Temporal monitoring of land use/land cover change in Kahramanmaraş city center

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ABSTRACT
Irregular urbanization causes problems such as decrease in fertile agricultural areas, irregular industrialization and urbanization. To provide a healthier life opportunity for future generations without disturbing nature, it is essential to determine the temporal changes in land use and to make land management plans accordingly. In this study, land use/land cover (LULC) change occurred in Kahramanmaras province within 30 years was investigated by remote sensing and integration of Geographic Information Systems. Landsat satellite images of 1988-1998-2008-2018 were obtained for the production of LULC maps. Each image was classified according to supervised classification approach using the support vector machines (SVMs) algorithms. The confusion matrix was created for each year to examine the accuracy of the LULC maps. The overall accuracy of the thematic maps was obtained as 91.76%, 93.56%, 86.89% and 88.29%, respectively. Also, Kappa values of thematic maps for each year were obtained as 0.88, 0.91, 0.81 and 0.84, respectively. When the results were examined, the development of industry in the city area and the construction of the airport contributed to the development of the social and economic structure of the city. The increase in the number of housing in the related regions has led to an increase in the amount of urban areas and a decrease in agricultural areas.

1. INTRODUCTION

Urbanization covers the processes from the first periods of humanity to the transition to settled life (Tok 2006). Humans need to fulfill their basic needs to survive on Earth. To supply these requirements, they have carried out land-use activities. Over time, population growth slowed down in rural areas and the population increased rapidly in urban areas (Işık 2005). The increase in urban population is caused by factors such as the attractiveness of the city's opportunities, the search for a job, the desire of parents to prepare a better future for their children, the expectation of benefiting from quality education and health opportunities, the feeling of being safer in the city, migration and industrialization (Başel 2007).

As a result of uncontrolled developments in urban area, many problems arise such as the use of productive agricultural lands in industrial activities and the establishment of settlements on unsuitable lands (Ercan 2020). To ensure regular development in cities, unplanned construction on land should be prevented,

temporal changes in land use should be determined and necessary land use planning should be made (Denizdurduran 2012). In order to supply the needs of the rapidly increasing urban population, rapid and reliable geographic information about the cities is needed. In this respect, remote sensing offers sufficient advantages for the production of data required for controlled planning in cities by means of data servers and analysis methods (İderman 2006).

It is important to identify the existing land use/land cover (LULC) of cities for successful urban planning. Although LULC is obtained through traditional inventories or surveys, satellite remote sensing saves time and costs in determining the geographical distribution of temporal changes in LULC on a regional scale. Satellite image analysis provides an effective way to learn about the temporal trends and spatial distribution of urban areas needed to understand land change, model the current situation and prepare future projections (Yuan et al. 2005). Monitoring of temporal LULC in urban areas is possible by temporal analysis of satellite images (Hegazy and Kaloop 2015; Leichtle et al.

2017; Jimoh et al. 2018; Göksel and Doğru 2019; Orhan et al. 2019). Different classification algorithms such as can be used in the supervised classification of images for selected periods (Otukei and Blaschke 2010; Karakuş et al. 2017; Göksel et al. 2018). The Support Vector Machines (SVMs), one of these algorithms, uses optimization algorithms to find the optimal boundaries between classes. These boundaries ensure that unstable pixels are assigned to the correct classes (Üstüner et al. 2013; Demirkan 2017). Since SVM has been shown to have a successful classification algorithm in many studies (Mondal et al. 2012; Kumar et al. 2015; Noi and Kappas, 2018), it has been preferred in this study.

In this study, it is aimed to determine the LULC change occurring in 30 years in Kahramanmaraş by using satellite images. Landsat 5 TM (Thematic Mapper) and Landsat 8 OLI (Operational Land Imager) images were used to achieve this goal (Table 1). SVMs algorithm was used in the production of LULC classes for each year. By comparing the generated LULC maps, the change in the urban area was analyzed.

2. STUDY AREA AND DATA SET

Kahramanmaraş, that was selected as the study area, is located at 37° 34' 31" latitude and 36° 55' 22" longitude locations. Kahramanmaraş is located at the junction of the Mediterranean Region, Eastern Anatolia Region and Southeastern Anatolia Region. Due to its location, it has been influenced by three different climates and has enabled many different types of fruits, vegetables and plants to be grown (Geography of Kahramanmaraş URL1).

