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URBAN GROWTH MONITORING AND TREND IN BASRAH CITY USING GIS AND REMOTE SENSING

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ABSTRACT
The greatest challenges in creating a practical and long-term model of urban planning are those that researchers, planners, decision-makers, and local authorities must overcome. Among these difficulties is the need to quantify and forecast urbanization trends in both space and time. When it comes to measuring and mapping patterns of urban growth, tools like geographic information system approaches and remote sensing have recently emerged as key strategies. There is a wide variety in the rates and patterns of growth in Basrah city, which is inside the Basrah governorate. Analysis of land use change detection can greatly benefit from the use of geospatial technologies and remote sensing approaches. Such is the setting for the discourse surrounding these approaches and tools. In this study, collected GIS data use in Basrah city between 2002 and 2022 to assess the ability to accurately detect alterations in land utilization. The goal of creating these urban growth maps was to use three Landsat ETM and OLI images taken in 2002, 2012, and 2022. The use of land-use maps allowed for the measurement of changes in urban areas from 2002 to 2022. In contrast to the 17.42% decline in vegetated land, the built-up area has increased by over 11.38%, rising from 80.77 km² to 224 km², as revealed by the change detection inquiry. The study's results demonstrate that the urban area has expanded and now covers most of Basrah's city area. Cities and their planners greatly benefit from studies documenting changes in land use, land cover, and urbanization. Future strategies for the city's environmentally responsible growth might benefit from this data.

Keywords: GIS, RS, assessment, LULC, urban growth, built-up.

1. INTRODUCTION
In recent decades, urban growth has become a global problem. As a result of population and economic development, cities are expanding swiftly in many parts of the world, but some urban areas are encroaching upon valuable natural ecosystems and farmlands (Haas and Ban, 2014). The steadily increasing number of urban residents exerts pressure on natural resources and the natural environment, with their consumption of materials, use of energy, and generation of waste (Zhao, 2011). Thus, in addition to the need for a good urban planning approach to resolve the current urban crisis in an urban economic way, with the use of strategies and policies, urban technological advances and urban innovation are good tools for addressing the growth of urbanization. The global urban population is growing rapidly. According to the United Nations, more than half of the world's population now lives in urban areas. Yet the urban land use impacts as much as 5 percent of the world's non-frozen surface. Scientists recently presented new work detailing the importance of urban land use as a control knob that can be either dialed up or down to influence the amount of on-the-ground change and impact on natural resources. After years of using coarse-resolution

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datasets, they present a convincing case for using high-resolution data to better understand and manage our urban areas.

The issue of urban growth and its influence on land-use and land-cover systems has attracted much attention for several reasons, for instance, population and economic development (Aburas et al, 2015). Urban expansion is driven by multiple factors: A recent study identified environmental, socio-economic, and physical forces behind the fast-growing trend in our urban fringes as well as the core centers of cities (Aburas et al, 2017). A set of methods using available geospatial techniques—like Geographical Information Systems (GIS) and remote sensing models—now makes it possible to measure this growth and understand the temporal and spatial dynamics of the expansion in development plans at both regional and local levels (for example, see Aburas et al, 2016 and Aburas et al, 2018).

Today's urban planners and policymakers apply modern methods like GIS and RS to their work when they contemplate the cities of tomorrow (Liu et al., 2015). They favor these techniques for many reasons, including their ability to analyze, control, and monitor the spatial-temporal dimensions of city life in their evaluations of urban change. Moreover, they find them good for creating the empirical and numerical measurements by which the growth of cities can be grasped and governed, not least at a time when the planet and many if not most of its cities are encountering intense pressure due to demographic and environmental changes.

Furthermore, these techniques can employ both quantitative and qualitative means to single out not just the what, but the why and the how of the current and future state of urban growth. This provides, on the one hand, ways to render the impacts of urban growth explicit and to project the most probable outcome of current trends in urban development into the future. On the other hand, it allows using social and environmental criteria to evaluate the desir(cumstances) of the present and coming patterns of urban development in both space and time.

Urban patterns can be typified using mathematical equations. These equations, like the one for Shannon entropy, can be utilized in remote sensing in a geographic information system (GIS) to characterize not only the forms that urban development takes but also the spatial distribution of those forms across the urban landscape (Aithal and Sanna, 2012). Ramachandra et al. (2012) and Yang (2010) provide more information on using entropy to accomplish this.

