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Monitoring Land Use/Land Cover Change in Tha Chin River Basin

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Abstract

Land use/ land cover (LULC) changes influence the whole natural system directly or indirectly, so monitoring these changes is essential to balance the natural environment. This research surveyed changes in LULC in the Tha Chin River Basin. Using Google Earth Engine and ArcGIS, Landsat 5 and Landsat 8 Thematic Mapping satellite photos were utilized to identify LULC classes for the years 2000, 2010 and 2020 for the Tha Chin river basin. Fifty training samples for five classes were collected by supervised classification to analyze land cover types in the Tha Chin basin. Among these five classes, the urban area shows a significant change from 2000 to 2020; the second significant change is the forest area. The monitoring of changes in LULC would provide a crucial basis for the region environmental management and integrity in the Tha Chin River Basin.

Keywords: *Land Use/Land Cover, Change Detection, Google Earth Engine, Monitoring, Hydrological Change*

INTRODUCTION

Information regarding LULC is significant in many parts of life, beginning with the sciences and extending through the economy and politics (Phan et al., 2020). Among these facets, the sciences play the most crucial role. The natural and manufactured features observed on the globe's surface are called the "land cover," an umbrella word. Some land cover types are water, built-up areas, deciduous trees, and wetlands. Water also includes built-up areas. On the other hand, the activities that take place on the land and are considered part of the LULC property are referred to as "land use," which is the phrase used to characterize them. Land use and land cover changes (LULCC) contribute to global environmental change. They influence other aspects of the Earth's atmospheric system, leading to unfavourable outcomes such as species extinction, the spread of desertification, and temperature fluctuations (Fonji and Taff, 2014). As a result, picking, planning, and putting in place land use schemes are necessary to satisfy the ever-increasing demands of fundamental human wants and activities. The dynamic monitoring of land use that occurs because of shifting needs brought on by an expanding population would be aided by information on LULC and the possibilities of their most effective usage [3]. It has been determined that remote sensing data are the most critical data sources, and they have been utilized extensively in mapping and monitoring changes in land cover over centuries, with Landsat serving as one of the most prevalent data sources (Wulder et al., 2016). Images obtained through remote sensing usually require geometry and radiometric adjustments to be made in order to remove noises such as cloud cover, cloud shadow, and snow cells or to correct geometric and

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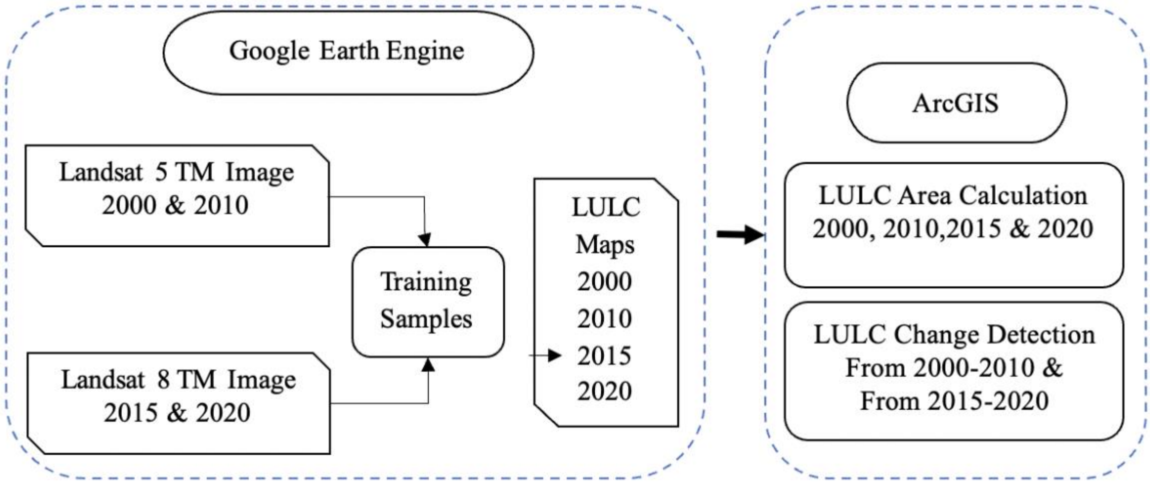
geolocation mistakes (Li et al., 2019). This is because of the impact of the atmosphere and the sensor's tendency to make systematic errors. NASA and the United States Geological Survey worked together to construct the Landsat satellite series, which is part of the Earth Observation category (USGS). This series is the world's longest-running optical remote sensing satellite system, and it was designed to collect data from land, coastal areas, and shallow water all over the planet. The mission of the Landsat series is to acquire repeated images of Earth's land and coastlines to track changes over time (Hörber, 2015). The classification of LULC frequently uses these Landsat photos as one of the essential sources. The classification procedure is the essential step in gaining an understanding of the LULC present in a given area. Supervised and unsupervised classification are the methods used to classify an image. The supervised classification technique requires the user to select the training samples before analyzing the classes found within the pixels of a picture. The categorization of supervised land cover relies on the following four primary steps: (1) the creation of training sites, (2) the delineation and investigation of the spectral characteristics of training areas, (3) the classification, and (4) an examination of the accuracy of the classification (Leroux et al., 2018). On the other hand, unsupervised classification identifies spectral classes or clusters without the analyst's participation. These supervised and unsupervised classifications of satellite pictures are used in a great deal of research about shifts in LULC across a wide swath of the planet. These shifts are the subject of many studies. Image classification can be accomplished on various platforms, including ArcGIS, QGIS, ENVI, Google Earth Engine (GEE), and many other image-processing software programs.

