Impacts of Urbanization on Agricultural Land in Multan District: Past and Future Trend Analysis Using Remote Sensing Approach

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(2021-NUST-MS-GIS & RS-000000361729)

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Remote Sensing and GIS

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August 2024

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ACKNOWLEDGEMENTS

All praises to Allah Almighty, and blessings upon Prophet Muhammad (PBUH). I owe my sincere gratitude to my respected research supervisor Dr. Ejaz Hussain, for his devoted guidance and encouraging attitude throughout the research. I am also very thankful to my Guidance Examination Committee (GEC) members, Dr. Muhammad Arshad (Prof., IESE, NUST) and Mr. Naqash Taj Abbasi (NDMA) for their constant support and guidance throughout the research phase.

Secondly, I would be delighted to thank my seniors Muhammad Arslan Tahir, and Muhammad Ali Awan for helping me during the whole period of my research. I am pleased to acknowledge the support of my family for showing me their love, support, and best wishes throughout my educational period. I am highly thankful for their continuous motivation and contribution to my self-confidence and success.

Aneeza Aslam

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
GDP	Gross Domestic Product
LULC	Land Use Land Cover
NDVI	Normalized Difference Vegetation Index
RS	Remote Sensing
GIS	Geographical Information Systems
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MBE	Mean Bias error
NPP	Net Primary Production
USGS	United States Geological Survey
CA-ANN	Cellular Automata-Artificial Neural Network
BOA	Bottom of Atmosphere
TOA	Top of Atmosphere
CCRI	Cotton Crop Research Institute
MDA	Multan Development Authority
DEM	Digital Elevation Model
AOI	Area of Interest
UA	User Accuracy
PA	Producer Accuracy
K	Kappa
OA	Overall Accuracy

SUSTAINABLE DEVELOPMENT GOALS (SDGs)

The Sustainable Development Goals (SDGs) are a collection of 17 global goals established by the United Nations in 2015. These are a part of the 2030 Agenda for Sustainable Development, which is a universal call to action to end poverty, protect the planet, and ensure that all people enjoy peace and prosperity by 2030. The SDGs are interconnected, addressing global challenges including poverty, inequality, climate change, environmental degradation, peace, and justice.

This study aligns with the following SDGs;

Urbanization reduces the availability of agricultural land, impacting the food production. Analyzing these trends can help make strategies to ensure food security.

The use of remote sensing technology in analyzing land use changes demonstrates the role of innovation and technology in sustainable development.

The study of urban expansion and its impact on land use supports creating sustainable urban policies and practices.

Land use changes due to urbanization contribute to climate change. Understanding these changes can help develop strategies for mitigation and adaptation.

Urbanization leads to the degradation of land and ecosystems. This study can help to understand and mitigate these impacts, promoting sustainable land use.

Through these alignments, this study not only serves the immediate needs of food security but also the sustainable development in future.

ABSTRACT

Agriculture plays a consequential role in the economy of Pakistan. Cotton being one of the major agricultural production supports the textile sector of the country, and is the main contributor to the Gross Domestic Product (GDP). The planned as well as unplanned land use changes in the urban areas are consuming the precious agricultural land, which in turn can severely affect food security and the industry, especially the textile sector. Thus, there is a need to timely monitor such changes for better-informed decisions making. Remote sensing is an advanced technology that has proved to be advantageous in the temporal Land use and Land cover (LULC) change analysis. The current study aims to explore the relationship between LULCs using multi-temporal, multi-sensor data to analyze how urban growth and other land use changes affected the agricultural land (especially the traditional cotton-cropped areas) in the Multan district. The LULC temporal analysis will help highlight the upcoming challenges for this highly agriculture-productive area and sustainability. This study used Landsat-7 data and Sentinel-2 (L1C) data for the years 2001, 2017 and 2021. LULC classification accuracy for the respective years was 80, 88, and 84%. The change analysis revealed that built-up area increased from 2% to 9% from 2001 to 2021, bare land increased from 2% to 5%, cotton decreased from 39% to 24%, and other agricultural production increased from 55% to 60%. Cellular Automata-Artificial Neural Network was used for the future LULC prediction for the year 2031. The model prediction accuracy was about 83%. The future LULC prediction results depict that the urban areas and bare land would increase at the expense of agricultural areas including the cotton-cropped areas. These results highlight the importance of sustainable land use planning, its effective implementation, and regular monitoring. The study results can help local stakeholders and development authorities in decision-making for sustainable.

CHAPTER 1

INTRODUCTION

1.1 Urbanization

Urbanization, globalization, and industrialization would be better alternatives if the transformation of human society since the Industrial Revolution were to be summarized. There is a close relationship between these three dimensions. Economic growth is a direct result of industrialization, and in both mature and newly industrialized nations, this expansion fuels the rapid process of urbanization (Henderson, 2003).

The developing world is now the focus of global urbanization instead of the developed world (Chen et al., 2014). Expansion of urban areas as a result of population growth and rural-to-urban shift is termed urbanization. Urbanization is closely associated with industrialization and the transformation of sparsely occupied land into densely occupied land.

Urbanization of time describes the extent of a specific condition at a certain interval thus, representing the period at which the proportion of urban areas is rising (Qasim et al., 2014). The global urbanization rate increased from less than 30% to over 50% between 1950 and 2010 (Brockerhoff & Nations, 2012).

Asia is rapidly becoming an urbanized region, home to over half of the world's major cities. The current urban population growth rate in Asia is 52.3%. In certain nations, like China and Korea, urbanization followed the well-known historical trend of income growth. However, in other regions, such as Pakistan, urbanization happened despite enduring poverty and ineffective governance (Glaeser, 2014).

1.1.1 Urban Growth in Pakistan

Pakistan is urbanizing at the highest rate in South Asia, i.e. at about 3 percent annually and approximately one-third of its population lives in cities (Pakistan Bureau of Statistics, 2022). Migration is a major factor in Pakistan's urbanization. People from rural areas are now moving to cities in search of better basic amenities and employment opportunities as well as to flee conflict, insecurity, and natural disasters.

The country's growing urban population can also be explained by the significant natural increase in Pakistan's overall population. As per the estimation of the United Nations Population Division, approximately half of the country's population is expected to live in cities by 2025 (Kugelman, 2013; Qasim et al., 2014).

1.2 Agriculture

Although the agriculture sector is diverse but also has discrepancies. The contribution of the sector to the global economy is relatively small but remains vital to a large number of the population. Out of 7.1 billion people globally, an estimated 1.3 billion were directly linked to agriculture, however, the added value of agriculture along with the modest hunting/fishing and forestry subsections stood at only 2.8 percent of GDP (Alston & Pardey, 2014).

1.2.1 Agriculture in Pakistan

Pakistan and other least developing countries (LDCs) rely heavily on agriculture for their economy. Agriculture is an integral part of Pakistan's economy. It contributes 22.04% to the national GDP (Jatoi, 2021). Instead of maximized production, this sector is geared to curtail food insecurity, provide the means of subsistence, and foster national connectivity.

The rural areas in Pakistan are occupied by almost 70 percent of the total population. About 45 percent of the labor force is involved in agriculture. Lessening poverty and unemployment are the primary objectives of the agriculture sector being a major demand of the country. Autonomy to profitability transformation of the agriculture sector is the need of the hour.

Wheat, cotton, sugarcane, rice, and maize are the major crops in Pakistan. According to the Economic Survey of Pakistan, these crops contribute nearly 25.6% of the agriculture sector and almost 5.4% to the country's GDP. Wheat is a staple food crop of Pakistan, dominating all crops in production. Cotton is a profitable crop that meets the needs of raw materials for the textile industry.

Rice is a cash crop and a food crop. Pakistan is known for producing high-quality rice which is most popular all over the world. Sugarcane is grown as a food crop as well as a cash crop. It serves as the primary source of sugar in Pakistan. The contribution of these major crops to the agriculture sector and GDP is shown in Table 1.1.

Pulses, oil seeds, gram, mustard, and barley are the minor crops in Pakistan. Their contribution to the agriculture sector is 11.6% (Usman, 2016). As per the Federal Bureau of Statistics (2015-2016), two-thirds population of the country is supported by this sector including a labor force of 42.3% (74.5% female and 36.2% male). It generates a significant portion of the foreign exchange profits for the nation (Azam & Shafique, 2017).

