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# Satellite Imagery Employed to Analyze the Extent of Urban Land Transformation in The Punjab District of Pakistan

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## Abstract:

Satellite imagery represents a vital resource for comprehensively analyzing and monitoring the consequences of rapid urbanization. With the continuous expansion of urban areas, satellite data enables the detection of changes in land use, the spread of urban sprawl, and the development of infrastructure. In the Punjab district of Pakistan, accelerated urban growth has had adverse effects on agricultural land, leading to a decline in agricultural productivity and contributing to a national shortage of food supplies. The utilization of satellite images facilitates the assessment of urbanization's impact on key natural resources, including arable land, forests, wetlands, and river systems. Moreover, satellite-based analysis allows for the annual comparison of land transformation ratios, particularly the conversion of agricultural land into urban settlements. This process aids in identifying land ownership patterns and in understanding the spatial extent and progression of urban expansion. Integrating machine learning classifiers such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) with satellite data further enhances the accuracy of applications like land cover classification, change detection, and object recognition. The insights derived from these technologies offer valuable support to policymakers and urban planners, enabling them to develop evidence-based strategies for managing urban growth. Ultimately, such information is instrumental in guiding sustainable urban planning efforts, protecting environmental resources, and prioritizing conservation initiatives in rapidly developing regions.

**Keywords**: *Urbanization Transformation; Machine Learning; Satellite Imagery; Punjab; Pakistan.*

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# صور الأقمار الصناعية المستخدمة لتحليل مدى تحوّل الأراضي الحضرية في منطقة البنجاب في باكستان

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**ملخص:**

تُعد صور الأقمار الصناعية أداةً أساسيةً لتحليل ومراقبة آثار التحضر السريع بشكل شامل. ومع التوسع المستمر للمناطق الحضرية، تتيح بيانات الأقمار الصناعية الكشف عن التغيرات في استخدامات الأراضي، وانتشار الزحف العمراني، وتطور البنية التحتية. في إقليم البنجاب بباكستان، أدى النمو الحضري المتسارع إلى آثار سلبية على الأراضي الزراعية، مما أسفر عن انخفاض في الإنتاج الزراعي وأسهم في حدوث نقص في الإمدادات الغذائية على المستوى الوطني. تُسهم الصور الفضائية في تقييم تأثير التحضر على الموارد الطبيعية الرئيسة، بما في ذلك الأراضي الصالحة للزراعة، والغابات، والمناطق الرطبة، والأنهار. كما تتيح هذه الصور إجراء مقارنات سنوية لنسب تحوّل الأراضي الزراعية إلى مناطق حضرية، مما يساعد على تحديد أنماط ملكية الأراضي وفهم الامتداد المكاني والتطور الزمني للتوسع العمراني. وتُعزز دقة التحليلات عند دمج صور الأقمار الصناعية مع خوارزميات تعلم الآلة مثل الغابات العشوائية (Random Forest)، وآلة المتجهات الداعمة (SVM)، وأقرب الجيران (KNN)، وذلك في تطبيقات متعددة مثل تصنيف الغطاء الأرضي، واكتشاف التغيرات، والتعرف على الأجسام. وتُقدم المعلومات المستخرجة من هذه التقنيات دعمًا قيّمًا لصانعي السياسات والمخططين الحضريين، مما يمكّنهم من تطوير استراتيجيات قائمة على الأدلة لإدارة النمو الحضري. وتُعد هذه البيانات ضرورية لتوجيه جهود التخطيط الحضري المستدام، وحماية الموارد البيئية، وتحديد أولويات مبادرات الحفاظ عليها في المناطق التي تشهد نمواً حضرياً متسارعاً.

**الكلمات المفتاحية:** *التحول العمراني؛ التعلم الآلي؛ صور الأقمار الصناعية؛ إقليم البنجاب؛ باكستان.*

# 1. Introduction

First of all, explanation of the topic in the light of the current literature should be made in clear, and precise terms as if the reader is completely ignorant of the subject. In this section, establishment of a warm rapport between the reader, and the manuscript is aimed. Updated, and robust information should be presented in the ‘Introduction’ section**.**

Images of the Earth taken by satellites and other comparable aircraft-based sensor systems are known as satellite imagery. These images are useful for gathering important information because they are updated frequently to reflect how humans' footprints are changing all across the planet. The dynamic process of urbanization keeps plenty of people confined to relatively small places. As a result of population growth, which has been occurring fast for several decades because of migration, urbanization, and a sharp increase in fertility rates, urban planning is becoming more and more important. Urban development causes a wide range of socioeconomic and environmental problems, both good and bad. In recent years, cities have been home to 50% of the world's population. This number is projected to rise above a billion by 2025. Accelerated, poorly managed urbanization causes air, land, and water pollution in addition to ineffective resource use and widespread agricultural land deterioration. Changes in land use and land cover have a global impact on the environment. Land use and Land cover alterations may be caused by manmade or natural factors. Factors affecting urbanization include population growth, urban expansion, changes in regional and regional environmental characteristics, loss of agricultural land and depletion of other natural resources (Zhao et al., 2022). People travel from rural to urban areas in nations like Pakistan in search of better facilities, putting strain on the natural resources that are available. Economic expansion makes urbanization inevitable, which increases the demand for housing and the density of urban areas (Busgeeth et al., 2008).

Unprecedented population increase results in a wide range of environmental and social issues, including inadequate livelihoods, law and order issues, a limited supply of water and a decline in its quality, and climate change (Patra et al., 2018; Murmu et al., 2019). By 2050, up to 70% of the world's population may live in urban areas, which is cause for concern (Zhang, 2016). The migration of thousands of people from rural areas to urban areas every day (Khan et al., 2024a) in order to improve living conditions causes great pressure on the city’s economy and business environment (Lin et al., 2019).

Cities Due to the growth of cities and people, cities expand spatially and physically (Zlotnik, 2017), leading to increased urban areas, inadequate cover, and changes in climate and oceans (Khan et al., 2023; Sakieh et al., 2015). Key problems resulting from unplanned cities include inadequate housing, traffic congestion, basic human services, health problems, unemployment, education (Raza et al., 2024; Al-Khasawneh et al., 2024; Khan et al., 2024b; Farooq et al., 2019), slums, violence, clean water and power outages, and the environment depression (Tanguay et al., 2010; Raza et al., 2023; Khan & Asif, 2024; Dai et al., 2024). These factors together have an impact on urban life (Ghalib et al., 2017). Unplanned housing projects resulting from the use of funds to transform agricultural land into urban centers are a major factor in urban expansion in developing countries (Khan & Khan, 2025; Li et al., 2017). Socioeconomic and biophysical factors have an impact on the size and scope of LULC changes in various regions of the world (Farooq et al., 2019). Some of the most important elements affecting any region's hydrological regime are variations in land use and land cover (Nyatuame et al., 2020). Unchecked population growth, rapid urbanization, and spatial agricultural expansion/contraction are the main factors influencing changes in land use and cover (Shahzad et al., 2024; Hassan et al., 2016; Raza et al., 2023).