GEE is a cloud technology platform enabling users to do advanced analyses to identify changes, map trends, and quantify surface differences. By utilizing the Integrated Development Environment (IDE) code editor and processing all remotely detected images, GEE users may choose, assess, and process vast amounts of data (Hörber, 2015). (Tamiminia et al., 2020) found that the number of publications using GEE has continuously increased since 2013. (Rantasewee et al., 2022) used the Landsat 5TM satellite picture in GIS to conduct their research on the disappearance of agricultural land in the Tha Chin River watershed. (Monprapussorn, 2018) used the province of Suphan Buri as a case study to evaluate the impact that climate change will have on the usage of irrigated agriculture in the Tha Chin River basin for rice production. In this study, among the datasets currently available in GEE, Landsat satellite pictures have been used to investigate the changes in LULC in the Tha Chin River basin during the years 2000, 2010, 2015, and 2020.

METHODOLOGY FRAMEWORK

In this study, the Google Earth Engine platform is used to load Landsat imagery collection, Landsat 5 Thematic Mapper images for the years 2000 and 2010, Landsat 8 TM images for 2015 and 2020, and it also defines the study area, Tha Chin River basin. All the tiles of image pixels that cover the Tha Chin basin were readily mosaic in the GEE code editor. As a supervised classification, fifty training samples representing each class, such as water, urban, crop, forest and bare land, were collected visually under supervision, validating with the google earth image. The classified LULC maps for the years 2000, 2010, 2015 and 2020 were processed in ArcGIS to calculate the area for each class. Finally, LULC change detection from 2000 to 2010 and 2015 to 2020 were estimated in ArcGIS using the intersection of geoprocessing tool. Figure 1 shows the methodological framework of the study.



METHODOLOGY

Study Area

This research focuses on Thailand's Tha Chin River Basin. The Chao Phraya River, which flows into the Gulf of Thailand from Chai Nat province, is the parent river of the Tha Chin river. The Chin River Basin is 13446.5 km2 and has 2 million people. The 300 km river is 0 to 25 m deep. This region receives 1100 mm of rain annually and 1350 million cubic meters of water. Wet season: 1237 million cubic meters; dry season: 120 million cubic meters. Figure 2 shows the Tha Chin River Basin location. It is an actively exploited area with high-yield agriculture, industrialized cattle, and expanding urbanization and industrialization (Chengcharoen et al., 2013). Chao Phraya, Tha Chin, and their neighbouring areas were most affected by flooding in Thailand in 2011. The middle stretch of the Tha Chin river was classified as a significant flood retention region (Tassi and Vizzari, 2020) to reduce peak flooding in the Chao Phraya and Tha Chin River Basins. Understanding riverine hydrology and LULC in the Tha Chin River basin may promote development and migration.