The method for urban growth measurement is the study of differing states of an object or phenomenon obtained through remote observation over time intervals. For any object observed remotely at any two different times, the image and information contents enable us to see and study the varying states of the object or phenomenon of interest. Since there is are partly stuck with images and their features (due to the presence of humans and our inability to create perfect description-preserving transformations), the key to urban growth monitoring lies in the formulation of good questions or a sequence of them. Determining the urban growth trends in urban development forms, over a long timeline, varies significantly when remote-sensing (RS) and geographic information system (GIS) technologies are used, as opposed to simple, ground-based data-gathering or statistical methods. Many researchers favor using RS and GIS over ground-based methods simply because they are more adept at capturing the complexities of the five dimensions of urban change at the global level in coming decades than the current ground-based, data-gathering methods can.

If the values of Shannon's entropy indices show a consistent increase, they may denote a pattern of urban growth. When these values are combined with those from the Peréa chicken theorem, the result may be more informative. The theorem is capable of separating two types of chicken

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behaviors into groups; these are "compact" chickens and "dispersed or aggregating" chickens. Compact chicken behaviors show that one chicken tends to be in contact with another chicken at a certain space—i.e., non-overlapping spaces for urban growth. Compact chickens tend to be close to other chickens. In contrast, the second type of behavior that of chickens being either dispersed or forming an increasingly sizable groupingdenotes urban growth of a grubby, elongated, and unattractive sort.

Furthermore, the link between urban expansion and various driving forces can be established (Alsharif and Pradhan, 2014). On the whole, the factors of urban growth can serve to reveal the differing ways that land uses sprawl (Ren et al., 2013).

When remote sensing data is used for change detection, researchers base their analysis on a phenomenon called "normal variation." This term fuses several ideas from the concept of "sample variation" that form the conceptual basis of most statistical analyses. The first comprises the understanding of "variation" as a characteristic of any phenomenon under study. In normal circumstances, that is, when there is accurately labeled training data, several machine learning techniques perform well in the identification of abrupt changes (not due to normal variation).

Land use and urban growth, as observed from remote sensing, unfailingly entail the comparison of two images that record two moments of spectral "truth" for the same geographic area. The comparison can be likened to a before-and-after photo shoot. The photo that is certainly the "after" shot is, more often than not, a terminus from which to consider and thoroughly comb through actually increased urban growth in the few kilometers that lie inside the image. After counting calories and added pounds, urban growth has a few undeniable "after" points in its favor, a "truth" that seemingly can be observed as increased electromagnetic energy from that second (after) image recording another spectral truth.

Land-use changes can be monitored at high temporal resolution in a very cost-effective way through the use of satellite remote sensing; they are less expensive when compared with traditional methods (El-Raey et al., 1995). The satellite remote sensing data are valuable characters in looking land-use changes because the satellites survey in a synoptic and repetitive way. They also supplement the human field surveys with timely, objective, and synoptic data,which give a broad and almost real-time view of the current situation of land-use change.

Urban planning can be greatly supported with a simple decision-support system called Geographic Information Systems (GIS). For a long time, it was a domain where mapmakers or engineers for local agencies displayed their projects. But planners have adopted it over the past 10 years as their go-to tool for making the best judgment about the topography and proximity that forms our urbanized regions. The upshot: the rise and sprawl of our metro regions can be flat-out visualized. Urban sprawl shows up in spatial arrangements when one uses GIS to measure, for instance, how far newly urbanized areas lie from old town centers and roads (Gar-On Yeh and Xia Li, 2001). And in an era when development within cities is something vacated neighborhoods are crying out for, urban simulations with GIS can show where on the undeveloped or re-developable periphery the next set of suburbs is likely to go up (if current trends are left by themselves), with how much of the next set of exurbs lying beyond. Here, the urban simulation is functioning as a geospatial early warning system (Lee, et al., 1998).