Particularly in low- and middle-income nations, unplanned urbanization and a rapidly expanding population frequently struggle to retain their multisource spatial data as well as to monitor and comprehend the city morphology. For planning and management, spatial data on urban sprawl and population growth have become essential, and RS & GIS play a vital part in this. Urban sprawl can be measured using traditional approaches, such as population census numbers, but these take time. Cost-effect metrics are ineffective for evaluating urban settings. In order to create integrative plans and mitigation measures, it is necessary to study population increase and urbanization spatially.

Cities Manandhar et al. (2009) have undoubtedly grown due to the rapid population growth, economic development, and infrastructure construction activities. Monitoring and anticipating urban growth in terms of settlement planning, transit, landscaping, etc. is crucial for sustainable cities. Currently, we are able to get the necessary data with high geographical, spectral, and temporal data.

This study's Giustarini et al. (2012) main objective is to analyze the geographic patterns of urbanization and population growth in four significant Pakistani cities by assessing the capacity of freely accessible datasets to understand the dynamics of spatially heterogeneous cityscapes. The distribution of land use and the spatial growth pattern with population density dynamically in four cities are explored using a variety of sensor data and high-resolution imageries. The cost-effective planning that can be done in middle-income cities that are rapidly urbanizing will undoubtedly benefit from this research.

Satellite imagery refers to photographs of the Earth or other planets taken from a camera mounted on a satellite orbiting the planet. These images provide a unique and often highly detailed perspective of the Earth's surface and are used for a wide range of applications, including mapping, monitoring natural disasters, urban planning, and environmental monitoring.

The land is the foundation of survival, but the human beings have been continuously transformed land for thousands of years, especially in recent decades the speed of urbanization has been incredible, and it is expected that this process will continue throughout the century (Hassan, 2016). This rapid transformation of agricultural land has become a core issue at the forefront of global environmental change and sustainable development. It can affect the vegetation coverage and can cause temperature changes and wind speed. It is continuously threatening the ecological security of regional land resources.

In land cover classification, satellite images are used to train ML model to recognize different types of land cover, such as forests, urban areas, and agricultural land. This model is trained to identify the distinctive features of each type of land cover, such as the spectral reflectance patterns, texture, and shape.

**Main contribution of this work as follow:**

The primary objectives of this study are to examine the spatial distribution of urbanization and population increase in two districts of Pakistan by using satellite imagery, which is a type of snapshot acquired from a satellite orbiting a planet of the Earth or other planets. In comparison to earlier years, the rate of urbanization is increasing significantly faster today. Therefore, it is difficult to anticipate the Land cover region in advance.

## 2. Related work

The machine learning-based approach for classification is one of the best approaches for classification. The major reason is that it is very difficult to have information in detail about the whole land area of interest in remote sensing satellite imagery field (Lin et al., 2019). Supervised machine learning is much better as compared to the unsupervised machine learning approach for classification because this provides the data for training data to classify the image for further analysis (Khan et al., 2023). The Selection of the machine learning classifier is the most challenging task, and the major reason is not just the wide range of machine learning classifiers available but also matters the accuracy and efficiency of the classifier. To cite only a few examples, researchers in (Sakieh et al., 2015) show that the ANNs were more accurate than both DTs either a single DTs or boosted DTs but move toward the opposed conclusion, that the DTs outperformed ANNs. The Naive Bayes classifier obtained higher accuracy in comparison with the DTs classifier when the number of samples is fewer, and the accuracy performance becomes a worse performance as the number of training samples exceeds a specific size. With the smaller sample points of training data, the machine learning classifier or the ANN classifier outperformed while the SVM classifier achieves high accuracy (Raza et al., 2024). Researchers in (Al-Khasawneh et al., 2024) RF and SVM performed nearly equal in terms of accuracy, while found that SVM performed better compared to RF.

Khan et al. (2024 b) mentioned that in current times, climate change is imposing severe impacts in the form of droughts all around the world. Machine learning approaches like SVM can be used for the prediction of drought situations to send early warning alerts to prepare the vulnerable communities for their adverse impacts. SVM is one of the popular binary classifiers and the widely used algorithm in the remote sensing field this is highly accurate classification results with small training data along with these samples are in closer proximity to the margin of the class that discriminates the classes in better manners as compared to another sample data of the training (Farooq & Beg, 2019). SVM machine learning algorithm emphasizes finding the appropriate optimal hyper-plane that splits the training samples and places them into numerous classes after this training sample data are placed near the marginal boundaries of the data class. The small distance to the hyper-plan is used as the support vector for actual training. The use of kernels in the SVM algorithm plays a vital role in obtaining the results of classifications. With the numerous ranges of kernels, the RBF kernel is better because it has user-defined parameters that help to control the influence of the training sample on the boundary margin of the decision, but these parameter values should be balanced if it is too higher than the is the chance of over-fitting increases. That's the reason to maintain the right decision for the selection of value for user-defined parameters (Tanguay et al., 2010; Raza et al., 2023)

Tehrany et al. (2015) conducted a trial where specialists performed Support Vector Machine (SVM) calculations in different fields of study such as flood vulnerability assessment and avalanche assessment. Hereditary computing is recognized as the most progressive and inevitably created heuristic pursuit models in artificial intelligence, finding applications in urban layout, environmental exploration, atmospheric demonstration, and remote sensing. Mueller et al. (2016) revealed that Landsat satellite symbology is profitable for different plans, for example, measuring the difference in the atmosphere and debacles identified with Earth and common asset managers. Landsat information is most regularly used in phenomena-oriented applications. Borra et al. (2019) proposed that the satellite image clustering methodology involves the collection of image data with respect to the area of highlight diversity, and various techniques are open for the characterization of satellite images to create a guide. These maps can get different characteristics or properties to achieve the perfect work. Several different techniques consolidate guided and unguided layouts to provide an estimate of the accuracy of remote sensing data, which is a fundamental essential part of characterization (Nyatuame et al., 2020).

Extraction of the land cover and its changes serves as the initial stage in monitoring and evaluating urban sustainability. The MLC-Maximum Likelihood Classifier and post-classification change detection were employed in the majority of experiments. This methodology was used to highlight the Hangzhou city recently urbanize areas last three years (2001-2003); In this study Ahmed and Ahmed (2012), authors have study the area covered by urban in Bangladesh, Dhaka city for twenty eight years (1975-2003) In the Egyptian desert of Kom Ombo (Faid and Abdulaziz, 2012), investigated the pattern of land cover change from 1998 to 2008 as a result of agricultural development and urban growth; Hepcan et al. (2013) researched the urban development in Izmir, Turkey; Meyer et al. (2014) found the land cover change and accompanying population increase and decline in Samara, Russia, around about thirty seven years (1972-2009).

