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Assessment of Urban Changes at the Residential Neighbourhood Level Based on Satellite Imageries

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Abstract

Ongoing urban expansion leads to the steady loss of green spaces. Residential units' gardens and green open spaces are a vital part of city life, contributing considerably to urban green infrastructure and ecological services. However, these areas are diverse, making it difficult to assess their changes over time to take advantage of their benefits and contribution to sustainable urban development. This study proposes a new methodology that combines survey data with high-resolution image analysis to construct maps and statistics of change in two residential neighbourhood areas in the Iraqi city of Baqubah. Three change detection techniques utilising very high-resolution multispectral Pléiades images were used to evaluate the changes: pixel value differencing, band index differencing, and categorical change detection. Then, a unique strategy employing geo-processing processes by the ModelBuilder tool was applied to the evaluation outcomes to assess the changes in a final manner. In addition to survey data that supported the final change detection outcomes, study validation was conducted through field verification, and the mean accuracy was 93%. The final results indicated that open or green spaces decreased over a period of seven years at rates of 24% and 14% of the total of both areas assessed. Policymakers and urban planners see such privately owned land as difficult to affect. However, reducing vegetative cover areas and turning them into impermeable surfaces may result in the areas becoming inefficient in the development of urban sustainability. Our developed method demonstrates the capability of utilising Very High Resolution (VHR) imagery with local survey data to accurately infer changes in urban vegetation within residential neighbourhood regions.

Keywords: Urban Change Detection; Pléiades Satellite Images; Machine Learning; Residential Areas; Urban Sustainability; ArcGIS.

1. Introduction

The global tendency to rapidly urbanise has made the frequent detection of urban area changes critical. The reduction of open and green spaces as a result of their exploitation in construction expansions, particularly gardens in private residences, may require constant monitoring. Hence, learning about any urban region necessitates exploring and comprehending how it has evolved. This has the potential to persuade policymakers to become aware of the impact of recent urban plans on the area and make changes accordingly. In addition, built-up areas have resulted in a slew of challenges, including decreased land efficiency, dwindling agricultural land, pollution, and ecological degradation [1]. As a result, precise measurement of changes in built-up areas is essential to promote local spatial development plans and accomplish long-term economic and environmental growth. It should be noted, nonetheless, that not all changes in the city occur in accordance with the plan. In other words, not all changes in a planned region will necessarily be in accordance with the plan. Aside from the judgements made regarding the plans, there are unauthorised or unlawful constructions in various regions everywhere.

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Plans' execution in cities may be subject to several restrictions [2]. Plans sometimes rely on forecasts and assumptions about the future, which may or may not be accurate. This is one restriction. If the actual population growth rate is higher or lower than anticipated, for instance, a plan may assume a specific rate of population increase, but this could cause problems with infrastructure and services. Another drawback is the challenge of coordinating and harmonising the actions of various stakeholders involved in the execution of plans. Cities are intricate systems with many diverse groups, agencies, and people working toward various goals [3]. This may lead to disagreements and difficulties when putting the intended efforts into action. The absence of funding and resources is one constraint. Even if a city has a clearly defined strategy, the lack of funding and resources may prevent it from being fully implemented. The implementation may be incomplete or delayed as a result. Cities are also dynamic, intricate systems that change throughout time. They are influenced by variables that can alter and have an impact on development, such as social, economic, and environmental ones. Despite having a plan, cities can face unforeseen problems or circumstances that necessitate modifying the original strategy. Therefore, even in cities with detailed plans, many circumstances might contribute to the implementation of urban planning being limited and lead to uncontrolled development. For these limits to be adequately addressed in upcoming urban planning projects, understanding them is essential [4]. Monitoring adjustments as well as large, fundamental changes at all societal levels are necessary for urban sustainability and proper land use [5].

To assess urban changes at the neighbourhood level, the change detection process entails, therefore, analysing and quantifying the temporal effects of objects or phenomena using multiple temporal datasets [6]. Change detection has progressed as the spatial resolution of remote sensing images has increased, and it has been employed for applications at various spatial indicators. Analysing images of the same research region over many years is an effective and reliable technique to detect change [5]. With the advent of commercially available very high-resolution (VHR) remote sensing images, precise information about land features has become available, allowing for the detection of changes. Textural characteristics are also more visible, allowing for the extraction of additional change information for terrestrial objects via comparison analysis [7]. As a result, change detection algorithms based on VHR satellite imageries must be capable of efficiently and accurately processing enormous datasets, which has become a challenge for researchers. One approach to evaluating how a region has evolved is through pixel value change detection; the discrepancies in optical imageries can be found at a pixel-by-pixel level. A substantial quantity of literature has been published on the subject of pixel value change detection [8–13]. This method of detecting changes has various downsides, such as determining the most acceptable threshold value of the change, which differs between areas and reasons for detection. Traditionally, pixel value change detection algorithms did not completely use the spatial context of real-world objects represented as pixels in an image [6].

On the other hand, the following studies employed the band index difference change detection method to detect changes in urban areas: [11, 14–16]. They used the normalised difference vegetation index (NDVI) technique with varied threshold values based on the VHR multi-spectral remote sensing data technique to extract changes in urban areas. Although the NDVI index is a legitimate metric for evaluating degrees of visible greenness in residential areas, it is highly associated with experts' recommendations of what greenness threshold value to use. Because NDVI's analysed vegetation also includes farmland, pasture, and wetlands, some researchers have turned to categorical change detection, which involves classifying satellite images to measure changes.

The categorical dataset is image data with a value for each pixel that represents a class or category. Comparing category raster datasets has the goal of identifying areas that have altered from one category to another over time. Various studies have examined the potential of classifying high-resolution satellite imageries using various classifiers and approaches to extract the change in urban areas, such as [17–20]. In comparison to algebraic techniques, the image classification-based approach provides significant accuracy [21]. Although there are several strategies for detecting urban changes, choosing the best and most accurate method can be difficult. Consequently, data mining researchers and engineers employ various methodologies and apply their knowledge to detect change.

For urban planning stakeholders in the local area, detailed knowledge of urban gardens and green spaces is valuable to implement targeted green space interventions within and outside gardens by, for example, identifying neighbourhood areas where green space is needed [22]. Recent years have seen a considerable rise in urban growth at the expense of open landscapes. Many change detection techniques (e.g. Detecting Image Pixel Value, Image Band Index, and Categorical Changes) are used to find urban changes. However, the most crucial fact is that each method of change detection offers a unique sort of information about the changes taking place in the urban environment. The research to date has, therefore, tended to focus on applying one of these techniques rather than testing it in combination. This integrated method may support urban planning, environmental evaluation, and sustainable development while enabling more efficient monitoring and management of urban areas. The importance of urban green open spaces has been the subject of countless studies, yet the approaches taken vary greatly. Setiowati & Koestoer [23], for example, used a life satisfaction method to valuation, emphasising the beneficial relationship between inhabitants' overall life pleasure and their access to green open spaces. Their research, however, was restricted to parks and only one kind of green space. This drawback emphasises the necessity of more thorough, broadly applicable research employing the life satisfaction paradigm. By examining gardens of various green space types and attributes, the current study seeks to close this gap. The efficiency and accuracy of feature classification in metropolitan public open areas have increased due to recent developments in deep learning. For example, Kim & Yoon [24] showed how well a multivariate time-series technique captures spectral and temporal fluctuations from poorly annotated data, classifying open space characteristics into 11 classes with 97.86% accuracy.

Nevertheless, their research was restricted to satellite images with a moderate spatial resolution and very small parks with extremely varied land cover. This emphasises the need for more studies that are able to identify tiny open places, such as house gardens. Using images from satellites with extremely high spatial resolution, the current work will examine this issue. For cities to adapt to heat, urban open areas are essential. To classify these areas for heat mitigation, recent studies have used creative approaches. For instance, Villaverde et al. [25] identified heat-adapted urban open areas in Spain using a cluster-based methodology. According to the paper, there is a lot of room to improve open spaces. The densely packed residential blocks seen within sprawl zones, however, were not taken into consideration. In Nairobi, Kenya, Odhengo et al. [26] carried out an extensive assessment of urban green areas, emphasising their advantages for enjoyment, the environment, and the economy. Their research did, however, also highlight the problems brought about by fast urbanisation, such as the loss of green areas and the unequal distribution of advantages. In order to evaluate the accessibility of urban green spaces, Hou et al. [27] created the Physical Activity Diversity Index (PADI), which measures the variety of physical activities that are supported by various kinds of green spaces. Their study was carried out in China; nevertheless, it highlights a knowledge gap about its performance in various urban contexts and the necessity of integrating it with other measurements. Therefore, our strategy will adopt a mixed-methods design, integrating field observations, user surveys, and GIS mapping and location analysis.

