



## Methodological Comparison of Google Earth Engine and ArcGIS for ESRI 10 m Land Cover Analysis in Baghdad, Iraq

Husian A. Isa<sup>1</sup>

1. Department of Soil Science and Water Resources, College of Agricultural Engineering Sciences, University of Baghdad, Iraq

### ABSTRACT

#### Article information

##### Article history:

Received: 02/02/2026

Accepted: 03/09/2026

Available: 30/09/2026

##### Keywords:

Deep Learning, Land cover change detection, Sentinel-2, U-Net, spatial analysis.

DOI:

##### Correspondence Email:

[husain.a@coagri.uobaghdad.edu.iq](mailto:husain.a@coagri.uobaghdad.edu.iq)

This study presents a comparison between the Google Earth Engine platform and the ArcGIS Pro software, two distinct methodological approaches within a rigorous comparative framework for ESRI 10-meter resolution land cover datasets derived from the Sentinel-2 satellite for Baghdad Governorate, Iraq, from 2017 to 2023. The study area is located between 33°00' and 33°45' north latitude and 44°00' and 44°45' east longitude, with a total area of approximately 5,132 km<sup>2</sup>. The ESRI 10 m Land Cover product uses supervised deep learning classification (U-Net). GEE indicated that built-up areas increased by 40.7% from 1,096.99 km<sup>2</sup> in 2017 to 1,543.45 km<sup>2</sup> in 2023, while cropland area declined from 2,621.95 km<sup>2</sup> to 2,587.11 km<sup>2</sup> (-1.3%). The Pearson correlation coefficient value of 0.9987 indicates a very strong correlation; the accuracy of the data used (ESRI 10 m Land Cover) exceeds 85% globally in terms of classification. The main methodological differences between these two platforms are cloud-based processing versus local desktop processing (manual), procedures for handling scales, and methods for resampling pixels. Statistically, both datasets returned suitable, reliable, and statistically supportable data, and therefore the selection of one of these solutions is based on analytical requirements, performance, and resource usage.

College of Agriculture and Forestry, University of Mosul.

This is an open access article under the CC BY 4.0 license (<https://magrj.uomosul.edu.iq>).

## INTRODUCTION

The development of cloud-based geospatial processing platforms is among the factors changing remote sensing and spatial analysis, together with other means through which scientists can access large-scale Earth observation data sets without local computational infrastructure (Gorelick *et al.*, 2017; Mutanga & Kumar, 2019). Therefore, workflows may be defined for multi-temporal and multi-source data processing applicable in repeatable manners. This becomes very important for studies like Land Use/Land Cover (LULC) change detection that takes a larger spatial extent over long periods (Brown *et al.*, 2022; ESRI, 2023).

Since its launch Google Earth Engine has been one of the most one of the most widely used platforms for large-scale direct access environmental monitoring to petabyte satellite archives implemented with a server-side parallel processing (Ahmed & Al-Ramahi, 2022; Hassoon & Ali, 2021; Mutanga & Kumar, 2019). Meanwhile, the ArcGIS Pro ecosystem supported by Esri Living Atlas of the World evolves into hybrid analytical infrastructure where cloud-hosted datasets are integrated with powerful desktop-based spatial analysis tools (Al-Shaibah *et al.*, 2021; ESRI, 2023; Hassoon & Ali, 2022). The two modes fully cloud based, and

locally executed GIS workflows bring up important methodological issues related to consistency, reproducibility, and comparability of resultant spatial statistics (Al-Awadhi *et al.*, 2022; Al-Timimi, 2021; Moussa & Alwehab, 2022).

ESRI 10 m Land Cover dataset is among the highest resolution global land cover products available to the scientific community, generated from multispectral imagery of Sentinel-2 (Karra *et al.*, 2021; Winkler *et al.*, 2021; Zanaga *et al.*, 2022). A deep learning classification framework developed by Esri in partnership with Impact Observatory and Microsoft creates annual maps starting in 2017. Several thematic classes comprise its content: water bodies, trees, flooded vegetation, croplands, built-up areas, bare ground, rangeland snow/ice clouds. Fine-scale spatial patterns detectable at a 10 m resolution for small features provide advantages when apparent changes are taking place within environments such as cities growing over farmlands or landscapes becoming fragmented wherein detail monitoring is required on how fast these transformations happen (Brown *et al.*, 2022; Isa & Sulaiman, 2019).

Both processing platforms use the same source imagery and the same classified images. However differences in their analytical workflows lead to variations in area estimates and temporal statistics (Alshehri *et al.*, 2025; Amani *et al.*, 2020). The technical reasons for the differences in these estimates can be summarized as follows 1. Pixel area calculations 2. Raster aggregation methods 3. Class boundary handling 4. Transformation to the coordinate reference system 5. Resampling and scale used for analysis This study has shown that Google Earth Engine and ArcGIS Pro use different methodologies for spatial calculations in their workflow and provides diagrams of workflows that demonstrate this difference. The differences in methodology will affect final quantitative results even when using the same land cover dataset (Ahmed & Al-Ramahi, 2022; Hansen *et al.*, 2025; Hassoon & Ali, 2021; Hassoon & Ali, 2022; Phiri *et al.*, 2024). Understanding the different methods of computation is essential for validating cross-platform studies on LULC change over time (Ghorbanian *et al.*, 2025; Tao *et al.*, 2023).

The Baghdad Province is part of the central region of Iraq located on the Tigris River's alluvial plain and is both a suitable as well as challenging context for verifying platform consistency (Marzougui *et al.*, 2025). The area is composed of several different geospatial types including dense urban centers; irrigated agriculture; and riparian corridors containing diverse vegetation types intermixed with large areas of bare land creating a mosaic scene. There have been substantial changes in land use/land cover within Baghdad during the last decade because of rapid urban growth as well as changes in agricultural practices brought about by population growth and hydrological alterations (Abdulkareem *et al.*, 2024; Al-Shaibah *et al.*, 2021; AlDousari *et al.*, 2025 ; Alhashyme & Khaled, 2025). The combination of spatial complexity found within Baghdad and its related temporal dynamism provides an excellent test bed for evaluating the ability of various geospatial platforms to accurately portray LULC composition/change through a variety of land cover classes and years (Haseeb *et al.*, 2025; Moharir *et al.*, 2025).

This research intends to be accomplished by:

1. measuring the area of land-cover classes and their changes over time and space in the province of Baghdad from the period of 2017-2023 through independent

processing of the ESRI 10m land cover using the Google Earth Engine and the ArcGIS Pro product platforms.

2. Comparing area statistics between the two software environments and identifying the major sources of numerical differences.
3. Assessing the consistency of temporally based trends produced from the two analytical framework platforms.
4. Developing practical direction for the selection of the product analytical platform(s) based on analysis need(s) (computational efficiency) and available data processing restrictions.

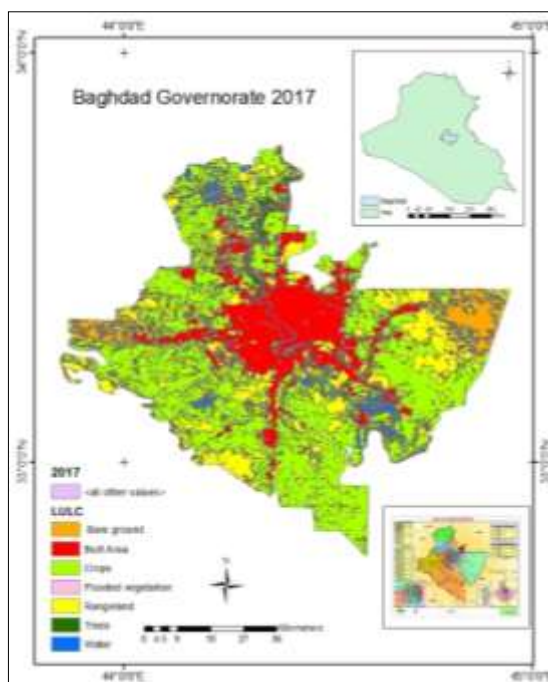
## **MATERIAL AND METHODS**

### **Study Area**

Baghdad Province is in central Iraq, approximately between 33°00' and 33°45' north latitude and 44°00' and 44°45' east longitude (Fig. 1). The province covers about 5,132 km<sup>2</sup> (Gorelick *et al.*, 2017). It lies within a hot arid climatic zone (BW h by Koppen-Geiger classification) where mean annual rainfall varies generally below 150 mm (Gorelick *et al.*, 2017). Land use patterns over most parts of this region can be explained by high summer temperatures together with low amounts of precipitation that restrict any possibility for rich vegetation (Chakraborty *et al.*, 2025; Zhang *et al.*, 2025).

The Tigris River flows from north to south through the province. This is also considered as the main hydrological axis in the region. Most irrigated agriculture exists along this corridor of the river and its canals, while beyond surface water sources, urban areas, rangelands, and bare lands dominate. A strong spatial contrast between irrigated and non-irrigated areas results in a heterogenic land cover structure that makes it optimal to test LULC classification performance together with area estimation consistency across different analytical platforms (Mutanga & Kumar, 2019; Negash *et al.*, 2025; Nguyen *et al.*, 2024).