## 3. Method and materials

The proposed method that is used to achieve the concerned study objectives consists of several steps, as seen in Figure 1. In this, we will use raw satellite imagery using Landsat 8 Satellite dataset and apply different necessary operations to pre-process it as mentioned below. The United States Geological Survey-USGS operates under the jurisdiction of the US Department of the Interior. It's a government lab dedicated to studying Earth's ecosystems. Its goal is to disseminate scientific knowledge to the public for the betterment of disaster preparedness, environmental policy, and resource management. The office also supplies information to legislators and civic leaders to aid in policymaking.

In 1879, the USGS was founded. The original purpose of the organization was to investigate the geology and geography of the country. The findings were supposed to be used to determine how to categorize public lands for planning purposes. The USGS was established in order to adapt to the developing needs of the country. It has, over time, done everything from mapping the environment to aiding conservation efforts to conducting surveys of flora and natural water supplies.

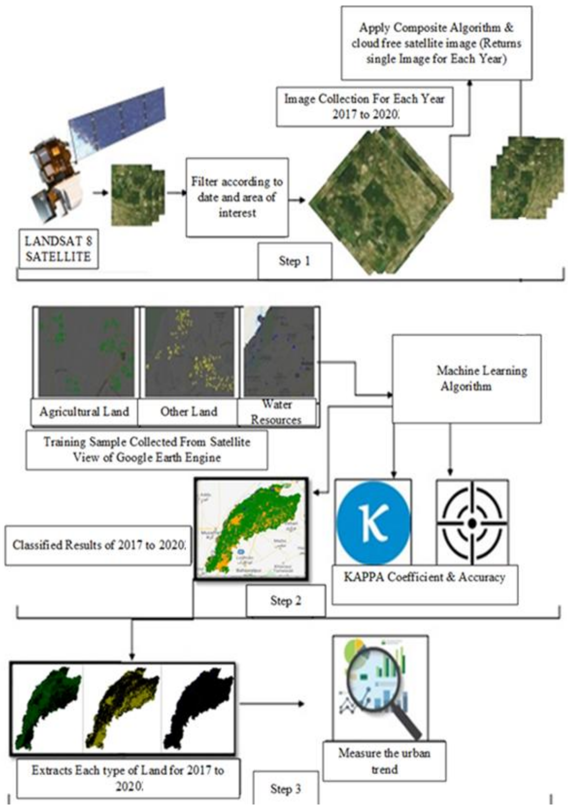


Figure 1 Overview of Proposed Methodology

### 3.1 Study Area

When discussing urbanization, the term "study area" is used to describe the precise area that is the focus of research into urbanization's patterns, processes, or effects. The scope of a study is determined by the questions or hypotheses to be tested. For this research, we combined the districts of Multan and Khanewal.

- **Multan**

***The city of Multan sits on the banks of the Chenab River in Punjab, Pakistan. According to the most recent census (2017), Multan was the seventh most populous city in Pakistan. Multan, Pakistan is located at latitude of 30.19838 and a longitude of 71.4687028000007. Information about Multan is tabulated below.***

Table 1 Multan Attribute Detail

| Variable | Details |
|---|---|
| Latitude DMS | 30º11'54.17"N |
| Longitude DMS | 71º28'7.33"E |
| UTM Easting | 737,662.27 |
| UTM Northing | 3,343,344.25 |
| UTM Zone | 42R |
| Position from Earth’s Center | ENE |
| Elevation | 125.42 Meters (411.482 Feet) |
| District | Multan |
| Province | Punjab |
| Country | Pakistan |

- **Khanewal**

Khanewal is a city in the Punjab province of Pakistan and the district capital of the same name. In terms of population, it is only the 36th most populous city in Pakistan. Khanewal, Pakistan may be found at coordinates 30.303934 and 71.9298795, respectively. Information about Khanewal is tabulated below.

Table 2 Khanewal attribute Detail

| Variable | Details |
|---|---|
| Latitude DMS | 30º18'14.16"N |
| Longitude DMS | 71º55'47.57"E |
| UTM Easting | 781,775.74 |
| UTM Northing | 3,356,101.75 |
| UTM Zone | 42R |
| Position from Earth’s Center | ENE |
| Elevation | 136.87 Meters (449.06 Feet) |
| District | Multan |
| Province | Punjab |
| Country | Pakistan |

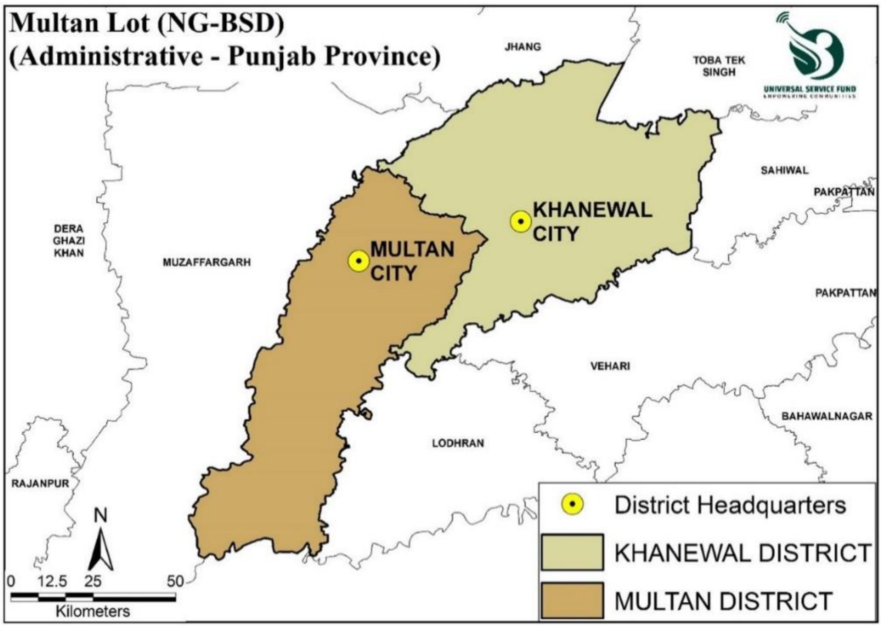


Figure 2 Study Area of this work

### 3.2 Dataset Preparation

We obtained four annual Landsat TM/ OLI images from the United States Geological Survey (https://glovis.usgs.gov/) (Table 1) for both Multan (30o1154.17N, 71o287.33E) and Khanewal (30o1814.16N, 71o5547.57E). The dates of 2017 through 2020 indicate when these photographs were taken. We will refer to these years from here on as IM2017, IM2018, IM2019, and IM2020. Three or four pictures were taken every year. The research area's winter and spring crops and other features are at their peak activity from October through December; thus, a four- to five-month interval is necessary between image captures at this time. This helps isolate impermeable surfaces from other forms of land cover. In these pictures, the cloud cover was around 20% over the research region. We have utilized the QGIS program to create the stack shown in Figure 23 (Bands 2-7) and to capture the three features (Vegetation, Urbanization, Water). After that, we performed radiometric calibrations and atmospheric corrections using the ENVI FLAASH software (Excelis Visual Information Solutions Inc, Boulder, Colorado), as displayed in Figure. We used Google Earth to collect basic geographical data, like place names (Multan, Khanewal), lakes, green or vegetation area, highways, buildings, airports, and slum regions.

