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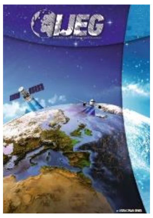

Classification comparison of Landsat-8 and Sentinel-2 data in Google Earth Engine, study case of the city of Kabul

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ABSTRACT

In recent years, Kabul city's rapid urbanization has adversely affected the urban land cover, such as surface water bodies and croplands. Surface water resources are threatened due to overpopulation in the city either qualitatively or quantitatively, also croplands are being lost with the development of urbanization activities through the city. To monitor and assess surface changes accurately, we classified the city area using satellite images of both Landsat-8 and Sentinel-2 and compared both of their findings. The Support Vector Machine classifier was applied to multi-senor data to classify four different land categories using the same training sites and samples with the same period. All the procedures were conducted in Google Earth Engine (GEE) cloud platform. The surface reflectance bands of both satellites were used for classification. Confusion matrixes were created using the same reference points for Sentinel-2 and Landsat-8 classification to compare the results and determine the best approach for classification of land cover. Results show that overall accuracy was 94.26% for Sentinel-2 while it was 85.04% for Landsat-8, similarly, the Kappa coefficient was calculated 91.7% and 78.3% for Sentinel-2 and Landsat-8, respectively.

1. INTRODUCTION

Observation of land changes is an important factor for urban and environmental management. Automatically extracting land coverage and land use information from remote sensing images in a particular region, especially in a big urban area, is not an easy activity (Cai et al., 2019). Moreover, accurate information about the land cover of a region allows for the best possible management, planning and monitoring of natural resources. High temporal frequency Earth Observation (EO) satellites are vital tools to be used (Shang & Zhu, 2019). Land surface changes could be surface water dynamics, forest disturbance, vegetation anomaly, phenology changes and agricultural practice. There are some other satellites with high temporal frequency such as Moderate Resolution Imaging Spectroradiometer (MODIS) (Pagano & Durham, 1993), Medium Resolution Imaging Spectrometer (MERIS) (Verstraete, et al., 1999), and Visible Infrared Imaging Radiometer Suite (VIIRS), which has already been used for classification and land observations and it has been established that they are not suitable for identifying land surface changes that typically occur on a far smaller scale than their pixel sizes (Shang & Zhu, 2019).

On the contrary, moderate resolution satellites, such as Landsat and Sentinel can provide higher special resolution observations with 30 meter and 10-60 meter each respectively (USGS). Also, the temporal resolution for Landsat is lower than the Sentinel, which is not enough for near-real-time observations. For instance, it takes16 days to revisit the same location for Landsat satellite; even with both satellites of Landsat 7 and 8 we can observe the same location in each 8 days, while this period is decreased to 5 days with the new launched Sentinel-2A and 2B. However, the same observations can be made by both the Sentinel and Landsat satellites, varying in field of view, spectral bandwidth, spatial resolution, and spectral response function (Zhang et al., 2018), some corrections can be done using the Bidirectional Reflectance Distribution Function (BRDF)

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correction method to minimize and overcome this discrepancy (Shang & Zhu, 2019).

Finding access to cloud-free, high-quality and high-resolution images over a large region for land-changing observations and land classification has been challenging and resource-intensive. To some extent, these challenges have been overcome through a recent development in remote sensing data collection, management and processing. For example, managing large volumes of satellite data for analysis over a large region is a major challenge when implementing typical remote sensing methods that use commercial image processing software on PC-based workstation systems. No matter how strong and powerful these systems are, the procedure takes a lot of time and is cumbersome, slow, and tedious. Fortunately, these limitations have been overcome by a powerful geo data processing platform of Google Earth Engine (GEE) developed with planetary-scale geospatial analysis (Ghorbanian et al., 2020). GEE is an ideal data organization platform that enables geospatial processing over a large region and comprehensive resources and computational capabilities (Teluguntla et al., 2018). Having all these capabilities, using GEE can reduce most of the time-consuming procedures required for traditional remote sensing approaches. Recently, several studies have been carried out using the GEE platform for various research topics in remote sensing (Kaplan & Aghlmand, 2020; Mobariz & Kaplan 2020; Mutanga & Kumar, 2019; Pu et al., 2020; Stromann, et al., 2020; Xiong et al., 2017).

