODS

The high-resolution KhalifaSAT (KHCS) data for the years 2021 and 2022 were used for urban change detection in this study. KhalifaSAT is one of the most advanced Earth Observation (EO) satellites, designed and manufactured in the United Arab Emirates (UAE) at the Mohammed Bin Rashid Space Centre (MBRSC). It was launched in October 2018 aboard an H-IIA rocket from the Tanegashima Space Centre, Japan. The satellite consists of a push-broom High-Resolution Advanced Imaging system (HiRAIS), which allows for the capture of images across four channels spanning the visible to near-infrared spectral range. Additionally, it acquired data with a very high spatial resolution of 0.75 m in panchromatic bands and 2.98 m in bands of the visible spectrum (red, green, and blue). The detailed specifications of the sensor are shown in Table 1.

For the achievement of framed objectives of the study, we followed the methodology shown in Figure 2. The overall methodology can be classified into five parts such as (i) data acquisition and pre-processing, (ii) preparation of training data, (iii) defining various model parameters to implement the U2- Net model for urban change detection, (iv) accuracy assessment to test the performance of the model, and (v) post-processing analysis to extract the accurate urban change information of the study area.

Table 1: Detailed specification of KhalifaSAT sensor

Orbit	Sun-synchronous orbit, nominal altitude = 613 km, inclination = 98.13º
Instrument type	Pushbroom imager
Design life	5 years
GSD (Ground Sample Distance)	0.75 m Pan, 2.98 m MS (4 bands, RGB+NIR) IFOV: Pan< 1.21 µrad, MS< 4.86 µrad
Swath	12 km at nadir (FOV> 1.15º for each band)
Data quantization	10 bit

3.1 Pre-processing

Pre-processing of raw KhalifaSAT data was initiated by upscaling the resolution of RGB and NIR bands as similar to the pan band of KhalifaSAT data to generate a super-resolution (0.75 m) image. This process was performed using the Machine-Learning Super-Resolution (MLSR) tool available in Eofactory, which is a Geo-AI platform for the analysis of EO data. In addition, image registration was performed, and the quality of the image was enhanced through histogram equalization and linear contrast stretching. Moreover, the data sets were divided into 512 ×512 patches, and the patches containing a higher portion of the target urban features were chosen. In addition, the ground truth is also converted into 512 ×512 patches, so that it became suitable as an input in the U2-Net model.

3.2 Training data preparation

To prepare the data for training, we stacked both the processed data and generated six band images which were for the implementation of the selected deep learning change detection model. Furthermore, training and testing data were separated. In this analysis, a total of 80% data was used for training and the remaining 20% data was applied for testing purposes. In the next step, augmentation was used for the training datasets. Data augmentation is a process of artificially increasing the size and diversity of data through the application of various transformations to the original data (Gomroki et al., 2023). As a result of applying augmentation in the training data, helps to increase the efficiency of the model as well as to improve the generalization ability of the model by reducing overfitting problems (Wang et al., 2018; Gomroki et al., 2023). In this study, five different augmentation techniques have been used as shown in Figure 3. Initially, we applied Gaussian Blur (GB) method to smooth out noise and small details from the training data, making the model more robust to the noise in the data (Figure 3b). In addition, augmentation method like rotation was used at an angle of 90° to make the model invariant to object orientation (Figure 3c). Moreover, Gaussian Noise was also added to the training data to introduce random variation in pixel intensities (Figure 3d). This variation could help our model to improve the ability of segmentation more effectively. Furthermore, Random Multiplication has been implemented to improve the robustness of intensity variation (Figure 3e). This method introduces variation in the intensity of input images by randomly scaling the pixel values. Also, this method helps in improving the model's ability to accurately segment objects as well as mitigate the overfitting problems in the input data (Gomroki et al., 2023). At last, horizontal flipping (fliplr) was implemented on training data with a probability of 0.5, which led the model to be more robust to objects appearing in horizontal orientation (Figure 3f).