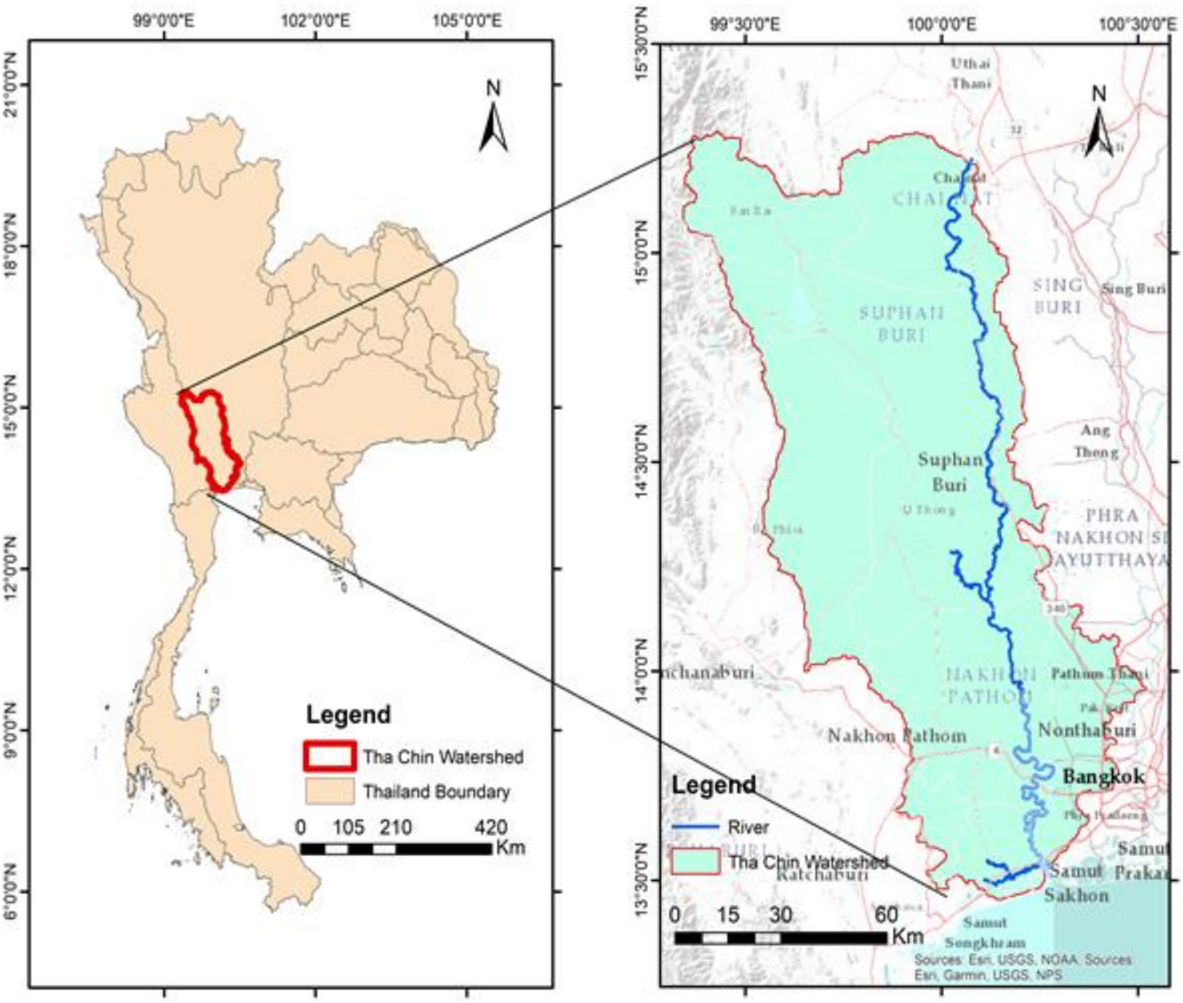


Figure 2: Location Map of Tha Chin River Basin

Data Acquisition

The application of multi-spectral and multitemporal satellite photos with a medium and high spatial resolution is excellent for analyzing and monitoring land take (Chengcharoen et al., 2013). [Note: We use images obtained with the Thematic Mapper (TM) aboard Landsat 5 and 8. The downloaded satellite images were selected during the month between February and March to maximize the likelihood of obtaining information that was not covered by cloud cover. Landsat-5 Missions equipment consists of a multi-spectral scanner and a Thematic Mapper, both of which have a spatial resolution of 30 meters. In contrast, Landsat-8 has an operational land imager (OLI) sensor and a thermal sensor, the first of which has a resolution of 30 meters and the second of which has a resolution of 100 meters (Patil et al., 2012). Both of these sensors have a spatial resolution of 100 meters. The critical information gathered for this inquiry is shown in Table 1, which can be seen here.

Table 1. Data Sources used in this study

Parameters	Data Source	Source Location
LULC 2000	Landsat 5 TM using GEE	https://code.earthengine.google.com/
LULC 2010		
LULC 2015	Landsat 8 TM using GEE	
LULC 2020		

Google Earth Engine Environment

The Google Earth Engine (GEE) is a Graphical User Interface (GUI) that runs on the web. Google's computer infrastructure provides users access to a multi-petabyte database of remote-sensing pictures and other datasets. Users can access the database by going to google.com. With the assistance of GEE, which can be accessed through a platform that allows for editing JavaScript code, the processing of satellite imagery is much simpler. Several methods of LULC classification can be applied by utilizing the classifier packages available in GEE. These classifier packages provide a variety of machine-learning methods(Tilahun and Teferie, 2015). This category includes a wide variety of different classifiers, some of which include regression and classification trees (CART), random forests, naive Bayes, support vector machines (SVM), and others (Congalton, 1991). This work sorts the training data into five categories using CART classifier coding to make predictions about the surroundings. These five settings are water, urban, agricultural, forest, and basic terrain.