One of the simplest and most direct methods to study urban land cover change is the technique of image classification and change detection. This allows researchers to select images with high spatial resolution and to choose suitable classifiers. They can work with simple but effective algorithms based on the pixel's "brightness" level and run them quickly across the whole image to

generate neighborhood-by-neighborhood cover proportions. And because these are not just smart but also simple techniques, if the same research team gathers remotely sensed images over many decades, they can map out the patterns of growth or shrinkage, showdowns and recoveries, or any other suite of changes that collectively form a picture of urban cover change.
In urban land use analysis, many different spatial statistical models are employed. Ren et al. (2013) used Pearson's chi-square statistics to examine the nature and condition of urban sprawl. They focused on the "what" and the "where" of land development and urbanization in top U.S. regions, allowing for an exploration not just of how many housing units and roads have been built but also of where the new stages of urban development are and what shapes they have taken. Páez and Suzuki (2001) employed a kind of spatial probit or logit model, which allowed them to examine how different neighborhoods were affecting land use change.

This study aimed to create a series of land use and land cover maps for a key city in the Basrah Governorate. Over recent decades, this city has experienced a very rapid urban population increase. The aimed is to record, map, and understand what this sharp increase in the number of people and buildings in the city has meant for the structure of the city and for the categories of land that are found in the city. Of particular interest are the very dominant forms of land referred to as "built-up."

2. MATERIALS AND METHODS

2.1. Description of study area

Basrah governorate is situated in the southeastern region of Iraq. From a geographical perspective, it is situated within the longitudes of 47°20’00” and 47°55’00” E, and the latitudes of 30°20’00” and 30°50’00” N. The Governorate shares borders with the governorates of Thi-Qar and Muthanna to the west, Iran to the east, the governorate of Missan to the north, and Kuwait to the south (see Figure 1). The city of Basrah, which serves as the capital of Basrah governorate, holds utmost significance within the region. The scope of the study encompasses an approximate area of 1162 square kilometers. The investigated area is situated in the central Basrah governorate and was selected due to its rapid urbanization and limited research conducted on it. The expansion of urban areas is a significant challenge as it diminishes the availability of the scarce, highly productive land in this city. Basrah city is currently facing a range of urban environmental issues. To ensure the sustainability of urban systems, it is necessary to carefully plan and maintain a balanced land use and land cover.

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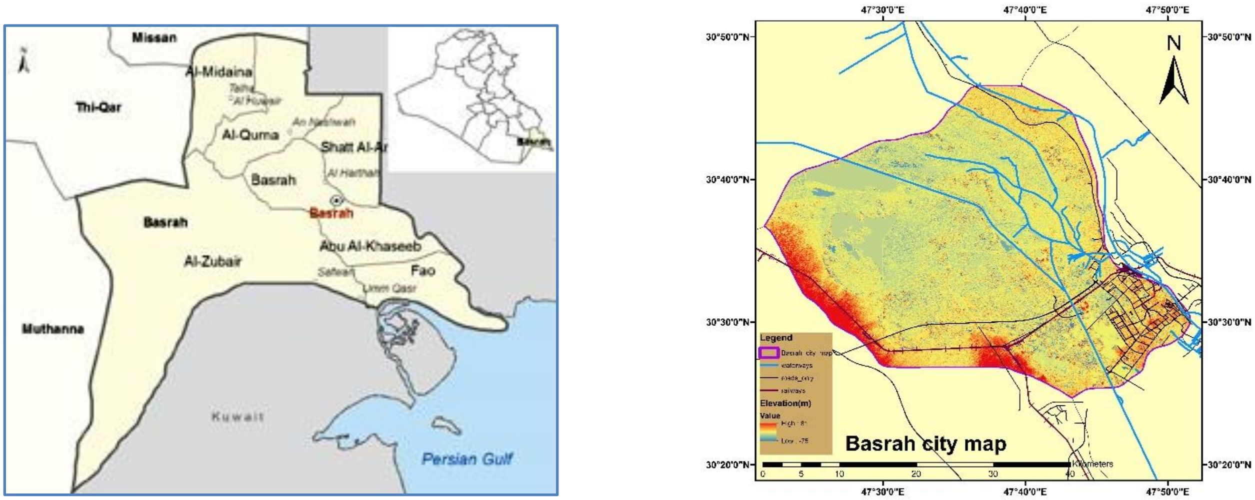