Table 1.1: Contribution of major crops in the agriculture sector and GDP

S No.	**Crops**	**Agriculture Sector (%)**	**GDP (%)**
1	Wheat	10.3	2.2
2	Cotton	4.1	1.4
3	Rice	3.1	0.7
4	Sugarcane	3.4	0.7

1.2.2 Textile Industry in Pakistan

Among all the cotton-producing countries in the world, Pakistan is the fourth and generates 5% of the global spinning capacity. Additionally, after China and India, it is the third-largest cotton producer in Asia (Javed, 2019). Punjab and Sindh provinces of Pakistan are widely recognized for cotton production while Punjab province leads in terms of cultivated area and production than Sindh. Over 80% of the total is produced in Punjab, with the remaining 18% coming from Sindh province (Ali et al., 2013; Ashraf et al., 2018). In Pakistan, cotton production is determined by the cost of fertilizers, rival crops, and the amount of land under cultivation (Pickett et al., 2002).

Manufacturing is the second-largest economic sector in Pakistan, accounting for 13.5% of the national GDP, which provides the base for the national economy. Because of the highest cotton production, the textile industry of Pakistan is a vital manufacturing sector that has the longest supply chain as compared to other industries. About 40 percent (19 million) of the country's workforce is employed in this sector, which contributes 8.5% of GDP and generates approximately one-fourth of the industrial value.

1.3 Impacts of Urbanization on Agriculture

Urbanization is a complex process of landscape and land surface transformation from their natural circumstances into altered urban settlements (Portela et al., 2020). The topographical features and social quirks of the urban areas determine the process of transition (Heusinger & Sailor, 2019; L. Li et al., 2020; Y. Li et al., 2020; Nwakaire et al., 2020).

Urban green spaces have undergone more significant changes and decreased as a result of urban sprawl. The transformation of natural vegetation into non-evaporating and non-transpiring surfaces is due to the thermal conductivities of asphalt, concrete, and metallic materials (Nwakaire, et al., 2020; Salazar et al., 2015; Shiflett et al., 2017; Vitanova & Kusaka, 2018).

The natural landscape has been significantly changed by the quick growth of built-up areas, with negative effects on the environment, ecosystems, and society (Haregeweyn et al., 2012; Yar & Huafu, 2019). According to the United Nations (2014), by the year 2050, over 66% of people will live in cities, with low-income nations accounting for 90% of the projected expansion. Smaller towns and cities will witness the majority of this urban growth.

1.4 Literature Review

A study conducted by Ahmad, (2022) on rapid urbanization and development in Bahawalpur district of Pakistan, used data from USGS Earth Explorer and GLOVISE from 2003 to 2018 (16 years) with an interval of three years. It included six Landsat ETM and ETM+ images. Urban areas, agricultural land, barren land, and forests were selected as the major LULC classes. Temporal LULC change analysis and their consequences on the study area were computed. The findings indicated that throughout the sixteen years from 2003 to 2018, the forests and barren land area reduced by 89.3 percent and 57.6 percent, respectively, while the agriculture and urban areas expanded by 34.5 and 45.5 percents, respectively. These changes in LULC might be leading towards urbanization, and deforestation in the study area.

Bağcı et al., (2023) detected the cotton and corn crops with the help of a novel deep-learning technique called Deep Transformer Encoder. Firstly, the satellite images were obtained for the study. Secondly, GPS-based coordinate points were overlaid with the satellite images. The temporal aspect of the satellite data was considered in view of the development and harvesting times of agricultural products from the years 2016-2021. In the final step, the satellite dataset was combined into three categories to identify the crop using deep learning techniques. These three combinations include identifying crops solely using the Sentinel-1 dataset, identifying crops using only the Landsat-8 dataset, and identifying crops using both the Sentinel-1 and Landsat-8 datasets. The overall accuracy for the Sentinel-1 dataset was 95%, 85% for Landsat-8, and 88% for the Sentinel-1 and Landsat-8.

Papadopoulos et al., (2017) researched two different multispectral sensing systems: an aerial and a ground-based systems to monitor two cotton fields in central Greece. For monitoring crops development, this study investigated the relationships between derived Normalized Difference Vegetation Index (NDVI). Results showed that cotton development stages were monitored successfully in terms of space and time by both systems. Ground-based systems retrieved the mean values of NDVI changes over time and were satisfactorily modeled by a second-order polynomial equation (R^2=0.96 and R^2=0.99). Moreover, the calculations of the aerial-based system showed a high correlation (r=0.90, and r=0.74). When it comes to undestructive, time-effective, and reliable way of soil and plant monitoring, the unmanned aerial system (UAS) can imitate crop scouting.

A study was carried out by Al-Bakri et al., (2013) on LULC modeling, assessment, and its consequences on land use planning. Remote sensing and geographical information systems (GIS) were integrated for mapping and predicting LULC changes near Amman (Jordan). Landsat data was used to derive LULC for the years 1983, 1989, 1994, 1998, 2003, and 2013. GIS was used for analyzing the output maps and cross-tabulation to quantify LULC. Urban areas, forests, agriculture, and rangelands showed the great changes. Based on past trends (1983-2013), the Markov Chain was used for LULC prediction. Results indicated the Prediction errors between 2% to 5%, while the prediction for agricultural areas was not very reliable. LULC trends revealed that by the year 2043, 33% of the study area would be urbanized at the expense of agricultural areas. An increase in water demand would be the consequence of these LULC changes.

Singla et al., (2018) proposed a model to extract the sugarcane crop yield information. In this model, different crop growth stages for thr yield information were considered. For the identification of reliable sugarcane yield estimation, correlation analysis was applied to spatial-temporal data. It was found that the best time for estimation of the crop yield was 210-270 days after sowing. Based on past trends of 10 years, it was identified that the prediction using the nonlinear modeling is significant (order of 0.6). root mean square error (RMSE) and Tukey test were identified to be the best-fit regression models for the study area.

Yar & Huafu, (2019) analyzed the consequences of urbanization on agricultural land in Peshawar with a focus on the land use change trajectories (1991–2014). Landsat time series images were classified using a supervised classification technique. Urban areas, barren land, water bodies, farmland, and productive wastelands were considered the major classes. The analysis showed that urban area that was 8.1% in 1991 increased to 18% in 2014 at the expense of productive land. For the future prediction, the Cellular Automata–Markov model was used which predicted that the urban area would increase for the next thirty years due to the lack of proper urban planning and management.

Hassan & Goheer, (2021) evaluated the capability of MODIS-derived vegetation indices by applying for the pre-harvest wheat yield estimation in the Potohar region. Two MODIS products (MOD15A2H and MOD13A1) were used to derive the indices. The independent variable used in the model was 16-day composite MODIS vegetation indices while the dependent variable was the crop yield data. The difference in the percentage average of yield was (-)1.986% between the predicted and actual yield values. The average RMSE values range between 34.28 to 76.50 kg/ha and that of the mean absolute error (MAE) was 108.09 to 129.99 kg/ha. The mean bias error (MBE) value ranged between 7.20 to 62.80 kg/ha. Results revealed that the use of geospatial techniques and statistical modeling approach, one can predict the reliable wheat yield almost 2 months before harvesting.

Akbar et al., (2019) did a spatial-temporal LULC analysis for the years 1988–2016, and its prediction for the year 2040 using the Markov model, and identified how LULC change affects urban growth. NDVI was used for classification which was further used to produce land cover maps. LULC changes were derived using the transformation matrix. The study concluded that there was a significant increase in built-up area from 9.58% to 20.80%; sparse vegetation from 18% to 20.10%; dense vegetation from 10.57% to 24.10% while water bodies decreased from 1.43% to 0.51%, barren land from 29.50% to 13.40%; and shrub/grassland from 30.57% to 21.10%. For District Lahore, rapid population growth and increasing rural-to-urban shifts can be the major factors behind the LULC transformation. This transformation had a progressive consequence on the economy, infrastructure, and water resources.