Accuracy Assessment

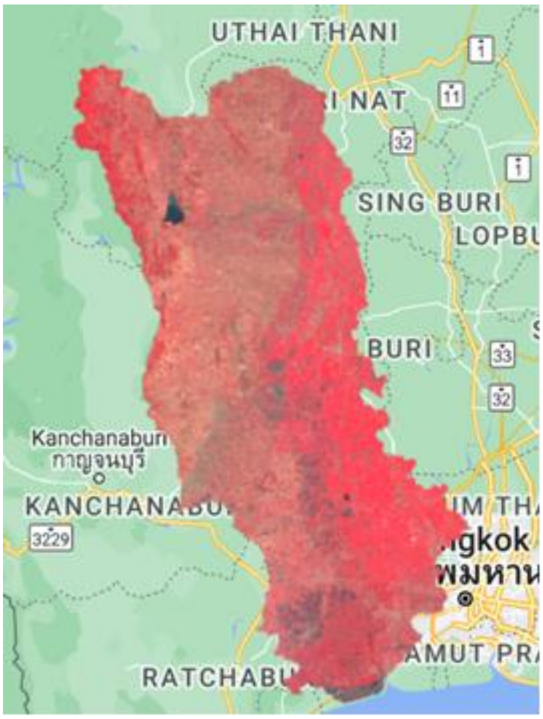
The final stage of the process of classifying satellite images involves performing an analysis of how accurately the categorization was performed. The accuracy helps evaluate the classification approach by quantifying an approximation with remotely sensed datasets to the classification circumstances. There are two names for what we do: accuracy assessment and evaluation (Lu and Weng, 2007). A necessary additional step is locating any possible errors that may have been made. Methods such as the following can be used in order to perform an accuracy assessment: (1) verification of the ground using a GPS (observing the area); (2) comparisons of a classified image with an image that is presumed to be correct; (3) asking the questions of authorities concerned whose members have previous information; and so on (Meshesha et al., 2014).

FINDINGS AND DISCUSSION

Four land use/land cover maps of 2000, 2010, 2015 and 2020 were brought from analyzing the Landsat images. False color composite images with bands 4,3,2 from Landsat 5 for 2000 and 2010 and bands 5,4,3 from Landsat 8 for 2015 and 2020 were classified under supervision to export LULC maps. These maps displayed land use land cover (LULC) classes and the changing pattern from 2000 to 2010 and 2015 to 2020. Every map is classified into five classes, Water, Urban, Crop, Forest and Barren land or Bare land.