Figure 1. Map Location of (a) Basrah governate and (b) Basrah city

2.2. Data Collection and Preparation

The current investigation entails obtaining the necessary satellite images for the study area by downloading it from the USGS Earth Explorer. The GIS 10.8 software is utilized to process the data and analyze images for the creation of land use/land cover maps. The urban growth maps were generated using Landsat ETM and LOI data from 2002, 2012, and 2022. Precision techniques were utilized within the GIS framework to produce precise categorization. Afterwards, a Maximum Likelihood method was employed to categorize Landsat photos into four distinct classes: water body, vegetation land, barren land, and built-up region. In order to assess accuracy, Google Earth and ground locations were utilized to determine the acceptability of the land-use classification. The acceptable values must exceed 0.85 according to Anderson's scheme (Anderson et al., 1976). The land-use map classification was validated using the methodologies of overall accuracy and Kappa coefficient (Jensen et al, 1986).

2.3. Classification of images

The pre-processed images are subsequently classified using a supervised classification approach. In supervised classification, the maximum likelihood algorithm is used to categorize an image based on the training sets (signatures) provided by the user, utilizing their field knowledge. The user's provided training data instructs the software on which pixels to select for specific land cover types. The classification ultimately provides the land use/land cover image of the area. The study region has been classified into four distinct land cover classes: vegetated land, built-up area, barren land, and water bodies.

2.4. Measuring Urban Growth Patterns

The growth of urban areas can be measured in many ways. Several researchers have used not just mathematical indices to calculate this but also a number of statistical measures (Jiang et al., 2007; Sudhira et al., 2004). When these indicators are all worked out, what’s common to all of them is

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that they're able to tell us about the increase in growth of urban morphology, and also about what goes into it—density, contiguity, neighborhood boundaries, and more. One number can't tell us all of these different things, but when take several of them together, it can integrate them and use the GIS environment to draw some remote-sensed information together (Batty, 2000; Sudhira et al., 2001). Figure 2 presents the methods used to measure the trends of urban expansion in Basrah city. The approach employed is the quantification of urban expansion through the utilization of two distinct methodologies. The initial method provides a visual representation of the historical expansion of urban areas, while the quantitative data on historical urban growth was derived from land-use maps (Aithal and Sanna, 2012; Yusoff, 2012).

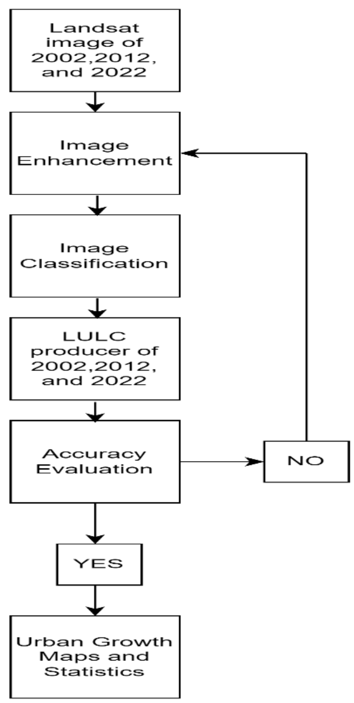

Figure 2. The methodology used to measure urban growth patterns.

2.5. Mapping Urban Growth Patterns

An essential component of analyzing urban growth trends often involves the interpretation of aerial and satellite photographs. Nevertheless, it is imperative to investigate more effective methods for charting the patterns of urban growth (Grey et al., 2003). Change detection is commonly employed for this objective (Suribabu et al., 2012). Currently, change detection is widely employed to observe, quantify, and assess alterations in land use and land cover, while considering both spatial and temporal variations (Güler et al., 2007). The utilization of multi-temporal satellite pictures with high spatial resolution is an efficient method for detecting urban expansion trends (Yagoub and Kolan, 2006).

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2.6. Analysis of LULC Change detection

There is little doubt that human activities have significantly altered the city's land cover throughout time. Land is one of the most valuable natural resources. The fertility of the soil determines all agricultural and animal production. The complete land ecosystem, which includes soil, water, and plants, supplies the community's requirement for food, energy, and other necessities of life. Viewing Earth from space is vital for assessing the impact of human actions on natural resources over time. In instances of rapid, frequently undocumented, and unrecorded land use change, observations of the Earth from space provide objective information about human activities and land use. Classified photos give comprehensive information on land use and cover in the research region.

Change detection analyses identify and quantify differences in photographs of the same scene taken at different periods. Classified pictures from three dates can be used to determine land use areas and track changes over time. This technique helps identify changes in land use, such as more urbanization or decreased agricultural land.