Hussain et al., (2022) evaluated the spatial-temporal changes in major crops in District Vehari, from 1984 to 2020. Results revealed that there was a significant change in wheat and cotton cultivated areas of almost 5.4% and 9.1% from 1984 to 2020, respectively. The NDVI values were greater than 0.4 for the green areas and that of 0 to 0.2 for the built-up. The high temperature (19.93 ◦C to 21.17 ◦C) was recorded during the Rabi season. Cotton, sugarcane, and rice crops were harmed by the temperature during the Rabi season while precipitation had a positive effect on these crops during the Kharif season.

Naveed et al., (2023) detected the cotton crop area and applied binomial probabilistic approach to obtain the probability distribution of cotton crops using an 8-day temporal enhanced vegetation index (EVI). With the help of crop reporting data, Gaussian kriging was used to determine the cotton output inside the identified cotton crop patches. Validation of cotton yield results was done by the field reference data. There was a strong correlation between satellite-based data and statistical data (R^2=0.84) for the required years (2004–2019). The yield prediction of the cotton crop was 92.1% and the overall accuracy of the cotton crop area detection was 84.6%.

Xun et al., (2021) identified the cotton pixels to map cotton-cultivated areas in China. For this purpose, MODIS satellite data was used along with the fused representation-based classification algorithm (FRC). The Fourier analysis was applied at a pixel level to obtain the harmonic features of the annual temporal EVI. The FRC algorithm used harmonic features as input to identify cotton-producing areas. After setting the threshold value based on the statistical data (2015-2017) and calculating fused residuals for each pixel, the cotton cultivated area was extracted efficiently. Subsequently, the efficiency of the FRC algorithm was evaluated and compared with integrated sparse representation-based classification (SRC) and representation-based classification (CRC) techniques. Results revealed that there was a high correlation between cotton-cultivated areas derived from satellite and statistical data having a 0.83 value of the coefficient of determination (R^2) for 3 years at the municipal level. When the FRC algorithm was compared with CRC and SRC algorithms for mapping results, the FRC algorithm proved to have a higher precision than the other two algorithms. It was demonstrated that for the identification of cotton-cultivated areas, the integration of temporal MODIS EVI data, statistical data, and the FRC algorithm would be effective.

Tariq & Shu, (2020) investigated the urban growth impact on Faisalabad. The Cellular Automata-Markov Chain was used to predict LULC and LST. For the mapping of seasonal LULC and LST distributions (1990, 1998, 2004, 2008, 2013, and 2018), Landsat 5, 7, and 8 images were used. For the future prediction of the year 2048, a CA-Markov Chain was developed. Moreover, the urban index (UI) was applied for the prediction of the surface temperature during summers and winters, showing the highest correlation of $R^2 = 0.8962$ and $R^2 = 0.9212$. Prediction analysis revealed that there would be urban expansion as concluded from the past trends (1990-2018). LST prediction results showed that the areas with summer and winter temperatures of range 24–28 ◦C and 14–16 ◦C would decrease from 10.75 to 3.14% and from 8.81 to 3.47% between 2018 and 2048, while the regions having summer and winter temperature of range 35–42 ◦C and 26–32 ◦C would increase from 12.69 to 24.17% and 6.75–15.15% of the city.

Sajid et al., (2020) detected and simulated LULC change in association with agricultural production. Quantitative techniques and post-classification contrast variation techniques were used for the change detection assessment. Landsat satellite data was used for the required years (2000, 2008, and 2016). Urban, water, bare land, dense vegetation, and sparse vegetation were the major

LULC classes. Supervised classification was used to analyze the temporal change in LULC. Past analysis revealed that agriculture was highest in 2000 and decreased in 2016, urban, water, and sparse vegetation increased during 2000–2016, while barren land and dense vegetation decreased during this time. Predictions showed that the urban area would expand at the expense of wheat and cotton crops.

Riaz et al., (2017) investigated how the LULC in Sargodha city was impacted by urban growth. Landsat TM and ETM+ data were used for the years 2000, 2005, 2010, and 2015. Supervised classification was done for the LULC classification. Ground control points and the kappa coefficient were used for the accuracy assessment. Results indicated the urban expansion and decreased agricultural trends along with all other classes for the past 24 years. The total urban area was 25381 hectares, which increased in 2000, 2005, 2010, and 2015 at the rate of 2.2%, 4.1%, 9.2%, and 17.4% respectively. The urban expansion resulted in the loss of agriculture. The overall change observed in the agriculture area was (-)11008.5 hectares, bare land 9492.7 hectares, and water bodies (-)38926.5 hectares.

Chao et al., (2018) studied how urbanization affected different environments and LULC. Carnegie-Ames-Stanford technique was applied to estimate the net primary production (NPP) in Shandong from 2001 to 2010. Spatial-temporal analysis of NPP was done. After that, spatial-temporal and supply-demand issues analysis for the cultivated land was done by using the pressure index. It was observed that almost 75% of total absorbed carbon (34.691012 g) was taken by farmland. Initially, the productive land was reduced but then there was an increasing trend. The total return in yield increased (with some variations) with the help of macroeconomic policy, science, technology, and other developments. Also, there was an increase in the productive area. The theoretical minimum cultivated area (per capita) improved due to these changes, and the pressure index decreased. The regional differences were revealed due to the pressure exerted on cultivated land, especially in Jinan City, Laiwu City, and the coastal regions. On the other side, the pressure was comparatively less due to slow economic growth in the western and northern regions.

Gerts et al., (2020) conducted a study on different geospatial data and techniques to evaluate which one produces the better results for multi-temporal monitoring of cotton growth. For this purpose, Landsat (medium resolution) and Sentinel (high resolution) satellite images were used for processing in the Tashkent province of Uzbekistan. The NDVI analysis was done by using the

Spectral Correlation Mapper (SCM) classification technique from 1994 to 2017. It was identified that the application of Spectral Correlation Mapper classification along with the optical and radar data had better classification results for a specific dataset. The other factors involved were labor and time.

A study was carried out on the features and process of urban growth in the National Capital Region (NCR) of India by Sharma & Joshi, (2016). The primary focus of this study was to evaluate the relationship between urban growth and the consequences on other land uses. Five major satellite-based parameters were used as the indicators of environmental dynamism. These include greenness (NDVI), bareness (NDBaI), moisture (NDWI), imperviousness (NDBI), and land surface temperature (LST). All the parameters had high correlations (0.71–0.99) except NDBaI and were considered reliable to measure environmental conditions. Change detection showed that the urban areas increased up to 82 km2 from 1998 to 2002/03 and 157 km2 from 2002/03 to 2011 while sub-urban areas increased up to 96 km2 from 1998 to 2002/03) and 281 km2 from 2002/03 to 2011. Agriculture to built-up shift resulted in the urbanization in the study area. LST and NDBI were found to increase in the same proportion as that of urban areas while NDVI and NDWI were found to decrease in corresponding. This highlighted how urban growth affected the environment of NCR, India.

Ahmed et al., (2015) assessed the urban and sub-urban changes in residential areas and their impacts on the socioeconomic status of the farmer. GIS was used as the primary source to map the spatial-temporal urban and sub-urban changes while secondary data was collected from the different sources. A questionnaire was generated for the identification of the socioeconomic status of farmers. It also elaborated on the spatial-temporal changes in residential areas at the cost of agricultural loss.

A study was carried out by Mamatkulov et al., (2021) on real-time crop monitoring and yield prediction of cotton in the case of low and high-productive areas of Jarkurgan district, Uzbekistan. Geospatial analysis of multi-temporal satellite data, ground truth data, groundwater conditions, and soil salinity were considered as the major factors. NDVI, SI (Salinity Index), and false color band combination were used to assess the cotton phenology and its prediction. To evaluate the consequences of groundwater on agricultural yield and development, IDW (Inverse Distance Weighting) interpolation was used to analyze the groundwater conditions.

1.5 Rationale

Remote sensing is the practice of acquiring data about the Earth from a distance without making direct physical touch with the subject of the study (Justice et al., 2002; Shanmugapriya et al., 2019). It plays a momentous role in sustainable land use planning through monitoring and management of land use activities. Integration of remote sensing and GIS has proved to be advantageous for analysis and evaluation of LULC and to attribute spatial meanings to these changes including the driving factors (Chaudhry et al., 2015). It effectively assesses soil moisture, crop health, crop cover, and agricultural production.

