

## **IMPACT OF LAND-USE CHANGE ON AGRICULTURAL PRODUCTION & ACCURACY ASSESSMENT THROUGH CONFUSION MATRIX**

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**ABSTRACT:** Land modification and its associated resources have grown considerably to be a serious issue that is currently attracting attention on a global scale, and they now form the core of environmental protection and sustainability. The current study used remote sensing and GIS techniques to evaluate land-use changes and their impacts on agricultural productivity over the study area, which included Tehsil Shorkot, District Jhang, Punjab, Pakistan. Arc GIS and ERDAS Imagine 15 software were used for image pre-processing in order to stack the layers, sub-set them, and mosaic the satellite bands. After pre-processing the photos, a maximum likelihood technique was used in a supervised image classification scheme to identify the land-use changes that had been noticed in the research area. The goal of the current study was. In 2010, there were 9.6 km<sup>2</sup> under water. By 2015, there were 21.04 km<sup>2</sup>, and by 2020, there were 19.4 km<sup>2</sup>. In 2010, there were 16.6 km<sup>2</sup> of built-up land; this number rose to 19.4 km<sup>2</sup> in 2015 and 26.8 km<sup>2</sup> in 2020. The total area covered by vegetation was estimated to be 513.2 km<sup>2</sup> in 2010, 601.6 km<sup>2</sup> in 2015, and 717.7 km<sup>2</sup> in 2020. The area covered by forest land use declined with time, from 90.8 km<sup>2</sup> in 2010 to 86.7 km<sup>2</sup> in 2015 to 61.84 km<sup>2</sup> in 2020, indicating a downward trend. The area used for bare land in 2010 was 528.54 km<sup>2</sup>, which significantly reduced to 429.64 km<sup>2</sup> in 2015 and then to 333.1 km<sup>2</sup> in 2020. The area of arid terrain that was once used for agriculture has dramatically shrunk. The results of this research will be beneficial for future land-use planning, urban and regional development, and a growth in agricultural production of different crops in the study area.

**Keywords:** Landuse; GIS; RS; agricultural production; Shorkot.

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### **INTRODUCTION**

Land alteration and the resources it affects have become important problems that are now at the centre of environmental sustainability and preservation on a worldwide scale. Maybe it's because to the growing effects of altered landuse and manifestation. Increased land-use changes as a result of faster population expansion and concurrent socio-economic development from various angles have brought the consequences to light more. Many people think that increased population and shifting purchasing patterns result in economic success. Rich urban residents' increased consumption of meat, nutrients, food, and dairy products has had a disastrous impact on the environment, the land, and agricultural production. A number of models, including CLUE, cellular automata (CA), and Markov chains, are used to predict changes in land use. The biophysical characteristics of a piece of land that make it appropriate for different types of agricultural production are just one aspect of land-use change in connection to agricultural

land. Planning for urban land-use has received considerable emphasis in a number of studies, whereas planning for rural land-use has gotten less attention. As has been observed in Pakistan's Bahawalpur city, agricultural land is extremely susceptible to being changed in many developed cities to non-agricultural unwanted uses (housing complexes, motorways, etc.). Consequently, it is vitally desirable to have adequate planning for the usage of agricultural regions in the future. This project's main objective was to establish a network that would enable future research into alternate approaches to the development of agricultural land use and output. Changes in land use are essential for maintaining the harmony of the world's ecosystems, but they are also highly influenced by human factors, such as governmental policies and the environment. To learn more about how land use has changed through time, consider historical practises, current land use patterns, and anticipated future land use trajectories.

On the pixel, which has been separated into three stages, its features, and the levels of the objects for

processing of images, several change detection algorithms are applied to classify land use. The potential for land-use changes to have a major natural impact on how agricultural land is used has been demonstrated by earlier study. Numerous studies have confirmed the environmental factors' effects on changes in land use. Remote sensing (RS) and geographic information systems (GIS) have shown to be very useful and important for evaluating and examining changes in land use. Remote sensing based on satellite data can offer synoptic land-use changes for a particular area and time period. For mapping the various vegetation species during the previous few years, studies have relied heavily on spatial remote sensing picture data.

Analysis of how changes in land use might impact agricultural production in the research region for the years 2010, 2015, and 2020 was the main objective of the current study. This involved taking into account important categories like water, vegetation, built-up areas, woods, and bare ground. To ascertain the effects of temporal fluctuations from 2010 to 2020, the crops of rice, wheat, and sugarcane were also added. It was found that while the areas of water, forest, and bare land use all

shrunk, the built-up area had increased.