3. RESULTS AND DISCUSSION

3.1. Land use/land cover images

Figures 3-5 display the classified images of the research area's land use and land cover, produced by pre-processing and supervised classification. These graphics depict the land use pattern of the research area. The red hue symbolizes the urbanized region, the dark green hue depicts the vegetated area, the blue hue signifies the presence of water bodies, and the light brown hue indicates the barren terrain.

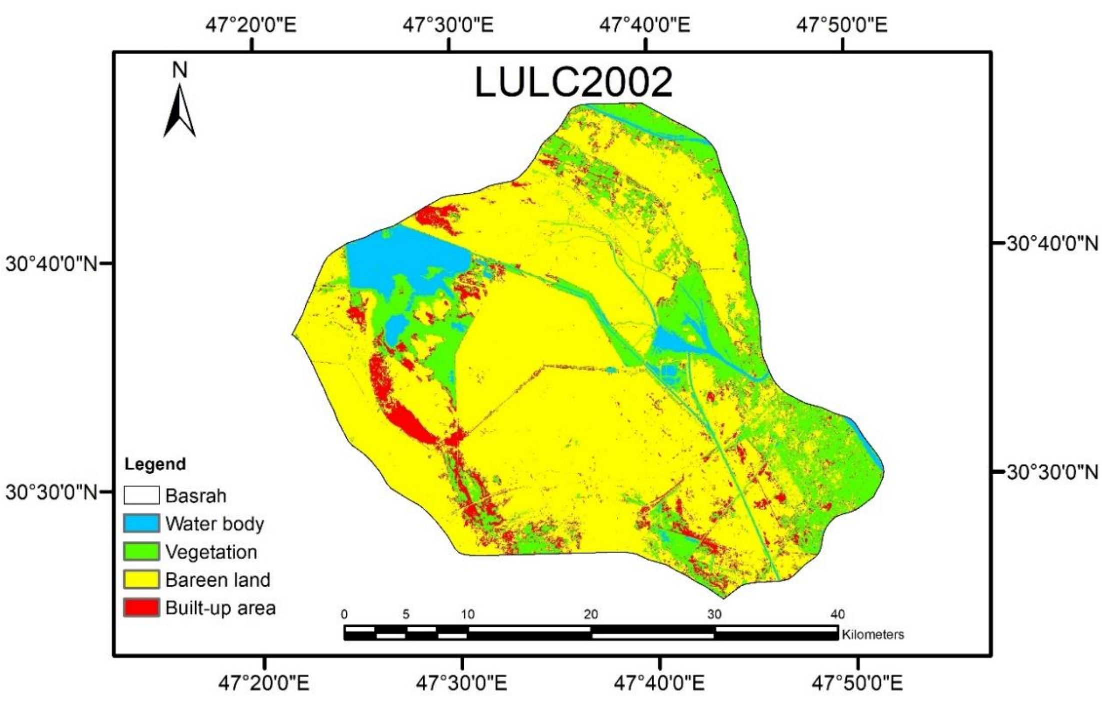

Figure 3. Basrah city land use map in 2002.