Therefore, one aim of this study is to assess the extent to which these methods extract the changes within the residential neighbourhood areas by employing remotely sensed data. These detected changes can let us take a thorough assessment of the proportions of land transition from permeable to impermeable areas by applying each technique. The detection of these changes means we have to evaluate the transformation of green spaces to built-up areas (e.g., the house built-up expansion), whether within the residential unit or outside the bounds of the residential area. Another aim is to develop an approach compatible with these techniques to achieve workable outcomes in assessing the transformation of residential areas from vegetative cover to built-up areas. Our sub-purpose in this regard is to assess the viability of our suggested integrated strategy in contrast to two distinct urban structures (planned and unplanned regions). By studying both types, the difference in the amount of change of each structure can be evaluated, which may help urban planners create more efficient, resilient, and habitable cities in the future. Because the difference between urban-planned and unplanned areas lies in their organisation, development, and management, our contribution is to better comprehend the conversion of vegetative land classes of the green or open spaces to developed land. This may lead to increased connection, more equitable distribution of amenities, better living conditions, and overall sustainability. The research was also carried out with a survey; the data was collected from an online residents' experience survey platform and may indicate the reasons for the changes in green spaces. Understanding the link between the outputs of image-based change detection and the perceptions of residents can provide useful evidence for policies related to local urban development. The paper proceeds as follows: the second section describes the materials and methods that were employed in our developed approach, the third section presents the change detection results and survey analysis, the fourth section discusses the findings, and finally, the last section presents the conclusion.

2. Material and Methods

2.1. Study Area and Sampling Delineation

The research was conducted in Baqubah, a city located about 60 km to the northeast of Baghdad, through which the Diyala River runs (Figure 1). Baqubah is the capital of Iraq's Diyala Governorate and is known as the heartland of the entire country’s commercial orange groves. It has been noticed recently that orange orchards and house gardens in this region have begun to shrink and be lost to view as a result of population growth and the consequently increasing demand for housing. This was one of the main reasons this city was chosen as the area of study. To assess this phenomenon, two samples that showed a difference in their urban structure and features were chosen to represent two different locations of the city: an unplanned residential area and a planned residential area.

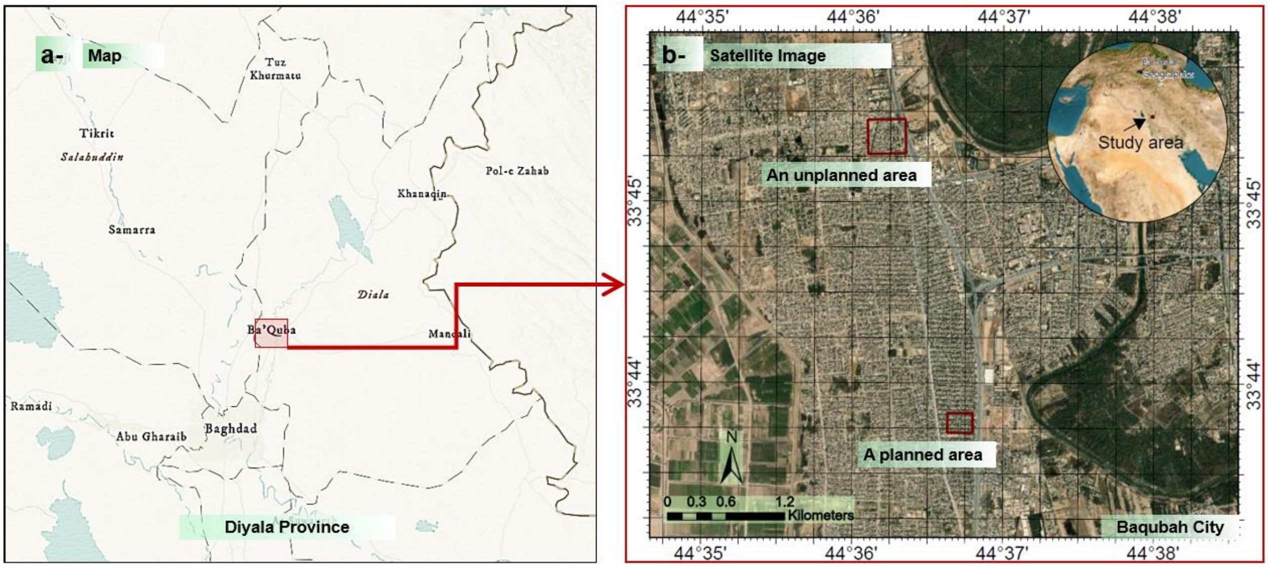


Figure 1. Baqubah's location in Diyala province, illustrated by the dashed line on the map (left), and the close-up satellite imagery of the city (right)*

2.2. Data Collection

2.2.1. Image Dataset

For conducting the change assessment at the residential neighbourhood level, the research was performed on two sets of pan-sharpened Pléiades 1A PX satellite image† with a spatial resolution of 0.5 m. The images were georeferenced and orthorectified to the Earth's surface UTM coordinate system. Each dataset had a radiometric resolution of 16 bits per band and the images contained four multispectral bands (Red (R), Green (G), Blue (B) and Near-Infrared (NIR)). Every dataset had two samples, Sample 1 and Sample 2. Each sample had two satellite images captured on two different dates: 6th July 2014 at 12:38:48 and 6th June 2021 at 12:38:31. Therefore, Sample 1 and Sample 2 each had one image captured in 2014 and one image captured in 2021. These datasets were selected to represent two main categories of urban areas, planned and unplanned residential neighbourhoods with diverse urban structures and features. The areas of Sample 1 and Sample 2 were 140,140.00 m^2 and 52,751.25 m^2, respectively. Since the proposed approach of change detection relies on the change of spectral and spatial characteristics, the images were carefully selected to minimise the seasonality difference and extensively cover varying fine spatial details that might be encountered during image collection. Also, due to the need to evaluate changes in the urban environment at the level of adjacent building units, the power of satellite images was required for this study, as they provide very high spatial resolution.

2.2.2. A Survey on the Changes in the Residential Neighbourhoods

Uncovering the reasons behind the changes within the adjacent residential regions was necessary to gain information and further insight. A short questionnaire was designed for the landlord or resident(s) of a household to complete to gather quantitative information regarding housing changes and structure, as well as living standards. The survey was conducted both before and after the analysis of the built-up change detection. The two key advantages of collecting data through the survey were: (1) a reliable analysis of the urban changes was obtained, and (2) the change detection processes were verified by gathering ground truth data. The main survey questions were related to housing type, monthly income, housing area, the number of families within one housing unit, the number of occupants within one family, the number of rooms, and the type of changes that happened in green and construction spaces.

2.3. Methods

The study uses remotely sensed data to analyse land transition in residential neighbourhoods, focusing on green space conversion into built-up areas. It explores the relationship between image-based change detection, urban development policies, and perceptions of green spaces, aiming to build smarter, more resilient cities. To this end, the assessment framework used in this study and its procedures are depicted in Figure 2. The purpose of the proposed framework is to quantify the changes in the proportion of construction areas at the expense of the green areas of residences and their surrounding built-up regions. The processes of the framework were carried out in their specific order to notice and evaluate the differences between the two chosen periods in the two samples. This is manifested by confining the three available techniques for detecting changes in the red box. The assessment framework can help to

* The boundaries of the two selected samples (planned and unplanned) of the study region are shown on the right side of the figure.

† The images were purchased from the Land Info agency for Aerial/Satellite Imagery Solutions & Digital Map Data.

better understand the reasons behind switching from a green area to a construction area within the residential areas. For the majority of the research, ArcGIS Pro[*] 2.8.3 was used for geospatial analysis, geo-processing tools and mapping. The remaining procedures were completed by utilising Microsoft Excel Spreadsheet Software to analyse the online survey of citizens' housing needs and by conducting a site survey to complete the field study.

