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Dramatically increase of built-up area in Iraq during the last four decades

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Abstract

Land Use Land Cover (LULC) detection is a crucial indicator of environmental change since it is associated with the climate, ecosystem procedures, land degradation, biodiversity and increased human actions. The objective of current study is to observe how main LULC class changed in Iraq from 1982 to 2019. Overall, 5259 Landsat 4, 5 and 8 images were utilized for land classification. In the study, Random Forest classification method was performed in Google Earth Engine (GGE) platform. The research has established the accuracy assessment of overall accuracy and kappa coefficient of four periods are 95% or higher. The trend of classes demonstrated that built up class increased dramatically by 248.6%. In contrast, bare soil, which covers most territories of Iraq decreased by 8.4% (30,212 km^2) from Period 1(1982-1989) to Period 4 (2010-2019). Likewise, vegetation class decreased by 20.2% (8,151 km^2) during the same period.

1. Introduction

Land is a significant natural resource, which covers the solid feature of the surface. Due to economic growth, land resources are now widely exploited in terms of industrial development, urban growth, and the conversion of forests to agricultural lands [1]. In recent decades, the subject of land use/land cover (LULC) has been a significant aspect of environmental change and climate change studies. LULC has a major impact on global modification due to its associations with the climate, ecosystem procedures, land degradation, biodiversity and increased human action [2]. The physical condition and biotic constituent of the earth surface are called land cover [3]. While alterations of land cover by man are called land use [4]. Determination of changes in physical land cover over a series of time is called change detection, which is the most significant aspect of environment alteration [5]. Furthermore, rapid modifications in LULC have caused a drastic drop in green area [6].

LULC is growing and changing rapidly around the world and this poses a very high risk to parts of the ecosystem such as water bodies, soil, and temperature, especially in urban centers [4]. Human actions have principally reflected the land cover change dynamics [7-8]. Atmospheric rotation, vegetation protection, biogeochemical and energy cycle are multiple processes of the earth that have an impact on the land cover changes [9]. Evaluation of LULC is a significant criterion for effectively planning land reserve management. It is a key component for up-to-date plans in protecting natural resources and observed changes in the environment which is assets to develop balance conservation strategies and enlargement pressure [10].

Urbanization plays an important role in LULC transition through the substitution of natural land cover for habituated area and vegetation for economic reasons and facilities. Urbanization involves changes in land cover by structural engineering constraints such as highways, houses [4]. Urban populations are expanded faster than rural places, with high migration levels in metropolitan sites. Urban dwellers were projected to be approximately (3) billion people, and it is predicted to rise to 60% by 2030.

The major driving forces for land use alteration are industrial development, urbanization, population growth and economic reforms [11]. LULC changes such as the abandonment of agricultural land are capable of being caused by an accelerated socio-economic alteration [12]. The researchers [13-14] demonstrate that political and socio-economic improvements influence urbanization. Their findings suggest that, in their case study, urban sites were key economic advancements. Political conflicts could have socio-economic, permanent or irrecoverable damage on cultivation. Thus, during the Iraq-Iran war of 1980-1988, the systematic desiccation of grassland led to devastating LCLU changes, biodiversity and human-induced operations. Not to mention that, in the period of 2003-2015, urbanization processes remarkably increased due to the socio-economic and political factors.

Currently, Google Earth Engine (GEE) is available as a powerful cloud computing platform that manages enormous volume of remote sensing data. It hosts a massive pool of remote sensing and geospatial datasets. In addition, a number of famous machine learning algorithms have been applied. Supervised classification is one of this filed. For instance, Decision Tree (DT), Support Vector Machine (SVM), and Random Forest (RF) classifier are available in the platform. Previous classification studies have demonstrated that RF outperformed and is easier than other classifiers such as DT. In addition, RF is overtraining and has presented high accuracies in several studies [15-19].