Thereby, this study's main goal is to classify the city of Kabul, one of the rapid development cities in the world, into four classes; Water, Cropland, Urban, and Bare land. using Landsat-8 and Sentinel-2 data and to compare the results. Kabul city is the capital of Afghanistan, the city with an upward trend in urbanization evolution during the recent years. Surface water is one of the important resources for tourism and urbanization, which is seriously affected by constructional activities and the indiscriminate use of water resources by the residents. Moreover, we intend to analyze and compare the results of the classification and accuracy of the Sentinel-2 and Landsat-8 moderate resolution satellites using the same training sites and samples with the same timeframe for each image. To do the accuracy assessment of each satellite image, overall validation accuracy and kappa statistic coefficients are calculated and compared. Similarly, the area covered by each class is calculated and compared.

2. DATA AND METHODS

2.1. STUDY AREA

This study is carried out over the city of Kabul; the capital city of Afghanistan, which ranges from longitude 68^0 57’ 00” E to 69^0 28’ 15’’ E and latitudes 34^0 16’ 15’’ N to 34^0 40’ 00’’ N (Figure 1). Kabul is not only one of the largest cities in Afghanistan in terms of population, but one of the largest in the world, ranking 64th. From the perspective of rapid urbanization, the city was ranked 5^{th} in the world (The Guardian, 2014). Kabul city has the total area of 1023 square kilometers and 4.22 million population estimated in 2020 with population density of 4500 persons per square kilometer (World Population Review, 2020).

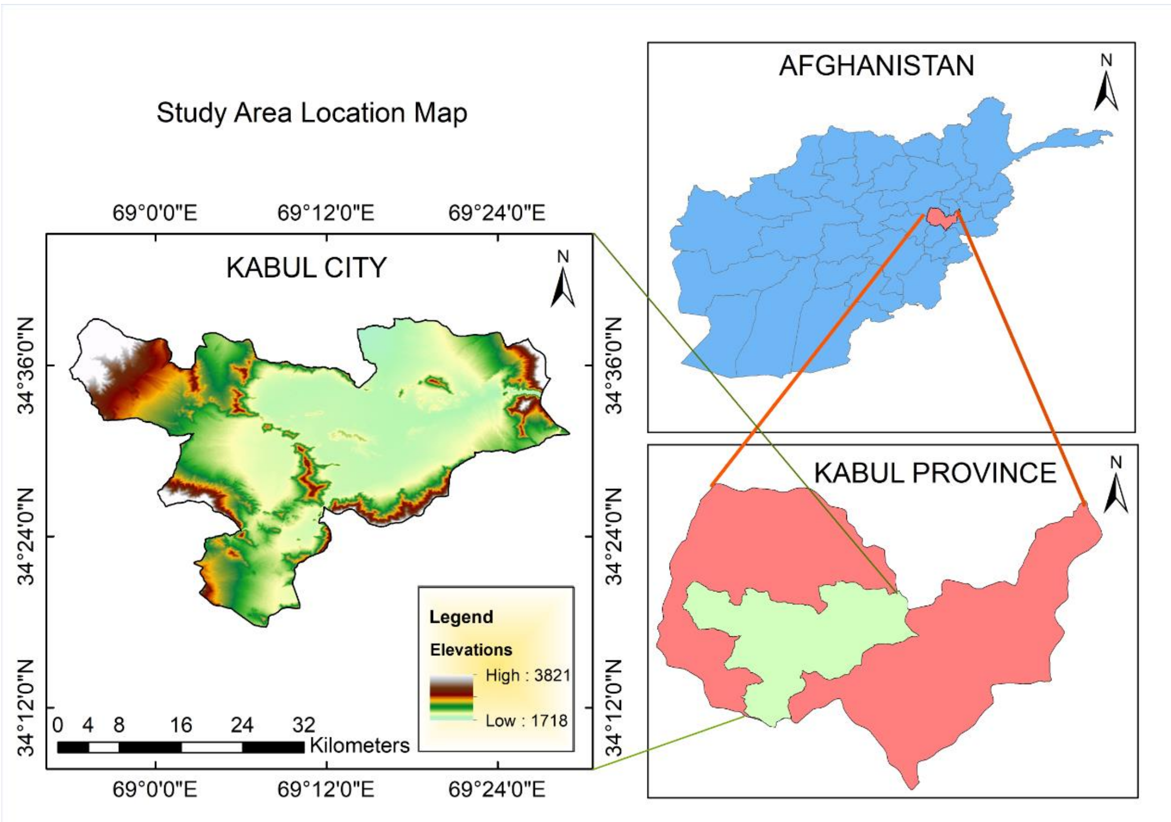

Figure 1. Location of study area, DEM of Kabul city

Kabul is a city with cold semi-arid climate, with precipitation concentrated in winter (almost exclusively falling as snow) (Köppen climate classification BSk) and spring months, with low humidity in summer. The lowest temperature is -6 ⁰C in January and the highest is 33 ⁰C in July through the year with the maximum 14.5 hours of sunshine in June (Figure 2). Kabul has an average of 312 mm of rainfall per year, or 26 mm on a monthly basis, where the maximum rainfall is 71.9 mm in April and the lowest rainfall is approximately 1 mm in June, as shown in (Figure 3) (World Climate & Temperature, 2017).