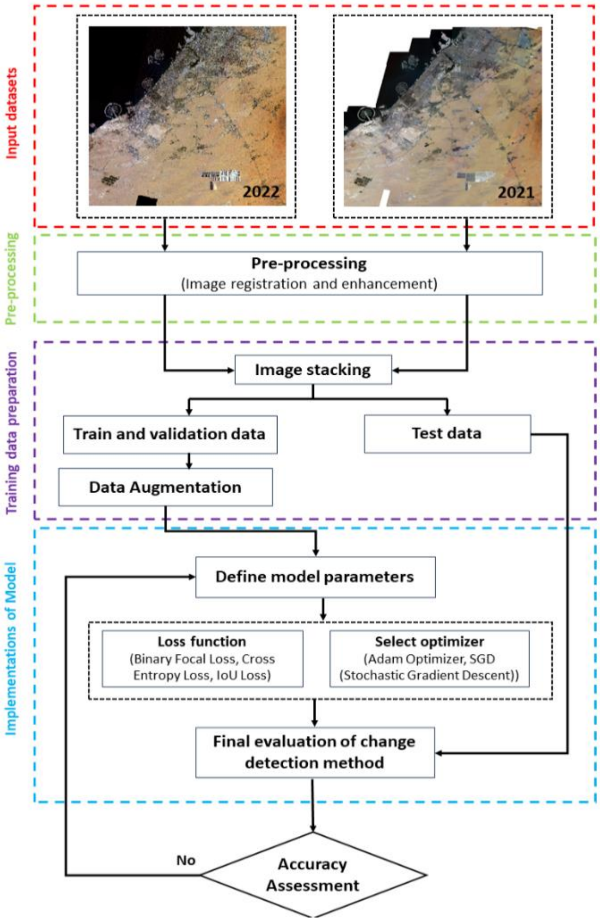

Figure 2. Flowchart of methodology

3.3. U2-Net model

In this study, we have implemented the U2-Net deep learning model for change detection of urban and associated vegetation within the study area. This model offers several advantages such as high segmentation accuracy, multi-level feature extraction, efficient parameterization, robustness to noise and variability, etc., compared to other deep learning methods, that makes it a significant choice for urban change detection (Fyleris et al., 2022; Hafner et al., 2023). The U-shaped architecture of the U2-Net model, consisting of encoder and decoder pathways and its multi-scale feature fusion mechanism enables the model to provide high segmentation accuracy and the ability to extract multi-level features which facilitate urban associated with vegetation change detection with better accuracy (Gomroki et al., 2023). The overall process of implementing the model was performed in Jupyter Notebook. Initially, different Python packages such as numpy, scikit-learn, pytorch, pillow, and gradio were installed in the Jupyter environment that allows processing and analysis of the data. After preparing the training datasets for different urban classes and vegetation (described in section 3.2), we initialize the model by defining several parameters (epoch: 100, and learning rate: 0.001), necessary to train the model. Additionally, different loss functions were used for image segmentation during the model's training, as these functions are necessary for quantifying the difference between models' predictions and ground truth labels. We have used a combination of various loss function techniques such as Binary Focal Loss (BFL), Cross Entropy Loss (CEL), and Intersection over Union (IoU), which are suitable for building change detection. Furthermore, two widely used optimizers, Adam optimizer and Stochastic Gradient Descent (SGD) were implemented to update model parameters during training. After defining all the necessary parameters to train the U2-Net model, we run the model on the satellite images of both periods to generate the change detection results.