The study area covers 321.84 km² and covers the city center and its surroundings (Fig. 1). The study area includes a wide range of LULC classes such as artificial surfaces, wetlands, cultivated agriculture, uncultivated agriculture, industrial area, forest, bare soil-rocky area.
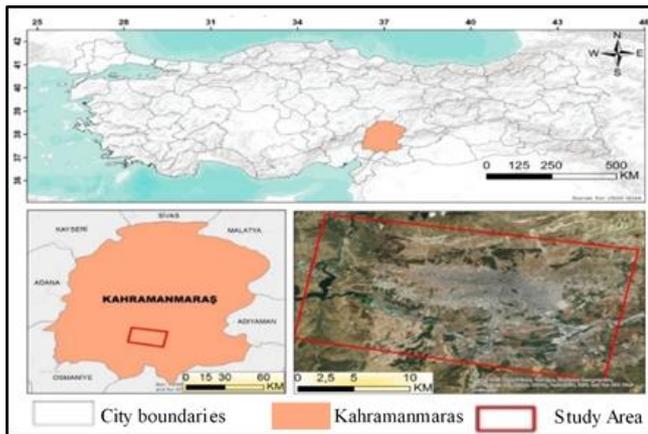

Figure 1. Study area, red boundary indicates application area

According to the number of population, Kahramanmaraş is the eighteenth largest city in Turkey. In the mid-1980s, migration from rural to urban areas started in parallel with the developments in the industry. After this period, there was a rapid increase in settlements in the city (Sandal and Karademir 2013). In this study, the general city center change of Kahramanmaraş province has been examined since the

industrialization period has increased. In order to reveal the general change, the temporal analysis was carried out in 10-year periods. Landsat images, free satellite images provided by the US government, were used to determine the 30-year changes in the study area. The research area was examined in four periods as 1988, 1998, 2008 and 2018. When the images were selected for analysis, Attention was paid to ensure that the images are close-dated and cloudless. LULC maps were generated for each period using multispectral bands common to both Landsat 5 and Landsat 8 images (Table 1).

Table 1. Spectral bands used in the classification process and image dates

Bands	Wavelength	Spatial resolution
Blue	0.45-0.52	30
Green	0.52-0.60	30
Red	0.63-0.69	30
Near Infrared	0.76-0.90	30
Shortwave Infrared -I	1.55-1.75	30
Shortwave Infrared -II	2.08-2.35	30
Images Date and Satellite Names		
15.07.1988 (Landsat 5)	27.07.1998 (Landsat 5) 22.07.2008 (Landsat 5)	18.07.2018 (Landsat 8)

3. METHOD

Each object on the Earth has spectral properties. The grouping of objects with the same spectral properties in satellite images is called classification (Oruç et al. 2007). It is classified under two headings as supervised and unsupervised classification. Unsupervised classification is generally the preferred method when there is no prior knowledge of the terrain. In this method, spectral classes of pixels with the same properties are created. (Çölkesen 2009; Kavzoğlu and Çölkesen 2010). In supervised classification, signature files are created for the objects to be subjected to the classification process, taking into account the sample regions on the Earth. According to this signature file, each pixel in the image is assigned to the class in which it is most similar (Ekercin 2007). In this study, SVMs, which is one of the supervised classification methods, is preferred (Vapnik 1995). SVMs are a learning method in the field of statistical learning theory. SVMs are based on finding the maximum separation boundary in different samples by transferring non-linear sample space to a high dimension where samples can be separated linearly (Demirci 2007; Eray 2008).

SVMs are a classification algorithm frequently used in the classification process in the field of remote sensing in recent years (Mondal et al. 2012; Kumar et al. 2015; Noi and Kappas 2018). The main advantage of this method is that it can easily generalize high-dimensional data with few training data. SVM works with pixels at the boundaries of classes called support vectors, so it is possible to obtain accurate classification with the small training set. DVMs use kernel functions for separate classes in complex datasets to identify hyperplanes with non-linear mapping operations. Generally, linear, polynomial, radial basis function (RBF) and sigmoid kernels functions are used in the classification of remote sensing images. Comparing the classification success of these four functions, it was observed that RBF kennel function given better results than others. In this study,

images belonging to different years were classified using the RBF kernel function (Kavzoğlu and Cölkesen 2009; Yang et al. 2011; Esetlili et al. 2018).