### 3.3 Preprocessing of Satellite Imagery

Image processing is a method to perform some operations on an image, to get an enhanced image or to extract some useful information from it. There are some consecutive operations which are performed to preprocess the data consisting of the satellite imagery and make it able for further processing to obtain the described results.

#### 3.3.1 Data Range Filtering

Based on the study area, we have captured raw satellite imagery and filtered it based on a date range (2017-2020). Specifically, our analysis is based on the years 2017 to 2021, and selects the timeframe from January 1st, 2017, to December 1st, 2020, for each year. To perform this date range filtering operation, we would need to process the satellite imagery data and extract the corresponding dates for each image. Then, you can compare the dates to specified range to determine if an image falls within the desired timeframe.

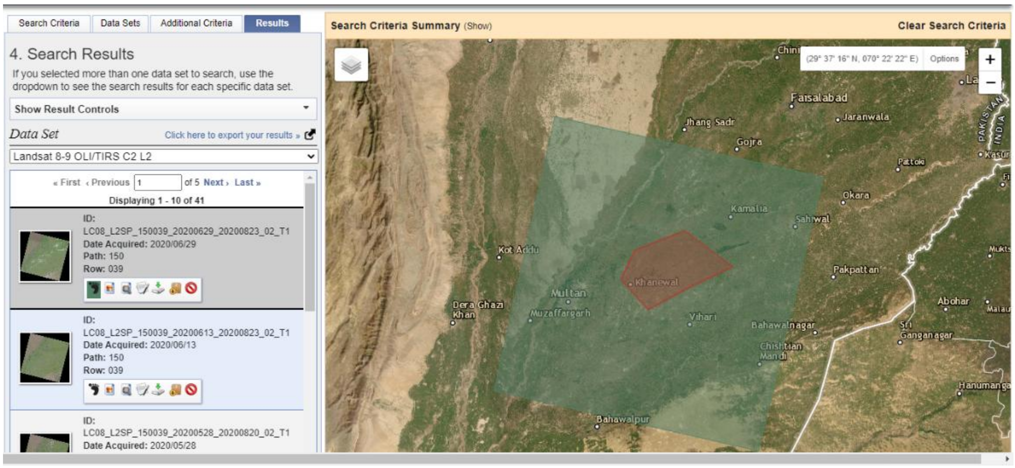


Figure 3 UGIS Sample Filter Data

### 3.3.2 Area Filter Band

Multan and Khanewal are cities situated in the southern region of Punjab, Pakistan. Here are some additional details about these cities:

– **Multan**

1. Coordinates: 30.1575° N, 71.5249° E
2. Multan is the sixth-largest city in Pakistan and is located on the banks of the Chenab River.
3. Multan is a major cultural and economic center in Punjab and is famous for its handicrafts, pottery, and textile industry.
4. The city has a significant agricultural sector, with major crops including cotton, wheat, sugarcane, and mangoes.

– **Khanewal**

1. Coordinates: 30.2864° N, 71.9320° E
2. Khanewal is a city located in the southern part of Punjab province, near Multan.
3. It is an important transportation hub, as it lies on the main railway line between Karachi and Lahore.
4. Khanewal district is predominantly agricultural, with crops such as wheat, cotton, and sugarcane being grown in the area.
5. The city has a railway junction and is a major stop for trains traveling between the southern and northern parts of Pakistan.
6. Khanewal is also known for its production of quality cotton yarn and textiles.

Both Multan and Khanewal have historical, cultural, and economic significance in the region, contributing to the overall development and prosperity of southern Punjab, Pakistan. To filter raw satellite imagery data for a specific administrative area like the Multan district and its tehsils, you would typically require specialized geographic information system (GIS) software or access to satellite imagery providers or data repositories. These tools can help you retrieve, filter, and analyze satellite imagery based on specific geographical boundaries and parameters.

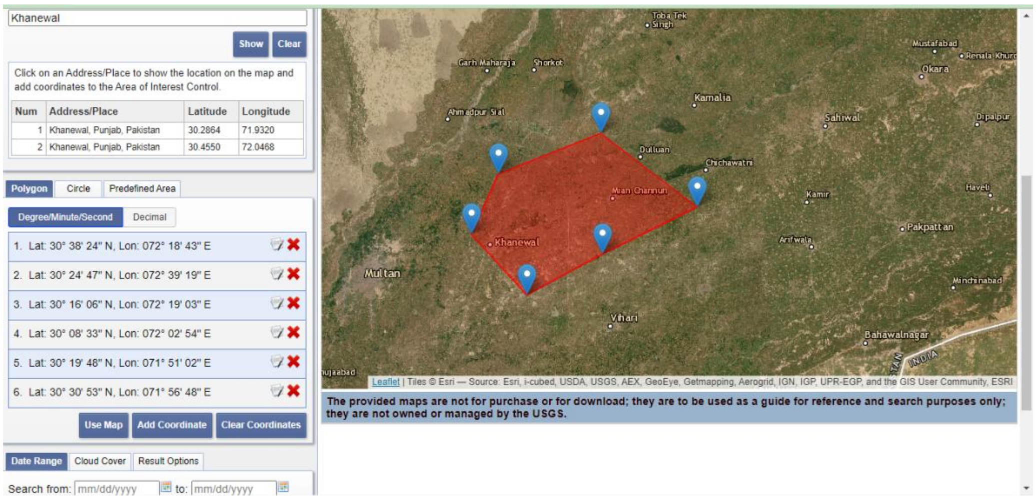


Figure 4 Sample of Study Filter

### 3.4 Cloud Filtration with Composite Algorithm

The composite algorithm combines the spatially overlapping satellite imagery from bands of different year's samples into a single image for each year. This process involves merging the data from years to create a consolidated representation that incorporates the best features from each image. By combining the spatially overlapping areas of the satellite imagery from bands years, the composite algorithm aims to create a single image that represents the best available information for each specific year, incorporating the strengths of both images while minimizing any limitations or gaps.

The composite algorithm is combining the spatially overlapping of both years' satellite imagery collection into a single image for each year from 2017 to 2020, but both images are based on aggregation function with to select the least cloudy raw images for further processing.