## MATERIAL AND METHODS

**Investigation site:** The meaning of the word Shor, which was used to create the name Shorkot in Urdu, is associated with salty and waterlogging. This is the provincial capital of Punjab, Pakistan's Tehsil Shorkot, District Jhang. The location of Shorkot is between  $30^{\circ} 30' N$  and  $72^{\circ} 24' E$ . Approximately 56 kilometres separate this city from the region of Jhang on the Jhang-Multan road. Toba Tek Singh is located in the NE, about 35 kilometres away. The Shorkot is located about 131 metres above sea level (433ft). Before 2001, Shorkot held the position of Town Council. However, the city later benefited from the Tehsil Municipal Administration status (TMA). According to the 2017 census, tehsil Shorkot has a total area of about 1,158 square kilometres and a population of 670,255 people. In this region, rice, wheat, and sugar cane are the three principal crops grown. The map of the study area is shown in figure 1.

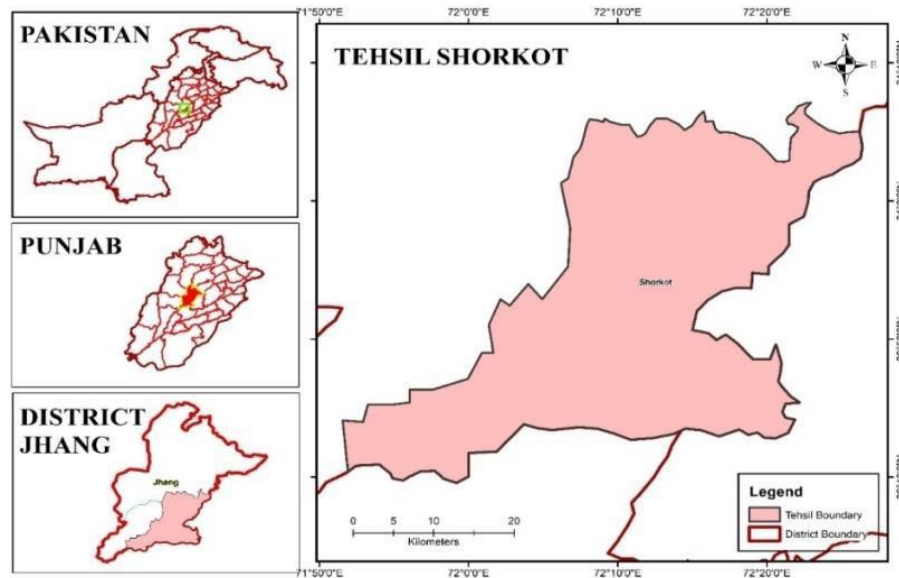


Figure 1. Study Site

**Material and method:** The United States Geological Survey's ([www.usgs.gov](http://www.usgs.gov)) and [Glovis.usgs.gov](http://Glovis.usgs.gov) websites provided the landsat satellite images for the years 2010, 2015, and 2020, which are presented in Table 1. The images were then categorised into the main land use groups. The statistics on crops for the years 2010 to 2020 were provided by the Tehsil Shorkot, District Jhang Office of the Punjab Agriculture Department.

**Image processing and classification (Maximum Likelihood):** Different methods, such as layer stacking in the ERDAS imagine 15 programme, were used on

Landsat/Sentinel-2 pictures made up of several bands (stacking is a technique to generate the multiband image from a distinct band) Mosaicing and subsetting (which blend the two separate images) (The research region was removed from the image after stacking)

In order to classify the land use and identify important changes in the research area, the maximum likelihood classification technique was applied to these composites. Following the creation of the polygons for each type of land use using Arc GIS 10.8, training samples were chosen [47, 48]. Ground validation using

differential GPS and spectral signatures were carried out to use training samples in supervised classifications. Using a supervised classification system, the land use photos were categorised; Table 1 contains details about these remote sensing images. Geostatistical modelling and multivariate techniques were used to forecast and analyse the impact of land subsidence on agricultural productivity.