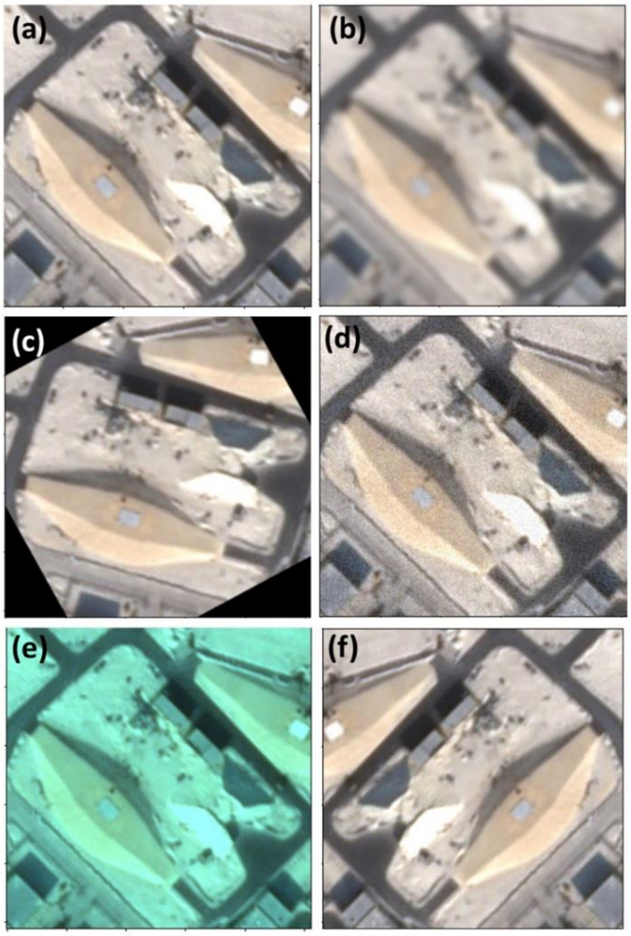

Figure 3. Results obtained from different augmentation techniques (a) Original image; (b) Gaussian Blur; (c) Rotate 90°; (d) Gaussian noise; (e) Random Multiplication, and (f) Horizontal Flipping (0.5)

Consequently, the results obtained from the implementation of the chosen model were qualitatively checked using high-resolution temporal reference images. In addition, an accuracy assessment was performed to test the performance of the model. Moreover, for improving the accuracy of detection results a post-processing operation was performed after a detailed qualitative assessment of the results. During the post-processing analysis, we removed or modified the wrongly detected change polygons (such as too-small polygons) to generate an accurate and efficient result that could reflect the real scenario of change that occurred in the study area during the time of 2021 to 2022.

4. RESULT AND DISCUSSION

The goal of the study was to detect the minute level of change in urban and associated vegetation cover in Dubai based on the implantation of advanced deep learning techniques on high-resolution KhalifaSAT imagery. The change detection results obtained from the application of the U2-Net model are shown in Figure 4. After a detailed assessment of the obtained results, it was observed that the model used in this study could efficiently identify the changes in different urban classes along with the associated vegetation. Many previous studies have mapped and detected changes in urban vegetation using open-source satellite images, employing various traditional as well as Machine-Learning models. These studies typically highlight the classification of broad classes such as urban areas, vegetation, roads, and water bodies (Gasparovic et al., 2020; Fan et al., 2023). Gasparovic et al. (2020) compared different machine learning algorithms using Sentinel 1 SAR images to classify urban land use features. They found that Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) classifiers efficiently detected changes in water, bare land, forest, built-up areas, and low vegetation. However, minute-level change detection of urban features such as new construction, building demolition, rooftops, and associated vegetation remains challenging. In contrast, the present study highlights the efficiency of the U2-Net deep learning algorithm for detailed and accurate detection of various urban features, vegetation, and their changes over time.

Figures 4a, & 4b exhibit the identification of a bunch of newly constructed buildings which show a transformation of a bare surface within the city into organized build-up lands within one year. In addition, the model has appropriately detected the boundary area of buildings that have been demolished as shown in Figures 4c and 4d (marked by yellow polygons). Figures 4e and 4f show the detected areas of extension of the building by blue rectangle polygons and yellow arrows. Moreover, the model used in this study shows promising results in detecting changes in building rooftops. Chen and Li (2019), have detected square-shaped building rooftops by implementing the CNN model with an accuracy of 79%. In the present study, rooftop changes of the building (with a circular shape) have also been correctly marked out automatically through the application of the U2-Net model (Figures 4g, and 4h) with an accuracy of 82%. Furthermore, a significant change has also been encountered in the urban-associated vegetation covers, shown in Figures 4i and 4j.