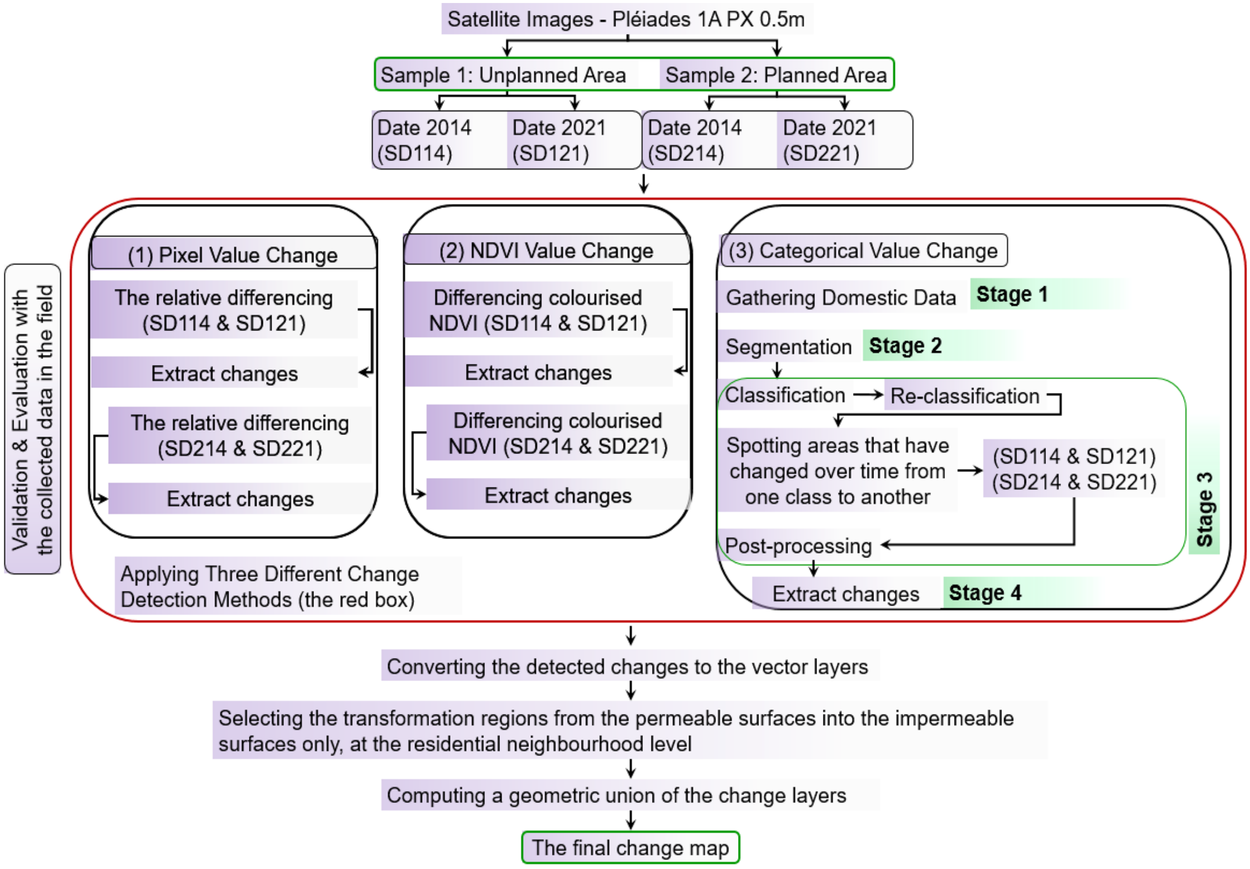


Figure 2. An analytical framework for evaluating the residential neighbourhood changes over some time.[†]

2.3.1. Detecting Image Pixel Value Changes

The detection of changes in the pixel values between numbers of images, frequently acquired at different times, is a technique known as image pixel value change detection. Each image band or channel, such as red, green, and blue, has its variance in pixel intensities quantified. According to the technical definition, it entails comparing the pixel values of various bands for each associated pixel position in the image datasets. A new image is produced when the differences are determined using mathematical operations like subtraction or the absolute difference between pixel values. The various images can be set at a threshold to further distinguish meaningful changes from background noise or random fluctuations. In this process, the changes within the two samples of the residential neighbourhood regions were calculated on a pixel-by-pixel basis. The process of performing pixel value change detection enabled us to compare two raster datasets over two periods of time. To compare the two captured dates of the images in each sample, the relative difference approach was used in the calculation. The relative difference in pixel values is when the quantities of the values being compared are taken into consideration. The relative difference is, therefore, capable of showing whether the area changed between the two dates by evaluating the amount of change. It can be computed as follows:

$$C_l = (I_{T2} - I_{T1})/max(I_{T2}, I_{T1}) \tag{1}$$

where C_l is a new raster layer of the computed change (ESRI-2020). I_{T1} and I_{T2} are Time 1 and Time 2 of the captured images in both Samples 1 and 2. The new layer C_l contains the difference between the two captured imageries' dates. Implementing this process was essential as it helped to discover how the built-up area changed from 2014 to 2021. Since our research focused on finding the decline in green spaces relative to the built-up area in the residential region, it was necessary to determine a value for the threshold to extract only transformed pixel values within this range. Therefore, we performed a relational greater-than operation utilising the spatial analyst on two inputs on a cell-by-cell basis with the following equation:

[*] ESRI's ArcGIS Pro is the company's most recent and powerful professional single desktop GIS software and/or application.

[†] SD114: S=Sample (1), D=Date 2014 (14).

$$M_l = GreaterThan\ (C_l\ , x) \tag{2}$$

where, M_l is the mask layer that includes only pixel values which are greater than the change threshold value (x) (ESRI-2020). The most suitable value of x that we found for this region was 0.25. The relational math process compared the C_l raster and the threshold value and provided a Boolean value of 0 for False and 1 for True. If the first C_l raster input was greater than the second (x) value, the output M_l was 1. If not, the output M_l was 0. All other pixel values of the decreasing change and/or no change were masked out. This step also excluded pixel values that showed a change that did not belong to the residential area.

2.3.2. Detecting Image Band Index Value Changes

Image band index value change detection is an advanced method that uses remote sensing indices to analyse changes in a particular band's spectral information over time. These indices, including NDVI (Normalised Difference Vegetation Index) and NBR (Normalised Burn Ratio), are created by combining two or more distinct band ratios from satellite imagery. To identify places that have significantly changed, the technique includes calculating these indices on a per-pixel basis for two images acquired at various intervals of time. This technique draws attention to certain landscape characteristics, including vegetation growth or burn scars left by wildfires, enabling a more focused investigation and interpretation of changes. Using band index difference, the retrogression of green and open spaces could be tracked, the extent of the deterioration of vegetation cover between two-time points could be measured and the change of these spaces' shapes and sizes could be better understood. Accordingly, we calculated the band index difference of the two samples by employing the NDVI using in Kadhim et al. [3]. This standardised index allowed us to generate a new raster displaying the density and intensity of vegetation areas using the red and the near-infrared (NIR) reflectance values bands as follows:

$$NDVI = (\rho_{NIR} - \rho_{Red})\ /\ (\rho_{NIR} + \rho_{Red}) \tag{3}$$

where ρ_{NIR} and ρ_{Red} are the reflectance of the near infrared and red band, respectively. The values of this index are listed on a scale of 0 to 1.0. The higher numbers (green) imply that the region has a lot of vegetation. A band index was computed for each image raster in both samples, then the difference between index values was determined. In this context, to highlight the changes in this range later in processing, we applied equation (2) to all captured image raster dates, which produced a new mask with an adjusted mask value. In this case, the mask threshold value x was 0.4, as recommended by the local experts. We found this value is the most suitable value allowing us to obtain a tangible outcome in providing information for the green spaces within the residences and their surroundings. Thereafter, to obtain the change, the Arithmetic function performed the following arithmetic operation between the corresponding pixel values for two NDVI mask raster layers:

$$C_{NDVI} = M_{NDVI,14} - M_{NDVI,21} \tag{4}$$

where, C_{NDVI} is the change between the two index values, while, $M_{NDVI,14}$ and $M_{NDVI,21}$ are the NDVI masks in 2014 and 2021, respectively, after applying a threshold value to the band index in each year. Calculations of the arithmetic difference of NDVI masks for a given pixel resulted in a number ranging from $-v$ to $+v$ (where v is the pixel value). We then categorised this change (arithmetic difference) into three main categories to differentiate the differences in pixel values. Negative values indicated that there was a great reduction in the green spaces, whereas positive values indicated enhancement in vegetation cover. Values that were zero indicated no change in the existing green spaces.

2.3.3. Performing Categorical Change Detection

The goal of categorical change detection is to recognise and define the changes over time that occur between various land cover classes. Using supervised or unsupervised classification techniques like Maximum Likelihood, K-means clustering, or Random Forest, this method first classifies the land cover of multi-temporal images. A post-classification comparison is carried out by assessing transitions across categories at each relevant pixel location over the time series after each image has been classified into the appropriate land cover categories (e.g. urban area, forest, and water body). The result is often displayed as a change matrix displaying the changes between various land cover classifications, giving details about the kinds and extent of land cover. Categorical raster data is, therefore, raster data in which each pixel represents a class or category with a value. Thematic data, discrete data, or discontinuous data is the result, and it represents land cover, land use, or other district-level information such as the urbanisation level. Comparing category raster data aims to identify regions that have changed from one class to another over some time. In this study, categorical change detection was performed to accurately detect the residential neighbourhood changes for two samples. The following steps were used to explain how to use this strategy in its entirety:

Stage 1: Gathering Domestic Data

Collecting real-world data is an important and supportive step for both study evaluation and validation purposes. To obtain quantitative and statistical information regarding the change in house layouts and occupants, an online survey and field investigation were created to be completed by the owner or resident(s) of a household. We adopted this strategy of combining citizen science data with high-resolution picture analysis to build a green spaces dataset presented by Baker et al. [22] as a cutting-edge approach to sustainable urban development. Therefore, in our present study, the survey included specific questions regarding the proportionate area and size of changes of domestic surfaces categories (built-up areas, green and open spaces) to better comprehend the amount of altered green space inside an individual domestic boundary and to verify the proportion of change analysed in these land covers from the satellite imageries. The online survey had more than 200 respondents, comprising of the landlords, residents and tenants.

For the study analysis and evaluation processes, many different house samples were randomly chosen within the residential neighbourhoods in the study area. Further survey questions were asked concerning personal data, socio-economic information, the number of members in every family, the number of families in an individual house or apartment and the housing types, but not all survey data was presented or analysed in the scope of this article. The data gathering stage also constitutes the accuracy assessment of the image classification outcomes in addition to all change detection processes. This step was accomplished after producing the classified maps and the extracted changes of the study area. We constructed randomly generated accuracy evaluation sites throughout the image to undertake a formal assessment. The categorisation result (permeable or impermeable) at each site was then compared to the actual land cover type depicted in the original imagery.

Stage 2: Image segmentation

The technique of partitioning a digital image into several segments is referred to as image segmentation in this paper. The objective of segmentation is to simplify and/or transform an image's representation into more relevant and easily understood characteristics of the objects. The outcomes that will be generalised can make the classification process of the images easier than that of thousands of pixels with unique spectral signatures and a considerably lower number of segments will be classified in the following level of data processing. Based on the image size and intended purpose, the optimal number of segments and the range of pixels grouped into a segment varies. For example, each house's roof was categorised as a distinct segment, as shown in Figure 3.