The workflow of determining the temporal change at Kahramanmaraş city center was shown in Fig. 2. First of all, Landsat 5 and Landsat 8 images of the related years were obtained. LULC classes were determined in the study area and training data were collected. According to the training data, classification process was performed with SVM algorithm for each year. In order to test the accuracy of the obtained LULC maps, 256 random points were placed in the study area. The error matrix was generated by these points and the classification accuracy was calculated. In the last stage of the study, the change of land use classes according to artificial surfaces was determined between the selected years.

Accuracy assessment was performed using error matrix (Table 2). In Table 2, the rows represent the classification values while the columns represent the reference values. $n_{i.}$ value is defined by the $\sum_{j=1}^{k} n_{ij}$ equation, while $n_{.j}$ is defined by the $\sum_{i=1}^{k} n_{ij}$ equation. Using error matrix, User's Accuracy (Eq. 1), Producer's Accuracy (Eq. 2), Overall accuracy (Eq. 3) and Kappa statistics (Eq. 4) were calculated for each LULC maps (Cohen 1960; Congalton and Green 1999; Jenness and Wynne 2005).
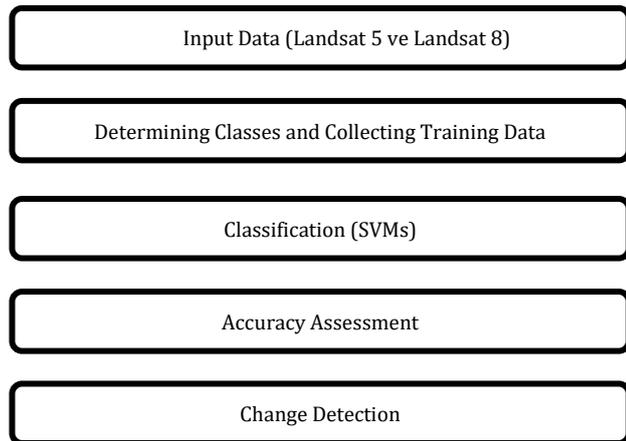
$$\text{Overall Accuracy} = \frac{\sum_{i=1}^{k} n_{ii}}{n} \tag{3}$$

$$\text{Kappa} = \frac{n \sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{i.} n_{.i}}{n^2 - \sum_{i=1}^{k} n_{i.} n_{.i}} \tag{4}$$

Table 2. Theoretical representation of the error matrix (Jenness and Wynne 2005)

		Reference Data			
		j_1	j_2	j_k	$n_{i.}$
Classification Data	i_1	n_{11}	n_{12}	n_{1k}	$n_{1.}$
	i_2	n_{21}	n_{22}	n_{2k}	$n_{2.}$
	i_k	n_{k1}	n_{k2}	n_{kk}	$n_{k.}$
	$n_{.j}$	$n_{.1}$	$n_{.2}$	$n_{.k}$	$n_{..} = n$

The explanations of the values given in the equations are as follows (Cohen 1960; Congalton and Green 1999; Jenness and Wynne 2005).

- k: the number of ROWS in the error matrix,
- n_{ii}: i th row and i th column element of the error matrix,
- n_{jj}: j th row and j th column element of the error matrix,
- $n_{i.}$: Sum of the i th row elements of the error matrix,
- $n_{.i}$: Sum of the i th column elements of the error matrix

3. RESULT AND DISCUSSION

In this study, LULC change of Kahramanmaraş city center from 1988 to 2018 was observed at 10-year intervals. Satellite images for each year were classified into seven classes that were artificial surfaces (asphalt roads, building) wetlands, cultivated agriculture, uncultivated agriculture, industrial area, forest, bare soil-rocky area (Fig. 3).

Accuracy analysis was performed on the LULC maps obtained after classification. During the accuracy analysis, 256 random points were generated. Reference class values and predicted values obtained by classification are assigned to the points. To determine the accuracy of the classification, Producer's Accuracy (P.A.), User's Accuracy (U.A.), kappa coefficient and overall accuracy values were calculated for each year over the error matrix (Table 3). According to accuracy results, the overall accuracy of the thematic maps was obtained 91.76%, 93.56%, 86.89% and 88.29%, respectively. Also, Kappa values for each year were obtained as 0.88, 0.91, 0.81 and 0.84, respectively.