Satellite images were widely utilized to study temporary LULC shifts. The application of remote sensing data has been implemented and accepted as an effective detection method for identifying LULC change [20]. Image satellites are capable of providing reliable and relevant data for decision-makers in different fields concerning vegetation and crop production [21]. Researchers [22-25] utilized satellite images to analysis, monitor and measure the patterns of LULC changes, principally in large areas that experience rapid alterations in land use. Remote sensing data is a potentially powerful tool for detecting changes in LULC at higher temporal resolutions, reduced coasts, synoptic views, repetitive coverage and gaining real-time and conventional methods [26]. Numerous studies have validated the successive application of several satellites such as MODIS, Aster, Landsat [27-33]. The Landsat TM/ETM/OLI data have been broadly utilized for many research as an accessible remotely sensed data [34-40]. Despite the significant conversion of LULC classes in Iraq during last four decades, not sufficient study was conducted in this field at the country scale. Mostly, LULC study in Iraq focused on specific cities and they relied on a short period of satellite data. Therefore, the objective of current research is to observe how main LULC class changed in Iraq from 1982 to 2019.

2. Material and Method

2.1. Study area

Iraq is one of the Middle-Eastern countries located in southwestern Asia. It shares a boundary with Turkey from the north, Iran from the east, Syria and Jordan from the west, Saudi Arabia and Kuwait from the South (Figure 1). The total area of Iraq is 438,320 km^2 and the northern part of the study area are mountainous regions, which are about 3,550 m above the sea level. Whereas, the south part of the study area includes the desert area which covers around 40% of the total land of Iraq [41]. LULC is growing and changing rapidly around the world and this poses a very high risk to parts of the ecosystem such as water body, soil, and temperature, especially in urban centers [4].

Iraq has a unique climate; a Mediterranean climate combined with a subtropical semi-arid climate, especially in the north and northeastern parts. These areas are the first to experience precipitation in the November to April. However, December to February is precipitation season in the middle and south of the country. Mean annual precipitation is 216. The most rain is fall in the northeastern parts, which is around 1200 mm on average. Contrastingly, the southern parts receive 100 mm. July and August are the hottest months of summer, with temperatures reaching 43 °C in the shade. The temperature in winter days is 16 °C on average, dropping to around 2°C during nighttime [42].

Iraq includes nineteen governorates. Farmland makes up around 26% of the total area of the country while the remaining areas are unused. Agricultural and other areas that are sited on the extreme northern border with Turkey and Iraq is covered by forests and woodlands [43].

Figure 1. Location of the study area

2.2. Data

For the first period from 1982 to 1989, the study utilized 150 images of Landsat 4 (TM calibrated top-of-atmosphere reflectance, orthorectified scenes only.) less than 25% of cloud covers. For second period 1990 to 1999, we utilized 810 Landsat 5 (Landsat 5 TM calibrated top-of-atmosphere reflectance, orthorectified scenes only.) with less than 10% cloudy images. For third period from 2000 to 2009, 626 Landsat 5 images (less than 10% cloudy) were utilized. For the last period from 2010 to 2019, we utilized 3669 Landsat 8 images (Landsat 8 Collection 1 Tier 1 calibrated top-of-atmosphere (TOA) reflectance) less than 10% cloudy. Overall, 5259 Landsat images were utilized for classification in this study. With Landsat 4 and 5, bands 1 to 7 were selected and for Landsat 8, bands 2–7 and 10–11 were utilized in the study. For each period, the mean value between selected images was calculated. Then, mean images of all periods clipped to shapefile of Iraq.

2.3. LULC classes

In the current study, we were attended to exemplify the fundamental LULC classes of a landscape conversion in Iraq. We recognized four main LULC classes of interest: Bare soil, Built-up, waterbody (e.g., rivers, lake, dam) and vegetation (e.g., grass, trees, cropland, agriculture and pasture). For LULC conversion that is associated with urban growth, conversion of vegetation and bare soil to build up is important. Furthermore, these classes are possible to identify in scale of Landsat images. The study period was divided into four periods; P1 from 1982 to 1989, P2 from 1990 to 1999, P3 from 2000 to 2009 and P4 from 2010 to 2019.

2.4. Methodology

GEE is utilized in this study for the images processing and performance of classification. The main steps are selecting images of Landsat within four periods; generating pixel-based mean value of each period, selecting samples of testing and validation points, producing classified maps, and post-classification to assess accuracy of classified maps.