**Table 1. Characteristics of acquired remote sensing images.**

| Sr No | Satellite   | Pixel-Size           | Year |
|-------|-------------|----------------------|------|
| 1     | Landsat 4-5 | 30 m                 | 2010 |
| 2     | Landsat 8   | 15 m (Pan-sharpened) | 2018 |
| 3     | Sentinel-2  | 10 m                 | 2020 |

**Classification Accuracy Assessment:** The overall accuracy of a particular image or classified map can be calculated using the classification agreement of the Cohen's Kappa coefficient [49]. Using kappa statistics, the overall classification accuracy was judged and rated. The accuracy of the results for each image for the categorise maps was assessed using the Kappa index. It is used to accept the impacts of accuracy changes, and its value shouldn't drop below 0.85.

$$\text{User Accuracy} = \frac{\text{Number of Correctly Classified Pixels in a class}}{\text{Total Number of Pixels in a Class}}$$

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in a class}}{\text{Total Number of Pixels in all Classes}}$$

$$\text{Overall Accuracy} = \frac{\text{Total Number of All Correctly Classified Pixels}}{\text{Total Number of Pixels in all Classes}}$$

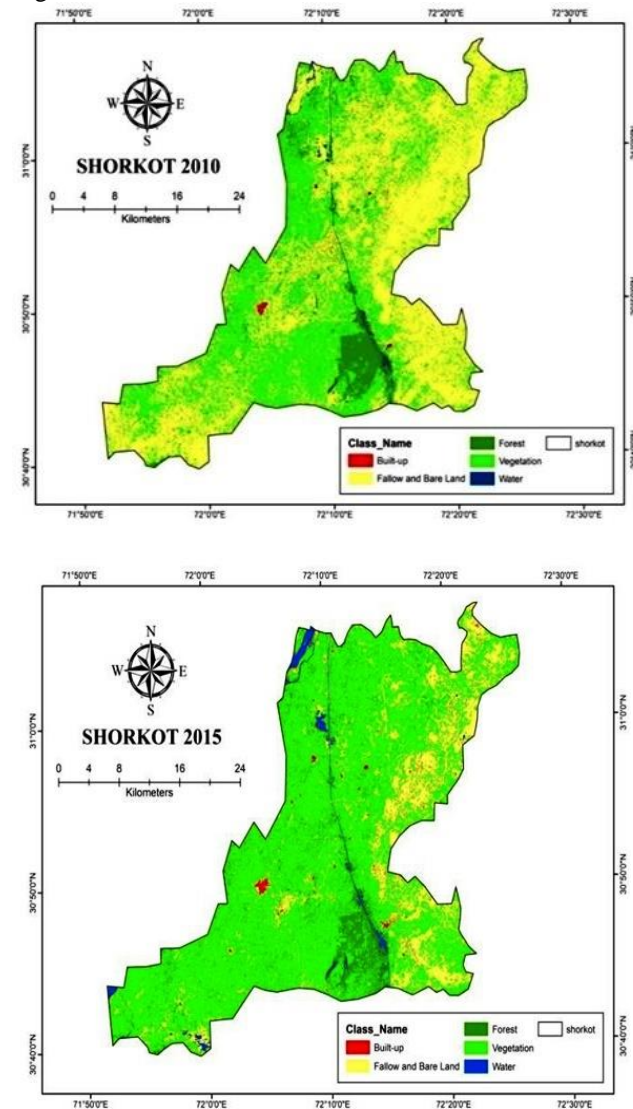
**Classification accuracy assessment:** The accuracy of categorisation was improved by the development of 100 reference points. The software recognised the pixel value of each point automatically. The user then manually assigned a class to each group of randomly generated points. The error matrix and kappa statistics were developed for the categorised photographs. The classification accuracy is displayed in the error matrix [50], where the rows represent the classes that were produced by classifying the image and the columns represent the classes that the user selected based on the reference values. The diagonal cells of the error matrix display the total number of successfully recognised pixels for each class of the reference and classified data. The erroneously recognised pixels represented by the off-diagonal cells represent a discrepancy between the reference data and the categorised data. There are two types of errors, namely omission and commission error, are occurred during the classification process.

Errors of commission occur when a categorization algorithm assigns pixels to a class to which they do not belong. The number of pixels that were

unintentionally assigned to a class could be counted in column cells of the class above and below the main diagonal. The accuracy of the Producer also indicated the number of commission errors. There are errors of omission for each class when pixels from one class are present in another class. The most removed pixels were in the row cells on the left and right of the major diagonal of the confusion matrix. The user's accuracy is another indicator of omission errors.

## RESULTS AND DISCUSSION

Due to haphazard and unplanned built-up areas, the study area's land-use changes are extremely important. As a result of these changes in land use, the amount of built-up area increased while the amount of forest and barren ground disappeared. The change in study sites from 2010, 2015, and 2020 are mapped in Figure 2.