Together with socioeconomic data, remote sensing provides useful and efficient analysis. The analysis of complex and large amounts of data is made easier with the help of remote sensing. Additionally, it is possible to mitigate the potential risk associated with natural hazards by developing an early warning strategy, preparation, and implementation of plans. Remote sensing is ideal for decision assistance, policy-making, and achievement of sustainable development goals since it is accurate, real-time, intuitive, and scientific.

1.6 Objectives

This research has two objectives;

1. To map and analyze the spatial-temporal changes and trends of urbanization and agricultural areas in the Multan District
2. To predict future trends of urbanization and its impacts on agriculture

1.7 Scope of the Study

This research would help understanding the relationship between urbanization, agriculture, and sustainable land use planning. The agriculture sector has significant importance in our country as it contributes almost 22.04% of the nation's GDP and is essential to the nation's socioeconomic development. The textile industry of Pakistan is a vital manufacturing sector that has the longest supply chain as compared to other industries. About 40 percent (19 million) of the country's workforce is employed in this sector, which generates approximately one-fourth of the industrial value.

Unfortunately, the decrease in cotton crop production is leading to the downfall of the textile industry. As it has significant importance in the economy, the use of Remote Sensing and GIS in this area can be useful. The unanswered questions to find out are to map the past and future urban patterns and land use and their impacts on agriculture, especially cotton crop. Multan district is distinct in agricultural production especially cotton compared to other districts of South Punjab. The district has plain yet productive land. Cotton is the major source of support for the textile sector of the country.

In Punjab, the Multan division is at the top for cotton production according to ascending order of production besides the Bahawalpur, Dera Ghazi Khan, Faisalabad, Sargodha, Lahore, Gujranwala, and Rawalpindi divisions respectively. This agricultural profile shows that there is a need to assess the land use impacts on agriculture. This study would help the local government to generate policies for sustainable urban planning and development, understand the importance of the agriculture sector for the economy, and provide timely information about urban growth and agriculture for better decision-making.

CHAPTER 2

MATERIALS AND METHODS

2.1 Study Area

Multan district of Punjab has been selected as the study area. According to the 2023 census, it has been declared as the fourth largest district of Punjab with a population of about 5.36 million and an area of about 3790 km^2 after Faisalabad and Rawalpindi respectively. Multan district is considered as the commercial and cultural hub of Southern Punjab.

The geographical location of the district extends from 30.1575° N to 71.5249° E and is almost 400 ft. above mean sea level. In the center of Pakistan, it is situated in a bend created by five rivers. Multan District has Vehari to the East, Khanewal to the North, Lodhran to the South, and Chenab River passes on its Western side. The study area map is shown in Figure 2.1.

2.1.1 Climate of the Study Area

Multan district has a subtropical desert climate. The district experiences 25.6°C average annual temperature and 175 mm of rain annually. However, during the monsoon season, Multan and Shujabad tehsils are more prone to flood being closer to the Chenab River. June is the hottest month of the year, with an average maximum temperature of 42°C and 29°C minimum temperature.

2.1.2 Agricultural Profile of the Study Area

Multan district has significance in agriculture, tourism, and industry. The district has plain yet productive land. Major crops grown in the district are wheat, sugarcane, and cotton while, maize, rice, oil seeds (mustard, rapeseed, and sunflower), and tobacco are minor crops. Among all the fruits, mangoes, guavas, citrus, and pomegranate are mainly cultivated there. Multan has the distinction for agricultural production, especially cotton and mango as compared to other districts of South Punjab.

In Punjab during the years 2000-2001, Multan district produced 93259 metric tons of mangoes out of total mango production of 634900. The total contribution of the district was about 4.6%. Cotton is the major source of support for the textile sector of the country. In Punjab, the Multan division is at the top in cotton production.

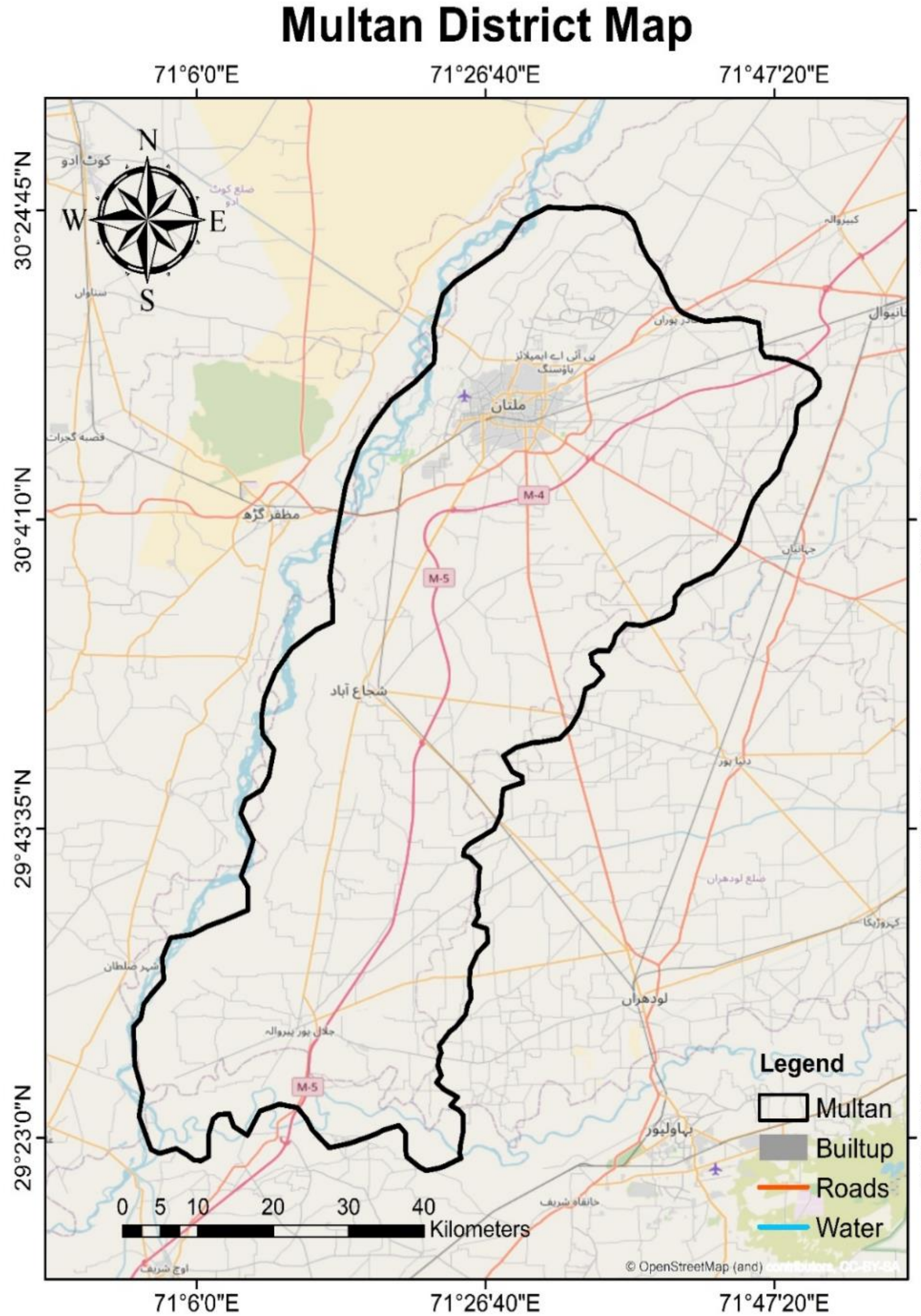

Figure 2.1: The Study Area Map

2.2 Methodology

Landsat 7 and Sentinel-2 satellites images were acquired from the USGS (United States Geological Survey). The supervised classification using maximum likelihood algorithm is used for LULC classification. Very High-resolution historical imagery of Google Earth is used as ground truth for the classified data to detect spatial-temporal changes and verification. To check the performance of classification results, an accuracy assessment is done using the confusion matrix. Accuracy is further improved by increasing the number of sample points. Future simulation model Cellular Automata-Artificial Neural Network (CA-ANN) is used to predict the LULC for the year 2031. The methodology flowchart is shown in Figure 2.2.