2.4.1. Random forest classification.

In this research, the RF procedure was utilized for pixel-based LULC classifications because previous studies confirmed that the performance of RF is higher than other classifiers [44]. An RF is fundamentally an aggregate method that creates a multitude of decision trees and produces the mean prediction of the individual trees [45]. In our classification, 600 samples were selected for each period; 150 samples of each class. Samples are divided into two categories; 70% of samples utilized as training points and 30% of samples utilized as testing points for validation. In each period, we utilized an RF classifier with 10 decision trees. Classified images exported from GEE to Google Drive then downloaded.

2.4.2. **Accuracy assessment**

The accuracy of a classifier is the ability of method to properly classify a collection of samples. The data that utilized to experiment with the performance of the method should be different than the data utilized to train the classifier [46]. In case of inability of ground truth samples, for instance, samples of the land cover of previous decades, reference data is usually separated to training and experiment sets. Four evaluation classifier, overall accuracy (OA), Kappa coefficient, producer accuracy, and user accuracy were measured. Overall accuracy verifies the overall efficiency of the method that is calculated by dividing the total number of correctly considered samples by the total number of the testing samples. While, the Kappa coefficient demonstrates the degree of agreement between the validation data and the predicted values [47]. In this study, we utilized 30% of samples from 600 samples as testing points for validation. For accuracy assessment, Kappa and overall accuracy were derived by using error Matrix of classified image of each period. Then classified images were utilized in GIS tools to create a comparative figure of LULC classes during the different periods in the country.

3. Results and discussion

3.1. **Accuracy assessment**

Post classification comparison is utilized to demonstrate LULC changes between 5259 Landsat satellite images for different periods. LULC changes were extracted from Landsat images satellite for different periods. The accuracy assessment of overall accuracy and kappa coefficient are 98% and 97%, 96% and 95%, 98% and 97%, 99% and 99% in the first, second, third and fourth period, respectively, as demonstrated in Table 1. The highest overall accuracy achieved was in 2010-2019 around 99%; moreover, the kappa coefficient for the same period was 99%. When kappa coefficient values are greater than 80% it represents strong agreement with the ground truth and this range is widely utilized as a minimum level of acceptable accuracy for LULC change classification [48].

Table 1. Accuracy assessment

Period	Overall accuracy	Overall Kappa coefficient
1982-1989	0.98	0.97
1990-1999	0.96	0.95
2000-2009	0.98	0.97
2010-2019	0.99	0.99

3.2. Land use/Land cover detection analysis

According to land cover classification (Figure 2), the bare soil class covers most of the territory of Iraq. Bare soil is distributed on the west and north-west of the study area. The trend of bare soil started to decrease from

1982 to 2019. The northern part of the study area was dominated by vegetation, while in the central and south of the study area are a combination of dense vegetation, built-up and water body.

Figure 2 and Table 2 illustrate the changes in LULC proportions over the examined periods. Bare soil area was changed from 17,584, 41,588, 50,753 and 61,296 Km^2 in the P1, P2, P3, and P4, respectively. From P1 to P4 it decreased by 8.4%. The trend observed the built-up class increased dramatically by 248.6% from 17,584 km^2 in 1982 to 61,296 km^2 in 2019. While, the trends observed in vegetation proportion follow the opposite direction; vegetation increased from 40,414 in P1 to 69,098 km^2 in P2, while the trends observed decreased to 37,496 km^2 in P3 and 32,264 km^2 in P4. Overall, from P1 to P2 vegetation class decreased by 20.2%. Waterbody coverage decreased from the first three decades from 9,596 to 3,983 km^2, however, the trend was increased through the last decade to arrive 7,111 km^2. The water bodies in the study area include rivers, lakes and irrigation water.