Apart from qualitatively evaluating the detected results by inspecting reference high-resolution images, an accuracy assessment was also conducted to evaluate the performance of the applied model. This evaluation included computing the Overall Accuracy (OA), F1 score, and kappa coefficient. The analysis revealed that the U2-Net model achieved an overall accuracy of 0.82, a kappa coefficient of 0.76, and an F1 score of 0.78. These findings validate the obtained results and indicate that the model is well-suited for urban and land cover change detection. We also have carried out a statistical analysis to check the areal changes of the detected features by computing the area of changed features in hectors (Figure. 5). It has been observed that the highest change has taken place in the construction of new buildings, covering an area of 873 hectares, while in the case of vegetation change, it is around 848 hectares. Additionally, the lowest area of change occurred in the class of extension of existing buildings, which covers an area of 74 hectares. Considerably, a significant change has been observed in the rooftops and demolished buildings, which cover areas of 313 hectares and 185 hectares, respectively.

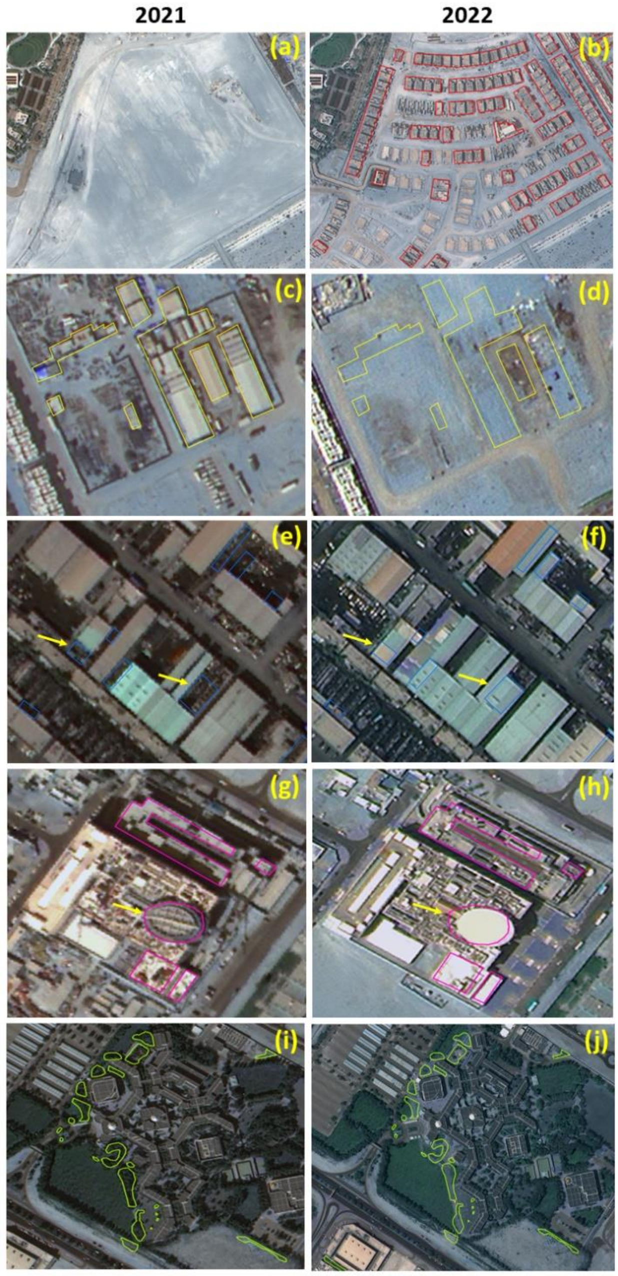

Figure 4. Change in urban extent in Dubai Emirate; (a, b) newly constructed building; (c, d) building demolished; (e, f) extension of the building; (g, h) building rooftop change; and (i, j) vegetation change (Data source: Khalifasat, Dubai Municipality)

In addition, after counting the number of changes in detected feature classes (Figure 6), it was found that around 20,600 new buildings were constructed from 2021 to 2022 in the study area. Additionally, a similar number of changes were observed in classes such as existing building extensions and demolished

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buildings, which are around 6,300 and 6,500, respectively. On the other hand, changes in rooftops were observed in a total of 5,400 buildings during the studied period, while around 14,000 polygons were found to have changed in vegetation cover in the study area.