LULC Maps

Figure 3 (a), (b), (c), and (d) represent the false color composite image before supervised classification for the years 2000, 2010, 2015 and 2020, respectively, while Figure 4 (a), (b), (c), and (d) shows the classified images for each year.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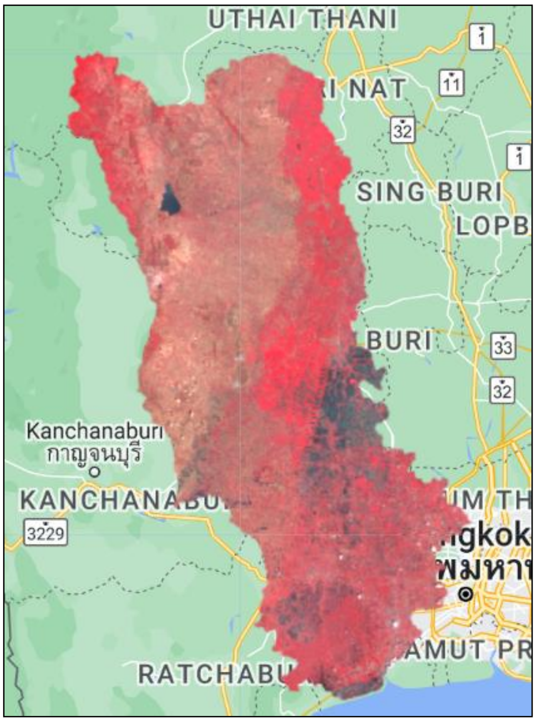
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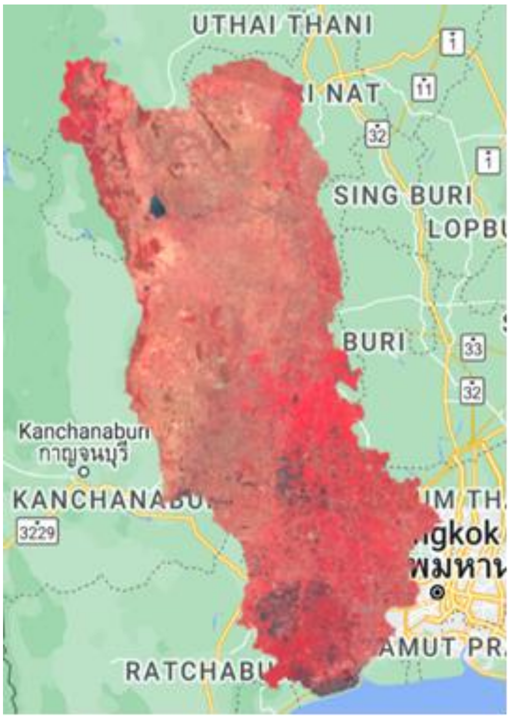
(a) (b)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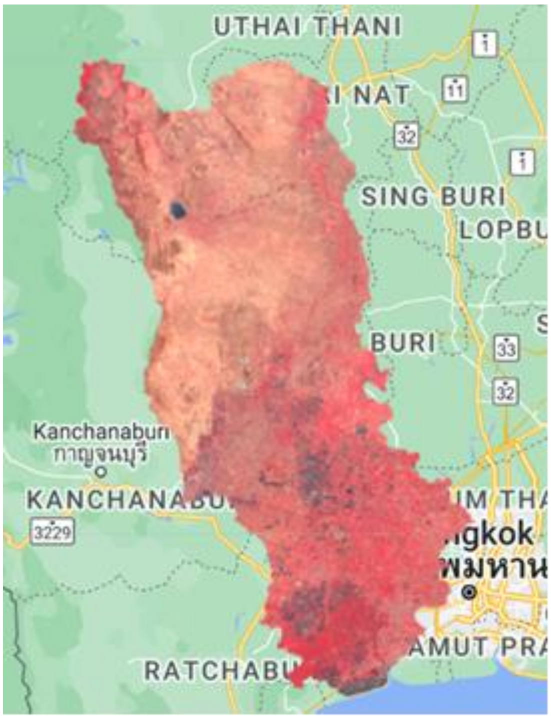
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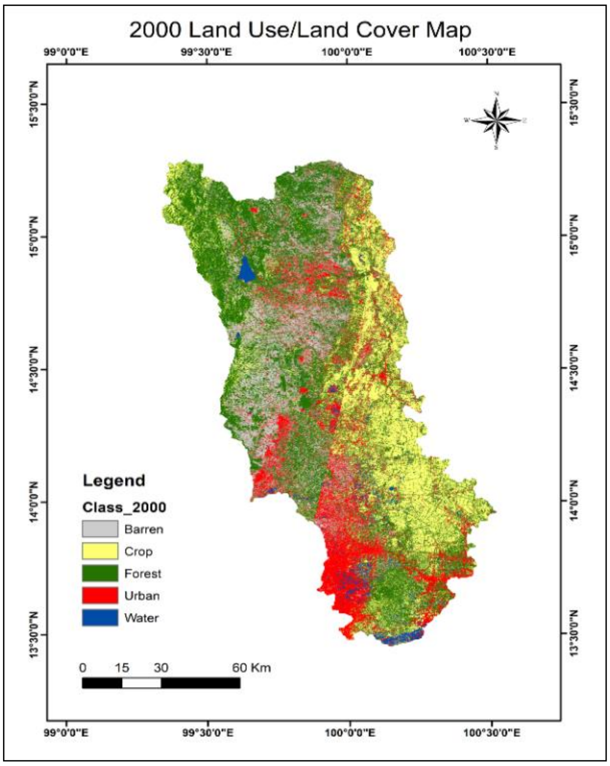
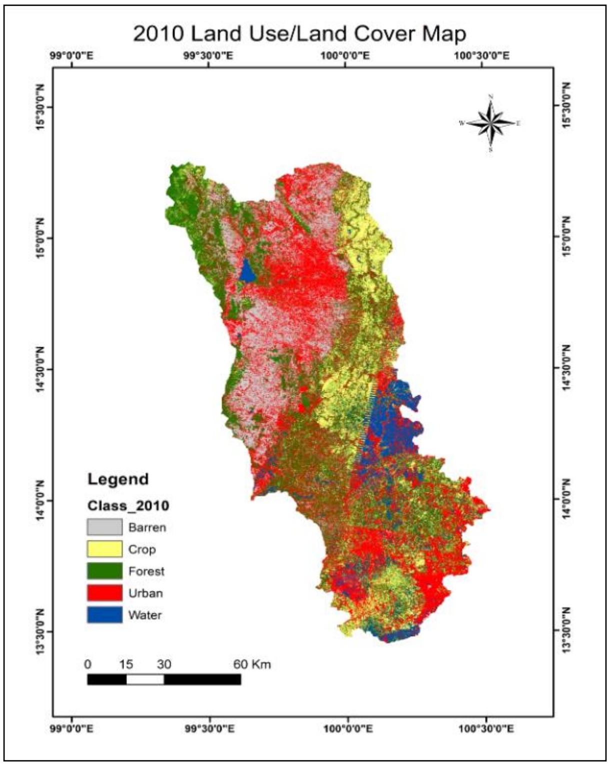
(c) (d)