#### 3.4.1 Collection Training

Utilizes the satellite view of the ENVI software and chooses the training sample points through the ROI tools for the ML-Machine Learning Classifier. Based on the collected training sample, teach the model, and we use feature sets to label training samples. Each element has an attribute, green means vegetation resources, dark brown means agricultural area, and blue means water resources. The process involves using the satellite view of ENVI software and utilizing ML classifiers to label training samples based on specific features. By utilizing the satellite view within ENVI software, along with machine learning classifiers and carefully selected training samples, this workflow allows for the automated labeling and classification of land cover classes based on satellite imagery.

#### 3.4.2 Machine Learning Classifier

In this process, a ML classifier is used to classify raw satellite imagery at the pixel level. This classification is performed based on labeled training data sample points, and the classifier generates classification results for further processing. The classification results involve multiple classes (Vegetation, Water, Urban), where each image is classified into various three categories. ML classifier classifies the raw satellite imagery on the bases of pixel-level classification according to the labeled training data sample points and generate the classification results for further processing. The classification results are based on multiple classes, where each image is classified on the bases of many classes. It's important to note that the number of classes and the specific categories used for classification can vary depending on the application and the objectives of the analysis. The ML classifier allows for the automated and efficient processing of large-scale satellite imagery to generate accurate and detailed classification results for further analysis and decision-making.

# 4. Results

The overall accuracy provides an assessment of the proportion of correctly labeled samples out of the total number of samples. It serves as a general measure of the model's performance but may not capture class imbalances or specific errors for different classes. Additional evaluation metrics like precision, recall, F1 score, or class-specific accuracy can provide more detailed insights into the model's performance for individual classes. By analyzing the confusion matrix and computing the overall accuracy, one can evaluate the effectiveness of the machine learning model in correctly classifying the samples and make informed decisions based on the classification results. The overall accuracy of classification is obtained by the confusion matrix of the machine learning model, which is the proportion of the total sample that the predicted value of the statistical sample is consistent with the actual value (measure the number of samples that are correctly labeled).

$$\text{Overall Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

## 4.1 Results Evaluation

It appears that a machine learning classifier generates results on a yearly basis, categorizing land into three different types: Urban Land, Agricultural Land, and Water Resources. Machine learning classifiers can be trained to analyze satellite imagery data and classify land cover based on various features and patterns. By utilizing satellite imagery data, a machine learning classifier can extract information such as vegetation, built-up areas, and water bodies to differentiate between different land cover types. Urban Land typically refers to areas with buildings, infrastructure, and human settlements. Agricultural Land represents areas where farming activities take place, including cultivated fields or pastures. Water Resources include lakes, rivers, reservoirs, and other water bodies.

The machine learning classifier can process the satellite imagery data and assign each pixel or region to one of the three land cover classes based on its characteristics and the patterns it identifies. This classification can be performed annually to monitor land cover changes over time and analyze trends in urban expansion, agricultural practices, and water resource dynamics. It's important to note that the accuracy of the classification results depends on the quality and resolution of the satellite imagery used, the training data provided to the classifier, and the algorithms implemented. Additionally, manual verification and validation of the results are typically necessary to ensure accuracy and address any misclassifications or errors that may occur. So, by using the classification results obtained from the machine learning classifier, it is possible to analyze the rate of change in land due to urbanization on a year-by-year basis.

### 4.1.1 Extraction of each kind of land

To extract each type of land (Urban Land, Agricultural Land, and Water Resources) from the results of the ML classifier for the years 2017 to 2021 and ENVI convert the classified pixels into square kilometers. ENVI will be able to extract the area of Urban Land, Agricultural Land, and Water Resources for the years 2017 to 2021 based on the similarity of the classified pixels and convert them into square kilometers. This information can help in analyzing the changes in land cover and quantifying the extent of each land cover class over time. From the results of the ML classifier, extract each type of land (Urban Land, Agricultural Land, and Water Resources) for the year 2017 to 2021 and then calculate all the pixels of a resultant classified image on the bases of similarity and convert them into square km from the pixel.

### 4.1.2 Analysis to measure the changing trends

After extracting the area of each land cover class (Urban Land, Agricultural Land, and Water Resources) for the years 2017 to 2021, we can apply analysis to measure the rate of change in the land and analyze the changing pattern. This information about urbanization trends can be valuable for various departments and stakeholders. Analyze the results of the rate of change and the changing pattern of land cover. This information can be valuable for various departments and stakeholders. For example, urban planning departments can use the data to understand the pace and extent of urbanization, agricultural departments can assess changes in agricultural land and plan accordingly, and environmental departments can monitor the impact of land use changes on water resources and ecosystems. After the extraction of each land, apply mathematical functions to measure the rate of change in the land occurred from 2017 to 2021 and by the changing pattern of land. Information about the urbanization trend is useful for many departments.

**4.2 Study Area (2017-2020)**

When examining urbanization, it is crucial to define the study area, which refers to the specific geographic region that serves as the focal point for investigating the patterns, processes, or impacts of urbanization. The selection of the study area is typically guided by the research objectives, questions, or hypotheses that need to be addressed. In the context of this research, the study area encompasses the districts of Multan and Khanewal. These districts were chosen based on the research objectives and their representation of urbanization phenomena in the region under study.

To gain a comprehensive understanding of urbanization in the study area, it is essential to analyze and compare data from different time periods. For this purpose, the ENVI tool, popular software used for remote sensing and image analysis, was employed. The tool enables the capture and visualization of the study area over a span of time, providing valuable insights into the temporal dynamics of urbanization.

The captured figure 5, obtained using the ENVI tool, depicts the study area from 2017 to 2020. These images likely consist of satellite imagery or other remote sensing data sources that have been processed and analyzed using the ENVI tool's functionalities. The resulting visual representations allow researchers to observe and quantify the changes in urban land cover, infrastructure development, and overall urban growth within the study area over the specified period. By examining the captured figures, researchers can identify notable spatial and temporal patterns of urbanization. This may include the expansion of urban areas, the conversion of rural or agricultural land into built-up areas, the emergence of new infrastructure or settlements, and other changes associated with urban development. These observations can be further analyzed and interpreted to draw insights and conclusions regarding the processes and impacts of urbanization in the Multan-Khanewal region. Overall, the utilization of the ENVI tool to capture the study area figures from 2017 to 2020 provides researchers with valuable visual information, enabling a detailed examination of urbanization dynamics over time. This data serves as a foundation for conducting in-depth analyses, modeling, and assessment of the urbanization phenomena in the study area.