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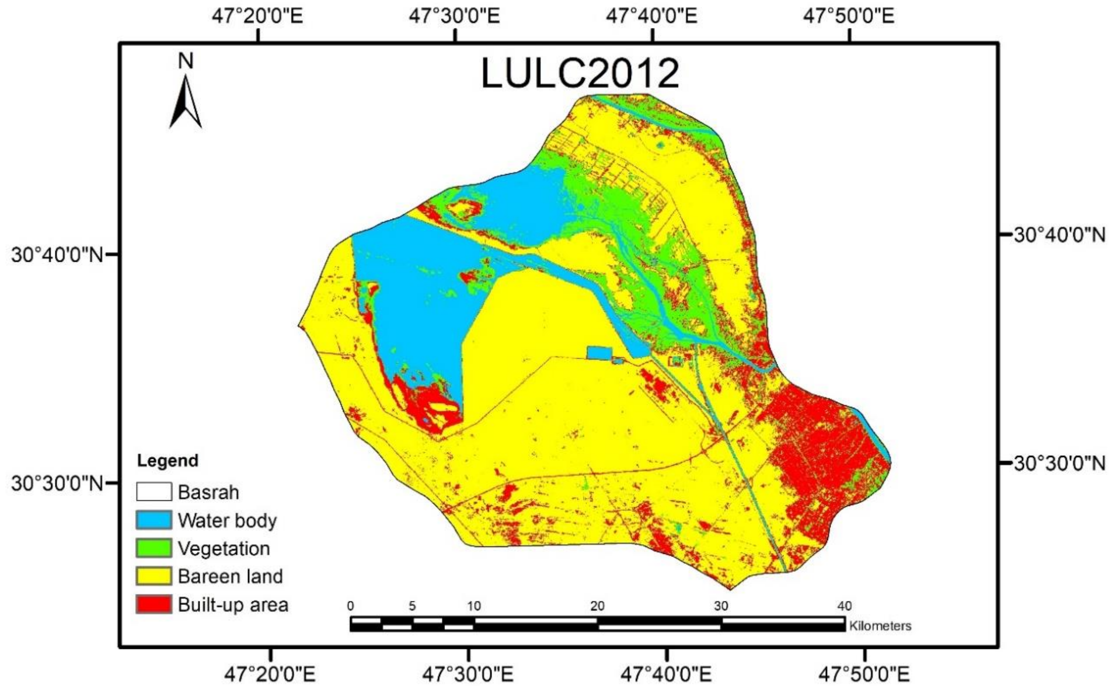

Figure 4. Basrah city land use map in 2012.

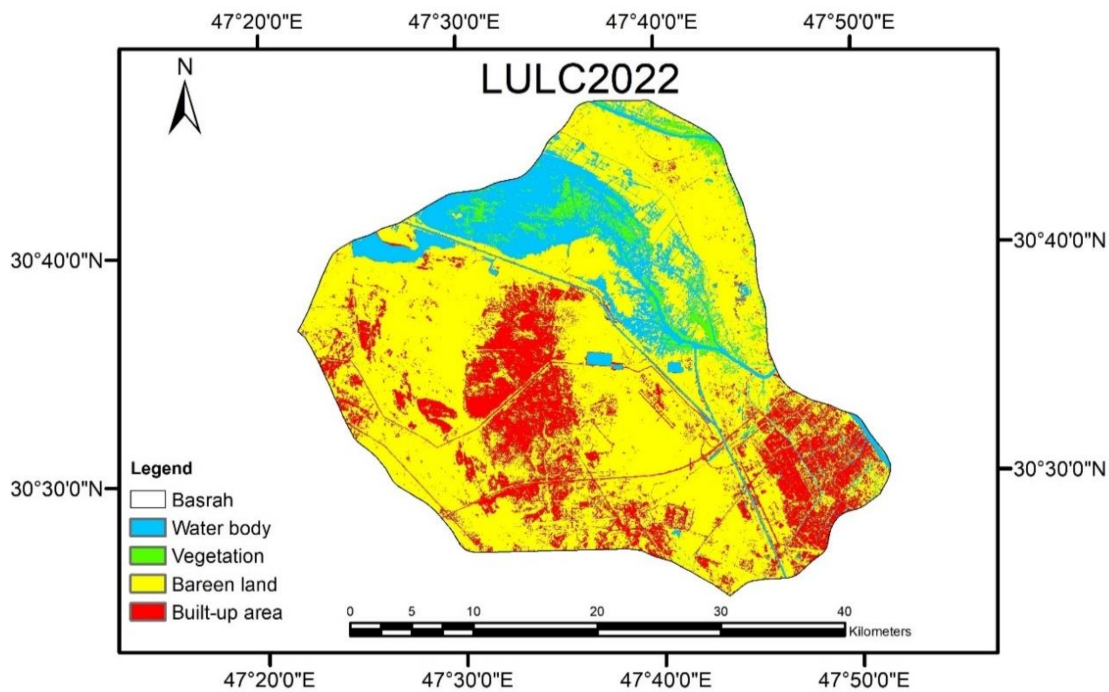

Figure 5. Basrah city land use map in 2022.

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3.2. Classification accuracy assessment

Each land use and land cover map was compared to the reference data to assess the correctness of the classification. Incorporating Google Earth, field knowledge, and random sample sites produced the reference data. While out in the field, researchers use a portable GPS (Global Positioning System) to pinpoint exact geographical coordinates (latitude and longitude) and visually inspect the type of site under study. To ensure the classification was accurate, we used the collected ground truth data.