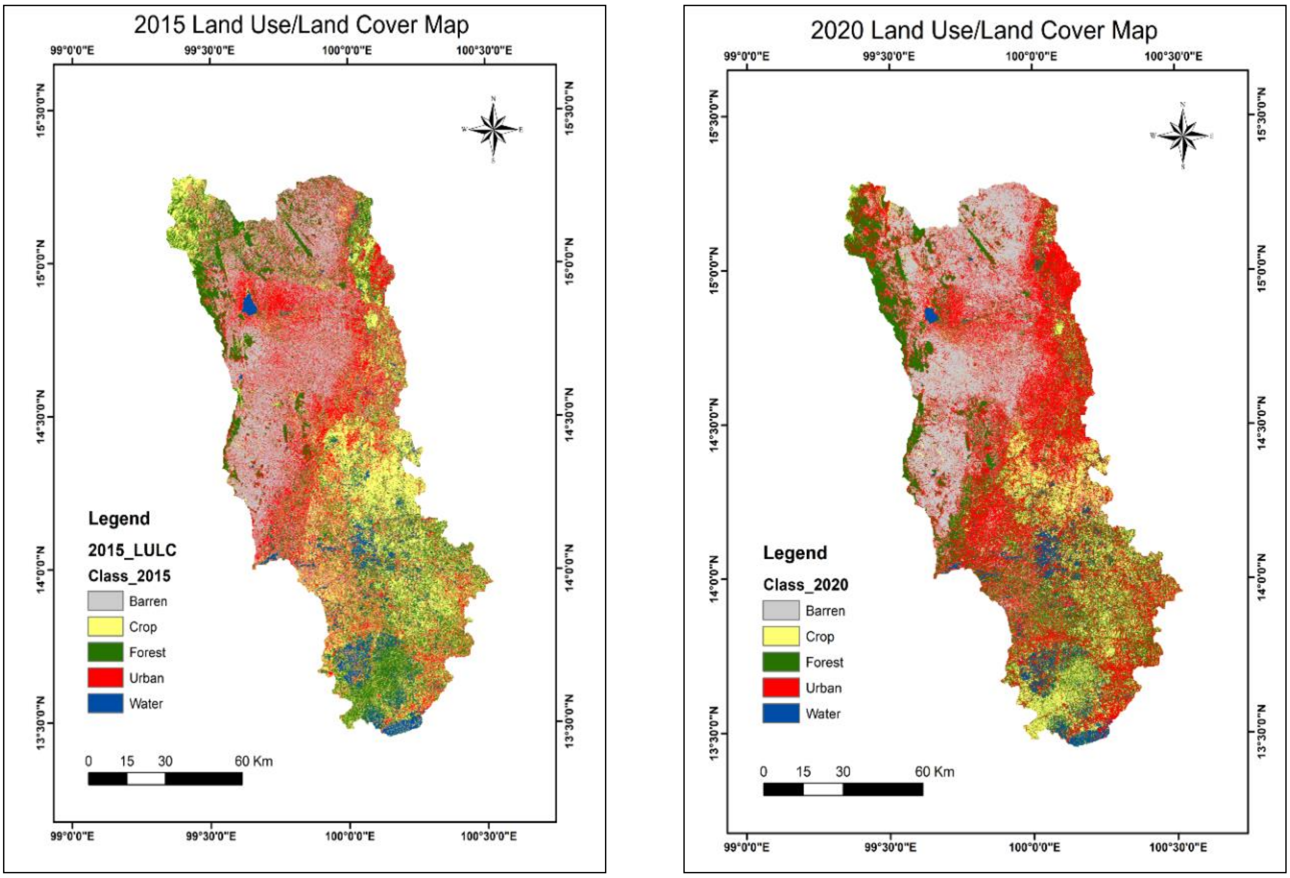
Figure 3: False Color Composite Maps of Tha Chin River Basin before Classification
(a) in 2000 (b) in 2010, (c) in 2015 and (d) in 2020





(a) (b)

(b)



(c) (d)

Figure 4: LULC Classification Maps of Tha Chin River Basin (a) in 2000, (b) in 2010, (c) in 2015 and (d) in 2020

Since LULC maps for the years 2000 and 2010 were available from Landsat 5 satellite, the resolution of maps for these years is not too good, and there are some distortions in the image. According to these figures, the water body in the basin was relatively small compared to other classes. Urban areas in the basin had changed significantly from 2000 to 2020; on the other hand, the Crop area's class became less in 2020 than in 2000. Forest area also decreased comparing between 2000 and 2020. In 2010, the urban area was too large, and the crop area was less than in 2015, which might be the effect of distortion of the image while taking the ariel photo from Landsat 5 satellite. It still gave the classification accuracy assessment as 0.8 for 2010 and 0.85 in 2000. Since Landsat 8 satellite image has better resolution, the accuracy assessment for 2015 is 0.92 and for 2020 is 0.95. The area in square meters of each class is described in Table 2. Figure 5 represents the graph of LULC classes in each year.

Table 2. Area of Land Use/Land Cover Classes for the year 2000,2010, 2015 and 2020

No.	**LULC Class**	**Area (km^2)**			
		Year 2000	**Year 2010**	**Year 2015**	**Year 2020**

1	Water	387.13	947.41	708.86	516.78
2	Urban	2207.41	4526.99	3432.60	4654.17
3	Crop	5247.08	1999.38	3370.49	1881.70
4	Forest	3252.48	3810.25	2893.55	2965.77
5	Barren	2288.00	2098.06	2976.60	3363.67