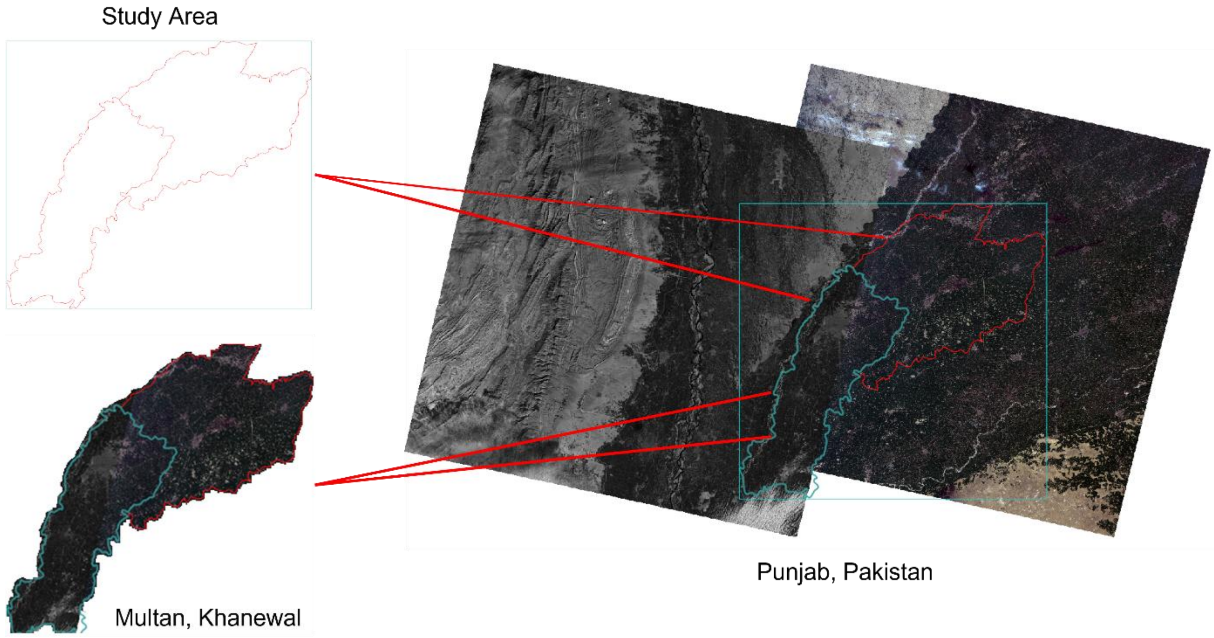


Figure 5 Capture study Area by QGIS Software

**4.3 Class Labeling**

In this research, the ENVI software's satellite view capability is utilized to analyze the study area and investigate urbanization patterns. The ENVI software provides a powerful platform for remote sensing and image analysis, allowing researchers to process and interpret satellite imagery effectively.

To train the ML classifier, the researchers employ the ROI tools within the ENVI software. These tools enable the selection of specific sample points within the satellite imagery that represent different land cover classes. By carefully choosing training sample points, the researchers ensure that the ML classifier learns to differentiate between various land cover categories accurately. Using the selected training sample points, the ML model is trained to recognize and classify different land cover classes. The researchers utilize a set of features extracted from the satellite imagery to label the training samples. These features may include spectral information, such as the intensity of different wavelengths of light reflected by the Earth's surface, as well as spatial attributes, such as texture or shape characteristics.

Each element or pixel within the satellite imagery is associated with a specific attribute based on the trained ML model's classification. In the context of urbanization classification, the researchers define certain categories based on their objectives and the characteristics of the study area. For example, they may assign the attribute "green" to represent vegetation resources, "dark brown" to denote agricultural areas, and "blue" to signify water resources.

By labeling the training samples with these attributes, the ML model learns to associate specific spectral and spatial patterns with each land cover category. As a result, when applied to the entire satellite image, the ML classifier can accurately classify the different land cover classes across the study area.

This approach allows for a comprehensive analysis of urbanization patterns by distinguishing between vegetation resources, agricultural areas, and water resources. By leveraging the ML classifier trained on the selected training samples and utilizing the feature sets derived from the satellite imagery, the researchers gain insights into the spatial distribution and changes of these land cover classes over time. Overall, the integration of the ENVI software's satellite view, ROI tools, and ML classifier facilitates a detailed and accurate classification of the study area. By assigning attributes to different land cover categories, the researchers can effectively analyze urbanization patterns and understand the dynamics of vegetation, agriculture, and water resources within the study area. As shown in Figure 6.

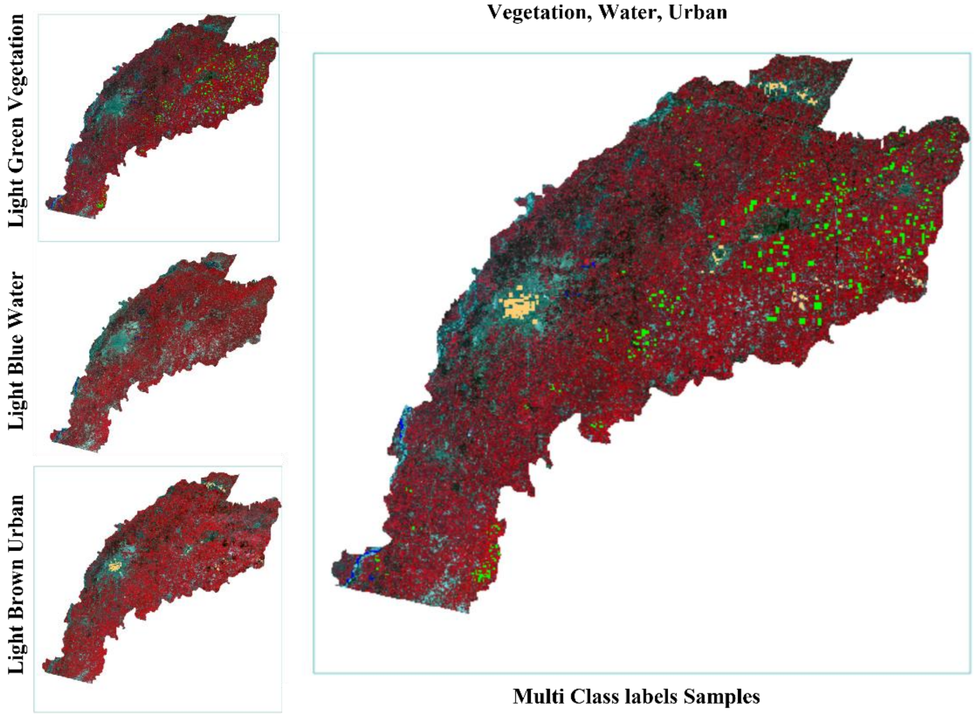


Figure 6 Features Labeling for Classification

### 4.4 Training KNN Machine Learning Algorithm

In the process described, a ML classifier is employed to classify raw satellite imagery at the pixel level. This classification aims to assign each pixel within the satellite image to a specific land cover class, such as Vegetation, Water, or Urban. The classifier's ability to perform this task is based on its training with labeled training data sample points.