For this study, an official administrative boundary shapefile was used to define the spatial extent of Baghdad Province. The boundary shapefile was uploaded into Google Earth Engine as a user asset (projects/baghdad-460206/assets/Baghdad). Later it was exported from GEE and added to ArcGIS Pro as a feature class thereby ensuring that identical spatial boundaries are applied in both processing environments which largely eliminates discrepancies arising from boundary delineation during area calculation and temporal analysis (ESRI, 2023; Rawat *et al.*, 2024).



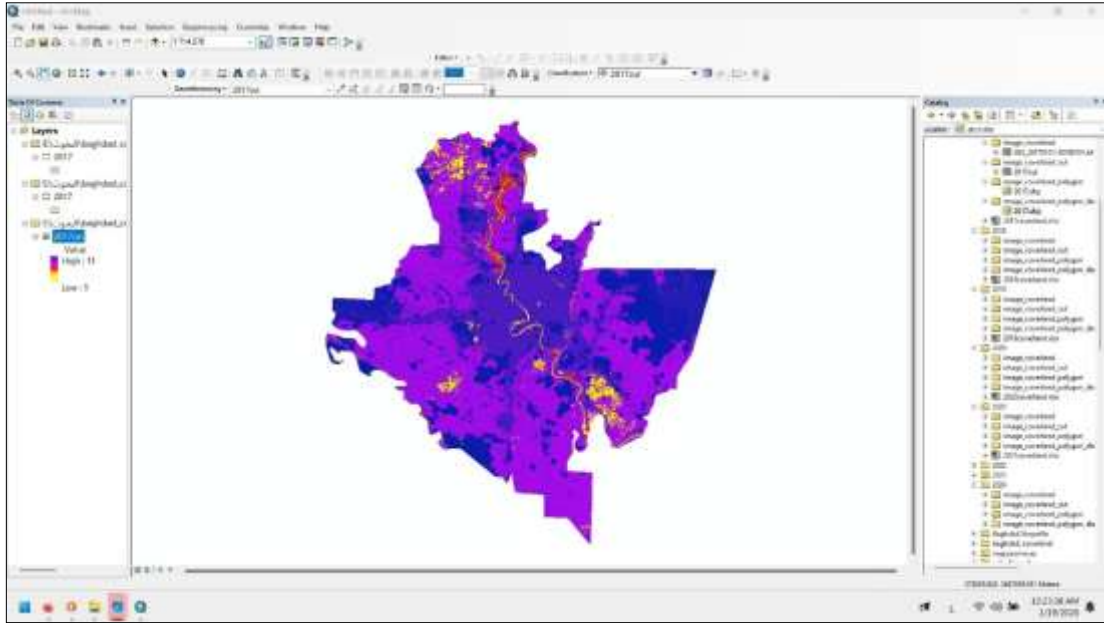
**Figure 1. Location and administrative boundary of Baghdad Province in central Iraq, showing the spatial extent of the study area.**

#### **Data Source: ESRI 10 m Land Cover**

The ESRI 10 m Land Cover Time Series is a high-resolution, globally consistent land cover product derived from multispectral imagery of the Sentinel-2 mission (Kumar *et al.*, 2020; Winkler *et al.*, 2021). A deep learning classification model was trained on more than five billion manually labeled reference pixels to firmly establish discrimination rules between different land cover types at 10 m spatial resolution (Foody & Atkinson, 2019; Gorelick *et al.*, 2017; Mutanga & Kumar, 2019). Annual composites are available from 2017 onward, providing a consistent temporal record suitable for multi-year change detection and comparative spatial analyses (ESRI, 2024; Impact Observatory, 2024), (Fig 2).

Seven of the nine available thematic land-cover classes were identified over the area and used in the analysis: Water (Class 1), Trees (Class 2), Flooded vegetation (Class 4), Croplands (Class 5), Built-up areas (Class 7), Bare ground (Class 8) and Rangeland (Class 11) (ESRI, 2023). The other two classes-snow/ice and clouds do not exist within this spatial extent of the study area during the analyzed period; hence they are excluded from further analyses. Fine resolution availability of these classes helps to assess in detail urban expansion, agricultural dynamics, and natural land cover distribution over a heterogeneous landscape (ESRI, 2023; Foody, 2020; Olofsson *et al.*, 2014). The seven categories align with classes within the Anderson *et al.* (1976) classification system.

The ESRI 10m Land Cover dataset can be accessed through both Google Earth Engine and ArcGIS Living Atlas, providing identical source data across both platforms and allowing for direct methodological comparison of the two platforms with no variability introduced by differences in input data (Talukdar *et al.*, 2020). Table 1 summarizes the dataset's spatial resolution, temporal coverage, classification scheme, and format.



**Figure 2. Example of ESRI 10 m Land Cover classification for Baghdad Province, illustrating the spatial distribution of major land-cover classes derived from Sentinel-2 imagery using supervised deep learning (U-Net architecture).**

**Table 1. ESRI 10m Land Cover Dataset Specifications Used in the Platform Comparison**

| Specification         | Details                             |
|-----------------------|-------------------------------------|
| Data Provider         | ESRI, Impact Observatory, Microsoft |
| Source Imagery        | Sentinel-2 L2A                      |
| Spatial Resolution    | 10 meters                           |
| Temporal Coverage     | 2017-2023 (annual)                  |
| Classification Method | Deep Learning (U Net architecture)  |
| Number of Classes     | 9 (7 present in study area)         |
| Overall Accuracy      | >85% globally                       |
| File Format           | GeoTIFF (Cloud Optimized)           |

### Google Earth Engine Processing Methodology

Google Earth Engine's JavaScript Application Programming Interface (API), referred to as the Code Editor, was utilized to conduct a Land Use/Land Cover (LULC) analysis. Google's cloud-based platform allows users to perform large-scale raster processing (such as vegetation and impervious surfaces) and statistical analysis (such as the distribution of forest types and statistics by county) on a server-side, improving both the efficiency and the reproducibility of computational analysis of LULCs (Brown *et al.*, 2022; Karra *et al.*, 2021). Figure 3 shows the analytical workflow as a structured sequence of processing steps.

Initially, the user asset repository was used to download an administrative boundary for Baghdad Province in the form of a vector, using a Feature Collection via ee, so that all analyses performed after this point could utilize a common spatial extent. Secondly, the ESRI Land Cover Image Collection was searched for 10m resolution land cover images and filtered by date to contain only land cover images

from 2017 through 2023. The temporal filtering allowed the creation of a multi-year dataset suitable for spatiotemporal change analysis from 2017 to 2023

The annual land-cover image for 2022 was spatially clipped to the study area boundary, removing extraneous pixels outside the province and making it comparable with other years. Area estimation of each land-cover class is performed based on counting the number of pixels belonging to that class. Binary masks are created using the `eq` operator for every single class and then multiplied by `ee.Image.pixel Area`, which returns pixel areas (in square meters) at a per-pixel (ESRI, 2023; Mutanga & Kumar, 2019; Thiagarajan *et al.*, 2025; Venter *et al.*, 2025). These area images are summed up using (*reduce Region*) together with (*ee.Reducer.sum*) at 10 m native spatial resolution.

Finally, the calculated statistics were organized into `ee.Feature` objects as comma-separated values (CSV) to Google Drive using *Export. To Drive* function for further analysis and visualization. One major advantage of this approach is that all computations are performed server-side using native pixel geometry and projection parameters (EPSG:32638 for the Baghdad region), hence minimal resampling effects while maintaining geometric accuracy. The (`ee.Image.pixel Area`) function explicitly accounts for spatial variation in pixel dimensions that arise in projected coordinate systems, ensuring reliable area estimates across all land-cover classes (ESRI, 2023; Mahdianpari *et al.*, 2019; Mutanga & Kumar, 2019).