The study area contains of four major classes; water, cropland, urban and bare land. Available surface water in Kabul city consists of Kabul River flows from west to east through the city, a large lake and wetland Kol-e Hashmat Khan protected area located just to the southeast from the city where some rare species of birds have been spotted, and Qargha reservoir located in northwest of the city a major attractive place for locals and foreigners for tourism. The altitude ranges from 1718m to 3821m above mean sea level. From March to June, the Kabul River's water level is at its peak when the snow; from the Paghman snow-capped mountains in the west of Kabul, melts and joins the river.

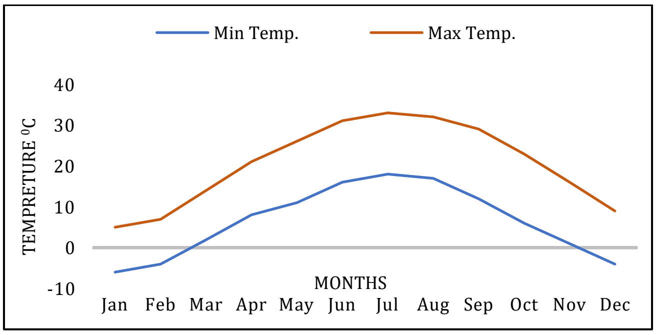

Figure 2. Temperature of Kabul city (Source: National Oceanic and Atmospheric Administration (NOAA)).

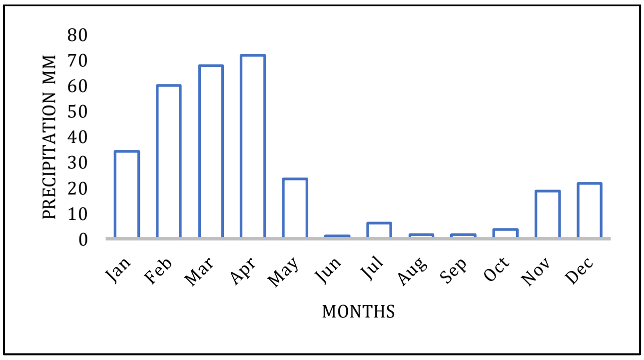

Figure 3. Precipitation in Kabul city (Source: (NOAA)).

2.2. Data

Image collections, a set of images from Sentinel-2 and Landsat-8 were used in this study. Furthermore, the image collection was combined into one image used for classification. The Sentinel-2 image collection was used to generate the satellite image of Sentinel-2 for Kabul city using GEE cloud platform (Figure 4). Sentinel-2 is a wide-swath, high-resolution, multi-spectral imaging mission funded by the European Union/ESA/Copernicus, supporting Copernicus Land Monitoring studies, covering vegetation, soil and water cover monitoring and observation of inland waterways and coastal areas. The data for Sentinel-2 L2 is downloaded from the scihub. The assets include 12 spectral bands of UINT16 that reflect SR scaled by 10000 (unlike in L1 data, there is no B10).

Figure 4. Sentinel-2 satellite image of Kabul city generated on Apr-June 2020.

The Landsat 8 satellite for the study area was also generated using the GEE cloud platform (Figure 5). This dataset is the atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS sensors provided by USGS since 2013-04-11. These satellite images have five visible and near-infrared (VNIR) bands, two short-wave infrared (SWIR) bands processed to orthorectified surface reflectance, with remaining two thermal infrared (TIR) bands processed to orthorectified brightness temperature. These data have been corrected atmospherically with Land Surface Reflectance Code (LaSRC) and contain a C code based on the Function of Mask (CFMASK) produced Cloud, shadow, water and snow mask and a per-pixel saturation mask. Strips of data collected are clustered in overlapping "scenes" measuring approximately 170 km x 183 km using a standardized reference grid.

Figure 5. Landsat-8 satellite image of Kabul city generated on Apr-June 2020.