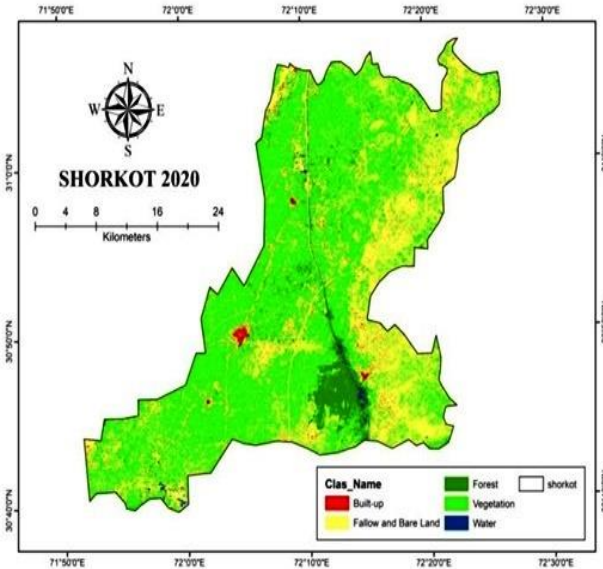


Figure 2. Land-use Change Analysis for the years 2010, 2015, 2020.

The area under water was occupied on 9.6 km<sup>2</sup> in 2010, 21.04 km<sup>2</sup> in 2015, and 19.4 km<sup>2</sup> in 2020, according to Table 2. Built-up area increased from 16.6 km<sup>2</sup> in 2010 to 19.4 km<sup>2</sup> in 2015 and 26.8 km<sup>2</sup> in 2020. A total of 513.2 km<sup>2</sup> was estimated to be covered by vegetation in 2010, 601.6 km<sup>2</sup> in 2015, and 717.7 km<sup>2</sup> in

2020. Indicating a negative trend, the area used for forest land decreased through time from 90.8 km<sup>2</sup> in 2010 to 86.7 km<sup>2</sup> in 2015 to 61.84 km<sup>2</sup> in 2020. In 2010, 528.54 km<sup>2</sup> of land was used for bare land; this amount considerably shrunk to 429.64 km<sup>2</sup> in 2015; and finally, to 333.1 km<sup>2</sup> in 2020. Arid land that was once used for agriculture has significantly decreased. The findings of this study will be beneficial for future land-use planning, regional and urban planning, and for boosting agricultural production of various crops in the study area.

According to the study area's research, changes in land use were the main factors affecting the region's agricultural output. Figure 3 analyses the study area's landuse change from 2010 to 2020. The rapid fall in the forest, vegetation, and barren ground plainly indicates the growth in the built-up and vegetated region. Another important objective of the current was to evaluate the impact of changes in land usage on agricultural production. 7.7 km<sup>2</sup> in 2020. According to the research, rice, sugarcane, and wheat each produced 34, 575, and 33 mounds (1 mound = 40 kg) per acre, respectively, in 2010. The agricultural output of wheat, sugarcane, and rice fell to 27, 900, 36, and respectively in the year 2020. Between 2010 and 2020, wheat production and arable land decreased, whilst rice and sugarcane production and arable land increased. (Table 3).

Table 2. Landuse change analysis of the study area for the Landsat images for the year 2010 to 2020.

| Landuse Class        | Area 2010 km <sup>2</sup> | Area 2015 km <sup>2</sup> | Area 2020 km <sup>2</sup> |
|----------------------|---------------------------|---------------------------|---------------------------|
| Water                | 9.6                       | 21.4                      | 19.4                      |
| Built-up             | 16.6                      | 19.4                      | 26.8                      |
| Vegetation           | 513.2                     | 601.6                     | 717.6                     |
| Forest               | 90.8                      | 86.7                      | 61.84                     |
| Fallow and Bare Land | 528.54                    | 429.64                    | 333.1                     |
| <b>Total</b>         | <b>1158.74</b>            | <b>1158.74</b>            | <b>1158.74</b>            |