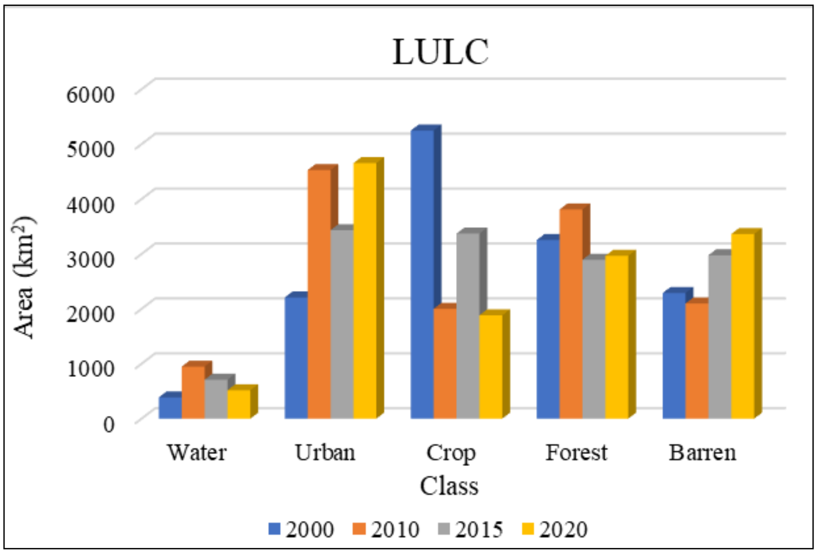


Figure 5. The Graph of LULC classes in each year

Land Use/Land Cover Change Detection

LULC change detection was calculated in ArcGIS using the intersection tool in geoprocessing. Observing the changes in the entire study showed the changes in the barren land, forest, crop area, urban area, and water bodies. Figure 6 shows the graph of LULC change detection, and we can see that only half of the forest area remains unchanged and the area changed from forest to urban area is significant. The LULC changes from 2000 to 2010 and from 2015 to 2020 are shown in figure 7, and the changed area in Table 3. The change detections of other classes are not too significant as the forest.