The main visible and near-infrared Sentinel-2A bands' spatial resolution is 10 meters, whilst the "red-

edge" (red and near-infrared bands) and two shortwave infrared bands have a spatial resolution of 20 meters. The spatial resolution of the coastal / aerosol, water vapor, and cirrus bands is 60 meters for Sentinel-2A.
The multispectral data recorded by each of the sensors has similar wavelength ranges (Table 1). The related characteristics of Sentinel-2 sensors to Landsat and shortened revisit time are now utilizing the combined multispectral observation capacity of three platforms observing the surface of the Earth at a resolution of 10-30 m, greatly expanding the ability to capture cloud-free observations at high latitudes (Runge & Grosse, 2019). In order to see the influence of the different spatial resolution of the images, no pan sharpening methods have been applied to the Landsat-8 imagery.

Table 1. Corresponding Landsat-8 and Sentinel-2 bands and characteristics

Landsat-8			Sentinel-2		
Bands	Pixel size (m)	Wavelength (μm)	Bands	Pixel size (m)	Wavelength (nm) (S2A)/ (S2B)
B1- Coastal	30	0.435-0.451	B1 - Coastal	60	443.9 / 442.3
B2 - Blue	30	0.452-0.512	B2 - Blue	10	496.6 / 492.1
B3 - Green	30	0.533-0.590	B3 - Green	10	560 / 559
B4 - Red	30	0.636-0.673	B4 - Red	10	664.5 / 665
B5 - NIR	30	0.851-0.879	B5 - Vegetation Red Edge	20	703.9 / 703.8
B6 - SWIR 1	30	1.566-1.651	B6 - Vegetation Red Edge	20	740.2 / 739.1
B7 - SWIR 2	30	2.107-2.294	B7 - Vegetation Red Edge	20	782.5 / 779.7
B8 - Pan	15		B8 - NIR	10	835.1 / 833
			B8A - Narrow NIR	20	864.8 / 864
B9 - Cirrus	30	10.60-11.19	B9 - Water Vapour	60	945 / 943.2
B10 - TIRS 1	30(100)		B10 - SWIR-Cirrus		
B11 - TIRS 2	30(100)	11.50-12.51	B11 - SWIR	20	1613.7 / 1610.4
			B12 - SWIR	20	2202.4 / 2185.7

Source: Earth Observing System (https://eos.com/sentinel-2/)

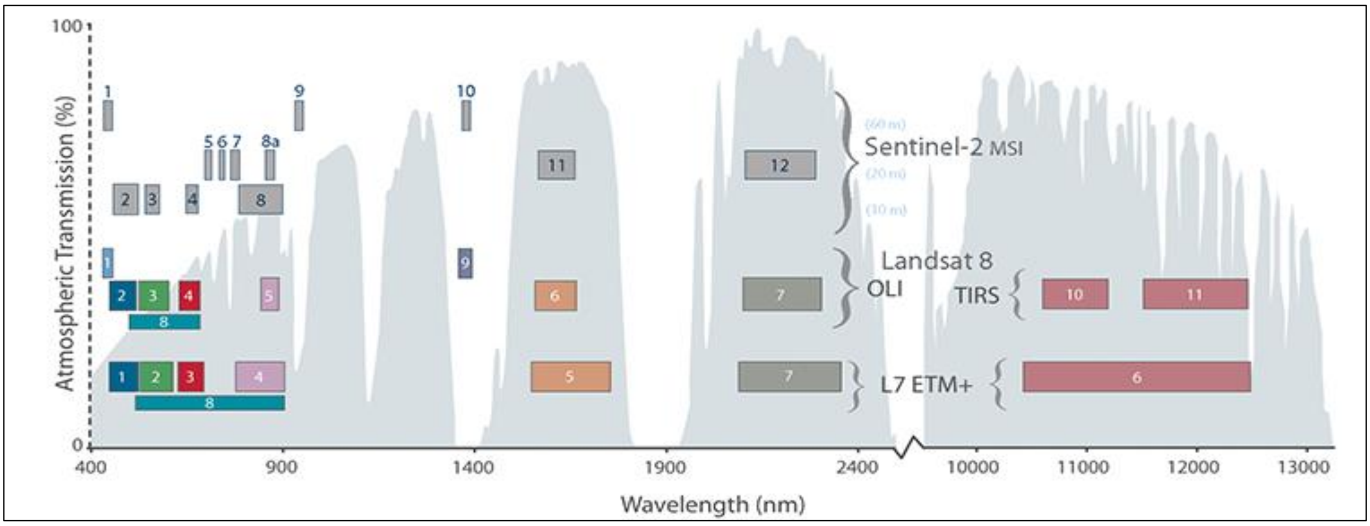

Figure 6. Comparison of Landsat 7 and 8 bands with Sentinel-2. (Source: USGS)

Spectral bands for both the images (Sentinel-2A and Landsat-8) are very similar except for Landsat 8's Thermal Infrared Sensor's thermal bands. According to Landsat 7 and 8 bands, the unique placement of Sentinel-2A bands can be seen in Figure 6 (USGS).