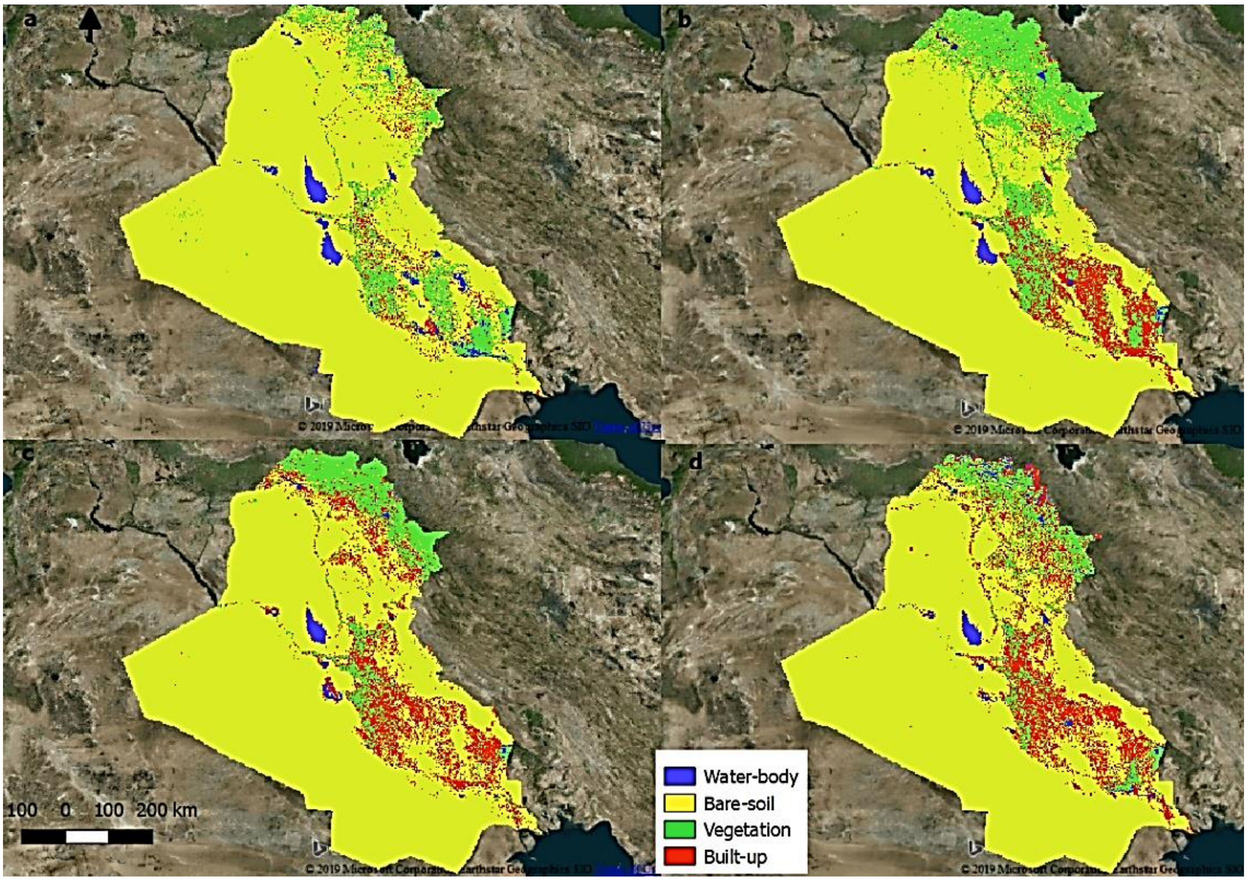

Figure 2. Land Use Land Cover Change. **a:** period 1982-1989, **b:** 1990-1999, **c:** 2000-2009, **d:** 2010-2019

Table 2. LULC classes change from period 1982_1989 to 2010_2019

	P1: 1982-1989		**P2: 1990-1999**		**P3: 2000-2009**		**P4: 2010-2019**		**Changes from P1 and P4**	
Classes	%	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)
Built-up	4.1	17,584	9.6	41,588	11.8	50,753	14.2	61,296	248.6	43,712
Water body	2.2	9,596	1.3	5,682	0.9	3,983	1.6	7,111	-25.9	-2,485
Bare-soil	84.2	360,977	73.0	315,067	78.6	339,202	76.7	330,765	-8.4	-30,212
Vegetation	9.4	40,414	16.0	69,098	8.7	37,496	7.5	32,264	-20.2	-8,151

The geographical distribution of different LULC classes was demonstrated in the four periods. The ratio between areas of land cover was utilized at different decades to illustrate land cover changes as demonstrated in Table 2. The main conversion to Built-up area occurred from Vegetation and Bare soil classes. From P1, P2, P3 and P4 the Built-up increased dramatically from 4.1, 9.6, and 11.8 to 14.2% respectively (Figure 3). This conversion is natural when we making a comparison between the populations of Iraq from 1984 to 2019. The population of Iraq increased 172.37% in the same period based on Worldometer's elaboration of the latest United Nations data. This increase in the population has already caused urban growth. Most bare soil in Iraq is a desert area. The conversion of bare soil areas into a built-up area has been reduced this class over time. In particular, Bare soil class decreased from 84.2 in P1 to 76.7% in P4.