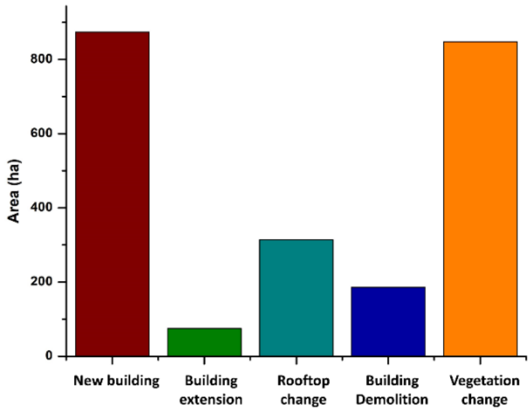

Figure 5. Areal changes in detected urban features and associated vegetation cover from 2020 to 2021

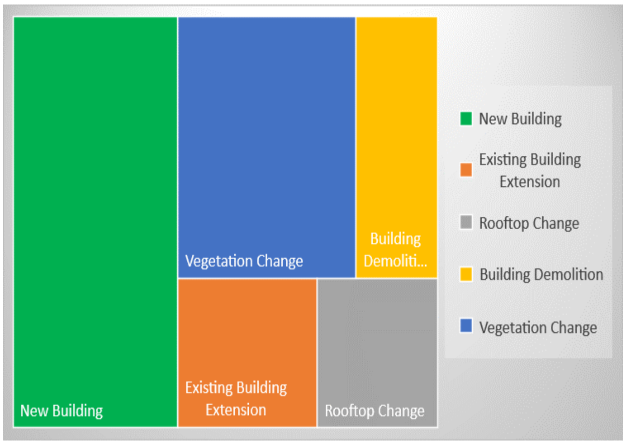

Figure 6. Counting the number of urban and land use feature changes during 2020-2021

5. CONCLUSION

The study was significantly focused on the change detection of urban features and associated vegetation cover from 2021 to 2022 in the emirates of Dubai using high-resolution KhalifaSAT data leveraging the cutting-edge deep learning method. After a detailed change detection analysis, the study found the VNIR bands of KhalifaSAT data to be tremendously suitable for minute-level urban change detection. For the generation of super-resolution images, a machine-learning-based tool was applied using the Geo-AI platform named Eofactory, found to be useful for improving the spatial resolution of satellite images, and for enhancing the data to be used in such detailed change detection analysis. The study highlighted the efficacy of implementing the U2-Net deep learning model of autoencoder networks for urban land cover change detection. The method has proven to be efficient in detecting the changes in various urban features such as newly constructed buildings, buildings that have been demolished, extension of buildings, as well as rooftop changes of buildings. The model has also revealed significant changes in vegetation cover associated with the urban areas efficiently. The detected changed features were validated based on a detailed qualitative investigation using high-resolution reference satellite data, and the model-derived change detected polygons were found to be an appropriate match with satellite images. Additionally, the performance of the model was found effective by assessing the obtained accuracy (OA =0.82, kappa coefficient = 76, and F1 score = 0.78). Moreover, the study has revealed that the maximum changes occurred during 2021-2022 in the construction of new buildings (approximately 20,600 buildings), along with associated vegetation covering an area of 873 ha and 848 ha respectively. Regarding the potential future scope of the research, the integration of multi-source data combined with spatiotemporal analysis could enhance the long-term understanding of urban dynamics, thereby facilitating the development of comprehensive urban planning and management strategies.

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