2.3. Methods

GEE is an on-scale cloud data analysis tool, powered by Google Cloud Platform to conduct geospatial data analysis. GEE offers an open forum for the development of geo-spatial algorithms, also GEE is designed to hold and process massive data sets (at petabyte-scale) for analysis and final decision making (Mutanga & Kumar, 2019). A user-friendly and easily accessible platform provides a convenient environment for the development of interactive data and algorithms.

The framework for mapping of Kabul city classification in this paper is shown in Figure 7. First, we extracted Sentinel-2 and Landsat-8 images in GEE platform. Then the images were filtered for boundaries, date and cloud, as a boundary filter we considered shapefile of Kabul city for clipping the images. The surface reflectance bands of both satellites were combined by Product stacking. After that, training site and sampling procedure was done. Afterwards, the LIBSVM (Library Supported Vector Machine) classifier method was used for classification of the study area. LIBSVM is an integrated software for support vector classification that supports multi-class classification. At the end, accuracy assessment was done and compared for both the images.

Sentinel-2 and Landsat-8 satellite images were imported in GEE platform for the study area and were clipped with Kabul city's shapefile. Both the images were filtered by date from April to July 2020 and were used to classify the study area. To get the best result of the work, the imported images were then filtered to mask clouds' images. Masking clouds and cloud shadows in Sentinel-2 surface reflectance (SR) data was done using Earth Engine. The Sentinel-2 image was filter for clouds with the metaData CLOUD_PIXEL_PERCENTAGE, for cloud pixel percentage of 10%. In case of Landsat-8, the metadata CLOUD_COVER of 10% was applied to mask the clouds.

Eleven Sentinel-2 bands (Blue, Green, Red, Red-Edge 1, Red-Edge 2, Red-Edge 3, NIR, Red-Edge 4, Water vapor, SWIR 1, SWIR 2) and six Landsat bands (Blue, Green, Red, Near Infrared, ShorthWave Infrared-1, ShorthWave Infrared-2), were used for the classification.

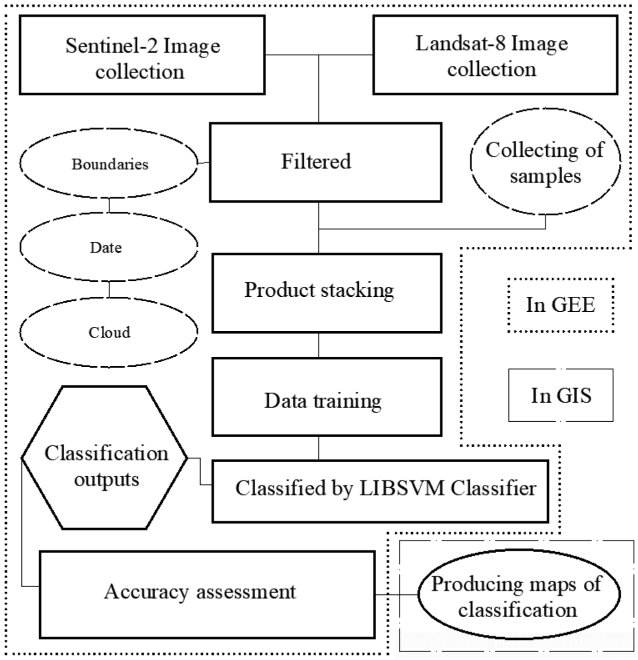

Figure 7. Flow chart of the overall procedure

In this paper, supervised classification for land cover classification was used. For both the images the same number of sample points with same position have been used which were collected for all four classes of (Water, Cropland, Urban and Bare land) Table 2. The sample training was done over the both the images with validation over high resolution imagery of satellite. The LIBSVM (Library Supported Vector Machine) _classifier was used for the classification. For both of the images, overall accuracy and kappa have been calculated.

Table 2. Training and sample points

Class	Sample points
Water	19
Cropland	83
Urban	70
Bare land	89

2.4. Accuracy Assessment

Accuracy assessment has been recognized one of the most important steps at classification process. The accuracy assessment aims to evaluate the effectiveness of sampling pixels in the right land cover groups (Rwanga & Ndambuki, 2017). Several methods have been used to assess the thematic accuracy of land cover classification. The confusion matrix helps us to measure the Overall Accuracy, User's accuracy, Producer's accuracy and Kappa coefficient. Overall accuracy shows the percentage of correctly mapped reference sites and is equal to number of correctly classified site per total number of reference sites. A statistical test is used to determine the accuracy of a classification to generate the Kappa Coefficient. Kappa basically examines how well the classification was carried out compared to just random assigning values (Humboldt State Geospatial Online, 2019).