The labeled training data sample points are carefully selected from the satellite imagery, representing different land cover classes of interest. These sample points serve as labeled examples that the machine learning classifier learns from. By analyzing the spectral and spatial characteristics of these labeled samples, the classifier develops an understanding of the unique features associated with each land cover class.

Once the ML classifier is trained, it can be applied to the entire raw satellite imagery. Each pixel in the image is evaluated based on its spectral values and surrounding context and the classifier assigns it to one of the predefined land cover classes. This process is known as pixel-level classification.

The classification results obtained from this process are valuable for further analysis and processing. The results provide information about the distribution and spatial extent of different land cover classes within the satellite imagery. For example, gain insights into the locations and patterns of vegetation, water bodies, and urban areas. It is important to note that the classification results involve multiple classes, typically more than just the three mentioned (Vegetation, Water, Urban).

The ML KNN classifier's ability to classify the raw satellite imagery into multiple classes provides a more detailed understanding of the land cover composition within the study area. This information can be used for various purposes, such as land use planning, environmental monitoring, or urban growth analysis.

In summary, the process involves utilizing a ML classifier to perform pixel-level classification on raw satellite imagery. Labeled training data sample points enable the classifier to learn the spectral and spatial patterns associated with different land cover classes. The classification results obtained from this process provide valuable insights into the distribution of land cover classes within the imagery, facilitating further analysis and applications in various domains. Figure 7 is showing the training classification of each feature.

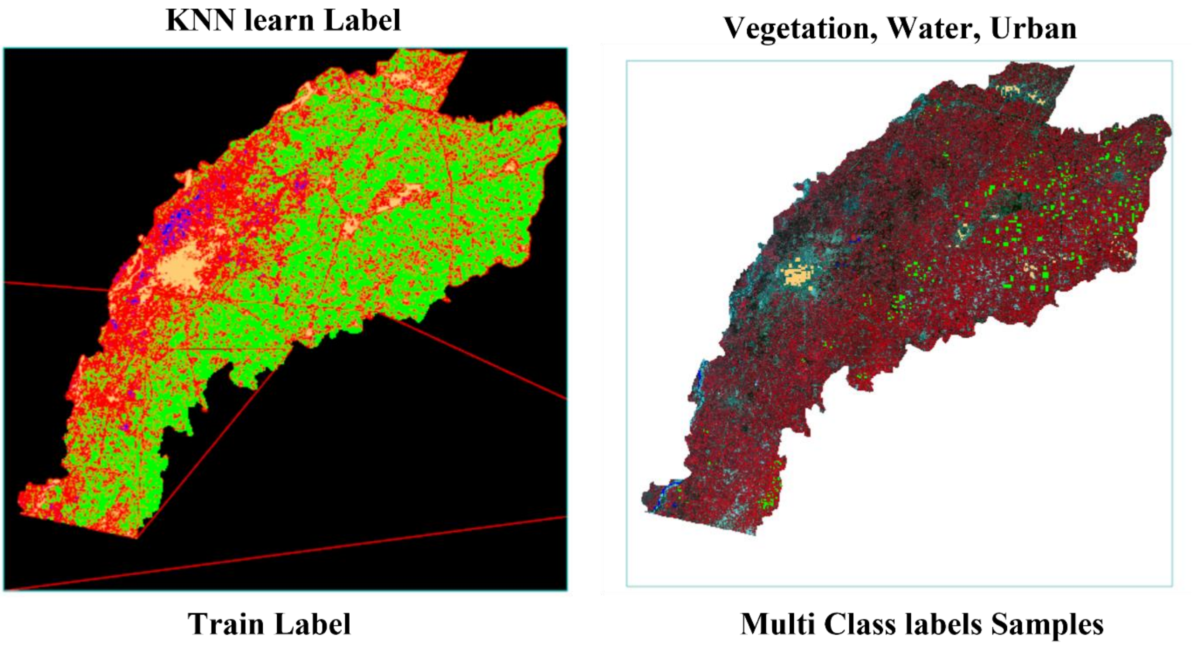


Figure 7 KNN Learn Labels

Table 3 KNN Train Classified Areas and types of land cover and use in Pixels (GT), measured in 2017-2020

| Year | Study No | Period | Vegetation Area | Water Area | Urban Area |
|---|---|---|---|---|---|
| | S1 | 01/12 – 03/12 | 635717 | 675093 | 1347875 |
| 2017 | S2 | 05/04 – 07/04 | 1246560 | 2133146 | 4999463 |
| | S3 | 09/09 – 25/12 | 6378587 | 264328 | 1749880 |
| | S1 | 03/04 – 06/04 | 6834368 | 103454 | 1459301 |
| 2018 | S2 | 08/12 – 09/12 | 6578212 | 446149 | 1364238 |
| | S3 | 12/10 – 12/12 | 4014892 | 29529 | 4346018 |
| | S1 | 01/17 – 03/17 | 6405752 | 834569 | 1149113 |
| 2019 | S2 | 06/27 – 08/27 | 7142768 | 45577 | 1211867 |
| | S3 | 10/09 – 11/09 | 6485874 | 705155 | 1211207 |
| | S1 | 01/22 – 03/16 | 6739925 | 537049 | 1123220 |
| 2020 | S2 | 08/04 – 09/04 | 6875440 | 108490 | 1400517 |
| | S3 | 11/13 – 12/25 | 6113693 | 745311 | 1545743 |

Based on the Vegetation label, Water label, and urban mark assigned during the pixel-level classification process, the resulting classification of the satellite imagery using the KNN algorithm can be compared to the ground truth values. These ground truth values serve as a reference or benchmark against which the accuracy of the KNN classification can be assessed.

Table 3, which displays the Pixel Ground Truth values of the KNN Training classification result, presents a comparison between the assigned labels by the KNN algorithm and the actual land cover classes based on ground truth data. This table allows for an evaluation of the accuracy of the KNN classifier in correctly identifying and classifying different land cover features.

By analyzing the tables, we can assess the performance of the KNN classifier in terms of accuracy. The accuracy is determined by comparing the assigned labels (Vegetation, Water and Urban) to the ground truth values for each pixel in the satellite imagery. If the assigned label matches the ground truth value, it indicates a correct classification, contributing to the overall accuracy of the classifier. The results presented in the table demonstrate the capability of the KNN algorithm to identify land cover features with acceptable accuracy. The acceptable accuracy achieved by the KNN classifier indicates its effectiveness in distinguishing between Vegetation, Water, and Urban classes within the satellite imagery. This information is valuable for understanding the spatial distribution and extent of these land cover categories and can be utilized in various applications, such as land management, environmental monitoring, or urban planning.