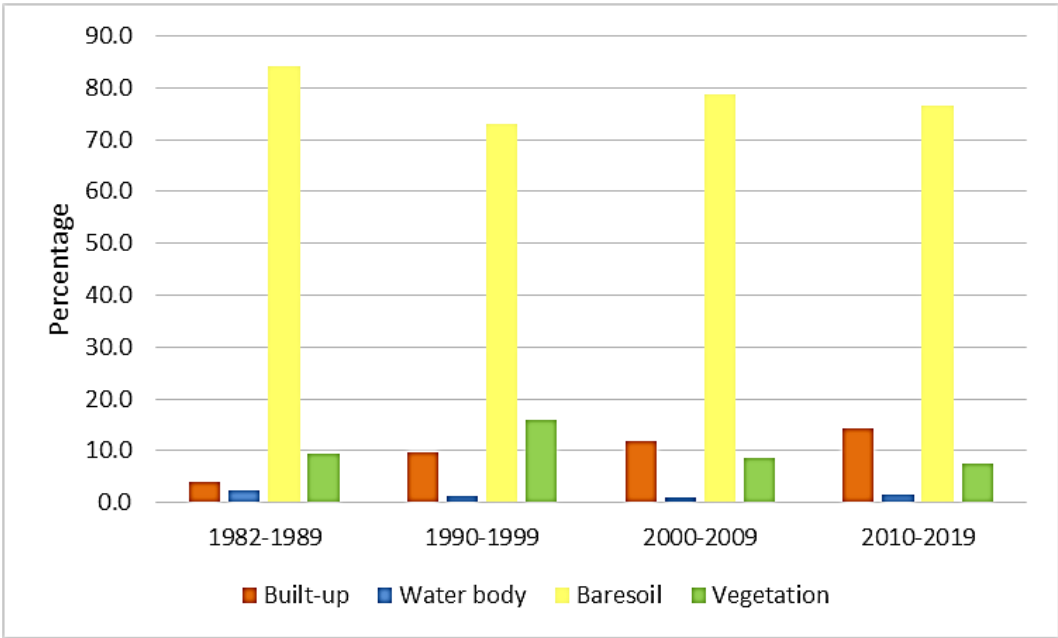

Figure 3. Land use land cover change in Iraq from 1982 to 2019 (%)