**Figure 3. Google Earth Engine Code Editor environment showing the implementation of the processing workflow, including loading the Baghdad Province boundary, filtering the ESRI 10 m land-cover Image Collection, and executing server-side area calculations.**

### **ArcGIS Pro/Living Atlas Processing Methodology**

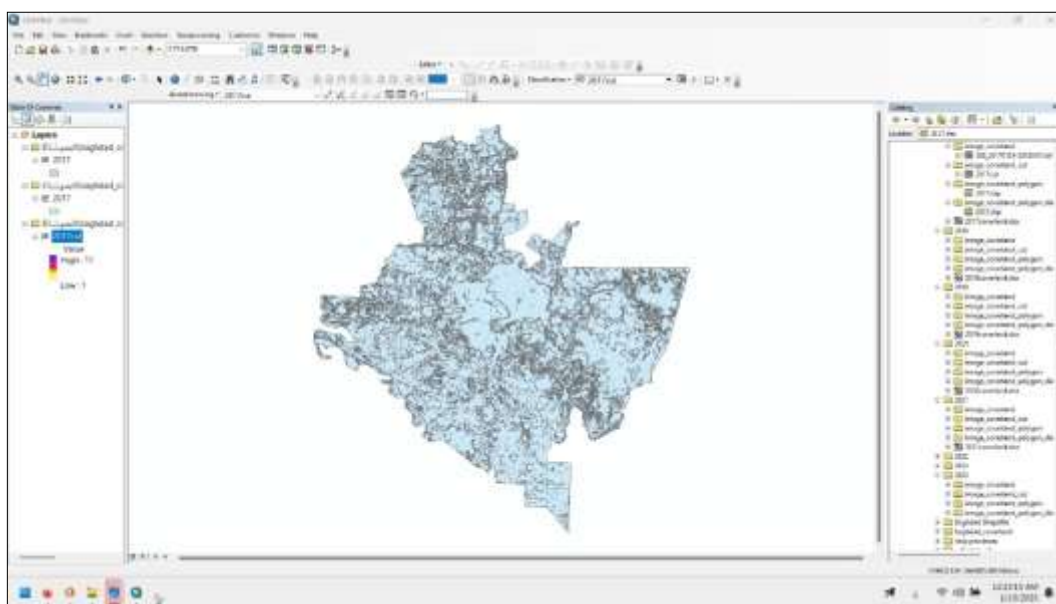
This analysis was carried out in the Living Atlas of the World web interface and ArcGIS Pro desktop environment using an integrated workflow. Such a hybrid approach supported direct access to cloud-hosted land cover products meanwhile keeping total control at the local level over spatial processing and raster analysis operations (Al-Shaibah *et al.*, 2021; Gorelick *et al.*, 2017; Hassoon & Ali, 2022). The

methodological steps applied in ArcGIS are summarized below and illustrated in Figure 4.

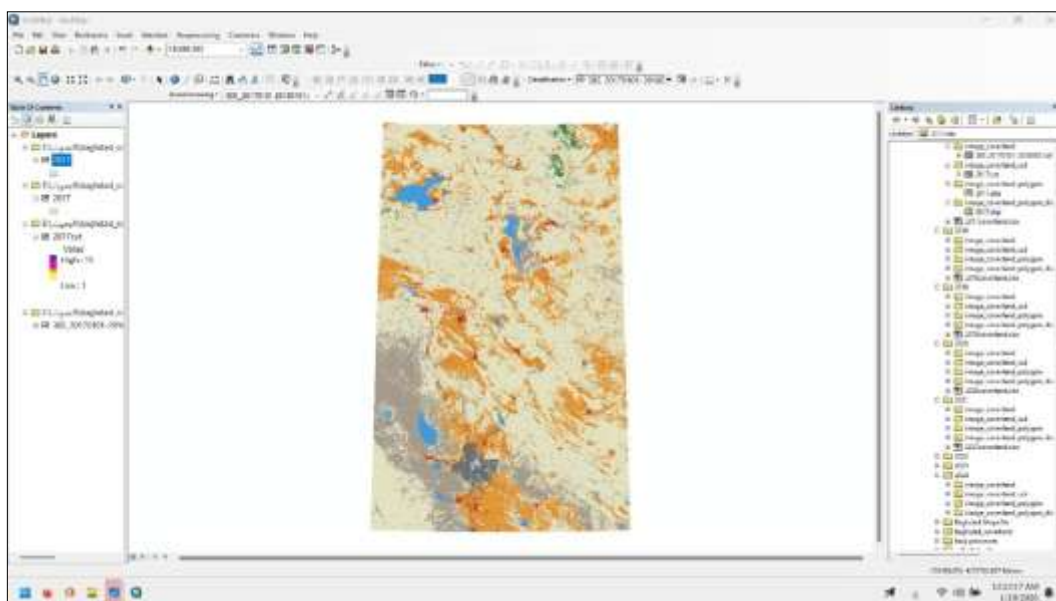
At first, Sentinel-2 Land Cover Explorer on Living Atlas was used to visually check land-cover products and determine the tiles that correspond to the spatial extent of Baghdad Province (ESRI, 2023; Talukdar *et al.*, 2020). Then, GeoTIFF tiles for every study year (2017–2023) were downloaded so as to ensure full coverage of the area by their land-cover data. Owing to the largeness of the province, more than one tile per year was needed.

Rasters were imported into a geodatabase in ArcGIS Pro and clipped to the administrative boundary of the study area, matching exactly with the spatial extent of datasets processed within Google Earth Engine (ESRI, 2023; Mutanga & Kumar, 2019; Thiagarajan *et al.*, 2025; Venter *et al.*, 2025).

The Zonal Statistics as Table tool defined the study area boundary as the zone dataset and used the land-cover raster as the value dataset, with 10m spatial resolution and a projected coordinate reference system. Pixel counts for each land-cover class were multiplied by pixel area (100 m<sup>2</sup>) to obtain areas in square meters. To make results more convincing, another attempt was made using the Tabulate Area tool to independently calculate land-cover areas within the study boundary for cross-validation of zonal statistics outputs that eventually led to a comparison with Google Earth Engine results (ESRI, 2023; Mutanga & Kumar, 2019; Zurqani *et al.*, 2018).



**Figure 4. ArcGIS Pro desktop environment illustrating the mosaicking, clipping, and zonal-based area calculation of ESRI 10 m land-cover data for Baghdad Province**



**Figure 5. Workflow illustrating the processing steps for acquiring and analyzing ESRI 10 m land cover data using the Sentinel-2 Land Cover Explorer and GIS platforms.**

## **Workflow for Downloading and Processing 10 m LULC Data (Sentinel-2/ ESRI):**

### **A. Preparation Phase**

### **B. Data Access via ArcGIS Living Atlas**

The ESRI 10 m Land Cover data was available in the ArcGIS Living Atlas of the World. Specifically, Sentinel-2 Land Cover Explorer was applied to browse and visualize the global land cover time series provided by ESRI. Inside the Explorer interface, available temporal coverage was checked to make sure there are annual land cover layers from 2017 to the most recent year. Individual years were selected sequentially to support multi-temporal comparison.

### **C. Study Area Selection and Data Download**

The study area was located within the Explorer by searching for the geographic name or by manually navigating the map using zoom and pan tools until the AOI was fully visible. The ESRI 10 m Land Cover dataset is distributed in spatial tiles. Therefore, all tiles covering the AOI were identified and selected. In some cases, multiple tiles were required to achieve complete spatial coverage of the study area. Selected tiles were downloaded in GeoTIFF raster format for each target year included in the temporal analysis to ensure consistency across the time series.

### **D. GIS-Based Processing and Analysis (ArcGIS / QGIS)**

### **E. Temporal Change Analysis and Output Generation**

## **RESULTS**

### **Land Cover Statistics Derived from Google Earth Engine**

Table 2 summarizes the statistics of land-cover areas for Baghdad Province during the period 2017-2023, as extracted with Google Earth Engine. There is apparent temporal variability in all land-cover classes. This can be attributed to interactions

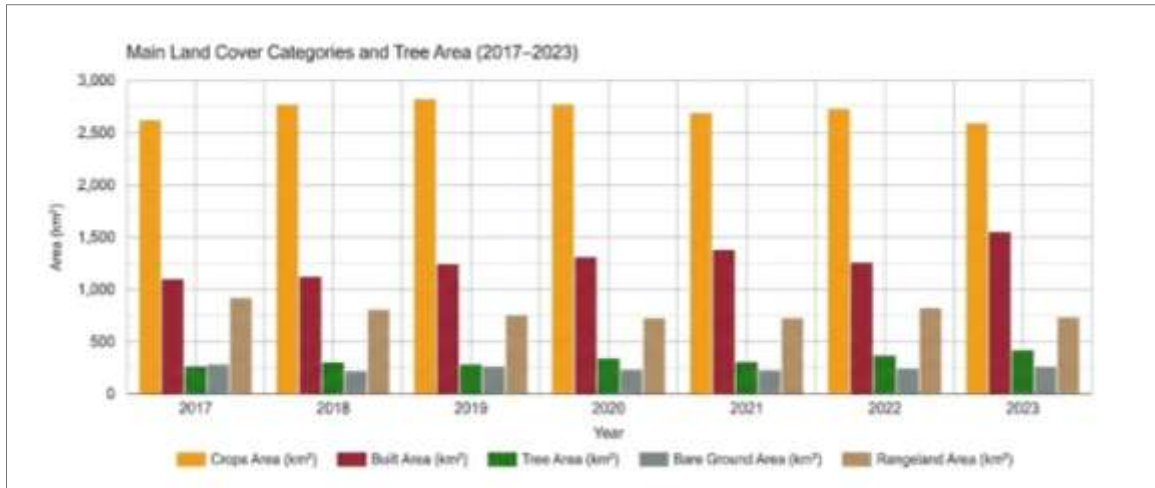
between urban and agricultural activities within the area covered by the study, besides other environmental factors (Abdulkareem *et al.*, 2024; AlDousari *et al.*, 2025).