2.3 Datasets

2.3.1 Satellite Data

Remote Sensing data were used for the temporal analysis. USGS provides free satellite data from different sensors with multiple spatial and spectral resolutions. High-resolution satellite data is more suitable for spatial analysis, at a local scale because it provides detailed information. USGS also provides the medium-resolution 30m Landsat imagery.

As the research planned a temporal analysis of two decades i.e., from 2001-2021, and Sentinel-2 was launched in 2013, therefore Landsat data for the year 2001 and Sentinel-2 data for the years 2017 and 2021 were considered and used for the analysis. Landsat 7 data for the study area was luckily available without any missing scanline.

Sentinel-2 is a European high-resolution satellite mission and provide two different image products at different levels, Level-2A and Level-1C. The L-2A products of Sentinel-2 at the Bottom of Atmospheric Reflectance (BOA) are already preprocessed geometrically, radiometrically, and atmospherically. However, for Level-1C products, there is a need to perform atmospheric, geometric, and radiometric corrections. For the current study, three cloud free tiles of Sentinel-2 L1C products were obtained from Copernicus Open Access Hub because of the unavailability of the L2A product. Table 2.1 gives the details of datasets used in the study.

2.3.2 Agricultural Data

Agricultural data is obtained from Cotton Crop Research Institute (CCRI) Multan. This data includes crop yield and coordinate points of the crop field. Crop yield data is useful for the cross-validation of the classified crops with the departmental data while coordinate points of the crops are helpful for the accurate classification.

2.3.3 LULC Zoning Data

LULC zoning data includes urban boundaries, road networks, parks, airports, and industrial areas. This data is obtained from the Multan Development Authority (MDA).

2.3.4 Spatial Variables Data

In this study, SRTM DEM of resolution 1-Arc is used for the future LULC prediction to generate better results. Other spatial variables used are the roads and rivers.

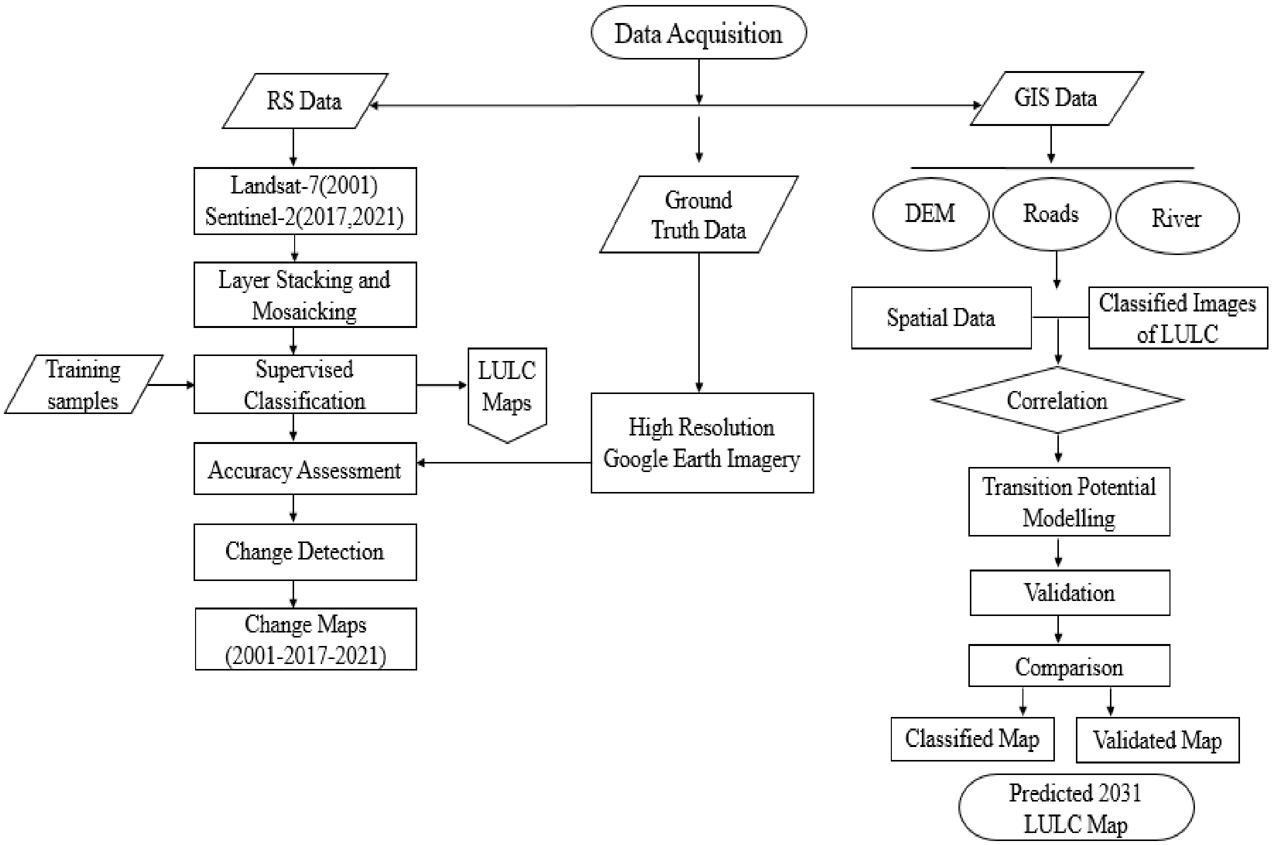

Figure 2.2: The Methodology Flowchart

Table 2.1: Datasets

S No.	Data Type	Specification	Source
1	Satellite Data	Landsat-7 ETM (2001) 30m*30m spatial resolution	USGS Earth Explorer
2	Satellite Data	Sentinel-2 L1C (2017, 2021) 10m*10m spatial resolution	Copernicus Open Access Hub
3	Agriculture Data	Crop Yield, Crop Area Coordinates	Cotton Crop Research Institute Multan
4	LULC Zoning Data	Urban Boundaries, Roads	Multan Development Authority
5	DEM	SRTM Resolution 1-Arc	USGS Earth Explorer

2.4 Data Preprocessing

Time-series Landsat remote sensing image collection was retrieved from USGS Earth Explorer. The Landsat 7 data for the year 2001 for the month of August was considered for analysis because of the peak growth of the cotton crop in this month. The image with less than 5% cloud cover was used for the analysis. By using the nearest neighbor interpolation technique, resampling of the image was done from 30 m spatial resolution to 10 m spatial resolution.

Four spectral bands (blue, green, red, and NIR) of Sentinel-2 were used. The images were converted from the top of the atmosphere (TOA) to the bottom of the atmosphere (BOA) as these were L1C products. The area of interest (AOI) was extracted once band composites were generated by using AOI boundary shape files.

2.5 Land Use and Land Cover Classification

The accrediting of land cover classes to every pixel of the image (urban, water, agriculture, forest, and grassland) is known as classification. LULC are the features on the surface of the Earth, including both natural and human-made. Identifying and mapping the LULC is an important aspect of the global and local level for monitoring studies, resource management, and planning activities.

LULC classification from 30m resolution Landsat time-series twenty years (2001-2021) images was far a complex process, therefore it was divided into three temporal time frame windows (2001, 2001 to 2017, 2017 to 2021). For the year 2001, Landsat-7 and for the years 2017 and 2021, Sentinel-2 L1C image collections of summertime were used for the LULC classification process.

2.5.1 Supervised Classification

In this study, we used a supervised classification technique. Supervised classification is generally preferable over unsupervised classification when it comes to the expertise of analysts who have good knowledge of the study area. In this classification technique, samples are selected for each land cover class. These training samples are then applied to the whole image.

Spectral signatures which are specified in the training set are used in this technique. The user also sets the similarity threshold for the pixels needed to be grouped in the same class and also the number of classes to be classified in an image (Nelson & Khorram, 2018).