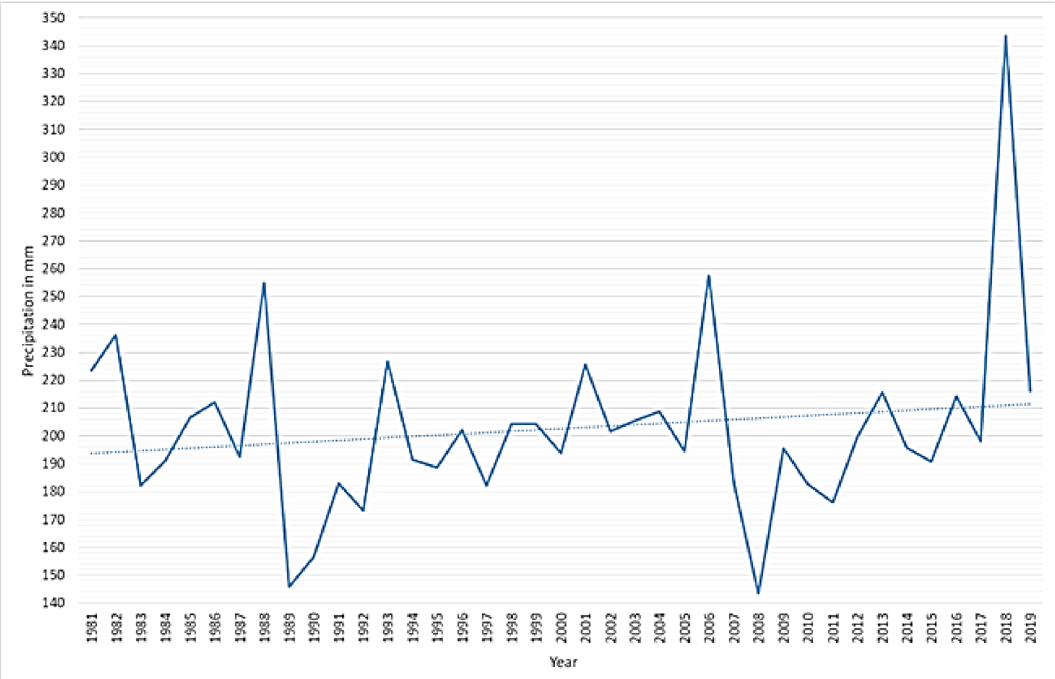

Figure 4. Trend of precipitation in Iraq from 1981 to 2019 based on Climate Hazards Group Infrared Precipitation with Station Data [49]

Vegetation cover was observed more density in the north part of the study area. The vegetation of the study area consists of agriculture, forest, pasture and grass areas. Most distribution of vegetation depends on the fed-rain. Therefore, there is a relationship between annual precipitation and the increase or decrease amount of vegetation in the study area. Figure 4 and Table 3 illustrate the trend of rainfall in the study area from 1981 to 2019. The trend of precipitation increased from P1 to P2. This change in the trend of rainfall effect on the amount of vegetation in the same period. Vegetation cover was increased from 9.4 to 16.0% from P1 to P2 which is associated with the same period of rainfall increasing, while vegetation cover was decreased by 8.7 to 7.5% from P3 to P4. Trend rainfall changes effect directly on the amount of vegetation distribution. There are several factors that additionally impact on vegetation such as wildfire and many political and economic crises that assist to land cover degradation such as Iraq and Iran war from 1980 to 1988, the economic blockade against Iraq from 1991 to 2003, poor state administration. Especially, in central and southern of the country has been leading to breakdown land cover management after 2003.

Table 3. Precipitation in Iraq from 1981 to 2019 based on climate hazards group infrared precipitation with station data

Year	Precipitation (mm)	Year	Precipitation (mm)	Year	Precipitation (mm)	Year	Precipitation (mm)
1981	222	1991	182	2001	224	2011	175
1982	235	1992	172	2002	201	2012	198
1983	181	1993	225	2003	204	2013	214
1984	190	1994	191	2004	208	2014	195
1985	205	1995	188	2005	194	2015	190
1986	211	1996	201	2006	256	2016	213
1987	191	1997	182	2007	182	2017	197
1988	253	1998	203	2008	143	2018	342
1989	145	1999	204	2009	194	2019	271
1990	156	2000	193	2010	182		

4. Conclusion

Investigation four decades of LULC change in Iraq demonstrated how classes converted besides population growth and environmental changes. Nowadays, LULC detection is a crucial indicator of environmental change because it is associated with the climate, ecosystem procedures, land degradation, biodiversity and increased human actions. The objective of current research is to observe how the main LULC class changed in Iraq from 1982 to 2019. Overall, in the study, 5259 Landsat 4, 5 and 8 images were utilized for land classification. We performed Random Forest classifier method in Google Earth Engine (GGE) platform.

Our result achieved 95% and higher accuracy assessment of both overall accuracy and kappa coefficient of four periods. The trend of classes demonstrates that bare soil which covers most territories of Iraq decreased by 8.4% (30,212 km^2) from 1982-1989 to 2010-2019. Moreover, vegetation class decreased by 20.2% (8,151 km^2) during the same period. In contrast, built up class increased dramatically by 248.6% (43,712 km^2). In the future, more research should be done to effectively treat the negative side effects of conversion vegetation and bare soil classes to build up areas in Iraq.

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Author contributions:

Azad Rasul: Conceptualization, Methodology, Software, Visualization, Writing-Reviewing and Editing. **Hasan Hameed:** Writing-Original draft preparation, Writing-Reviewing and Editing. **Gaylan Faqe Ibrahim:** Writing-Original draft preparation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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