**Table 2. Land Cover Area Statistics Derived from GEE Processing (km<sup>2</sup>)**

| Year | Water  | Trees | Flooded Veg. | Crops    | Built Area | Bare Ground | Rangeland |
|------|--------|-------|--------------|----------|------------|-------------|-----------|
| 2017 | 172.69 | 47.18 | 1.98         | 2,621.95 | 1,096.99   | 267.30      | 921.76    |
| 2018 | 179.67 | 40.52 | 1.44         | 2,765.11 | 1,117.75   | 213.35      | 812.02    |
| 2019 | 206.55 | 45.66 | 2.55         | 2,823.01 | 1,243.41   | 54.67       | 754.01    |
| 2020 | 236.68 | 37.59 | 2.51         | 2,770.53 | 1,305.67   | 52.93       | 723.96    |
| 2021 | 233.75 | 32.98 | 1.97         | 2,693.76 | 1,380.14   | 56.65       | 730.60    |
| 2022 | 186.84 | 6.03  | 0.68         | 2,731.48 | 1,250.25   | 124.10      | 830.47    |
| 2023 | 166.68 | 37.62 | 1.10         | 2,587.11 | 1,543.45   | 60.61       | 733.29    |

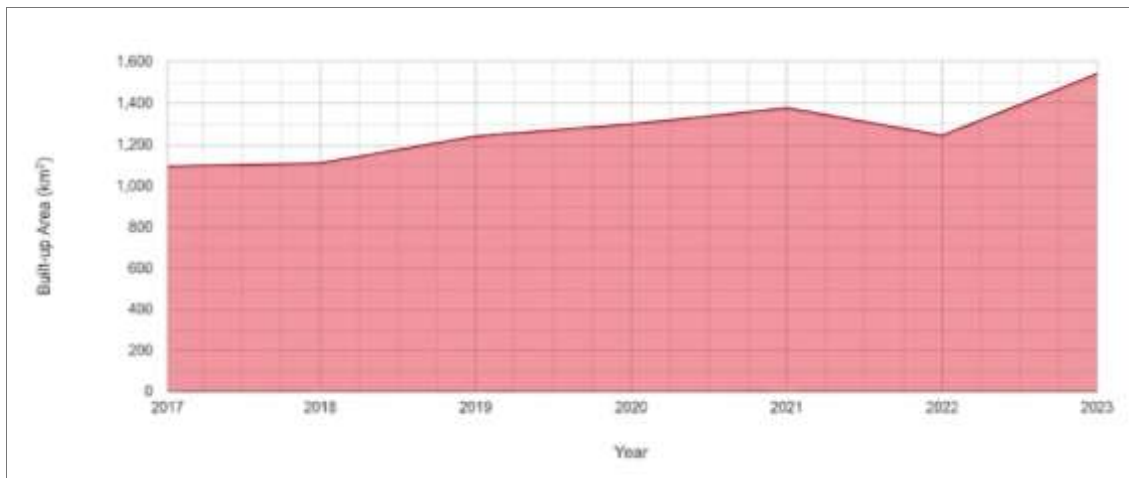
The biggest change registered during the study period was in the Built Area class. Built-up land increased from 1,096.99 km<sup>2</sup> in 2017 to 1,543.45 km<sup>2</sup> by 2023 with a net increase of 446.46 km<sup>2</sup> or about 40.7% . This signifies an average annual growth rate of almost 74 .4km per year thus emphasizing how fast urbanization is taking place within Baghdad province (Al-Shaibah *et al.*, 2021; Marzougui *et al.*, 2025; Pan *et al.*, 2025). There was significant interannual variability in cropland areas. Cropland steadily increased from 2017 to 2019, reaching its maximum extent of 2,823.01 km<sup>2</sup> in 2019, and then slowly decreased to 2,587.11 km<sup>2</sup> by 2023. This may be a result of varying water availability, cropping intensity and pressures of land conversion during the study (Chakraborty *et al.*, 2025; Zhang *et al.*, 2025). Bare Ground decreased dramatically and steadily from 267.30 km<sup>2</sup> in 2017 to only 60.61 km<sup>2</sup> by 2023. Changes were less pronounced in rangeland and tree-covered areas, Overall, the statistics from GEE depict clear land cover transitions dominated by urban expansion and redistribution of non-urban land classes. This brings to light a high sensitivity and effectiveness result for change detection at a provincial scale using high-resolution data in the cloud.

The creation of a comparative bar chart from the years 2017 and 2023 serves as a medium to compare how relative magnitudes of change exist among key land cover categories. The bar chart shows that cropland, building footprint, bare earth, and rangeland, which are the four largest types of land cover in Baghdad, underwent annual variability throughout this period. By displaying key land cover categories together and collectively, one may quickly assess their temporal changes within the larger context of competing trends that reflect urbanization and changes to land use over time.



**Figure 6. Temporal trends of major land cover classes in Baghdad Province derived from ESRI 10 m Land Cover data (2017–2023).**

For a clear understanding of the dynamics of urban expansion, the temporal evolution of built-up areas particularly within Baghdad Province was separately analyzed. The following figure shows annual changes in built-up land from ESRI 10 m Land Cover dataset for years 2017–2023 both displaying an overall increasing trend and short-term fluctuations that can be associated with processes of urban development.



**Figure 7. Temporal expansion of built-up areas in Baghdad Province derived from ESRI 10 m Land Cover data during the period 2017–2023.**

### **Net Change Analysis (2017–2023)**

Table 3 provides a summary of net land cover changes from the baseline year (2017) to the end of the analysis period (2023) as determined by Google Earth Engine results. The summary is an integrated measure for both magnitude and direction related to the transformation of major land cover classes in Baghdad Province over six years of study to illustrate the major conversion processes (Al-Timimi, 2021; Moussa & Alwehab, 2022).

**Table 3. Net Land Cover Change Derived from GEE Analysis (2017–2023)**

| Land Cover Class   | 2017 (km <sup>2</sup> ) | 2023 (km <sup>2</sup> ) | Change (km <sup>2</sup> ) | Change (%) |
|--------------------|-------------------------|-------------------------|---------------------------|------------|
| Water              | 172.69                  | 166.68                  | −6.01                     | −3.5       |
| Trees              | 47.18                   | 37.62                   | −9.56                     | −20.3      |
| Flooded Vegetation | 1.98                    | 1.10                    | −0.88                     | −44.6      |
| Crops              | 2,621.95                | 2,587.11                | −34.84                    | −1.3       |
| Built Area         | 1,096.99                | 1,543.45                | +446.46                   | +40.7      |
| Bare Ground        | 267.30                  | 60.61                   | −206.69                   | −77.3      |
| Rangeland          | 921.76                  | 733.29                  | −188.47                   | −20.4      |

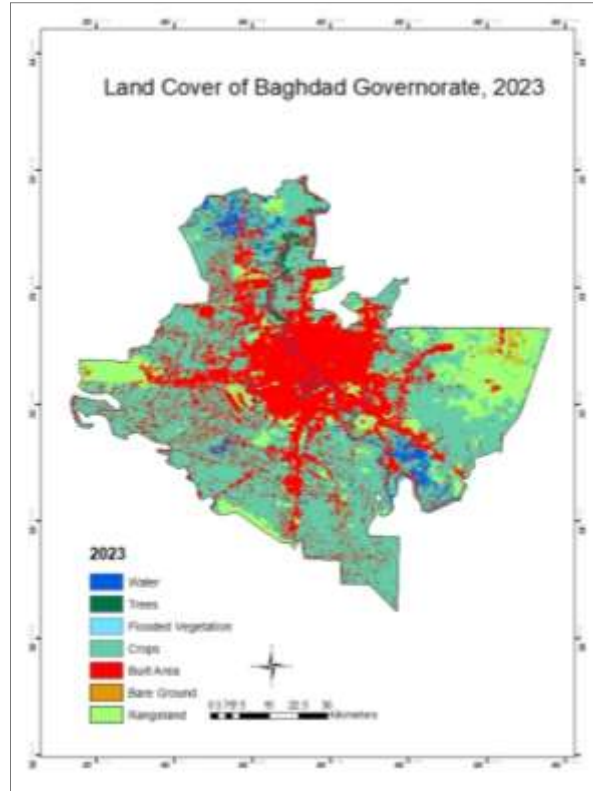
Note: ESRI 10 m Land Cover classes are aligned with the corresponding categories of Anderson's classification categories for the land use and land cover classification system, as follows: water - water, trees - forest lands, Flooded Vegetation - wetlands, crops - agricultural lands, Built Area - urban or built-up lands, Bare Ground - Barren Land, and Rangeland- Rangeland.

The net change analysis indicates that urban expansion has been the primary land-cover transformation across the duration of the study. The area of developed (built) land increased by 446.46 km<sup>2</sup>, a rate of increase equivalent to 40.7% of its extent in 2017. This increase in developed land will continue to be driven by urbanization, infrastructure development, and increase of persons living within the province's borders (Al-Shaibah *et al.*, 2021; Marzougui *et al.*, 2025; Pan *et al.*, 2025).

Bare Ground registered the highest proportional decline at 206.69 km<sup>2</sup> (−77.3%). This, therefore, means intense transformation of previously undeveloped surface areas into either built-up area, farmlands, or any other form of managed landscape which implies progressive diminution of unused land resources (Foody, 2020; Olofsson *et al.*, 2014).