For the current study, a maximum likelihood classifier is used. The key element of the maximum likelihood classifier is the probability of pixels having a distinct class. For every class, these probabilities are likely to the same extent. It is a statistical classifier that uses the second-order values for the Gaussian Probability Distribution Function (PDF). If class PDFs are Gaussian and considered as a reference for comparing the different classifiers, this classifier would be the best choice (Jog & Dixit, 2016).

2.6 Training Sample Data

Training samples are required for the LULC classification. The collection of training samples depends upon the human evaluation, the ground truth of features of interest in the study area, or the required number of classes. The more the number of training points/samples, the better the classification results. Samples were collected manually and used for five major LULC classes including built-up, water, bare land, cotton, and vegetation.

2.7 Accuracy Assessment

Accuracy assessment needs ground truth/reference data. For this purpose, high-resolution temporal imagery from Google Earth was used for all three years 2001, 2017, and 2021. Accuracy assessment gives the details of the user accuracy (UA), producer accuracy (PA), overall accuracy (OA), and kappa coefficient (k).

2.8 Prediction for LULC 2031

The future prediction of LULC for the year 2031 is done using the CA-ANN model, the methodology shown in Figure 2.2. CA-ANN model is known as a Cellular Automata-Artificial Neural Network; that is used for prediction by using modern Artificial intelligence technology (Faisal et al., 2021).

This model is very useful for the prediction for future years, as it has multiple hidden layers where the data are given to train the model (Abdullah-Al-Faisal et al., 2021). The hidden layers of the model were trained by already classified LULC and the multiple iterations by giving the input data which predicts the results accordingly, therefore the input data must have good accuracy to predict the valid results. The workflow of the algorithm is shown in Figure 2.3.

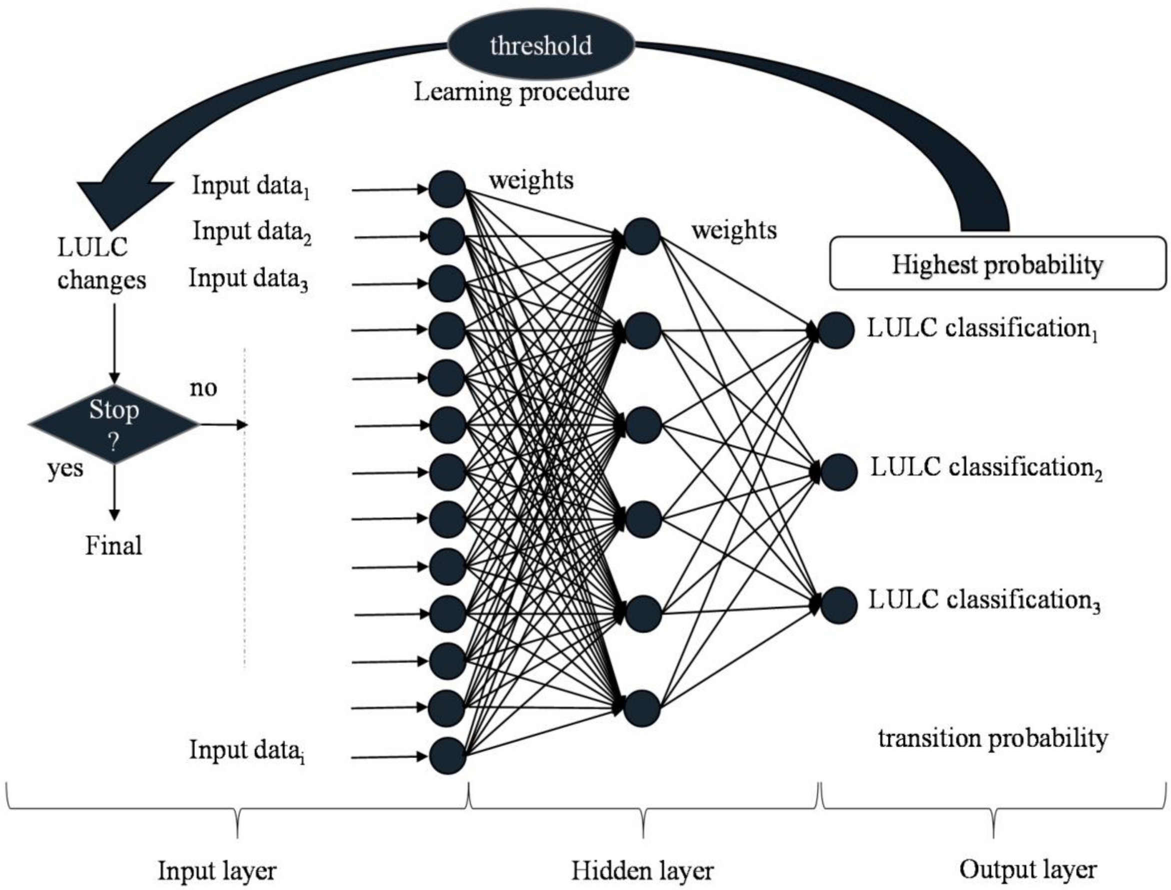

Figure 2.3: Workflow diagram of Cellular Automata Artificial Neural Network (CA-ANN)

CHAPTER 3

RESULTS AND DISCUSSIONS

3.1 Extraction of LULC Classes

Landsat-7 and Sentinel-2 images were classified using the Maximum Likelihood classifier. The sample points for training are generated manually and validated using the Equalized Random technique. 100 points were taken for each LULC class. The reference data to validate the classification results through sample points were very high-resolution Google Earth Images.

3.2 LULC Classification

LULC classification was performed using a maximum likelihood algorithm. Five LULC classes were evaluated in the study area to analyze the variations/changes over time., namely built-up area, water, bare land, cotton, and other vegetation. The LULC classified maps are shown in Figures 3.1, 3.2, and 3.3.

3.3 Accuracy Assessment

LULC classification accuracy assessment was performed through the confusion matrix. For each LULC class, 100 sample points were selected by using the equalized random technique. For this purpose, high-resolution temporal imagery from Google Earth was used for all three years 2001, 2017, and 2021. The certainty and reliability of the classification results were the primary aspects of the classification outcomes. The following Tables 3.1, 3.2, and 3.3 represent the different matrices of accuracy including user accuracy, producer accuracy, and kappa coefficient.

It was observed that the overall accuracy for the LULC classes in Landsat was 80% due to its low resolution while that of Sentinel-2 for the year 2017 was 88 % and for 2021 was 84 %, which depicts that the results of Sentinel-2 are more accurate than that of Landsat and it can be used for further analysis of this study. The results for overall accuracy are shown in the Table 3.4.