3. Results and Discussion

The results obtained after running the Google Earth Engine platform code editor are shown in Figure 8 for Sentinel-2 and Figure 9 for Landsat-8. The results obtained from the classification of Kabul city on the Google Earth Engine platform clearly show that all four classes of water bodies, cropland, urban and bare land in the study area were successfully extracted, but it is also a fact that the system could not eliminate most of the misleading information in both Sentinel-2 and Landsat-8 cases. Some urban parts were misleadingly classified as water, possible building shadows, dark objects and asphalt with the Sentinel-2 image, and some parts of croplands appear to be classified as water with Sentinel-2 because the images were filtered by April to July dates; the time of irrigation of the croplands "Figure 10e".

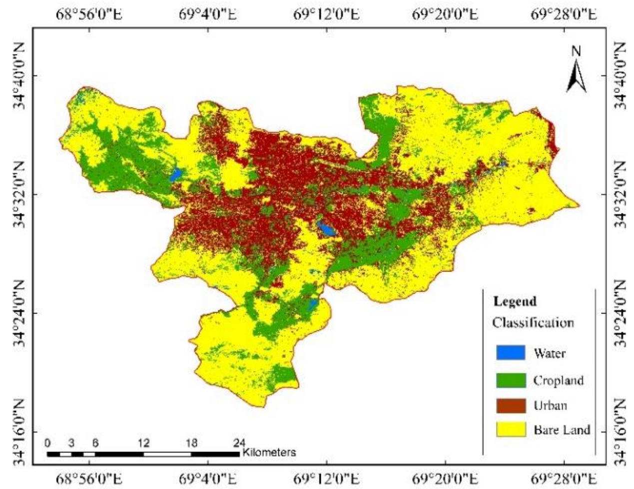

Figure 8. Sentinel-2 image classification Apr-July 2020

However, in the case of Landsat-8, there are some parts of the urban and cropland zone that are misleadingly classified as water bodies, but the number of such water bodies is less than that for Sentinel-2 Figure 10e and 10f. Some parts of Kabul River were missing and were not classified as water Figure 10f with Landsat-8, while those parts were purely classified as water with Sentinel-2 Figure 10e. The total area classified as water for Landsat-8, approximately 50 percent less than that of Sentinel-2.

In general, we can divide the water bodies into two categories in Kabul city, the water bodies which are permanently available such as Qargha Lake and Kabul River, and the temporarily available water bodies such as cropland irrigation areas.

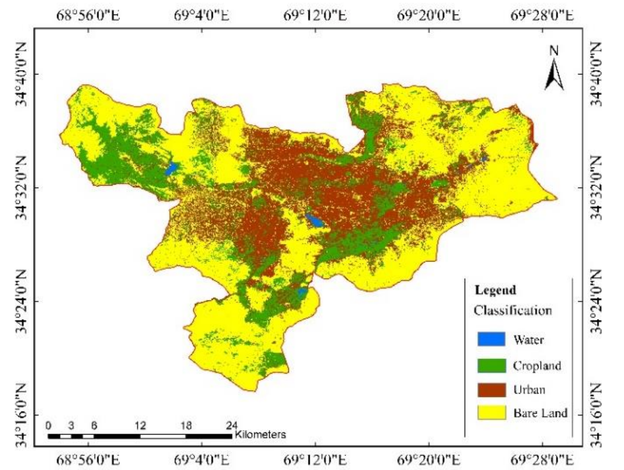

Figure 9. Landsat-8 image classification Apr-July 2020

Most of Kabul city's western and southern parts have been classified as cropland with both Sentinel-2 and Landsat-8 Figure 8 and 9, although there is less cropland in the northern and eastern parts of the city, the main reason is that high mountains occupy the area. For cropland region, both the cases could classify it well at all, but some misleading information were there with Landsat-8 image which could not classify the cropland and trees within the urban area Figure 10a and 10b, while it was well classified with Sentinel-2. This could be why the cropland area classified with Sentinel-2 is 233.5 square kilometers while it was 199.6 square kilometers in case of Landsat-8; approximately 15% less than that of Sentinal-2.