Land Use Change Analysis from 2010 to 2020

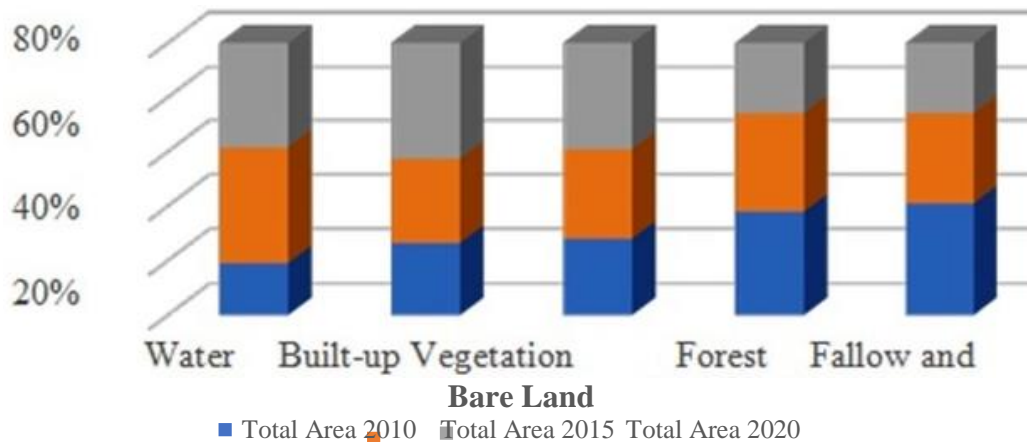


Figure 3. Landuse change analysis of the study area for the year 2010 to 2020

**Table 3. The production of wheat, sugarcane and rice crops in the years 2010 to 2020.**

| S. No | Year | Wheat Per Acre Production (mounds) | Cultivable Land (acres) | Sugar cane Per Acre Production (mounds) | Cultivable Land (acres) | Rice Per Acre Production (mounds) | Cultivable Land (acres) |
|-------|------|------------------------------------|-------------------------|---|-------------------------|-----------------------------------|-------------------------|
| 1     | 2010 | 34                                 |                         |   |                         |                                   |                         |
| 2     | 2011 | 34                                 | 185,980                 | 600                                     | 50,240                  | 34                                | 56,350                  |
| 3     | 2012 | 33                                 | 182,350                 | 600                                     | 49,550                  | 34                                | 56,900                  |
| 4     | 2013 | 34                                 | 179,990                 | 650                                     | 51,600                  | 35                                | 57,200                  |
| 5     | 2014 | 34                                 | 175,250                 | 700                                     | 52,250                  | 35                                | 57,730                  |
| 6     | 2015 | 31                                 | 175,550                 | 700                                     | 52,503                  | 34                                | 59,195                  |
| 7     | 2016 | 35                                 | 167,340                 | 650                                     | 52,350                  | 32                                | 60,250                  |
| 8     | 2017 | 31                                 | 168,250                 | 800                                     | 53,450                  | 33                                | 59,540                  |
| 9     | 2018 | 29                                 | 166,500                 | 900                                     | 61,350                  | 35                                | 60,450                  |
| 10    | 2019 | 26                                 | 163,460                 | 900                                     | 53,500                  | 35                                | 68,500                  |
| 11    | 2020 | 27                                 | 160,215                 | 900                                     | 52,400                  | 36                                | 68,800                  |

**Source:** Agriculture Department, Tehsil Shorkot (2020) accuracy of classification that was 81%, 80% and 83%  
 The confusion matrix were drawn to compute for the years 2010, 2015 and 2020,

**Table 4. Confusion matrix indicating the producer's accuracy, user accuracy, and overall accuracy 2010 LULC map of the study area.**

| Classified Data                     | Reference Data |       |       |            |        | Row Total | User Accuracy (%) |
|-------------------------------------|----------------|-------|-------|------------|--------|-----------|-------------------|
|                                     | Built-up       | Soil  | Crop  | Vegetation | Water  |           |                   |
| Built up                            | 29             | 6     | 0     | 0          | 0      | 35        | 82.86             |
| Soil                                | 1              | 12    | 2     | 0          | 0      | 15        | 80.00             |
| Crop                                | 0              | 1     | 19    | 3          | 0      | 23        | 82.61             |
| Vegetation                          | 0              | 1     | 3     | 14         | 0      | 18        | 77.78             |
| Water                               | 0              | 1     | 1     | 0          | 7      | 9         | 77.78             |
| Column Total                        | 30             | 21    | 25    | 17         | 7      |           |                   |
| Producer's Accuracy (%)             | 96.67          | 57.14 | 76.00 | 82.35      | 100.00 |           |                   |
| Overall Classification Accuracy (%) | 81             |       |       |            |        |           |                   |