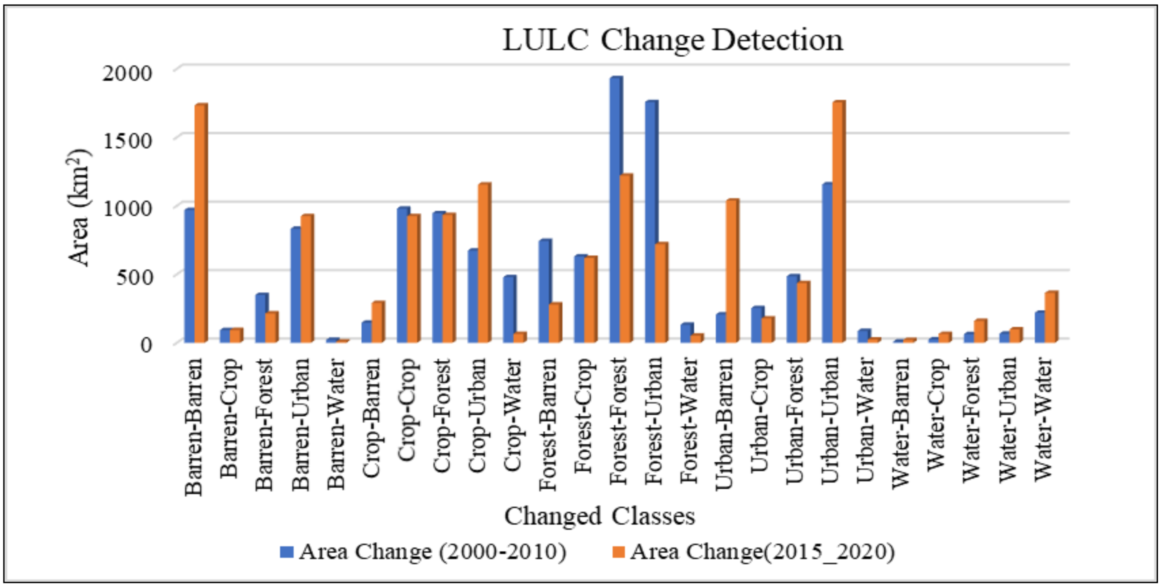


Figure 6: Graph of LULC Change Detection

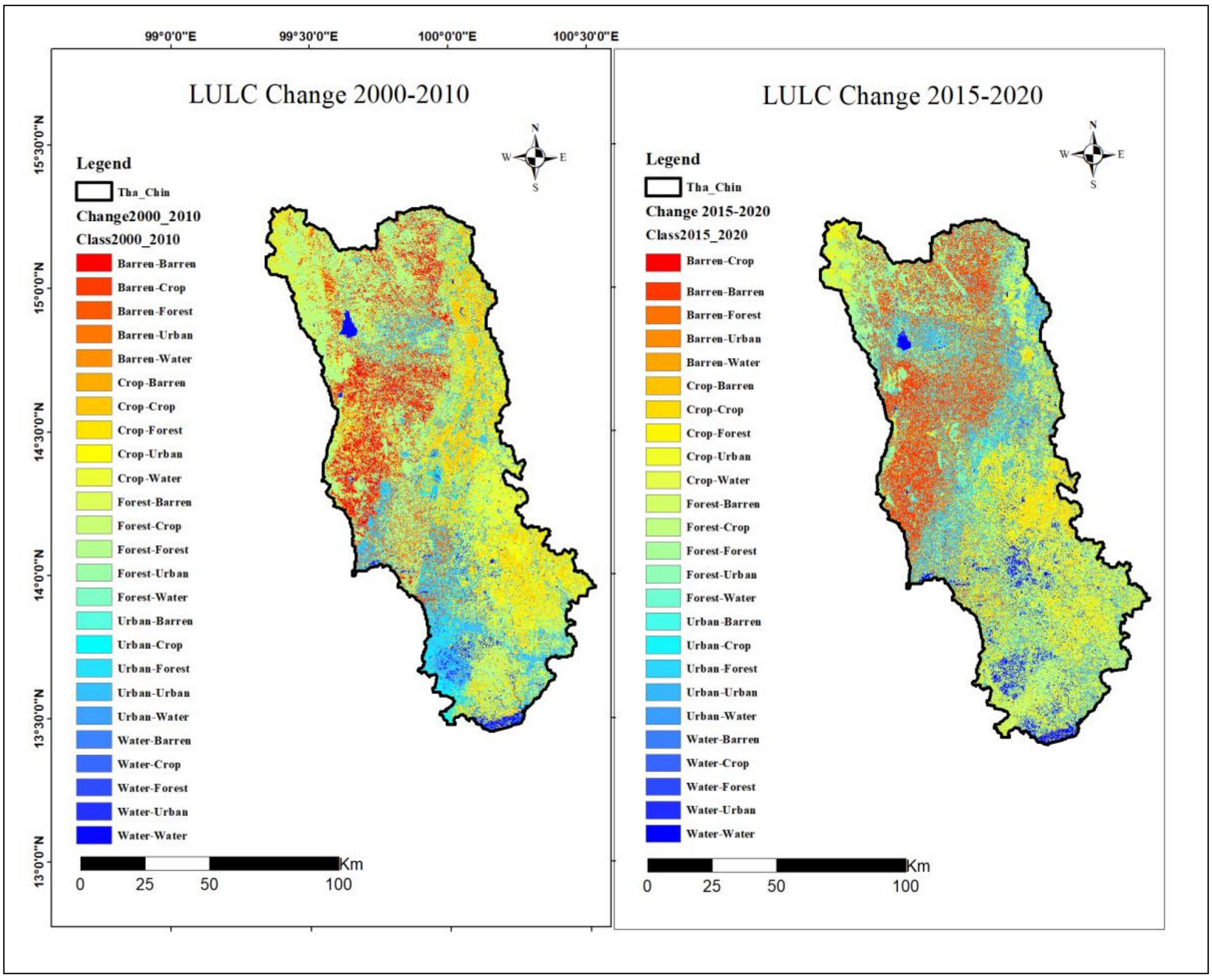


Figure 7: LULC Change Detection from 2000 to 2010 and from 2015 to 2020

Table 3- LULC Changed Area

No.	Changed Classes	Area Change (2000-2010)	Area Change (2015_2020)
1	Barren-Barren	969.45	1733.45
2	Barren-Crop	92.97	93.46
3	Barren-Forest	349.22	214.97
4	Barren-Urban	832.79	925.24
5	Barren-Water	21.68	9.46
6	Crop-Barren	146.96	291.12
7	Crop-Crop	978.99	925.05
8	Crop-Forest	945.99	933.46

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9	Crop-Urban	673.06	1155.76
10	Crop-Water	479.60	65.08
11	Forest-Barren	743.95	279.99
12	Forest-Crop	630.96	619.89
13	Forest-Forest	1931.48	1220.87
14	Forest-Urban	1757.10	719.55
15	Forest-Water	132.34	53.24
16	Urban-Barren	207.21	1038.05
17	Urban-Crop	253.98	178.29
18	Urban-Forest	485.71	436.35
19	Urban-Urban	1156.58	1755.56
20	Urban-Water	86.56	24.32
21	Water-Barren	9.04	21.03
22	Water-Crop	25.14	65.00
23	Water-Forest	63.38	160.10
24	Water-Urban	66.79	98.06
25	Water-Water	219.70	364.67

CONCLUSION

The Google Earth Engine platform was used to create LULC maps of the Tha Chin River Basin for 2000, 2010, 2015, and 2020. The overall change in the Tha Chin river basin between 2000 and 2020 was analyzed using the change detection method in ArcGIS. The results showed that the classification of the five categories—water, urban, crop, forest, and barren land—showed good accuracy and the changing trend of urbanization and deforestation. When the entire research area was observed, it was discovered that the most significant sorts of change occurred in the urban and woodland areas, but changes in the water, agricultural, and barren areas were not readily apparent. These kinds of studies on detecting changes in LULC would be helpful in land management, the growth of urbanization, the economy, and other areas.

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