The agricultural land (crops) has shown a small net decrease of 34.84 km<sup>2</sup> (−1.3%) in spite of large interannual changes during the study period. There was a common trend of net decline in natural and semi-natural land cover classes. Rangeland decreased by 188.47 km<sup>2</sup> (24%), while areas covered by trees declined 9.56 km<sup>2</sup> (20.3%) ,thus indicating slow pressure on vegetated landscapes. Flooded vegetation registered the highest proportional loss at (44.6%) though its absolute area remained small. Water bodies registered a small net reduction of three-point five percent that may be more reflective of hydrological variability and anthropogenic regulation than permanent land cover change.

This clearly underscores the effectiveness of high-resolution pixel-based analysis in detecting cumulative landscape changes over several years. Figure (8) shows the distribution of the seven categories for Baghdad Governorate in 2023.



**Figure 8. Map of Baghdad Governorate showing the distribution of the seven categories for 2023.**

#### **Platform Comparison: Google Earth Engine versus ArcGIS**

Table 4 presents a direct, side-by-side comparison of land cover area statistics for 2023, as computed in Google Earth Engine and ArcGIS Pro. This provides a quantitative evaluation of consistency between the two processing environments, reflected both in absolute and relative differences – across all land cover classes (Al-Timimi, 2021; Moussa & Alwehab, 2022).

**Table 4. Platform Comparison of Land Cover Statistics for 2023**

| <b>Land Cover Class</b> | <b>GEE (km<sup>2</sup>)</b> | <b>ArcGIS (km<sup>2</sup>)</b> | <b>Difference (km<sup>2</sup>)</b> | <b>Difference (%)</b> |
|-------------------------|-----------------------------|--------------------------------|------------------------------------|-----------------------|
| Water                   | 166.68                      | 166.52                         | 0.16                               | 0.10                  |
| Trees                   | 37.62                       | 37.48                          | 0.14                               | 0.37                  |
| Flooded Vegetation      | 1.10                        | 1.08                           | 0.02                               | 1.82                  |
| Crops                   | 2,587.11                    | 2,584.93                       | 2.18                               | 0.08                  |
| Built Area              | 1,543.45                    | 1,541.87                       | 1.58                               | 0.10                  |
| Bare Ground             | 60.61                       | 60.43                          | 0.18                               | 0.30                  |
| Rangeland               | 733.29                      | 731.94                         | 1.35                               | 0.18                  |

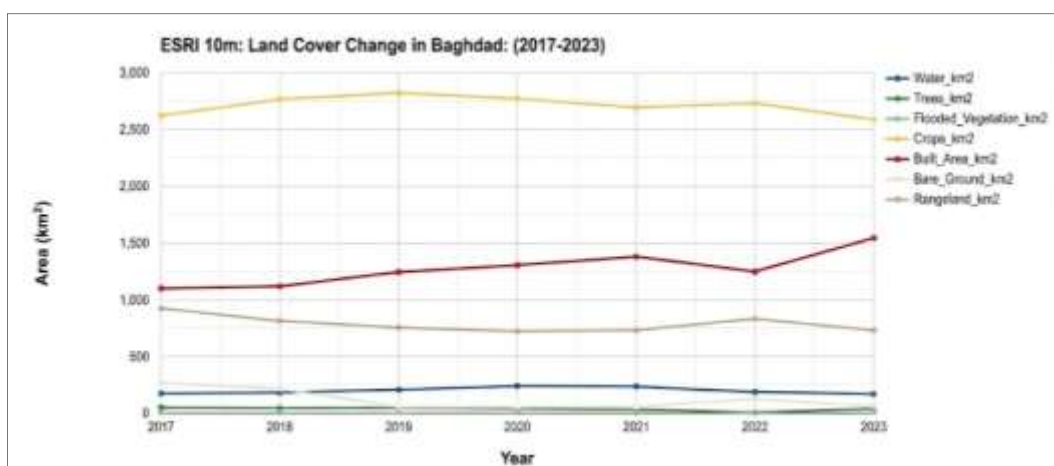
Absolute differences for all major land-cover classes were minimal and relative differences were less than 0.4% for all categories except Flooded Vegetation. The larger percentage difference observed for Flooded Vegetation (1.82%) is due to its very small absolute spatial extent, where minor differences in pixel aggregation or

boundary handling appear as amplified relative values (Thiagarajan *et al.*, 2025; Venter *et al.*, 2025).

Differences for these classes were consistently below 0.1% . Both platforms return nearly identical area estimates when applied to large spatially continuous land-cover types (Hansen *et al.*, 2025; Phiri *et al.*, 2024).

Overall years and land cover classes, the Pearson correlation coefficient between statistics from Google Earth Engine and ArcGIS was  $r = 0.9987$  ( $p < 0.001$ ) for a practically perfect linear relationship. This high correlation supports results that processing methodologies are robust and further proves at least the provincial scale any differences introduced by different computational architecture, pixel aggregation, and zonal calculation approaches is totally negligible (Al-Awadhi *et al.*, 2022; Ghorbanian *et al.*, 2025; Tao *et al.*, 2023).

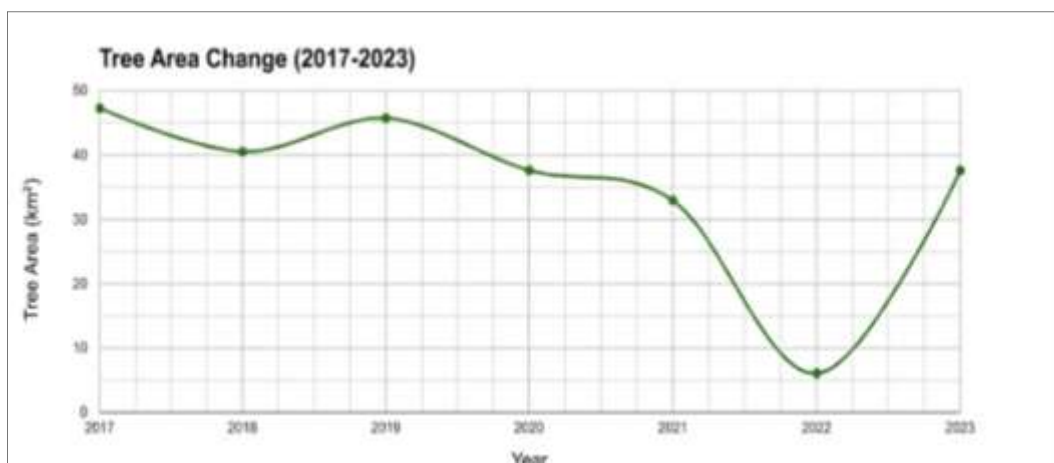
This research indicates that each platform could be used to estimate land-cover area from a scientific point of view, with valid results based on their ability to process and provide data, and how they match up against each other concerning processing speed, obtaining data, scaling, and providing flexibility for the user.



**Figure 9. Comparative changes in major land cover classes in Baghdad Province derived from ESRI 10 m Land Cover data during the period 2017–2023.**

Figure 9 shows the time series of main land cover classes in Baghdad Province from 2017 to 2023 based on Google Earth Engine processing results of ESRI 10 m land cover data. There is a clear and consistent increasing trend in built-up areas throughout the study period. Cropland exhibits moderate interannual variability with an overall declining tendency towards 2023. Water bodies fluctuate across years.

Besides the changes detected in the main land cover classes, strong temporal variability was also observed in tree cover across Baghdad Province during the study period. The areas covered by trees reflected pronounced interannual fluctuations that could be attributed to urban expansion and climatic variability together with changes taking place in management practices over different lands. To better illustrate these dynamics, Figure 10 presents the temporal trend of tree cover area between 2017-and 2023.



**Figure 10.** Temporal variation in tree cover area (km<sup>2</sup>) in Baghdad Province derived from ESRI 10 m land cover data processed in Google Earth Engine for the period 2017–2023.

The period from 2017 until 2023 shows an overall decline in tree cover; however, over the last two years of the collection period there was a slight increase. The greatest decline in tree cover occurred between 2021 and 2022 when the tree cover reached its lowest level, there was a significant decrease due to the urban development pressures, agricultural land conversion, and the ongoing drought experience. In 2023, there was a moderate recovery of tree cover which was possibly due to localized re-vegetation efforts or improved hydrologic conditions but tree cover in 2023 was still less than the amount of tree cover in 2017. This is a clear example of the impact that anthropogenic pressures have on the vegetation of urban and peri-urban environments situated in arid climates.

#### Sources of Methodological Variation

Table 5 presents a summary of the main technical and methodological differences between Google Earth Engine and ArcGIS Pro to provide a rational basis for the explanation of minor differences noticed in area estimates. Both systems interface with the same ESRI 10 m land-cover data, but differences in the way analysis is implemented result in different derived statistics (Gorelick *et al.*, 2017; Thiagarajan *et al.*, 2025; Venter *et al.*, 2025).