In conclusion, the comparison between the Pixel Ground Truth values and the KNN Training classification result provides insights into the accuracy of the KNN classifier in identifying different land cover features. The acceptable accuracy achieved by the classifier demonstrates its effectiveness in distinguishing Vegetation, Water, and Urban classes within the satellite imagery, enabling valuable applications and analysis in various domains.

**4.5 Testing Result**

Table 4 presents the technical details of a study, indicating different periods of observation and the corresponding areas covered by Vegetation, Water, and Urban land cover classes. The values in the table represent the area in square meters and the percentage of the total study area covered by each land cover class during specific periods. For example, Table 4 in Study No "S1" during the period from January 2012 to March 2012, the Vegetation Area covered approximately 1,121,904,000 square meters, which accounted for 14% of the total study area. The Water Area covered approximately 1,919,831,400 square meters, accounting for 9% of the study area. The Urban Area covered approximately 4,499,516,700 square meters, representing 23% of the study area.

Similarly, the table provides the respective values for Vegetation, Water, and Urban land cover classes during other study periods (S2 and S3) with their corresponding percentages. These technical details allow researchers and stakeholders to quantitatively analyze and compare the extent of different land cover classes over time, providing insights into the changes in vegetation, water bodies, and urban areas within the study area.

Table 4, In addition to the absolute area values, the table includes percentages in parentheses. These percentages represent the proportion of each land cover category relative to the total area of the study area during the corresponding period. For example, in S1, the Vegetation Area covers 26% of the total study area, the Water Area covers 8%, and the Urban Area covers 25%.

By presenting the area values and percentages for each land cover category across different study periods, the table allows for the comparison and analysis of changes in land cover over time. Researchers can examine the variations in the extent of vegetation, water bodies, and urban areas, providing insights into the dynamics of land cover patterns and the effects of factors like urbanization, climate, or land management practices.

It is important to note that the specific units used for area measurement (e.g., square meters, square kilometers) are not mentioned in the table, so it is assumed that the units are consistent across all values within each column. Additionally, the percentages provide a relative understanding of the land cover composition but do not represent the absolute changes in the area values between study periods.

Overall, the table offers a technical representation of the area and proportion of different land cover categories within the study area for each study period, facilitating the analysis and comparison of land cover dynamics over time.

Table 4 Areas and types of land cover and use, measured in 2017-2020

| Year | Study No | Period | Vegetation Area | Water Area | Urban Area |
|---|---|---|---|---|---|
| | S1 | 01/12 – 03/12 | 1121904000.00 (14%) | 1919831400.00 (9%) | 4499516700 (23%) |
| 2017 | S2 | 05/04 – 07/04 | 1101904000.00 (10%) | 1619831400.00 (7%) | 5499516700 (24%) |
| | S3 | 09/09 – 25/12 | 5740728300.00 (25%) | 237895200.00 (1%) | 5499617770 (24.2%) |
| | S1 | 03/04 – 06/04 | 5920390800.00 (26%) | 1819831400.00 (8%) | 5590016700 (25%) |
| 2018 | S2 | 08/12 – 09/12 | 1920390800.00 (16%) | 401534100.00 (1%) | 5599987700 (25.3%) |
| | S3 | 12/10 – 12/12 | 3613402800.00 (16%) | 36576100.00 (0.9%) | 5790087722 (27%) |
| | S1 | 01/17 – 03/17 | 1121904000.00 (14%) | 1919831400.00 (9%) | 5790088800 (27.01%) |
| 2019 | S2 | 06/27 – 08/27 | 6428491200.00 (28%) | 411534700.00 (1%) | 5793286700 (27.05%) |
| | S3 | 10/09 – 11/09 | 5837286600.00 (25%) | 634639500.00 (2%) | 5796244770 (27.08%) |
| | S1 | 01/22 – 03/16 | 6065932500.00 (27%) | 483344100.00 (2%) | 5796244770 (27.08%) |
| 2020 | S2 | 08/04 – 09/04 | 6187896000.00 (27%) | 976418000.00 (1%) | 5799244770 (28%) |
| | S3 | 11/13 – 12/25 | 5502323700.00 (25%) | 670779900.00 (3%) | 5997777770 (30%) |

## 5. Discussion

This study provides detailed technical data for three different study periods (labeled as S1, S2, and S3) within the years 2017 to 2020. The data focuses on three land cover categories: Vegetation Area, Water Area, and Urban Area. Each table corresponds to a specific study period, while each column represents one of the land cover categories.

For each study period, the table presents numerical values that represent the area of each land cover category within the study area. The area values are measured in appropriate units (e.g., square meters) and indicate the extent of each land cover category during the respective study period. This information allows for a quantitative analysis of the changes and patterns in land cover over time within the study area.

The tables provide valuable insights into the dynamics of land cover classes by presenting the area values for each category during different study periods. It allows us to examine the shifts and changes in land cover categories over the specified timeframe.

The cross-tabulation matrices often referred to as the Pixel Ground Truth, further depict the nature of changes in the land cover classes. Specifically, they illustrate the transition or shifts that occur between different lands cover categories. For example, the matrices show that within the agriculture class, there was an increase from 10% to 25% between 2017 and 2020. Out of this increase, around 25% to 27% originated from a conversion of Vegetation, while the remainder came from changes in Settlement areas.

The Water class, on the other hand, retained a relatively small portion throughout each year from 2017 to 2020. Meanwhile, the other land cover classes, such as Urban and potentially other categories not specified experienced overall increases in their areas each year.

By examining the cross-tabulation matrices, we can gain a deeper understanding of the changes in land cover classes over time and the interactions between different categories. These matrices provide valuable information on the transitions and dynamics within the land cover composition of the study area, shedding light on the processes driving the changes observed. Overall, this study presented, along with the cross-tabulation matrices, enable to analyze and interpret the patterns and changes in land cover over the study period, facilitating a comprehensive understanding of the dynamics and transformations within the study area's land cover composition.

## 6. Conclusion

We conclude that land cover/land use practices in the study area have changed dramatically over the past 20 years based on results collected using GIS, QGIS, and ENVI software to meet the specified research objectives. The LULC change in the watershed region was reflected in the smaller share of land used for vegetation and water (3%), and the larger share of land used for agriculture (25%), and urban development (30%). The deforestation and water scarcity that resulted from this expansion were its most noticeable effects on the Vegetation and Water classes. Furthermore, by 2020, all of these shifts in land cover and land use patterns had negatively impact water quality and accessibility, which could become a future limiting factor. Vegetation cover in watershed areas is decreasing, and urbanization and agricultural practices may be to blame. Mapping and analyzing land use change via Remote Sensing and GIS can help. This rich water resource will soon be lost or unable to play its needed role in agricultural production and social and economic development of the area if it is not properly managed. The present study concludes with several recommendations for the sustainable management and conservation of the depleting forest, water, and soil resources in the watershed.

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