**Table 5. Confusion matrix indicating the producer's accuracy, user accuracy, and overall accuracy 2015 LULC map of the study area.**

| Classified Data                     | Reference Data |      |       |            |       | Row Total | User Accuracy (%) |       |
|-------------------------------------|----------------|------|-------|------------|-------|-----------|-------------------|-------|
|                                     | Built-up       | Soil | Cro p | Vegetation | Water |           |                   |       |
| Built up                            | 27             | 3    | 0     | 0          | 0     | 30        | 90.00             |       |
| Soil                                | 2              | 7    | 1     | 0          | 0     | 10        | 70.00             |       |
| Crop                                | 0              | 2    | 18    | 5          | 0     | 25        | 72.00             |       |
| Vegetation                          | 0              | 0    | 4     | 15         | 1     | 20        | 75.00             |       |
| Water                               | 0              | 1    | 1     | 0          | 13    | 15        | 86.67             |       |
| Column Total                        |                |      |       | 29         | 13    | 24        | 20                | 14    |
| Producer's Accuracy (%)             |                |      |       | 93.10      | 53.85 | 75.00     | 75.00             | 92.86 |
| Overall Classification Accuracy (%) |                |      |       | 80         |       |           |                   |       |

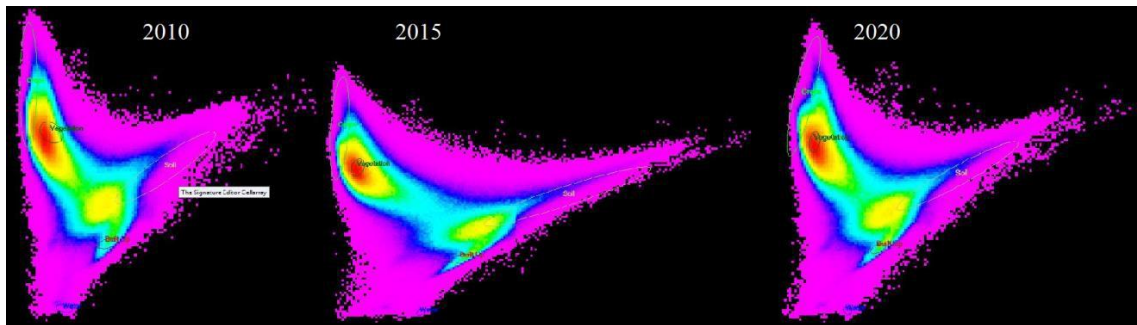


**Table 6. Confusion matrix indicating the producer's accuracy, user accuracy, and overall accuracy 2020 LULC map of the study area.**

| Reference Data<br>Classified Data   | Built-up | Soil  | Crop  | Vegetatio<br>n | Water | Row Total | User Accuracy<br>(%) |
|-------------------------------------|----------|-------|-------|----------------|-------|-----------|----------------------|
| Built up                            | 28       | 2     | 0     | 0              | 0     | 30        | 93.33                |
| Soil                                | 3        | 17    | 0     | 0              | 0     | 20        | 85.00                |
| Crop                                | 0        | 2     | 19    | 4              | 0     | 25        | 76.00                |
| Vegetation                          | 0        | 0     | 4     | 10             | 1     | 15        | 66.67                |
| Water                               | 0        | 1     | 0     | 0              | 9     | 10        | 90.00                |
| Column Total                        | 31       | 22    | 23    | 14             | 10    |           |                      |
| Producer's Accuracy (%)             | 90.32    | 77.27 | 82.61 | 71.43          | 90.00 |           |                      |
| Overall Classification Accuracy (%) | 83       |       |       |                |       |           |                      |

The scatterplots of results of classification are mapped in Figure 4. Confusion matrix indicating the producer's accuracy, user accuracy, and overall accuracy

for LULC map of the study area is presented in Table 3, 4, 5 and 6.



**Figure 4. Scatter plots.**

**Conclusion:** The investigation revealed a rapid and extraordinary transition in the land-use class from desert, wooded, and water to populated area and vegetation. The drop in the forest and dry land use groups was one of the main reasons for the decrease in agricultural output and increase in built-up area. The findings showed that historic conversion took place in the study area as a result of a reduction in forested and desert terrain caused by an accelerated growth in population density, the construction of infrastructure, and urban expansions. In addition, there has been constant change in the land-use classes from forested and arid to built-up and vegetated. To increase the country's agricultural output and economy, a fair check on the land-use changes is necessary.

Therefore, the current study will aid in enhancing the government's capacity to offer various corrective actions for reducing the impact of the conversion of agricultural or forest land to built-up area for sustainable management of land use. Planning for future land use and estimating agricultural output will both benefit from it.

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**Author's Contribution.** All the authors contributed equally.

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**Project details.** Nil

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