Figure 2. The workflow in Kahramanmaraş city center temporal analysis

$$\text{User's Accuracy} = \frac{n_{ii}}{n_{i.}} \tag{1}$$

$$\text{Producer's Accuracy} = \frac{n_{jj}}{n_{.j}} \tag{2}$$

Table 3. Accuracy analysis results of the produced LULC maps for each year

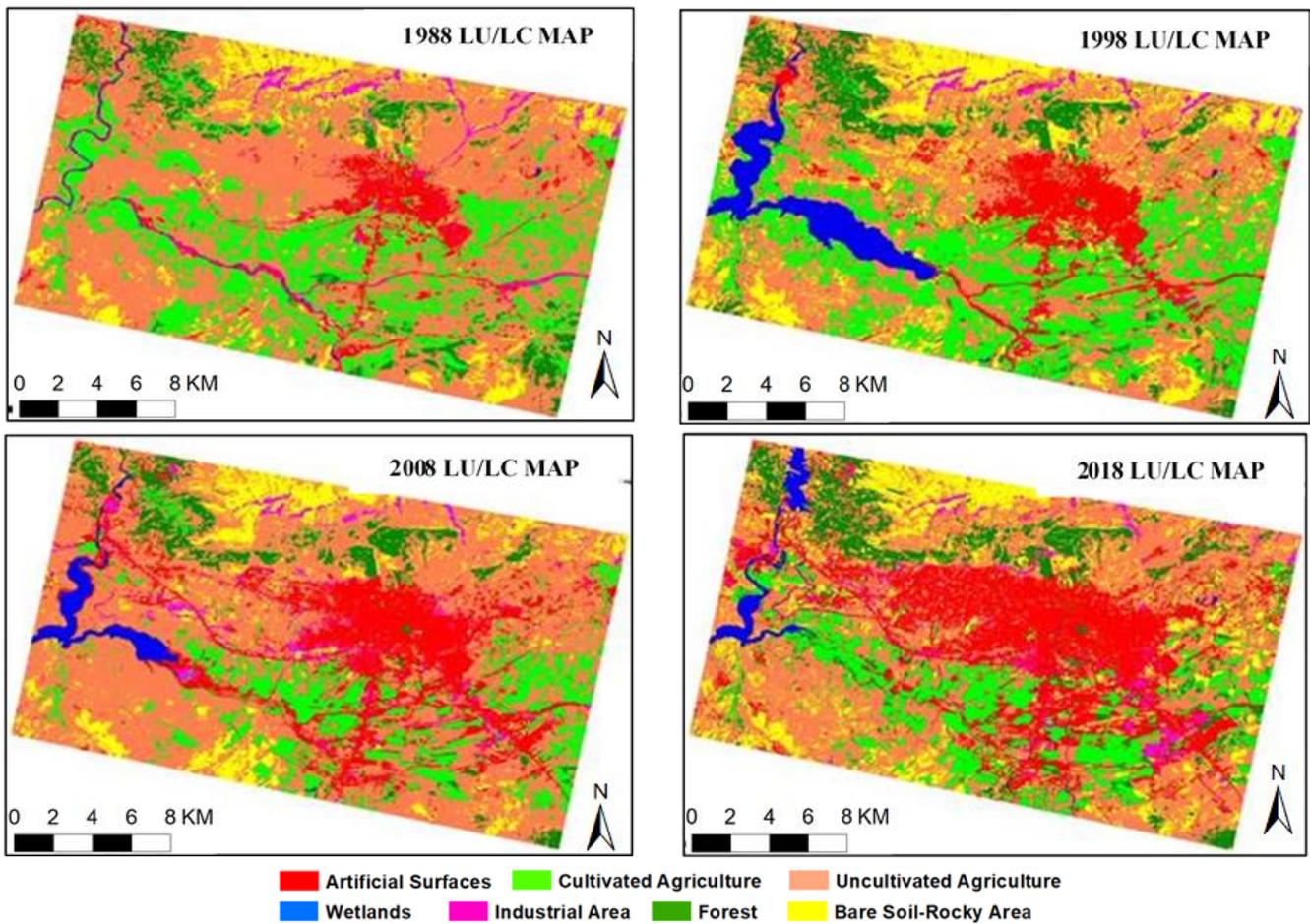| LU/LC Classes	1988		1998		2008		2018	
	U.A.	P.A.	U.A.	P.A.	U.A.	P.A.	U.A.	P.A.
Wetlands	87.80	100	72.41	95.45	100	100	100	100
Bare Soil-Rocky Area	68.42	76.47	100	66.67	68.42	81.25	56.00	87.50
Uncultivated Agriculture	96.26	89.57	96.30	89.66	87.79	92.23	96.43	81.82
Industrial Area	66.67	100	100	97.87	71.43	71.43	100	100
Artificial Surface	100	100	100	93.75	87.50	84.85	88.10	97.37
Forest Area	100	93.33	100	100	83.33	76.92	85.00	100
Cultivated Agriculture	87.80	100	90.00	100	95.83	79.31	91.30	87.50
Overall Accuracy	91.76		93.56		86.89		88.29	
Kappa	0.88		0.91		0.81		0.84	