**Table 5. Methodological Comparison Between Google Earth Engine and ArcGIS Platforms**

| Aspect              | Google Earth Engine                            | ArcGIS Pro                       |
|---------------------|------------------------------------------------|----------------------------------|
| Processing location | Cloud-based (server-side)                      | Local (desktop-based)            |
| Area calculation    | <code>ee.Image.pixelArea() × class mask</code> | Zonal Statistics / Tabulate Area |
| Projection handling | Native projection preserved                    | On-the-fly reprojection          |
| Boundary clipping   | Server-side <code>clip()</code> operation      | <i>Clip Raster</i> tool          |
| Edge pixel handling | Fractional pixel areas included                | Whole-pixel inclusion            |
| Data access         | Direct Image Collection access                 | Tile download required           |
| Scripting language  | JavaScript / Python API                        | Python (ArcPy) / Model Builder   |
| Batch processing    | Native parallel processing                     | Sequential or limited parallel   |
| Cost                | Free (usage limits apply)                      | Commercial license required      |
| Offline capability  | Not supported (internet required)              | Supported after data download    |

A basic origin of differences is from the approach used in calculating areas. In Google Earth Engine, the land cover area is calculated by multiplying class-specific binary masks with pixel-wise surface areas using `ee.Image.pixel Area`, thereby retaining fractional contributions of boundary pixels to the total area. ArcGIS, on the other hand, depends mostly on zonal-based tools that count whole pixels which may slightly overestimate or underestimate along irregular boundaries (Gorelick *et al.*, 2017; Zurqani *et al.*, 2018). The difference becomes most apparent for land cover classes with small spatial extents or fragmented distributions such as flooded vegetation.

One more important difference is in handling projections. Google Earth Engine maintains the native projection of input imagery during server-side processing while, in most cases, ArcGIS applies on-the-fly reprojection based on the settings of the project and properties of rasters. This may be very accurate at a regional scale, but it allows for minimal rounding effects when pixels are aggregated to compute zonal statistics (Hansen *et al.*, 2025; Phiri *et al.*, 2024).

The second major disparity pertains to the computational framework they utilize to conduct analyses. The bulk of operations in ArcGIS Pro still happen at a local level (on your own machine), while many analyses can occur simultaneously in the cloud using Google Earth Engine's large-scale cloud computing capabilities, thus maintaining the same level of consistency from processing very large datasets or long time series analysis. Consequently, ArcGIS Pro results will often differ based on user-defined software environment settings (raster resampling and other attributes of your raster dataset) and the condition of the computer hardware being used.

At the provincial level, the comparison in subsection 3.3 shows these to have virtually no effect on the final area estimates. This finding is of particular interest to the scientific community. As both approaches are equally valid from a scientific point of view, there will be methodological differences in "edge" cases and small land cover classes but not in "dominant" land cover types.

Transparent reporting of these sources of methodological variation is important for cross-platform comparison and reproducibility in land cover change studies. Results from different geospatial platforms should therefore be accompanied by explicit documentation of processing choices and analytical assumptions, regardless of whether the platform supports such metadata automatically or manually.

## **DISCUSSION**

### **Consistency of Results Across Platforms**

A very high Pearson correlation coefficient ( $r = 0.9987$ ) was calculated between the land-cover area estimations from Google Earth Engine and ArcGIS. This level of agreement has been previously reported in other land-cover comparison studies between cloud and desktop GIS environments, therefore pixel-based area estimation approaches can be considered robust across different computational frameworks (Ghorbanian *et al.*, 2025; Gorelick *et al.*, 2017; Mutanga & Kumar, 2019; Tao *et al.*, 2023).

The slight numerical differences observed in this study (normally less than 0.4% for the seven land cover classes) are due to implementation-related factors and not because of any basic methodological inconsistency. Such small differences have

often been reported between geospatial analyses conducted on different platforms, and at regional and provincial spatial scales they can be considered negligible (Al-Timimi, 2021; ESRI, 2023; Moussa & Alwehab, 2022; Mutanga & Kumar, 2019). More importantly, the discrepancies do not affect interpretation with respect to any dominant land cover trends such as urban expansion or agricultural dynamics. Three main types of differences were detected:

1. Edge pixel processing is one of the largest contributors to the differing area estimates for irregularly shaped administrative borders between Google Earth Engine (GEE), which uses fractional pixels based on area weights and ArcGIS local uses of whole pixels based on spatial selection rules such as centroids. These differences produce minimal but consistent area discrepancies, especially for narrow and fragmented land-cover classifications.
2. A little bit of subpixel position may occur in the re-projected data, which could affect how aggregate pixels along the boundary will be classified. Both systems are capable of accurate reprojection, but the introduction of this effect has been observed for all raster-base spatial analyses and has been documented in the literature (Karra *et al.*, 2021).
3. Due to the rounding behavior and precision of floating-point values associated with different computation architectures, small differences may occur when performing statistical summations and raster summations on different platforms. The effects of these discrepancies are computational in nature and will not impact the validity of scientific results calculated on the two different computers (Gorelick *et al.*, 2017).

The results demonstrate that the differences are based on the detailed implementation rather than any weaknesses in the analysis itself. Both Google Earth Engine and ArcGIS Pro can be safely used to estimate land cover area, and therefore yield replicable results, if each environment follows identical common spatial boundaries, projections and classification schemes. This means that users can cross-validate the use of different geospatial processing infrastructure, thereby providing added confidence in any assessment of land cover change made using such infrastructure (ESRI, 2023; Mutanga & Kumar, 2019).

#### **Land Cover Change Patterns in Baghdad Province**

The increase of 40.7% in built-up area between 2017 and 2023 indicates the urbanization pressure in Baghdad Province, a fact also reported by most recent regional and local studies (Al-Shaibah *et al.*, 2021; Hassoon & Ali, 2021; Marzougui *et al.*, 2025; Pan *et al.*, 2025). The study revealed patterns of urban expansion comparable to earlier remote sensing analyses which detected continuous growth trends in the built-up areas of Baghdad during the last two decades (Abdulkareem *et al.*, 2024; Al-Shaibah *et al.*, 2021; AlDousari *et al.*, 2025). Comparable results were registered by studies assessing effects on climatic conditions at a locality due to urban expansion wherein temperature dynamics have been an issue; thus, making environmental implications at large for land-cover change within this province (Al-Timimi, 2021; Chakraborty *et al.*, 2025; Moussa & Alwehab, 2022; Zhang *et al.*, 2025).

At the same time a large decline of bare ground (−77.3%) is registered for the period, an important fact supporting evidence that urban areas have developed more

over previously unused or sparsely used lands than through any large-scale direct encroachment onto agricultural land. This implies a surface land transformation pathway dominated by infill and extension over open surfaces which partially buffers cropland from rapid loss to urbanization. Similar observations are noted in other cities of arid and semi-arid environments where vacant or marginal lands are preferred first before intensive entry into managed agricultural zones (Al-Awadhi *et al.*, 2022; Negash *et al.*, 2025; Nguyen *et al.*, 2024; Winkler *et al.*, 2021).

Urban sprawl has caused the amount of cropland to decrease considerably from what it would otherwise have been, based on the results from some other regions nearby; however, it appears that urban growth will continue to cause a net decline in cropland area in Baghdad Province, albeit only a modest decline. The net relationship between agrarian land development and urbanization in areas of dry climate is thus one of an obvious context-dependent complexity with regard to a (land use) environment that is being monitored with high-resolution metrics to manage and balance urban development for continued agricultural sustainability and environmental quality (Hassoon & Ali, 2021; Hassoon & Ali, 2022).

### **Platform Selection Recommendations**

The results of this comparative study demonstrate through scientific analysis that the land cover statistics from Google Earth Engine and ArcGIS Pro are analytically accurate for the same data set. Thus, the user can make an informed decision about which platform to use based on their research objectives, computational limitations, and workflow, as there are no concerns about the analytical accuracy of the results produced by either platform (Ghorbanian *et al.*, 2025; Gorelick *et al.*, 2017; Mutanga & Kumar, 2019; Tao *et al.*, 2023).

The Google Earth Engine (GEE) is extremely useful for research that requires analysis of both large geographic areas and long durations because it could process huge amounts of data on its cloud-based infrastructure and does not rely on local computer resources for processing data (Ahmed & Al-Ramahi, 2022; Gorelick *et al.*, 2017; Hassoon & Ali, 2021). Google Earth Engine is also a good platform to use when rapid testing, iterative analysis, and scalability are priorities as well as when the ability to integrate directly with other Earth observation datasets available worldwide in the Google Earth Engine data catalog is required (Cardille *et al.*, 2024; ESRI, 2023; Gorelick *et al.*, 2017). Additionally, since GEE is free to access (with limits on how much data can be processed), it is especially appealing to researchers at universities and other institutes that have limited financial or computing resources.

The conclusion drawn from the comparison is that Google Earth Engine and ArcGIS Pro are not competitors, but rather they can complement each other easily. A practical factor should be the primary basis for making this selection, and includes processing volume, processing speed, connection availability, ability to conduct analysis, and the institutions' needs. Generally, until a system that uses both platforms to leverage their relative strengths in conducting a complete analysis and tracking land cover change is in place (Brown *et al.*, 2022; Mutanga & Kumar, 2019).