Figure 3. A comparison between two blocks/units of residential neighbourhoods: the non-segmented (left) and segmented (right) images

The minimum segment size in pixels and spectral and spatial details are the three main parameters that were required to accomplish this stage of processing. The parameter values presented in Table 1 were chosen based on examining various values that gave the best outcomes of the segmentation. In this regard, the minimum mapping unit was directly tied to the minimum segment size in the pixel parameter [28]. Therefore, segments that were smaller than this are combined with the neighbouring segment that fits the best. Since the two samples were taken from the same satellite scene, the value of this parameter was 20 for both. Regarding spectral details, the acceptable range is 1.0 to 20.0. When features that you want to identify separately but have somewhat comparable spectral characteristics call for a greater value [29]. Smaller numbers cause more smoothing and take longer to process. For instance, a higher spectral detail value will make it easier to distinguish between the various land use types in a scene of an unplanned residential area. The valid range is 1 to 20. When the scene's objects of interest are condensed and small, a higher value is suitable. Spatially smoother outputs are produced by smaller values [30]. For instance, you could identify impervious surface features in an urban environment using a lower spatial detail value (as shown in sample 1), or you could use a greater spatial detail value to classify buildings and roadways as different classes, as shown in sample 2.

Table 1. The image segmentation parameters

Samples	Spectral details	Spatial Details	The minimum segment size in pixels
1	18	6	20
2	15	8	20

Stage 3: Classifying and Reclassifying the Segmented Images

The second process is to classify the segmented images in each sample. A supervised classification is based on user-defined training samples that specify which sorts of pixels or segments should be categorised in which form. First, the images were categorised into broad land use groups. Then, the land use types were classed into more specific classes. This method allowed for a more precise classification. Training samples were produced to achieve a supervised classification. Training samples were described as polygons representing different sample regions of the various land-cover categories shown in the images. They provided information to the classifier on the different spectral characteristics that each land cover might have. Since the support vector machine (SVM) can handle larger images and is less sensitive to inconsistencies in training sets, it was chosen as a classifier. The SVM was trained with the training samples and created the classified images. Lastly, all classes were reclassified a second time to merge them into classes that allowed for the detection of the changes within the residential areas. The classification method and its classes in both the classification and re-classification processes are described in Table 2. The land use classes were chosen depending on the nature of the study area, which included the planned and unplanned residential areas. For this reason, the two areas' classes differ slightly. This will allow us to investigate the differences between the two built-up area samples as well as to detect the insignificant changes in these land use classes.

Table 2. Method for categorising images

Subclasses	Main classes	Description related to the residential neighbourhood areas categories
Buildings (S1 & S2)	Buildings (S1 & S2)	Permanent buildings including main houses, garages and sheds within one block/unit of residential neighbourhoods in the planned areas and detached buildings in the unplanned built-up areas.
Driveways (S1 & S2)	Driveways (S1 & S2)	Permanent manmade surfaces such as concrete sidewalks, asphalt streets and paths in the planned areas, gravel and unpaved with asphalt streets and paths in the unplanned built-up areas.
Trees (S1 & S2)	Vegetation (S1 & S2)	Vegetation cover including trees, grass, green pasture and gardens with different shrubs in both samples.
Grass (S1 & S2)		
Bare land (S1 & S2)	Bare land (S1)	Non-vegetative exposed natural surfaces (distinguished from non-vegetative artificial surfaces), i.e. soil that has been stripped of all vegetation, is more dominant in the unplanned areas than the planned built-up areas.
Shadow (S1 & S2)	Shadow (S2)	Shadows aren't real surfaces; thus, they can't be defined as permeable or impermeable surfaces. However, shadows are generally cast by tall objects like houses. They appear more in the planned areas than the unplanned built-up areas.

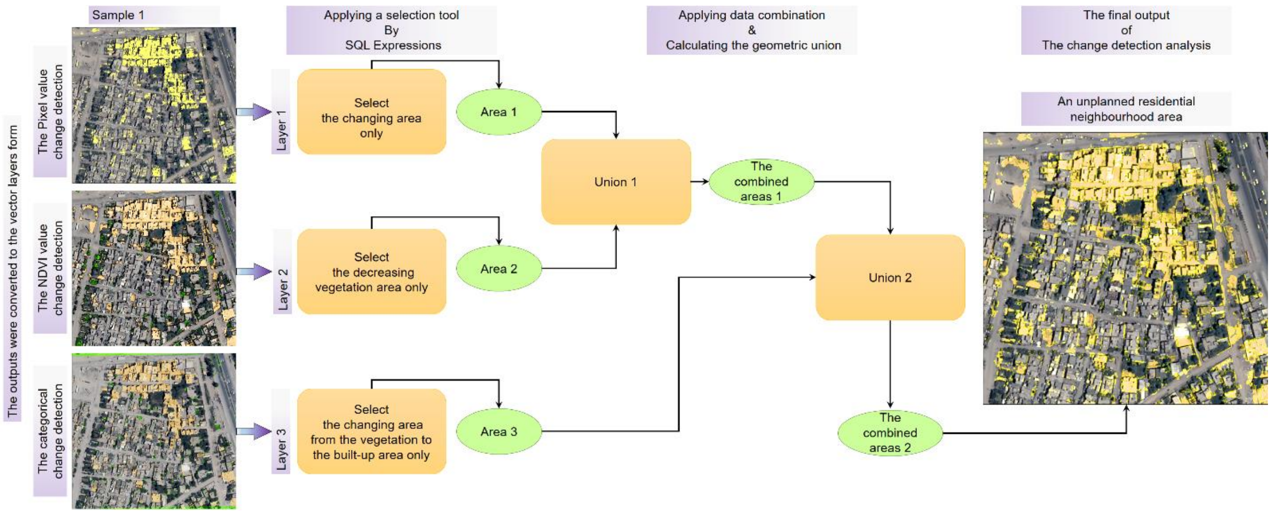
S1 refers to Sample 1 and S2 refers to Sample 2 for both the permeable and impermeable surfaces.

Although comparing the classification map to the original imagery is beneficial in some cases, it does not give a formal evaluation of the classification's accuracy. In this regard, and to additionally support the goals and needs of Baqubah's city authorities in a classification of impermeable and permeable surfaces in order to aid in their attempts to manage sustainable development, we performed the classification's quantitative accuracy assessment by statistically comparing it to the original imagery. The accuracy of assessment points was generated throughout the image and compared with the corresponding ground truth. A confusion matrix was then computed to determine the classification accuracy percentage. This technique of evaluating the outcomes of satellite image classification has been applied in earlier investigations [18, 19, 22].

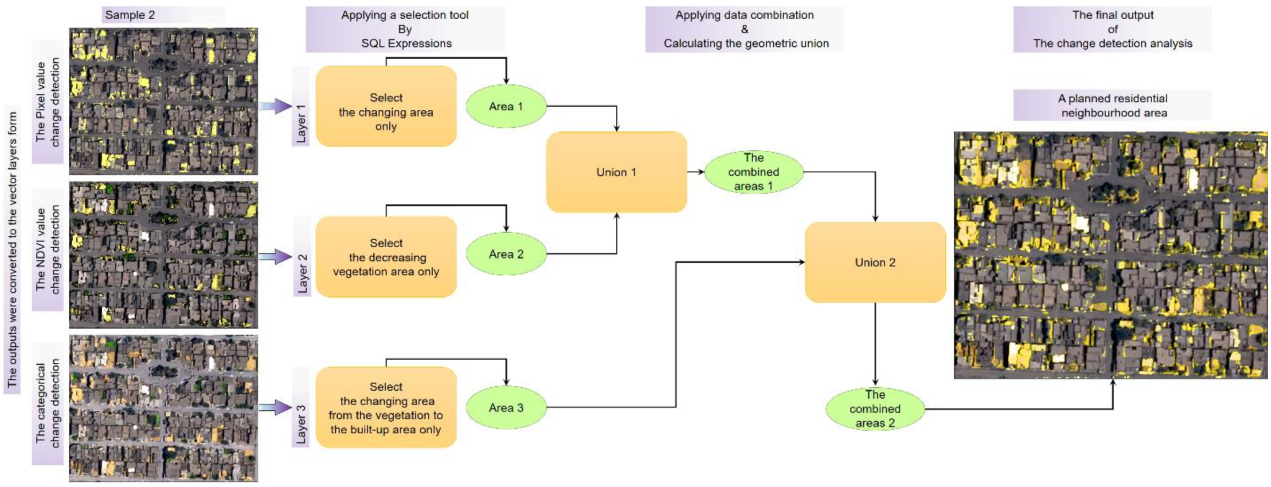
Stage 4: The Changes at Building and Neighbourhood Scales

The classified maps were used to detect and quantify the change in the two samples between 2014 and 2021, with an emphasis on the changes that are likely to occur as a result of population growth. We were able to identify regions that have changed from one class to another over time by performing categorical change detection in the ArcGIS Pro environment. Thereafter, noise removal was performed by setting the smoothing neighbourhood to a 3x3 median filter. This post-processing step let us recalculate pixel values within the neighbourhood for a smoother result of the detected changes.