Figure 3. Land use and land cover maps for each year

The area information for each class was calculated in hectares (ha) and the results are given in Table 4. Agricultural areas are presented as total of cultivated and non-cultivated agricultural areas. Considering the Table 4, wetlands were 133.92 hectares in 1988. After the Sır dam started to operate in 1991, wetlands increased by 1323.63 hectares in the first ten-year period. When the second and third ten-year periods were examined, a decrease of 851.31 hectares and 23.31 hectares was observed in wetlands, respectively. In the thirty-year period there has been a decrease of 7204.9 hectares of agricultural land. An increase of 500 hectares in forest areas and 4867.4 hectares in artificial surfaces have been observed. Also, industrial areas increased 35.3 hectares.

Table 4. Area of LULC classes for each year

LU/LC Classes	1988 (ha)	1998 (ha)	2008 (ha)	2018 (ha)
Wetlands	133.9	1457.5	606.2	582.9
Bare Soil-Rocky Area	2565.1	4726.71	2916.1	3618.5
Agriculture Area	25142.2	20115.1	20579.7	17937.3
Industrial Area	752.9	425.6	965.5	788.2
Artificial Surface	1899.2	3090.9	5090.2	6766.6
Forest	1690.7	2368.4	2026.5	2190.4

Scope of the study, in addition to the 30-year change between 1988 and 2018, change maps were prepared in 4 different periods (Fig.4). When the change map from 1988 to 2018 is analyzed, it is seen that the city shows great development, especially in the West direction. It can also be said that there is a considerable expansion in the East and South-East direction. It can be seen that artificial surfaces caused a great decrease in agricultural areas. In parallel with the expansion of the city area, it is seen that a large amount of agricultural land has disappeared.

Population data from the Turkey Statistics Institute (TUIK) was obtained to demonstrate the relationship between population growth and urban development (TUIK: URL-2). The relationship between population and urban area expansion was given in Fig. 5. When the figure is examined, it is seen that artificial surfaces increase in parallel with the increase in the urban population.