By comparing Landsat 7 and 8 images with high-quality Google photographs, it were able to assess the accuracy of land-use classification. The overall accuracy of the land-use maps from 2002, 2012, and 2022 is 93.75%, 100%, and 94.73%, respectively, which is satisfactory. The findings indicate that the assessment of the overall accuracy of the land-use classification is quite satisfactory. The years 2002, 2012, and 2022 achieved kappa values of 0.91, 1.0, and 0.93, respectively. The overall quantity of the error matrix in those years was no more than 4%. To ensure the time series accuracy, the researchers performed a direct visual comparison of the land-use classification maps and Google Earth images during the year errors were committed. Google Earth is used by a consortium of geospatial scientists and researchers as a free tool around the clock. It is instrumental for individuals or groups working with limited resources to do their best.
The main benefits of employing Landsat 7 and 8 are their accessibility, low cost, and ease of processing. These satellites provide trustworthy data, allowing for extensive land-use studies to be conducted over extended periods of time. The increased calibration and higher spectral contrast of Landsat 8 make it a better land-use categorization tool than Landsat 7. This is according to Roy et al. (2016). Landsat data is freely available online, so researchers and professionals in the field of land-use analysis and remote sensing can save money by using it. It is critical to extensively evaluate the precision of land-use classification to guarantee the dependability of the generated maps. The results shown here are consistent with earlier studies that have proposed an 80% accuracy rate for LULC categorization (Chughtai et al., 2021).

Land cover maps must undergo thorough accuracy tests using kappa statistics to guarantee their utility (Rwanga et al., 2017). Dash et al. (2023) and Mountrakis and Heydari (2023) both state that the study's classification methods and Landsat data were quite accurate. There was a high degree of agreement between the reference data and the classified maps; kappa coefficients for 2002, 2012, and 2022 were 0.91, 1.0, and 0.93, respectively. Chughtai et al. (2021) and Rwanga and Ndambuki (2017) state that the values range from being virtually perfect to being regarded significant, indicating that the classification methods utilized are credible.
One popular statistic for gauging how well predicted and observed categories match up is the kappa coefficient. Values close to 1 indicate a high level of accuracy.

3.3. Change detection analysis

The fieldwork and review of existing technical papers helped identify the primary variables responsible for the various forms of land degradation. Urbanization is the most common kind of land degradation caused by humans in the places that have been studied. According to Seifollahi-Aghmiuni (2022) and Assennato (2022), this process has caused a number of changes in land use patterns, which in turn have affected the ecosystem. Soil quality is impacted by urbanization, which in turn contributes to ecosystem deterioration (Ferreira, 2018; Higgitt, 2022).Table 1 displays the changes in land use from 2002 to 2022. The built-up area grew at a faster rate of 7.56% between 2002 and 2012 than it did between 2012 and 2022, at 4.82%. The growth in cities and industries are the main causes of this increase (Dadashpoor, 2019; Nath, 2021). According to Table 2, the area of vegetation shrank by 9.41% between 2002 and 2012, whereas it grew by 7.32% each year between 2012 and 2022. Reasons given for this drop include the spread of cities and the cutting down of trees (Qi, 2023; Yang, 2021). From 2002 to 2012, water areas grew at a remarkable 17.88% per year, whereas from 2012 to 2022, they would develop at a slower rate of -1.57% per year (Frimpong, 2023; Li, 2023).

Table 1. Rate of growth (Annually) of LULC changes from 2002 to 2022.

LULC Class	Area (%) for 2002	Area (%) for 2012	Area (%) for 2022	Annual Rate of Growth (2002-2012)	Annual Rate of Growth (2012-2022)
Water body	5.66	15.78	13.31	17.88	-1.57
Vegetation	20.21	10.8	2.79	-4.66	-7.42
Barren land	67.18	58.91	64.57	-1.23	0.96
Built-up area	6.95	14.51	19.33	10.88	3.32