The benefit of using our proposed method to detect urban changes, with the multiple tools and functions approach, is that the changes are confirmed with a certain spatial reference, leaving no room for doubt. For accurate measurement and quantification, the extracted urban area changes from the three stages of data processing were then converted from raster form to vector form. Subsequently, the structured query language (SQL) expression was applied to the extracted three layers to select only the transformation regions from permeable to impermeable surfaces for both samples (unplanned and planned urban areas), as shown in Figure 4. The selection process was performed with the query builder in the ArcGIS Pro geo-processing environment. It is necessary to mention that the spatial selection analysis was built based on the increase or decrease in values of the vegetation cover within these regions. This means that the number of altered areas (polygons) in the change layer, which was derived from the pixel value detection and the categorical change detection, was the selection of the increase in the areas of impermeable surfaces at the expense of the areas of permeable surfaces at the residential area level. In contrast, the decrease in permeable surfaces, such as all types of vegetation cover within the housings and their surrounding areas was selected from the NDVI change layer. The final stage of the analysis comprised the calculation of the geometric union of the three layers of the extracted changes. This process caused the features to fracture and cluster. Clustering snaps together vertices that are within the *x*,*y* tolerance; cracking adds vertices at the intersection of feature edges. Geometric correlations (overlap) between features from all change layers were also discovered. This allowed us to generate the final map of the residential neighbourhood changes and quantify them.



(a) The unplanned residence area sample



(b) The planned residence area sample

Figure 4. A representation of the geo-processing workflow sequence for selecting a subset of spatial changes from three layers in the residence area samples

3. Results

3.1. Spatial Analysis of Residential Areas Changes

This study set out with the aim of assessing the changes in private and public green spaces, such as gardens and parks, particularly within residential areas and generally in urban areas. Figure 5 illustrates the results of using the ModelBuilder to combine all the differences in the change detection findings between the two specific years. The results of the pixel value change detection in Figure 6 demonstrate the preliminary and actual location of the developed areas in both samples. The threshold value of 0.4 proves its relevance for indicating which areas are considered to include change as the change map was inferred and validated with the field comparison.

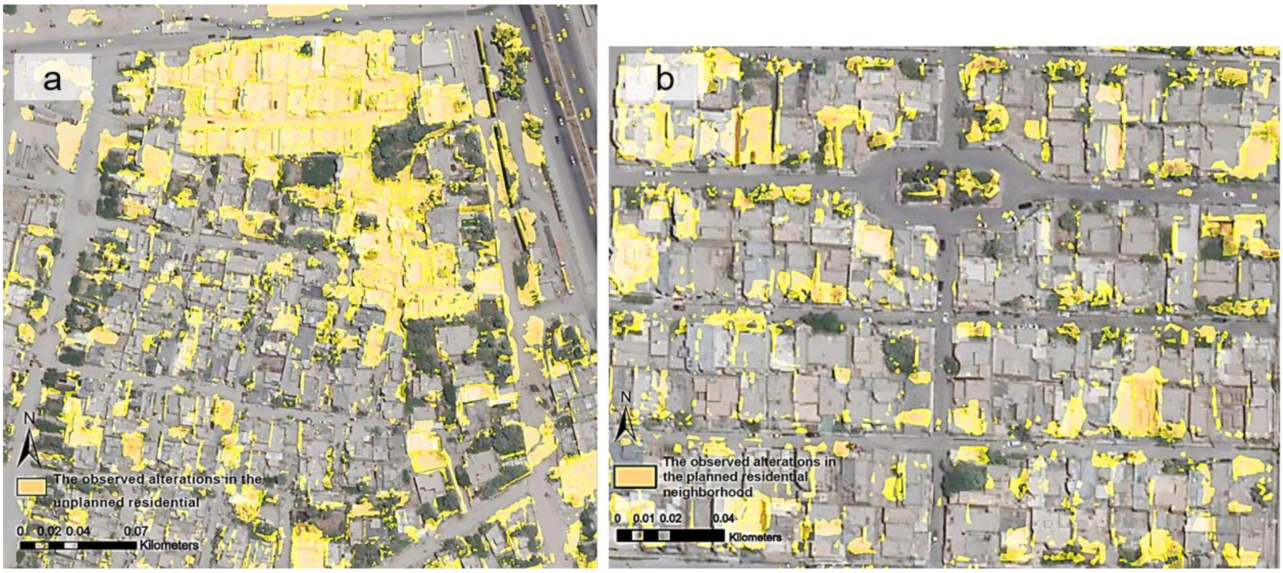
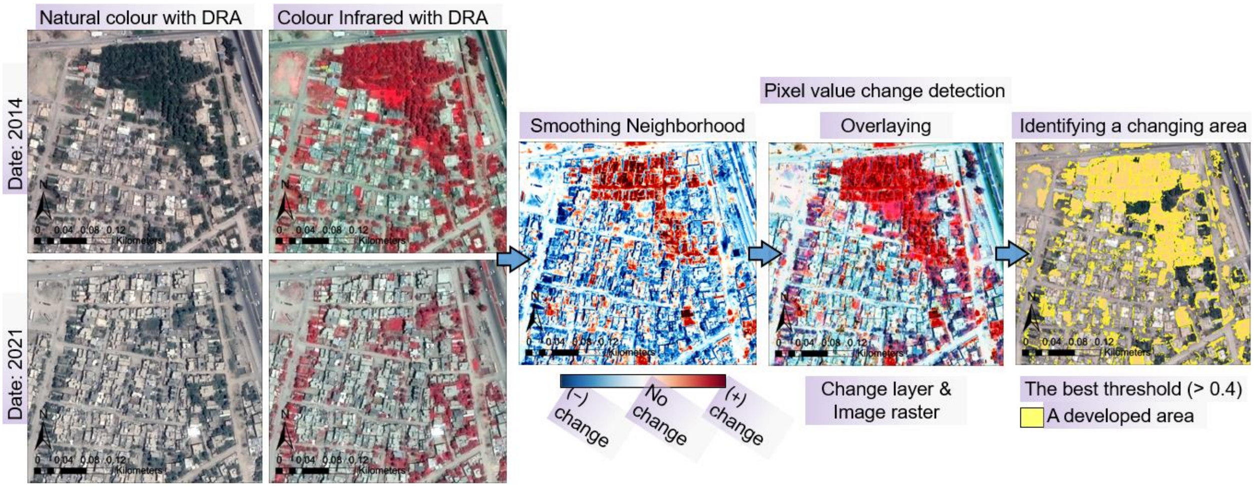
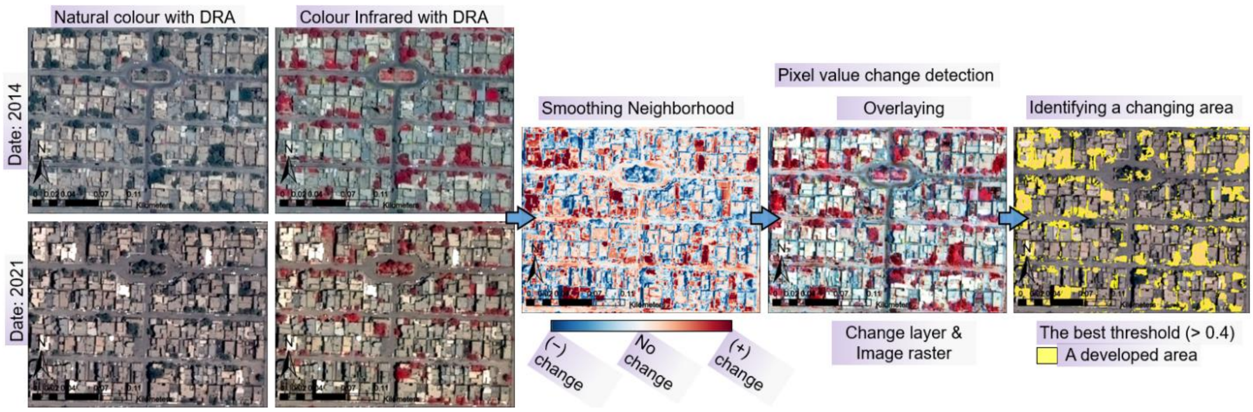


Figure 5. The final output of the change detection analysis: (a) Sample 1: an unplanned residential area and (b) Sample 2: a planned residential area



(a)



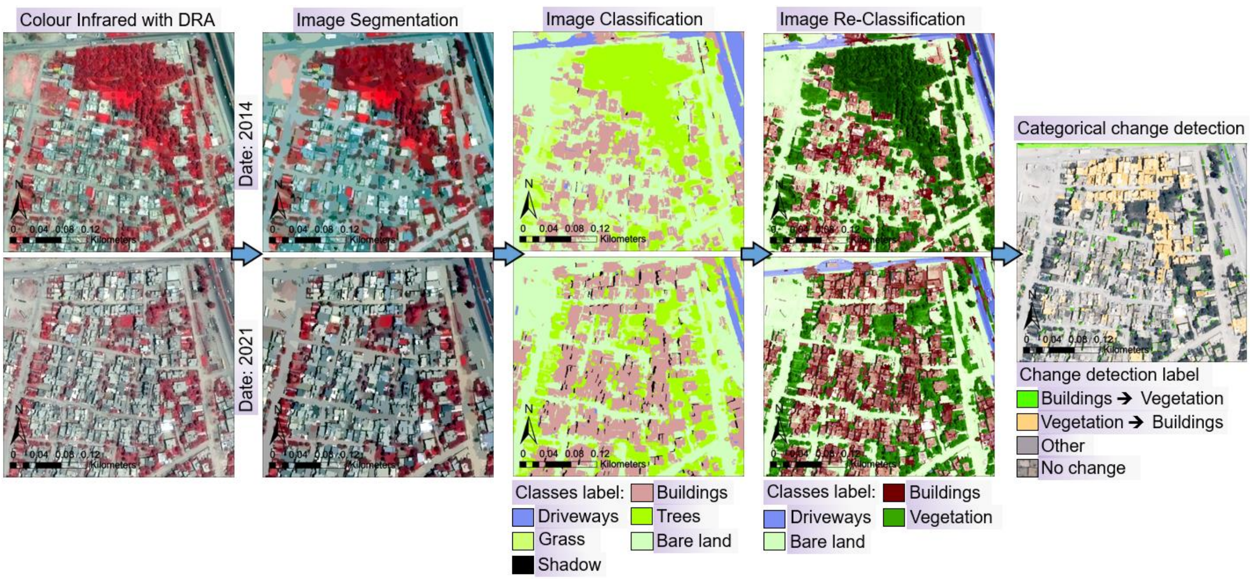
(b)