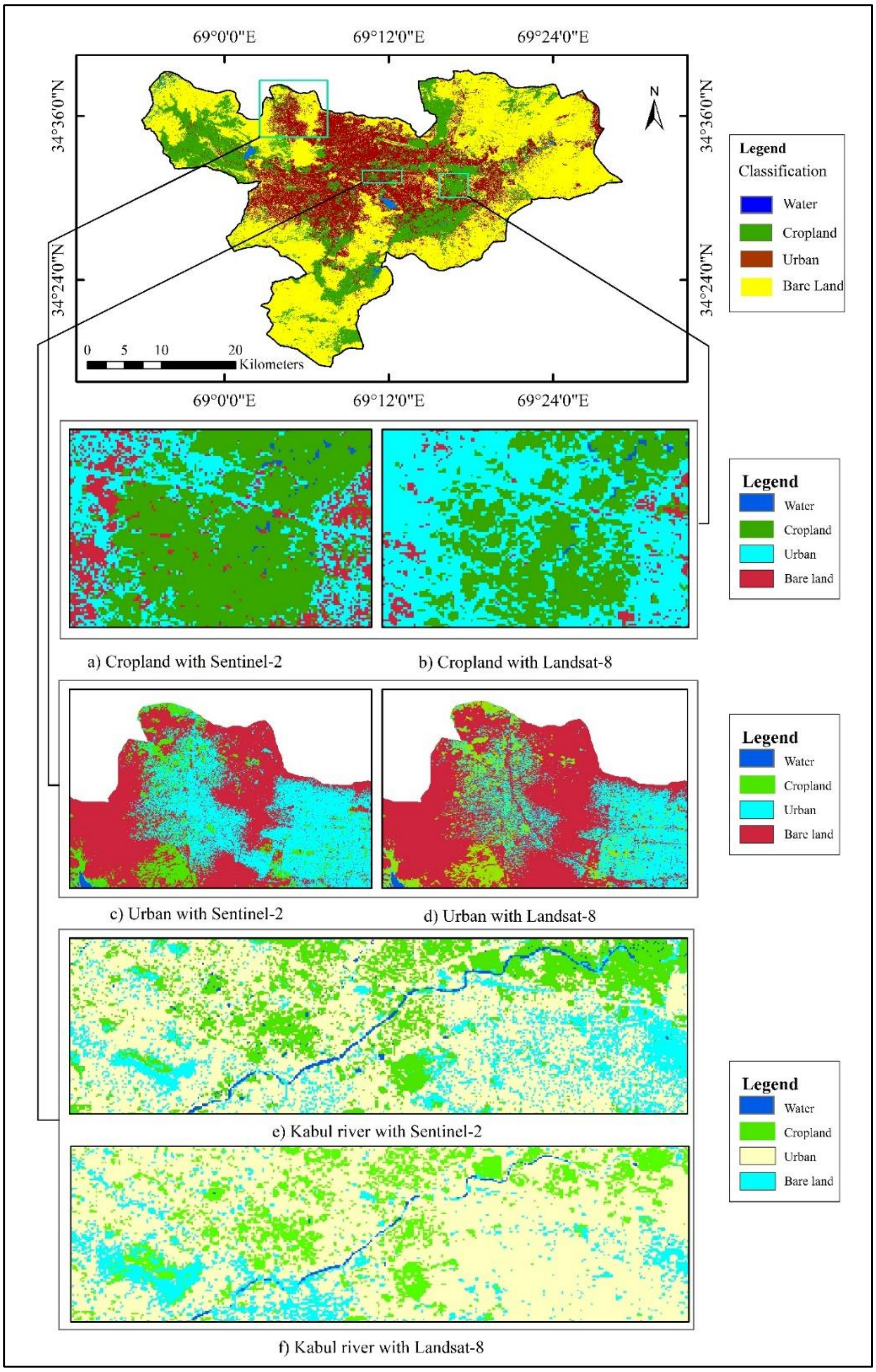

Figure 10. Detailed map of Classification of Kabul city

In case of urban region, the central and mostly flat part of the city is classified as urban area with both the images "Figure 8 and 9", and it is the second large class in terms of area in the city. Some parts of residential area were misleadingly classified as bare land with Landsat-8, while the results were most accurate with Sentinel-2 Figure 10c and 10d. The area classified as urban was 236.4 square kilometers for Sentinel-2 and it was 285.3 square kilometers for Landsat-8; higher by about 17% than that of Sentinel-2.