The speed and direction of urban development are essential in terms of future city planning. In this study, changes occurring in the 30 years in Kahramanmaraş were investigated with Remote Sensing techniques. One of the most important results occurring in the region between the years 1988-2018 is the decrease in the agricultural areas, while the increase in the residential areas is observed regularly. Due to the continuous increase in the population of Kahramanmaraş, agricultural areas are destroyed. The continuous decrease of these agricultural areas may interpret that the city has been converted into urban areas to meet the settlement needs. As a result of this transformation, it has been clearly observed that agricultural areas are used irregularly and land management plans for these areas should be made.
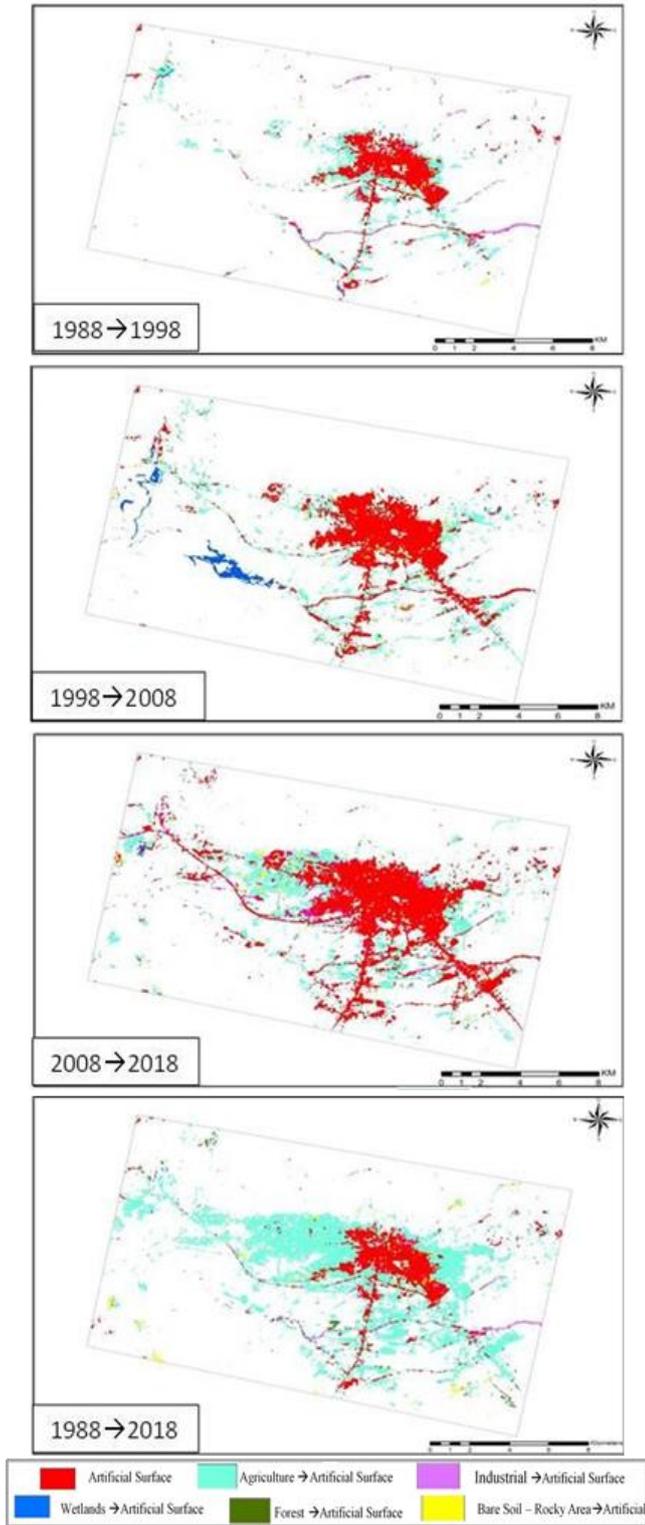
Figure 4. LULC change detection maps from 1988 to 2018

5. CONCLUSION

In this study, the temporal change of LULC classes of Kahramanmaraş city center was investigated. Accordingly, Landsat satellite images were used in 10-year periods between 1988 and 2018. Satellite images for each year was classified by the SVMs algorithm. The direction and amount of urban development is revealed through the obtained maps. In this context, the artificial surfaces in Kahramanmaraş city center have increased by 304% in the 30-year period. While this increase was

realized, especially a large amount of agricultural land disappeared. When the growth in the artificial surfaces is compared with the population data, it is seen that the urban areas increase with the increase in the population.
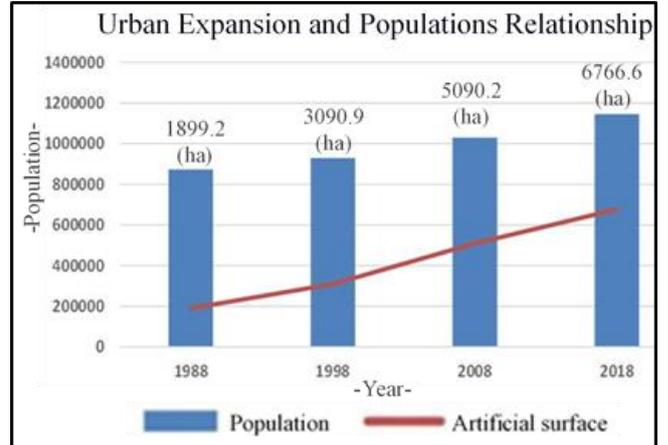

Figure 5. The relationship between population and artificial surfaces

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