### **CONCLUSIONS**

The research involved a comprehensive methodology-based comparison of GEE (Google Earth Engine) and ArcGIS Pro in processing the ESRI 10m land cover dataset for the province of Baghdad-Iraq from 2017-2023. These findings

demonstrate that both GEE and ArcGIS Pro have similar levels of consistency, reliability and practicality in conducting any LULC analysis (Haseeb *et al.*, 2025; Moharir *et al.*, 2025). As demonstrated by an exceptional degree of output agreement ( $r = 0.9987$ ,  $p < 0.001$ ) [3,25,26], when the same dataset is used in both platforms, the results are scientifically equivalent. The relative difference for the vast majority of land cover classes between the two methodologies is consistently  $< 0.4\%$ , which is well within acceptable limits (Gorelick *et al.*, 2017; Mutanga & Kumar, 2019) of analytical accuracy for the province as a whole; there is no compromise on quality between the two methodologies.

Second, results of the GEE-based analysis indicated there had been major changes in land cover within Baghdad Province over the study period. Built-up areas increased by 40.7%, from 1,096.99 km<sup>2</sup> to 1,543.45 km<sup>2</sup> at the same time bare ground was drastically reduced by 77.3%. There was a relatively small net decline of cropland area by 1.3% which shows that agricultural land has remained quite stable despite supposed strong pressures of urban expansion. This indeed reflects the main role that provincial landscape is playing through urbanization and falls in line with trends reported in previous studies at regional scale (Abdulkareem *et al.*, 2024; AlDousari *et al.*, 2025; Brown *et al.*, 2022; Cardille *et al.*, 2024; ESRI, 2023; Karra *et al.*, 2021).

Third, most of the small differences seen between ArcGIS and GEE results were at the level of how each program carried out its functions (the way edge pixels are handled by both programs, differences in the way coordinate reference systems were used/transformed by both programs, and the way floating-point precision in raster aggregation between the two programs acts). These are technical issues and not actual differences in methodology at a fundamental level and thus have no impact on the interpretation of overall land-cover change patterns (Hassoon & Ali, 2021; Mutanga & Kumar, 2019).

In practical terms, this highlights the complementary features of both systems. In particular, the GEE will have much better performance due to its cloud-based architecture, which has built-in support for parallel processing, large-area, and multi-temporal analyses at no cost to users. Alternatively, A GIS, such as ArcGIS Pro, is still preferred by users who require high-quality maps and offline processing for an institutional GIS workflow that has already been incorporated into their system (Ahmed & Al-Ramahi, 2022; Cardille *et al.*, 2024; Gorelick *et al.*, 2017; Mahdianpari *et al.*, 2019).

Based upon the present findings, researchers can conveniently select from either platform (GEE or ArcGIS Pro) based on their practicality (data size; computing capabilities; connectivity; and workflows), and they will not be compromising scientific integrity of the investigation. GEE is optimal for large-scale (rapid, over multiple years) studies that measure land cover, while ArcGIS Pro can be appropriately applied in local-scale, detailed analyses and decision-making information systems. Future studies should pursue the use of this comparison framework applied to different land cover types (with various spatial resolutions) in multiple geographic locations to allow for the generalization and validation of these results (Brown *et al.*, 2022; Hassoon & Ali, 2022; Pekel *et al.*, 2016; Zurqani *et al.*, 2018).

### Acknowledgments

The author thanks Esri, Impact Observatory, and Microsoft for making the 10-meter resolution annual land use/land cover time series freely available; the European Space Agency (ESA) under the Copernicus program for providing the Sentinel-2 imagery from which this product was derived; and Google for granting free access to the Google Earth Engine platform for scientific research purposes.

### Conflict of Interest

The author declares no conflict of interest regarding the publication of this research and has received no financial funding or support from Esri, Google, or any other entity whose products are evaluated in this study.

### مقارنة منهجية بين google earth engine و ArcGIS لتحليل بيانات الغطاء الأرضي ESRI بدقة 10 أمتار في بغداد، العراق

حسين عبد علي عيسى<sup>1</sup>

<sup>1</sup> قسم علوم التربة والموارد المائية/ كلية علوم الهندسة الزراعية/ جامعة بغداد

### الملخص

تقدم هذه الدراسة مقارنة بين منصة Google Earth Engine وبرنامج ArcGIS Pro منهجين منهجيين متباينين ضمن إطار مقارنة صارم لمجموعات بيانات الغطاء الأرضي ESRI بدقة 10 أمتار المشتقة من القمر الصناعي Sentinel-2 لمحافظة بغداد، العراق للفترة من 2017 إلى 2023. تقع منطقة الدراسة بين دائرتي عرض 33°00' و 33°45' شمالاً وبين خطي طول 44°00' و 44°45' شرقاً بمساحة كلية حوالي 5132 كم<sup>2</sup> يستخدم منتج ESRI للغطاء الأرضي بدقة 10 أمتار تصنيفاً موجّهاً قائماً على التعلم العميق باستخدام نموذج U-Net أظهرت نتائج التحليل من منصة Google Earth Engine زيادة حادة في المناطق المبنية بنسبة 40.7% من 1,096.99 كم<sup>2</sup> عام 2017 إلى 1,543.45 كم<sup>2</sup> عام 2023، في حين انخفضت مساحة الأراضي الزراعية انخفاضاً طفيفاً من 2,621.95 كم<sup>2</sup> إلى 2,587.11 كم<sup>2</sup> (-1.3%) تشير قيمة معامل ارتباط بيرسون البالغة 0.9987 إلى وجود ارتباط قوي للغاية، وتتجاوز دقة تصنيف بيانات (ESRI 10 M Land Cover) المستخدمة 85% عالمياً. تمثلت الفروقات المنهجية الرئيسية في استراتيجيات حساب مساحات البكسلات، والمعالجة المتوازنة السحابية مقابل التنفيذ المحلي على الحاسوب المكتبي، وإجراءات التعامل مع المقياس وإعادة التشكيل. تُنتج كلتا المنصتين إحصاءات LULC سليمة علمياً وعالية الاتساق. وعليه، ينبغي أن يُوجّه اختيار المنصة بناءً على المتطلبات التحليلية، واعتبارات الكفاءة الحاسوبية، والبنية التحتية التقنية المتاحة، بدلاً من أي قلق بشأن صحة النتائج.

**الكلمات المفتاحية:** سننبل-2، التعلم العميق، شبكة يون-نت، التحليل المكاني، الكشف عن تغيّرات الغطاء الأرضي.

### REFERENCES

- Ahmed, S. M., & Al-Ramahi, F. K. M. (2022). Evaluate the effect of relative humidity in the atmosphere of Baghdad City urban expansion using remote sensing data. *Iraqi Journal of Science*, 1848-1859. DOI: <https://doi.org/10.24996/ij.s.2022.63.4.41>
- Al-Awadhi, T., Mansour, S., & Al-Belushi, M. (2022). Urban growth prediction using cellular automata and Markov chain models in GCC mountainous cities. *Kuwait Journal of Science*, 49(2), 1–18.

- AlDousari, A. E., Al Kafy, A., & Rahaman, Z. A. (2025). Unveiling the dynamic interplay of biophysical, morphological, and temperature extremes in arid regions of Kuwait: Decoding sustainable urban resilience by utilizing remote sensing techniques. *Arabian Journal of Geosciences*, 18(6), 131. <https://doi.org/10.1007/s12517-025-12266-6>
- Alhashyme, G.A., Khaled, K.A. (2025). Assessing soil weathering and micromorphological characteristics under different land use practices in northern Iraq. *International Journal of Design & Nature and Ecodynamics*, Vol. 20, No. 10, pp. 2471–2478. <https://doi.org/10.18280/ij dne.201023>
- Al-Shaibah, B., Liu, X., Zhang, J., Tong, Z., Zhang, M., El-Zeiny, A., Freeshah, C., & Elmahdy, M. (2021). Remote sensing-based urban sprawl modeling using multilayer perceptron neural network Markov chain in Baghdad, Iraq. *Remote Sensing*, 13(20), 4034. <https://doi.org/10.3390/rs13204034>
- Alshehri, B., Zhang, Z., & Liu, X. (2025). A review of Google Earth Engine for land use and land cover change analysis: Trends, applications, and challenges. *ISPRS International Journal of Geo-Information*, 14(11), 416. <https://doi.org/10.3390/ijgi14110416>
- Al-Timimi, Y. K. (2021). Monitoring desertification in some regions of Iraq using GIS techniques. *Iraqi Journal of Agricultural Sciences*, 52(3), 620–625. <https://doi.org/10.36103/ijas.v52i3.1351>
- Alsalam, O., Isa, H. A., Al-Bayati, M. A. L., & Alserae, H. (2025). Topographic effect on the total oxides distribution of calcareous soils in northern Iraq. *Pakistan Journal of Agricultural Research*, 38(2), 162-174. <https://dx.doi.org/10.17582/journal.pjar/2025/38.2.162.174>
- Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., Moghaddam, S. H. A., Mahdavi, S., Ghahremanloo, M., Parsian, S., Wu, Q., & Brisco, B. (2020). Google Earth Engine cloud computing platform for remote sensing big data applications: A comprehensive review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 5326–5350. <https://doi.org/10.1109/JSTARS.2020.3021052>
- Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). *A land use and land cover classification system for use with remote sensor data*. U.S. Geological Survey Professional Paper 964. <https://doi.org/10.3133/pp964>
- Belgiu, M., & Drăguț, L. (2016). Random forest in remote sensing: a review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24–31. <https://doi.org/10.1016/j.isprsjprs.2016.01.011>
- Brown, C. F., Brumby, S. P., Guzder-Williams, B., Schmitz, T., Fasullo, F. A., Ilgen, I., Zhao, A., Schmon, M., Lingenfelter, P., Aston, C., Buman, M., Hao, J., Lingerfelt, E., & Tait, A. M. (2022). Dynamic World, Near real-time global 10 m land use land cover mapping. *Scientific Data*, 9(1), 251. <https://doi.org/10.1038/s41597-022-01307-4>
- Cardille, J. A., Clinton, N., Crowley, M. A., & Saah, D. (2024). Cloud-Based Remote Sensing with Google Earth Engine: Fundamentals and Applications. *Springer Nature*. <https://doi.org/10.1007/978-3-031-26588-4>