The bare land class in Kabul city is the largest class in terms of the area, containing deserts and mountainous areas surrounding the city's urban region. In bare land region, some parts of bare land were classified as urban in the eastern of the study area with both images. The bare land class area was calculated with a slight difference of 3.2 square kilometers, 550.7 square kilometers for Sentinel-2 and 547.5 square kilometers for Landsat-8, which show the best result for both images.

Classification outputs are compared only using the surface reflectance of spectral bands of Seninel-2 and Landsat-8 datasets and produce average validation overall accuracy of 93% and 85% respectively. The Classifier package with traditional ML algorithms in GEE platform was used to assess both the experiments' accuracy for classification of Kabul city with Sentinel-2 and Landsat-8. Based on the information from confusion matrix, the overall accuracy of the identification of all four classes with Sentinel-2 and Landsat-8 are 93.3% and 85% respectively, the Kappa coefficients are calculated 90% for Sentinel-2 and 78.3% for Landsat-8 Table 3.

Table 3. Confusion matric and accuracy evaluation for the classification of Kabul city map based on Sentinel-2 and Landsat-8

	Sentinel-2						Landsat-8					
Classes	Water	Cropland	Urban	Bare land	Total points	User accuracy (%)	Water	Cropland	Urban	Bare land	Total points	User accuracy (%)
Water	8	1	0	0	9	88.89	8	1	0	0	9	88.89
Cropland	0	37	0	1	38	97.37	1	33	4	2	40	82.5
Urban	0	0	26	4	30	86.67	0	2	21	3	26	80.77
Bare land	0	1	0	44	45	97.78	0	1	5	46	52	88.46
	Validation overall accuracy					**94.26**	**Validation overall accuracy**					**85.04**
				Kappa		**91.7**				**Kappa**		**78.3**

From the confusion matric shown above, water appears to have been classified with the same user accuracy of 88.9% with both Landsat-8 and Sentinel-2 images, while Sentinel-2 did better with 97.37% user accuracy in the case of cropland than Landsat-8 with 82.5%. In the same way, two remaining classes of urban and bare land were classified with higher user accuracy of each 86.67% and 97.78% respectively in Sentinel-2 image, while they were classified with lower accuracy of 80.77% for urban and 88.46% for bare land in case of Landsat-8 image. Similarly, for each urban and bare land classes with Seninel-2, the user accuracy was calculated 86.67% and 97.78% with a better result, whereas, urban was classified with 80.77% and bare land was classified with 88.46% in case of Landsat-8 image.

Similar studies also showed that Sentinel-2 preforms better than Landsat-8. Thus, Korhonen et al. (2017) compared the two sensors for estimation of boreal forest canopy cover and leaf area index. They have concluded that the better performance of Sentinel-2 may be related to the red-edge-vegetation bands, as their investigation of the mutual bands of the two sensors did not show any significant difference. On the other hand, in a comparison of the two sensors for assessing burn severity (García-Llamas et al., 2019), Sentinel-2 also showed better results, however, this performance was linked with the better spatial resolution of the sensor. Comparison for detection and mapping of soil salinity (Wang et al., 2020) also showed better results for Sentinel-2, where according to the authors, the higher temporal resolution of the sensor played curtail in the performance. Our study is another example of the better performance of Sentinel-2 in comparison with Landsat-8, using GEE.

4. CONCLUSION

Images from the Landsat-8 and sentinel-2 sensors were compared for classification of four classes each; Water, Cropland, Urban and Bare land in Kabul city to see which one present more accurate results. To compare the results, we considered the same interval of date, same training of samples, same number of points picked up for each class, and the same percentage of cloud masking for each image. Despite the overall good results gained from both of the sensors, there were slight differences between the results obtained from both images that can be linked to several parameters, including poor masking of the cloud, cloud shadow, and mixed pixels. The results earned from both the images were effective in their own area for instance, in water extraction maybe Sentinel-2 has some misleading information, but in urban area and agricultural part the Landsat was not good enough to classify it. The assessment was done based on the use of cloud platform of GEE; which could be the best option for future studies such extraction of a specific land cover class in the study area. Given that the results show that Sentinel-2 image with overall accuracy of 94.26% is more accurate than the Landsat-8 with an overall accuracy of 85.04% for classification of the study area, we recommend the Sentinel-2 satellite image for conducting such kind of studies. Since our results were in line with the studies done before, we acknowledge that the GEE cloud platform is a useful and valuable tool for such comparison studies. For future studies, we recommend investigating the changes over a period of time and doing cross-comparison between Sentinel-2 and Landsat-8.

Author contributions

Abdul Baqi Ahady: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Validation. **Gordana Kaplan:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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