Figure 6. Pixel value change detection between the two satellite images with a time difference of seven years, (a) Sample 1: an unplanned residential area and (b) Sample 2: a planned residential area

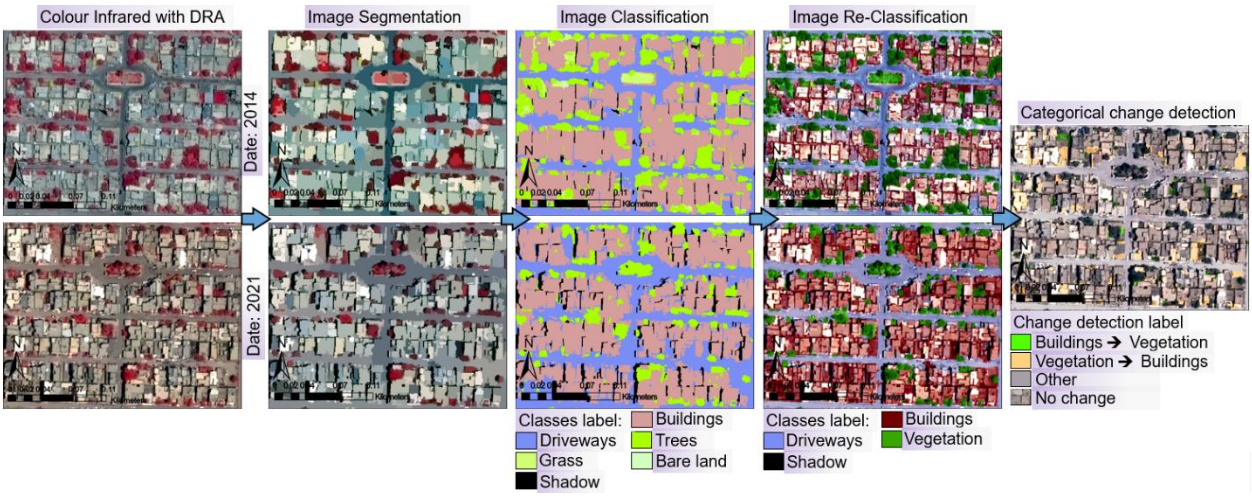
The percentage of the area of change for both the unplanned and planned residential areas is 12% and 6%, respectively. It can be seen from the results in Figure 7 that the band index difference calculated by applying NDVI reported the changes more significantly in Sample 1 than Sample 2. Whereas the area of change in Sample 1 (the unplanned area) was estimated at 20% of the total area, the change detected in Sample 2 (the planned area) was estimated at 8% of the total area. This interesting result demonstrates that having more open or green spaces in residential neighbourhoods can result in more area changes over time.

Figure 7. Band index difference by applying the NDVI value change detection to the two samples (unplanned and planned residential areas)

On the other hand, by applying the categorical change detection, the further analysis findings shown in Figure 8 illustrate that the developed class sizes have altered over some time and determine how much of a given region is covered by a particular type of land cover. As seen in Table 3, the confusion matrix yielded a high percentage of correct responses, indicating that the classification is reliable. The findings show that the building and vegetation classes within the research areas have altered considerably during the last seven years. Approaching earlier research, we discovered that the outcomes of the earlier studies—which were based on machine learning and deep learning classification approaches in analysing and identifying the changes—were supported by our current findings. It was discovered that the change vector analysis method offers greater accuracy than the change detection strategy based on algebra. The overall accuracy of the earlier research using these methods, e.g., [31, 32], and our methodology was 90%. As shown in Table 4, the changes that occurred from vegetation class to building class are 12% and 7% for each of the samples of the first and second models, respectively. Because the focus of this study is on the conversion of vegetation land classes (green or open spaces) to developed land, this is what we concentrated on in Figure 9. However, as seen in Table 4, the other and no-change classes have the largest count values, but we did not consider them since our interest was in the classes that switched to the developed class in residential areas. The changes within a specific research region for a certain land cover type were accurately recovered from the three analytical approaches; thus, the most essential point that the results of our unique approach indicate is its effective performance in measuring the changes. Figure 10 depicts the final change maps in the residential regions. The final findings of the geo-processing models process suggest that Sample 1 had 24% of open and/or green spaces converted into built-up areas (the unplanned residential area), while Sample 2 had 14% of open and/or green spaces, such as gardens, exploited to be housing or for housing expansion (the planned residential area). These findings provide vital information about urban expansion at the expense of green spaces such as orchards, parks, and gardens, as well as the amount of area that has changed.



(a)



(b)

Figure 8. The categorical change detection including the process of image segmentation, classification, reclassification and the extraction of the changes and their labels for the two samples, (a) Sample 1: an unplanned residential area and (b) Sample 2: a planned residential area.

Table 3. The overall accuracy and the Kappa coefficient for the image classification results

Classified raster data	Overall Accuracy (%)	Kappa Coefficient (%)
SD114	0.92	0.80
SD121	0.94	0.92
SD214	0.96	0.95
SD221	0.90	0.87

Table 4. The quantification of the changes in the residential neighbourhood areas by applying the categorical change detection

		Sample 1			Sample 2		
No.	**Changes between Classes**	**Count Pixel**	**Area m2**	**% of the total area**	**Count Pixel**	**Area m2**	**% of the total area**
1	From Impervious to Pervious	34583	8645.75	6.17	3800	950.00	1.82
2	From Pervious to Impervious	65312	16328.00	11.65	14512	3628.00	6.95
3	Other	289414	72353.5	51.63	85845	21461.25	41.10
4	No Change	171251	42812.75	30.55	104711	26177.75	50.13
Total		**560560**	**140140**	**100.00**	**208868**	**52217**	**100.00**

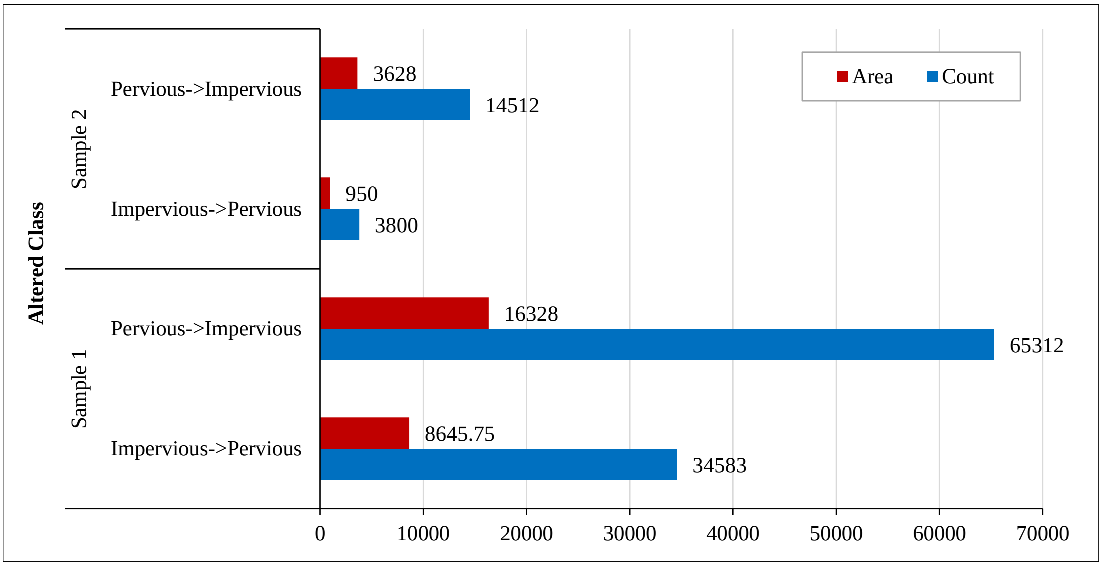


Figure 9. Comparison of the change between the planned and unplanned residential areas

Figure 10. The total detected changes within the selected urban regions

3.2. Resident Survey Responses of Residential Areas Changes

The 200 respondents to the citizens' housing survey in Baqubah City provided a fair representation of household and garden categories. The number of survey responses, nevertheless, varied remarkably between the two selected samples, with the planned residential area sample in Baqubah receiving more reasonable responses, highlighting the importance of using a robust methodology when using citizen data to validate and expand the datasets beyond locations with large response rates. The highest percentage of change, shown in Figure 11, was found in housing units where gardens within the housing unit's space were being reduced in size to create a larger building area. This comprised 23% of the total number of housing units, with 70% of housing units with an area of more than 400 m^2 having open areas.