- Chakraborty, A., Islam, I., Saha, A., & Pal, S. (2025). Urban land use transformation and declining cooling services: A 40-year assessment of heat stress mitigation in a hot and arid city. *Earth Systems and Environment*, 9, 932. <https://doi.org/10.1007/s41748-025-00932-4>
- ESRI. (2023). ArcGIS Living Atlas of the World: Sentinel-2 Land Cover Explorer.
- ESRI. (2024). Esri Releases Latest Land Cover Map with Updated Sentinel-2 Satellite Data. *ESRI Press Release*.
- Foody, G. M. (2020). Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps. *Remote Sensing of Environment*, 239, 111630. <https://doi.org/10.1016/j.rse.2019.111630>
- Foody, G., & Atkinson, P. (2019). Trends in Remote Sensing Accuracy Assessment Approaches in the Context of Natural Resources. *Remote Sensing*, 11(19), 2305. <https://doi.org/10.3390/rs11192305>
- Ghorbanian, A., Zaghian, S., Asiyabi, R. M., Amani, M., & Mohammadzadeh, A. (2025). Accuracies, discrepancies, and challenges of the 10 m global land cover products in mountains. *GIScience & Remote Sensing*, 62(1), 2556064. <https://doi.org/10.1080/15481603.2025.2556064>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2025). Tracking U.S. Land Cover Changes: A Dataset of Sentinel-2 Imagery and Dynamic World Labels (2016–2024). *Data*, 10(5), 67. <https://doi.org/10.3390/data10050067>
- Haseeb, M., Qamar, S., Khan, A. R., & Rehman, S. (2025). Predicting land use and land cover changes for sustainable land management using CA-Markov modelling and GIS techniques. *Scientific Reports*, 15, 87796. <https://doi.org/10.1038/s41598-025-87796-w>
- Hassoon, A. F., & Ali, B. B. (2021). Irregular urban expansion and its effects on air temperature over Baghdad city using remote sensing technique. *Iraqi Journal of Science*, 62(6), 2110–2121. <https://doi.org/10.24996/ij.s.2021.62.6.36>
- Hassoon, A. F., & Ali, B. B. (2022). Effect of urban expansion indices change by (R.S.) on height of convective radix layer around Baghdad Airport. *Iraqi Journal of Science*, 63(5), 2234–2248. <https://doi.org/10.24996/ij.s.2022.63.5.40>
- Impact Observatory. (2024). 10m Annual Land Use Land Cover (9-class). *Registry of Open Data on AWS*.
- Isa, H. A., & Sulaiman, A. A. (2020). The relationship between reflectivity and the some physical properties of desert soils using geospatial techniques and spectroradiometer in najaf governorate of Iraq. *Plant Archives*, 20(1), 1657–1665.
- Karra, K., Kontgis, C., Statman-Weil, Z., Mazzariello, J. C., Mathis, M., & Brumby, S. P. (2021). Global land use/land cover with Sentinel-2 and deep learning.

- IEEE International Geoscience and Remote Sensing Symposium*.  
<https://doi.org/10.1109/IGARSS47720.2021.9553499>
- Kumar, L., & Mutanga, O. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 164, 152–170.  
<https://doi.org/10.1016/j.isprsjprs.2020.04.001>
- Mahdianpari, M., Salehi, B., Mohammadimanesh, F., Homayouni, S., & Gill, E. (2019). The first wetland inventory map of newfoundland at a spatial resolution of 10 m using Sentinel-1 and Sentinel-2 data on the Google Earth Engine cloud computing platform. *Remote Sensing*, 11(1), 43.  
<https://doi.org/10.3390/rs11010043>
- Marzougui, F., Chokmani, K., Agili, H., & Lhissou, R. (2025). Deep Learning-Based Spatial Pattern Modeling for Land Use and Land Cover Classification Using Satellite Imagery. *Meteorological Applications*, 32, 70064.
- Moharir, S., Raut, S., & Shinde, M. (2025). Predicting changes in land use and land cover using remote sensing and land change modeler. *Frontiers in Environmental Science*, 13, 1540140.
- Moussa, Y. K. H., & Alwehab, A. A. (2022). The urban expansion impact on climate change for the city of Baghdad. *Iraqi Journal of Science*, 63(11), 4923–4936.  
<https://doi.org/10.24996/ijis.2022.63.11.41>
- Mutanga, O., & Kumar, L. (2019). Google Earth Engine applications. *Remote Sensing*, 11(5), 591. <https://doi.org/10.3390/rs11050591>
- Negash, T., Yimer, F., & Tadesse, M. (2025). The impact of urbanization on land use land cover change using geographic information system and remote sensing. *Scientific Reports*, 15, 94189. <https://doi.org/10.1038/s41598-025-94189-6>
- Nguyen, V. T., Vo, T. N., & Phan, T. A. (2024). Multi-spectral remote sensing and GIS-based analysis for decadal land use land cover changes and future prediction using random forest tree and artificial neural network. *Journal of Environmental Management*, 350, 119636.  
<https://doi.org/10.1016/j.jenvman.2023.119636>
- Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, 148, 42–57.  
<https://doi.org/10.1016/j.rse.2014.02.015>
- Pekel, J. F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540, 418–422. <https://doi.org/10.1038/nature20584>
- Phiri, N., Morgenroth, J., & Xu, C. (2024). Comparative validation of recent 10 m-resolution global land cover maps. *Remote Sensing of Environment*, 310, 114341.
- Rawat, K. S., Kumar, S., & Garg, N. (2024). Statistical Comparison of Simple and Machine Learning Based Land Use and Land Cover Classification Algorithms. *Computational and Applied Mathematics*, 43, 524.  
<https://doi.org/10.14796/JWMM.H524>
- Talukdar, S., Singha, P., Mahato, S., Shahfahad, Liou, Y.-A., & Rahman, A. (2020). Land-use land-cover classification by machine learning classifiers for satellite

- observations—A review. *Remote Sensing*, 12(7), 1135. <https://doi.org/10.3390/rs12071135>
- Tao, H., Hashim, B. M., Heddami, S., Yaseen, Z. M., & Al-Sudani, Z. A. (2023). Megacities' environmental assessment for Iraq region using satellite image and geo-spatial tools. *Environmental Science and Pollution Research*, 30, 30984–31034. <https://doi.org/10.1007/s11356-022-24153-8>
- Thiagarajan, R., Kumar, A., & Singh, R. (2025). Land use classification using multi-year Sentinel-2 images with deep learning ensemble network. *Scientific Reports*, 15, 12512. <https://doi.org/10.1038/s41598-025-12512-7>
- Venter, Z. S., Barton, D. N., Chakraborty, T., Simensen, T., & Singh, G. (2025). Sentinel-2 Land Cover Classification: State-of-the-Art Methods and the Reality of Operational Deployment—A Systematic Review. *Sustainability*, 17(22), 10324. <https://doi.org/10.3390/su172210324>
- Winkler, K., Fuchs, R., Mounsevell, M., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications*, 12, 2501. <https://doi.org/10.1038/s41467-021-22702-2>
- Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., MacFadhoin, G., Voltersen, M., Alvarez-Vanhard, E., & Arino, O. (2022). ESA World Cover 10m 2021 v200. Zenodo. <https://doi.org/10.5281/zenodo.7254220>.
- Zhang, Y., Chen, X., Li, X., & Wang, Y. (2025). Sensitive shrubland and unique urbanization patterns: the key to understanding emerging towns growth in arid regions. *Scientific Reports*, 15, 1814000. <https://doi.org/10.1007/s10661-025-13693-4>
- Zurqani, H. A., Post, C. J., Mikhailova, E. A., Schlautman, M. A., & Sharp, J. L. (2018). Geospatial analysis of land use change in the Savannah River Basin using Google Earth Engine. *International Journal of Applied Earth Observation and Geoinformation*, 69, 175–185. <https://doi.org/10.1016/j.jag.2017.12.006>