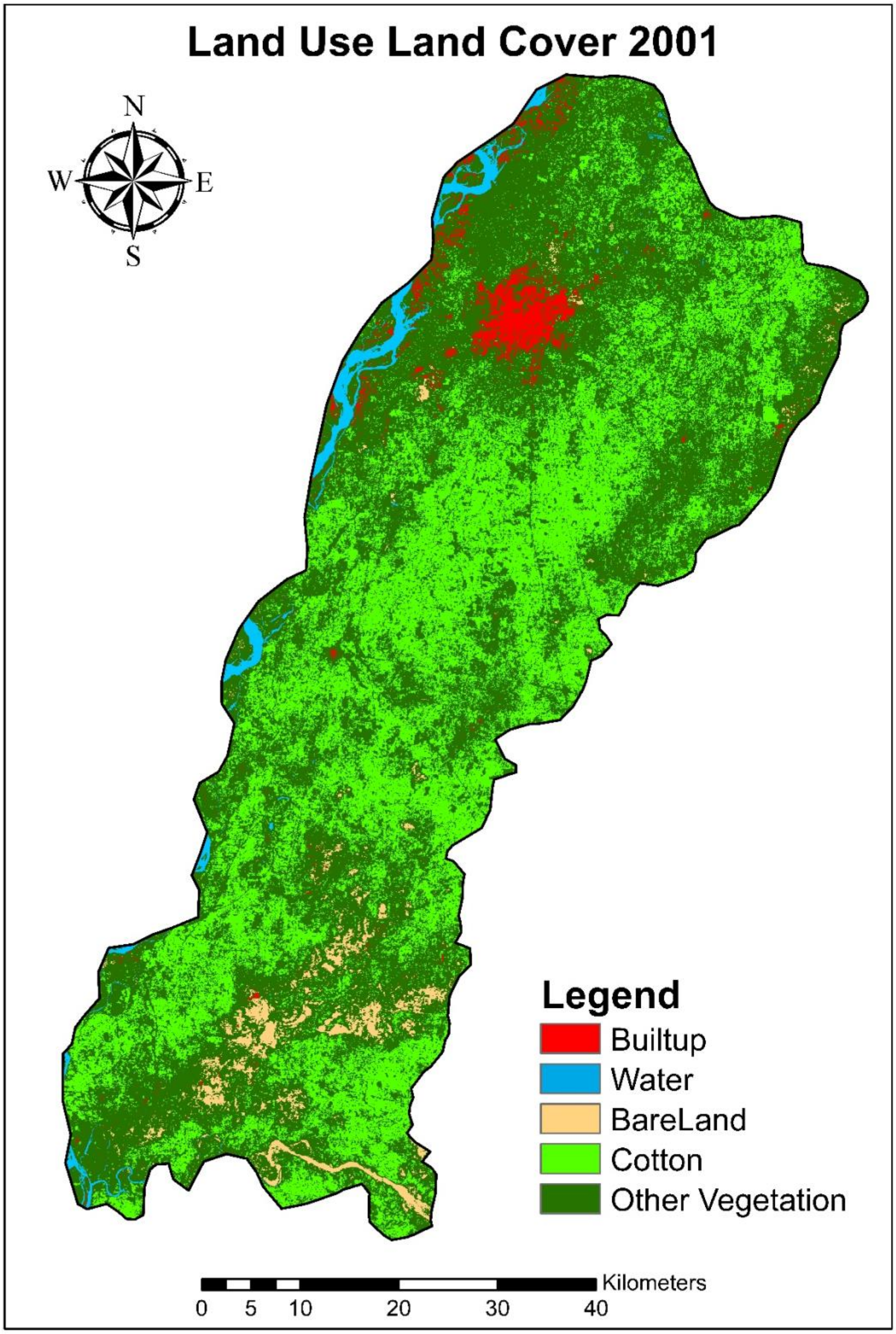

Figure 3.1: LULC Classification Map for the Year 2001

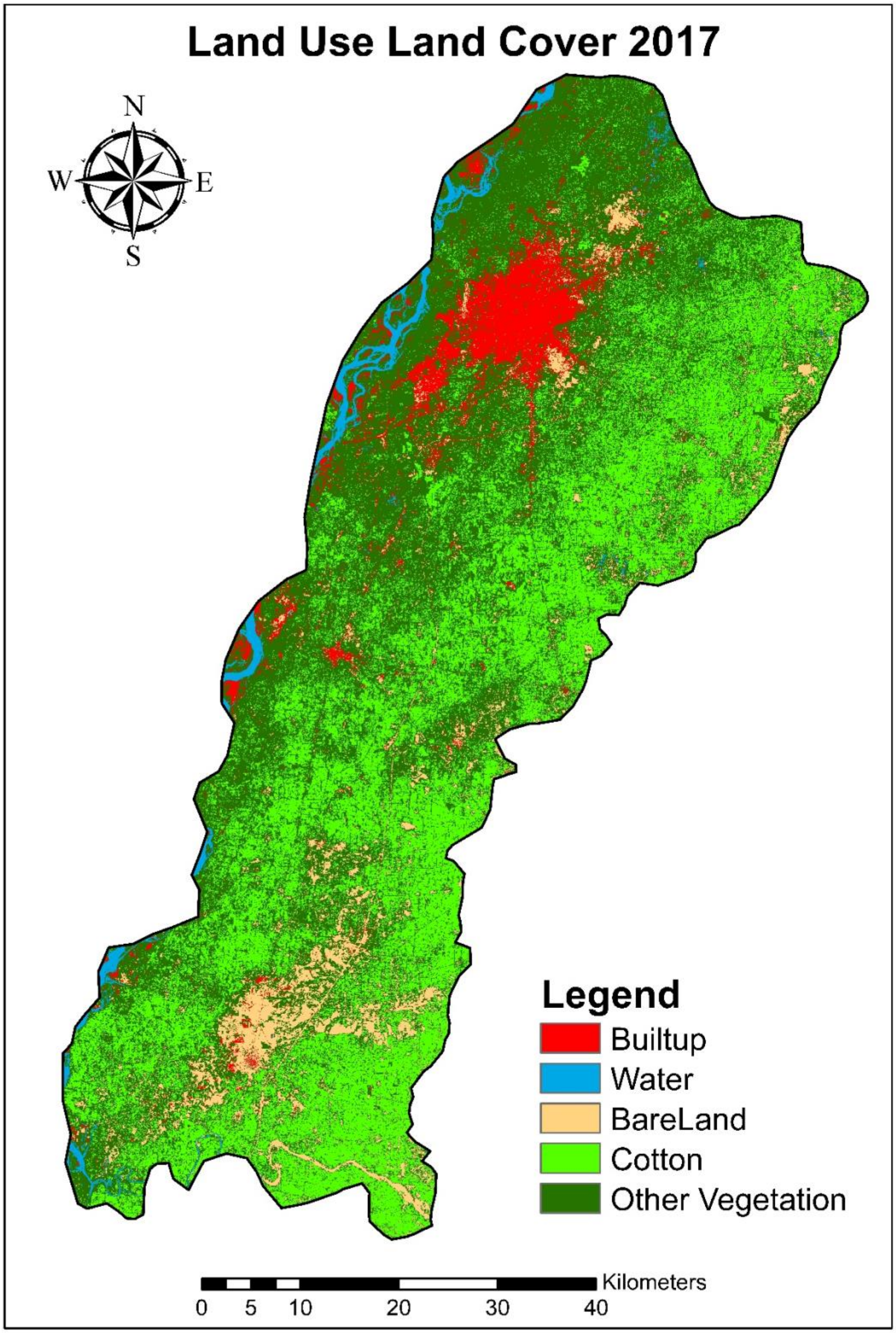

Figure 3.2: LULC Classification Map for the Year 2017

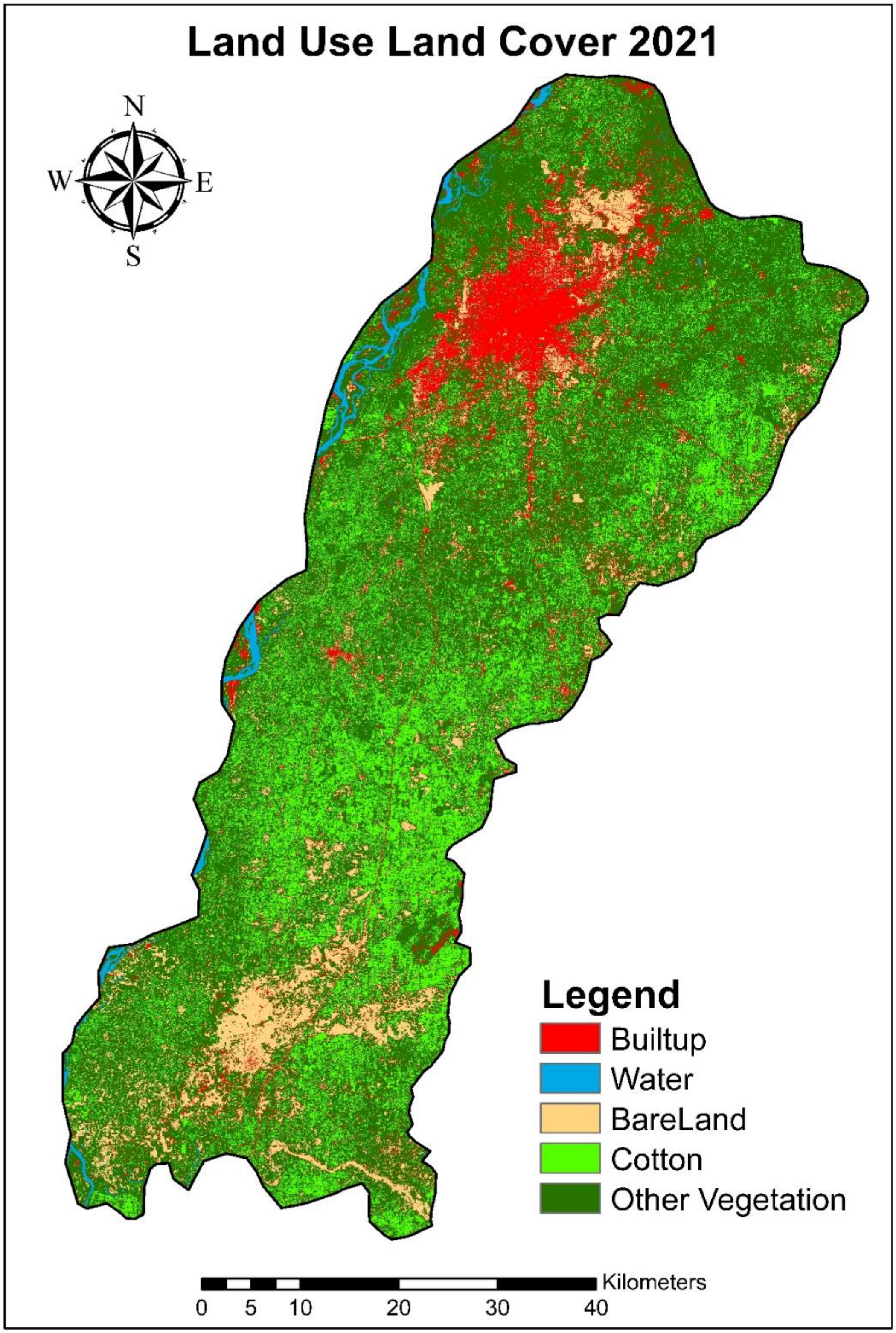

Figure 3.3: LULC Classification Map for the Year 2021

Table 3.1: Accuracy Assessment for the Year 2001

LULC Classes	Built-up	Water	Bare Land	Cotton	Other Vegetation	Total	Users Accuracy
Built-up	11	0	5	3	1	20	55%
Water	0	20	0	0	0	20	100%
Bare Land	0	0	17	0	3	20	85%
Cotton	0	0	3	17	0	20	85%
Other Vegetation	0	0	4	1	15	20	75%
Total	11	20	29	21	19	100	
Producers Accuracy	100%	100%	58%	80%	78%		

Table 3.2: Accuracy Assessment for the Year 2017

LULC Classes	Built-up	Water	Bare Land	Cotton	Other Vegetation	Total	Users Accuracy
Built-up	16	0	4	0	0	20	80%
Water	0	20	0	0	0	20	100%
Bare Land	0	0	18	0	2	20	90%
Cotton	0	0	1	15	4	20	75%
Other Vegetation	0	0	1	0	19	20	95%
Total	16	20	24	15	25	100	
Producers Accuracy	100%	100%	75%	100%	76%		

Table 3.3: Accuracy Assessment for the Year 2021

LULC Classes	Built-up	Water	Bare Land	Cotton	Other Vegetation	Total	Users Accuracy
Built-up	14	0	6	0	0	20	70%
Water	0	20	0	0	0	20	100%
Bare Land	2	0	17	0	1	20	85%
Cotton	0	0	0	16	4	20	80%
Other Vegetation	0	0	2	1	17	20	85%
Total	16	20	25	17	22	100	
Producers Accuracy	87.5%	100%	68%	94%	77%		

Table 3.4: Comparison of Overall Accuracy Assessment for LULC Classes

Year	2001		2017		2021	
	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
Built-up	100%	55%	100%	80%	88%	70%
Water	100%	100%	100%	100%	100%	100%
Bare Land	58%	85%	75%	90%	68%	85%
Cotton	80%	85%	100%	75%	94%	80%
Other Vegetation	78%	75%	76%	95%	77%	85%
Overall Accuracy	80%		88%		84%	

3.4 Spatial-Temporal Analysis of LULC