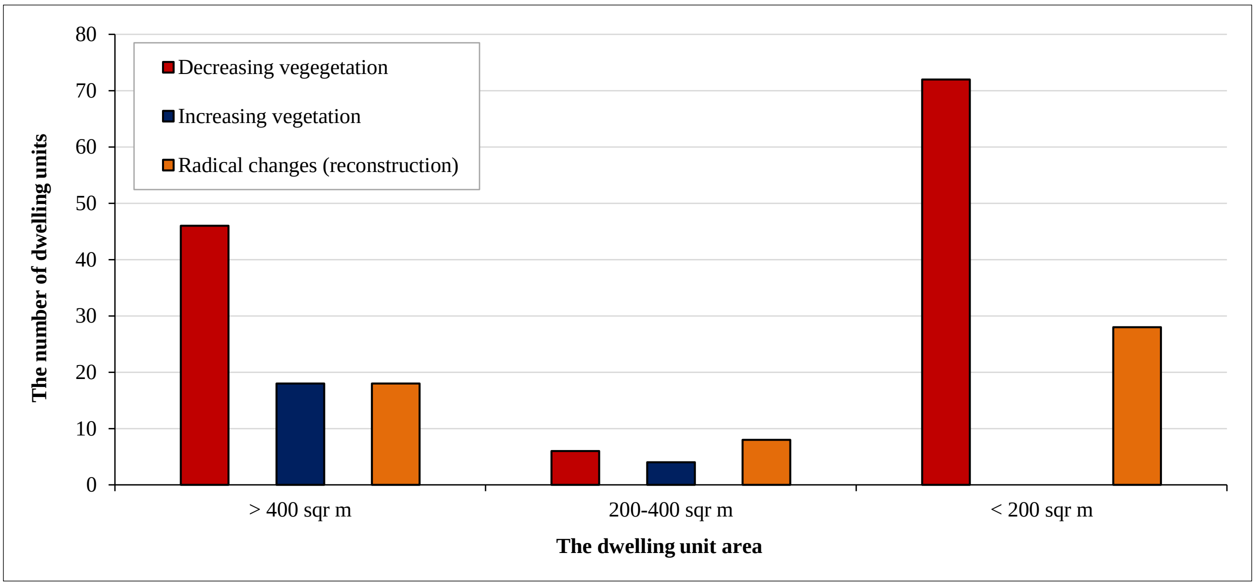


Figure 11. The changes in green spaces in housing units over seven years

The highest percentage of dwindling gardens was observed by 36% of the total number of housing units included in the survey for residential units with an area of less than 300 m^2, which represented 40% of the open spaces. The results of the survey also showed that the lowest percentage recorded was an increase in green areas. As shown in Figure 12, the results of the survey revealed that residences with a modest area of 200 m^2 were 75% of the remainder of the areas of other residences and that they are currently the most prevalent in residential areas, with the greatest percentages of residents, averaging at 5–7 residents per housing unit. On the other hand, the results showed that the percentage of the number of residents in housing units with an area of 400 m^2 was estimated at 5%, which is a minuscule percentage compared to the rest of the residential areas.

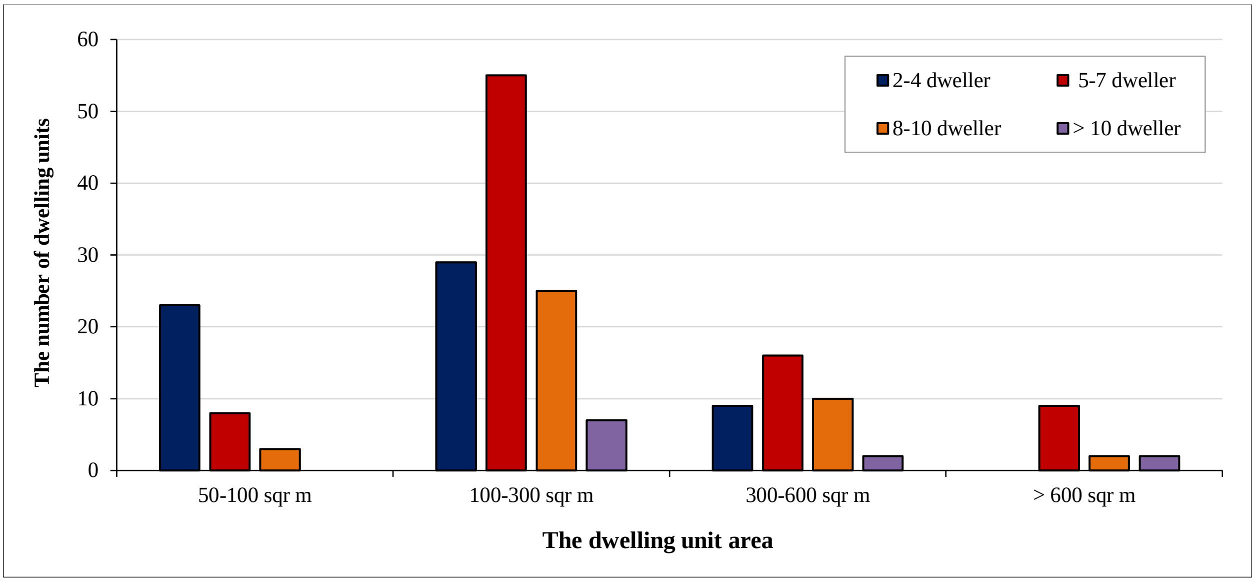


Figure 12. The number of residents in relation to the housing unit area

The average monthly income of families also plays a role in the enlargement of housing units. In Figure 13, the relationship between average monthly income and homeownership is depicted. The findings revealed that among all types of housing units, 85% of families have an average monthly income of 1.5 million Iraqi dinars (IQD), and 3% have an average monthly income of 3.5 million IQD, which was limited to families who own their homes. The findings also revealed that 30% of substandard housing units are owned by occupants with a monthly income of less than 0.5 million IQD.

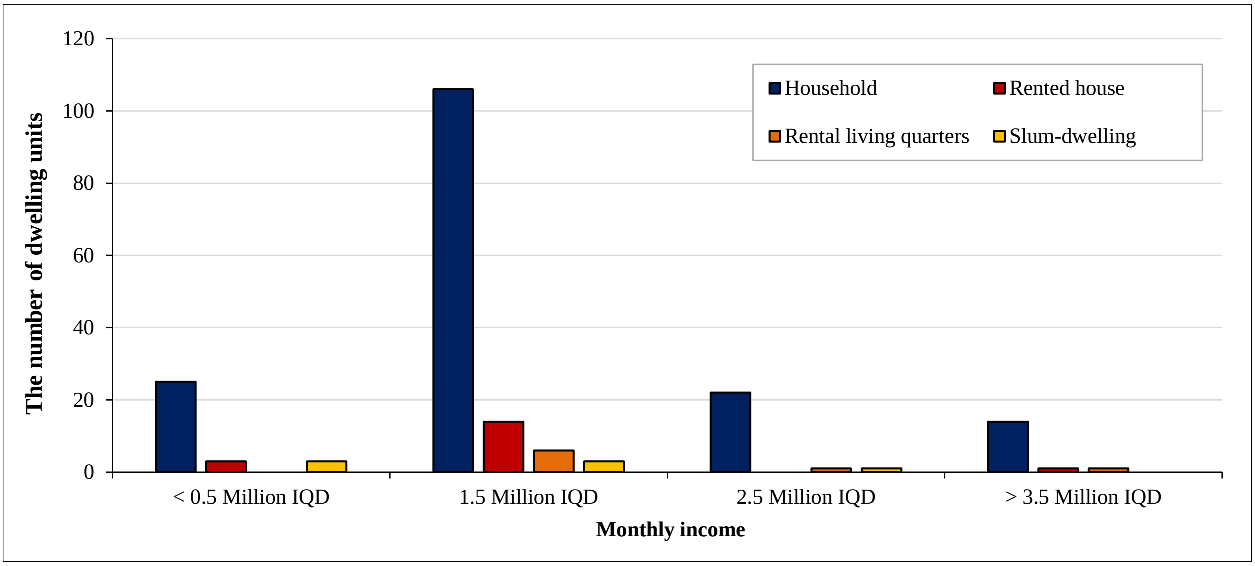


Figure 13. Ownership of the housing unit and the monthly income of the residents

Areas of land partially or entirely covered in grass, trees, shrubs, or other vegetation are known as green spaces. These consist of green roofs, parks, and gardens. Urbanisation and human development are the main causes of the loss of green space. Our results illustrated that natural landscapes are being transformed increasingly into developed environments, such as streets, parking lots, and buildings, as cities and populations rise. The loss of green space in our case studies has several effects on the environment, human health, and the economy. Destroying these green areas can result in the decline, extinction, and disturbance of ecosystems for various plant and animal species. Additionally, because plants absorb carbon dioxide and create oxygen, they contribute to rising greenhouse gas levels and climate change. Because built-up areas absorb and retain heat, the loss of green space can worsen the Urban Heat Island Effect (UHIE), making cities noticeably warmer than nearby rural or natural areas. It can also lead to water contamination and flooding. In terms of health, the lack of green spaces can have a detrimental effect on mental health and raise the incidence of anxiety and sadness. Their disappearance leads to respiratory problems, heat-related ailments, and sedentary lifestyles. In addition, community cohesiveness, economic impacts, and inequality are a few socioeconomic aspects. For instance, green areas foster social interaction and a feeling of place by acting as community hubs. Social ties and the general well-being of the community may suffer in their absence.