Significant changes in land utilization are shown by the growth trends of Basrah city from 2002 to 2022, as shown in Table 1 and Figures 3-5. The area occupied by buildings has grown significantly, rising from 6.95 km² in 2002 to 14.51 km² in 2012 and further to 19.33 km² in 2022, according to the assessment of land-use change. This trend lines up with the global tendency toward urbanization, as metropolitan areas grow in response to rising populations and improved living standards (Shteiwi et al., 2021).The land covered by vegetation, however, has shrunk dramatically. They were 20.21 km² in 2002, 10.8 km² in 2012, and 2.79 km² in 2022, a further reduction. Most people believe that the conversion of rural and forested areas into cities and subsequent urban sprawl is to blame for the shrinking land supply (Al-Taei et al., 2023).From 2002 to 2012, the water body's surface area increased from 5.66 km² to 15.78 km², but by 2022, it had decreased to 13.31 km². Climate change and human interference can both affect the variability of these variations (Ul Din and Mak, 2021).From 2002 to 2012, the area of desolate land decreased to 58.91 km², and then increased to 64.57 km² in 2022. Urban sprawl and the reclamation of previously used land are common causes of these fluctuations (Al-Hinkawi et al., 2021).According to Shteiwi et al. (2021), the total changes from 2002 to 2022 were as follows: an increase of 143.41 km² in built-up area, a loss of 202.35 km² in vegetative lands, an increase of 88.84 km² in water bodies, and a decrease of 30.41 km² in barren land.

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Table 2. LULC change analysis in 10 years interval from 2002 to 2022.

LULC Class	2002-2012		2012-2022		2002-2022	
	Area (km²)	Change (%)	Area (km²)	Change (%)	Area (km²)	Change (%)
Water body	117.58	10.12	-28.74	-2.47	88.84	7.65
Vegetation	-109.29	-9.41	-93.06	-8.01	-202.35	-17.42
Barren land	-96.14	-8.27	65.73	5.66	-30.41	-2.61
Built-up area	87.81	7.56	56.05	4.82	143.86	12.38

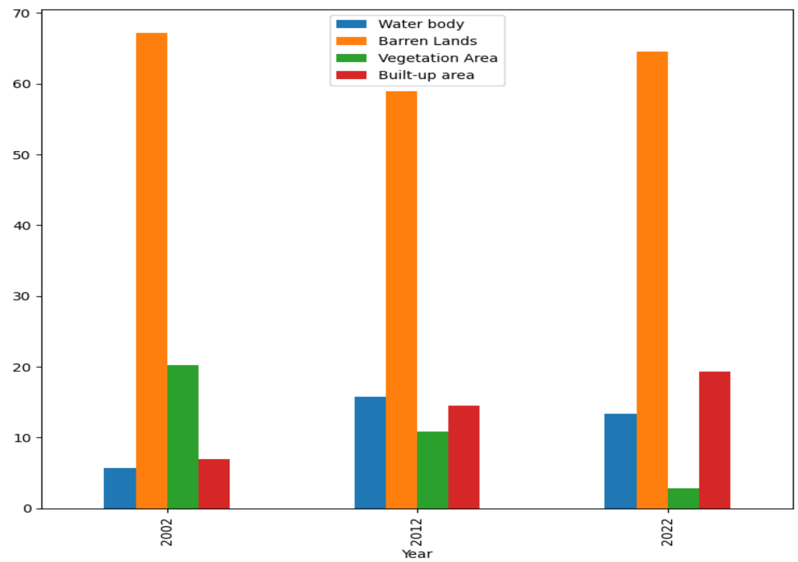

Figure 6. LULC Area percentages for Basrah city (2002-2022).

5. CONCLUSION

It may be argued that the present trend of monitoring and mapping urban growth patterns incorporates quantitative and spatiotemporal methodologies. This type of integration can be planned, executed, and evolved inside a GIS and RS framework. The geographical, temporal, and dynamic features of urban expansion processes can be determined using GIS and RS data, as well as approaches such as satellite photography, land use, and cover change detection. Based on this study, the analysis of the results yields the following conclusions:

- In 2002, the urbanized area covered 6.95 km², but in 2012, the built-up area comprised 14.51% of the total area, while the vegetation area dropped by -9.11%. Furthermore, by 2022, the built-up area will have expanded considerably to 19.33 km², representing a 4.82% increase in total area, while barren land would have increased significantly by 5.66%. As a result, urban expansion in Basrah can be regulated through the activities of high-level administrative organizations and city decision-makers.

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