Our examination of trends in urban growth is consistent with a number of other research studies. For example, Zhou et al. [33] claimed similar rates of growth in cities in the “Kozhikode Urban Area”, whereas Grover et al. [34] recorded similar rates in “Beijing”. Similar to our own, these studies draw attention to the difficulties in controlling urban growth while maintaining open spaces and environmental quality.

But our findings also offer some original perspectives. According to the spatial analysis, compared to the city of Manchester, which was the subject of a study by Baker et al. [22], urban expansion in Baqubah has been more concentrated at the residential neighbourhood level. This discrepancy implies that the spatial patterns of urban development may be influenced by municipal infrastructure planning.

Important insights are revealed when comparing our findings to traditional urban planning concepts. The American Planning Association recommends compact, mixed-use development to promote walkability and reduce reliance on cars. However, our research shows that Baqubah's recent growth has primarily been mixed-use and high-density, indicating a need for significant improvement in terms of alignment with best practices. A geographic information system (GIS), a common method in urban planning, was used in our study to examine urban expansion in terms of planning tools. However, in an inventive use of technology in the industry, we also included machine learning algorithms to forecast future growth scenarios.

Urban planning in Baqubah will be significantly impacted by the comparisons with other studies and accepted techniques. According to the data, Baqubah has some of the same urban growth issues as other cities, but there are also particular local elements at work. Planners can create more specialised plans to manage growth in a sustainable manner by acknowledging these variations. For instance, the analysis emphasises how crucial it is to coordinate the development of transport infrastructure with land use planning in order to direct more condensed and integrated growth. Furthermore, anticipating future possibilities and difficulties through the use of predictive analytics in the planning process can facilitate more proactive decision-making.

4. Discussion

Our combined change detection approach provides a comprehensive insight into the significant occurrence of spatial changes resulting from the transformation of green space into built-up areas within residential areas. One objective of this study is to evaluate how well three selected change detection techniques extract changes in residential neighbourhood regions using remotely sensed data. Thereafter, we examined our developed combined approach compatible with these techniques to achieve workable outcomes in detecting the total transformation of residential areas from vegetative cover to built-up areas. The integrated strategy aims to compare it to two distinct urban structures, planned and unplanned. Our results illustrated the investigation of the impact of urban expansion on green spaces, whether within the residential unit or beyond the residential area's boundaries. The most interesting finding was that the level of green space transformation in the unplanned residential neighbourhood area increased by 5% compared to the expansions in the planned residential area. One possible explanation is that the municipality's planned distribution of housing units prohibits building from being done at random. Nonetheless, it is interesting to note that in both samples of this study, the built-up areas were developing over the seven years.

The results of the geo-processing models also indicate that there is an overexploitation of green and open spaces without any limitations or controls to ward off the expansion. We found that Sample 1, the unplanned residential area, was changed in approximately 33633.6 m² (24%) of the total area, while Sample 2, the planned residential area, was changed in 7310.38 m² (14%) of the total area. These findings are most likely due to overcrowding versus a lack of services and infrastructure. The reasons for exploiting residential gardens as space for additional residential units for the houses themselves were based on the medium and/or low income of families residing in these neighbourhoods, as gathered from the residents’ survey responses. Converting a garden into a residence is less expensive than purchasing a plot of land and constructing housing on it. This economic aspect compelled many families to turn their gardens and green spaces into smaller living units to rent or sell. It is important to acknowledge that cities are intricate systems with a vast number of interconnected variables, making it challenging to forecast or manage all consequences [3]. However, it should be emphasised that not all alterations to the city take place in accordance with the plan. In other words, not every modification in an area that has been planned will necessarily be in line with the plan. In addition to the decisions made on the plans, there are unapproved or illegal buildings around. Plans have inherent limits, even if they are useful tools for directing urban growth. Due to differences between expected and actual growth [3], the dynamic character of urban systems [4], and external forces outside the control of city planners, cities can develop in unintended ways [5]. The implementation of plans in the residential area is constrained by several factors, such as resource restrictions, the dynamic character of cities, unforeseen events, and stakeholder involvement [2]. Even if this area starts with a plan, these factors increase the chance of uncontrolled city growth. Thus, future research can employ our suggested strategy to study these changes in both types of residential neighbourhood regions. To build more resilient and sustainable cities, it is crucial for city planners and decision-makers to periodically examine and modify plans to account for changing circumstances and uncertainties.

According to the image processing and survey outputs, we can infer that there has been a major reduction in green spaces in exchange for a significant increase in building areas within housing units in the residential areas. It can therefore be assumed that this result may cause the air quality in the surrounding environment to be negatively impacted and the temperatures to rise as a consequence of the absence of vegetation cover. These findings also raise important concerns about the nature and scope of high population densities in residential areas. Based on data from the local administration, the population of Baqubah increased by 28% between 2014 and 2021, with 209,412 and 292,619 people living there in 2014 and 2021, respectively. Noise pollution is one of the challenges that arises as a result of the enormous number of cars and vehicles that are used within these congested, built-up areas. Infrastructure services such as sewage disposal and liquefied water networks are also impacted, as well as the people's quality of life. However, even though the union tool maintains attributes from both layers to the same extent, it can be a bit messy, particularly if there are substantial overlaps. As a consequence, the final geo-processing form generates a large number of features. All input feature borders and properties are preserved in the output feature class by the union tool. Union layers have proved especially helpful in detecting urban changes since you can see where distinct change zones overlap, although the fact that this constraint is always taken for granted. There is plenty of potential for advancement in determining changes in green spaces within and outside housing units by detecting changes in green spaces not only at the residential area level but also within individual housing units. This type of follow-up work requires strengthening the presented strategy by using deep learning technology to recognise the area of the garden in the housing unit from VHR satellite images. Furthermore, the threshold value used to evaluate the NDVI results should be determined automatically rather than based on the analyst's reasoning. It is also challenging to determine heterogeneity in the garden area and surface composition from a highly biased survey sample. Nonetheless, because the spatial heterogeneity of garden surfaces is evaluated from the union of three geo-processing outputs, the advantages of combining the three change detection techniques are clear.

Since our study is the first of its sort to be carried out in Baqubah City, it is difficult to draw direct parallels with earlier studies. Its research investigation is distinctive not only because of its regional focus but also because of its creative methodology. We offer a more comprehensive and nuanced understanding of the progressive loss of green spaces within residential neighbourhood regions by combining three change detection techniques: categorical change detection, image band index value detection, and image pixel value detection. A more thorough study is made possible by this multifaceted approach than by any one technique alone. Because of the unique nature of our research, we are unable to directly compare our findings to those of other studies; however, we think that our integrated methodology and concentration on the city of Baqubah significantly advance the subject. Our results offer insightful information that can guide future studies conducted in different regions.

5. Conclusion

The main goal of the present study was to assess the changes that occurred within urban areas at the residential area level. Multiple image processing analyses revealed that 24% of the total area of the first sample area and 14% of the total area of the second sample area were converted from open or green spaces to building spaces. These findings have major implications for understanding how domestic gardens evolved into built-up areas over seven years in the city of Baqubah. Overall, the citizens' responses in the survey strengthened the idea that unused spaces inside and outside of housing units, such as open spaces or green spaces, pave the way for future urban expansion, especially in places where no previous urban planning has taken place or the determinants and conditions for housing units in the neighbourhoods have not been formally established. This has ramifications for the resilience of the city's environment in the future as well as the quality of life and well-being of its occupants.

The contribution of this study has been to confirm the merits of VHR multispectral satellite imageries in detecting urban changes within residential areas. In terms of detecting changes in other impermeable surfaces, such as housing units and driveways or roads, the scope of this investigation was limited. When the spatial resolution of the VHR optical satellite images is increased, spectral heterogeneity between its feature surfaces becomes more prominent. Residential roofs, for example, are spectrally similar to driveway surfaces in some circumstances. Thus, when using change detection techniques, it may be difficult to distinguish between these surfaces. Despite this difficulty, the study significantly contributed to the understanding of the changes that occurred within the housing units of residential areas. Furthermore, because the focus of this study is on the loss of open and green space within these units, this limitation has no bearing on the findings.

For future work, the assessment of the number and area of houses formed by partitioning the area of one dwelling into separate areas within the same plot of land will require a significant amount of additional effort. Therefore, residences within residential units will be recognised using deep learning technology, and the dwindling of their open and garden spaces over time will be estimated. From a broader perspective, planning for the long-term care of green spaces should be a key priority for policymakers, as the reduction of these spaces directly impacts people's health, quality of life, and well-being, as well as urban sustainability.

6. Declarations

6.1. Author Contributions

Conceptualization, N.K. and N.M.K.; methodology, N.K.; software, N.K.; validation N.K. and N.M.K.; formal analysis, N.K.; investigation, N.M.K.; resources, N.M.K.; data curation, N.M.K.; writing—original draft preparation, N.K.; writing—review and editing, N.K.; visualization, N.K.; supervision, N.K.; project administration, N.M.K.; funding acquisition, N.K. and N.M.K. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.5. Conflicts of Interest

The authors declare no conflict of interest.

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