Five LULC classes were evaluated in the study area to analyze the variations over time. It has been observed that in 2001, the built-up area was 83 km^2 which increased to 200 km^2 in 2017 and 345 km^2 in 2021. Water was 70 km^2 in 2001 which reduced to 60 km^2 in 2017, and further reduced to 55 km^2 in 2021. Bare land was 90 km^2 in 2001 which increased by 130 km^2 in 2017, and then by 200 km^2 in 2021. The cotton-cropped area was 1467 km^2 in 2001 which reduced by 1400 km^2 in 2017, and then by 900 km^2 in 2021. Other vegetation was 2080 km^2 in 2001 which reduced by 2000 km^2 in 2017 and then increased to 2290 km^2 in 2021. These LULC statistical changes are shown in Table 3.5.

Percentage changes of LULC classes are shown in Figure 3.4. The urban area was about 2% in the year 2001, increased to 5% in 2017, and to 9% in 2021. Bare land was 2% in 2001 increased to 3% in 2017, and then to 5% in 2021. Cotton crop area was 39% in 2001 reduced by 37% in 2017, and then by 24% in 2021. Other vegetation was 55% in 2001 which reduced by 53% in 2017 and then increased to 60% in 2021. The overall increase in the urban area between 2001 to 2021, is about 7% with an increase of 3% in bare land and 5% in overall vegetation while cotton reduced to 15%.

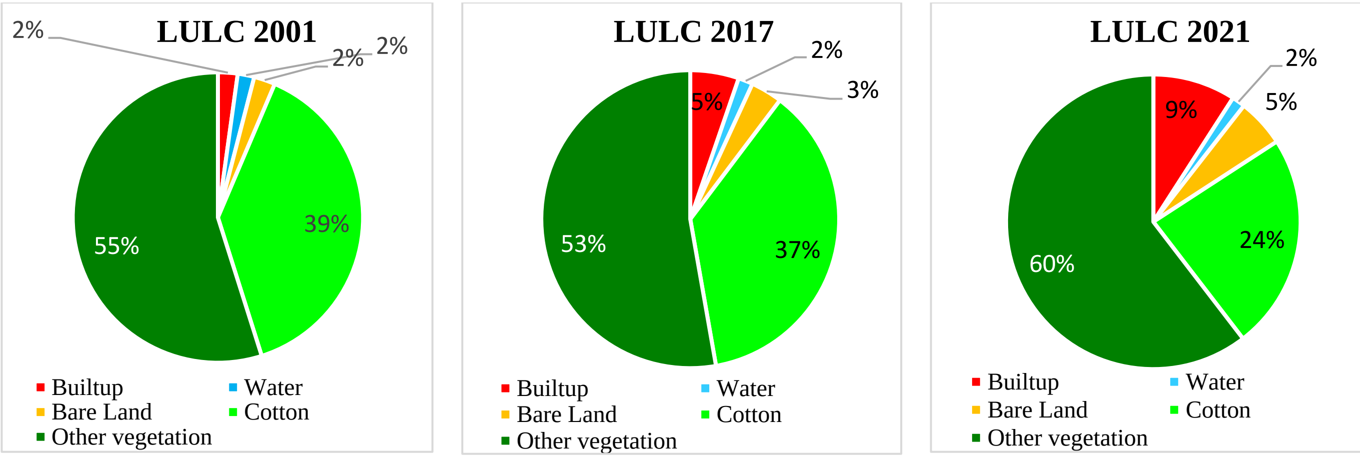

Figure 3.4: Percentage Changes in LULC Classes

Table 3.5: Total Area Covered by Each LULC Class

Year	**2001**		**2017**		**2021**	
LULC Class	**Km^2**	**%**	**Km^2**	**%**	**Km^2**	**%**
Built-up	83	2	200	5	345	9
Water	70	2	60	2	55	2
Bare Land	90	2	130	3	200	5
Cotton	1467	39	1400	37	900	24
Other Vegetation	2080	55	2000	53	2290	60
Total	3790	100	3790	100	3790	100

3.5 Urban Expansion (2001-2021)

The urban expansion started in the early 2000s but it geared up after 2015. The increase in the population demands the development of housing sectors and the addition of different towns in the city. After the year 2017 onwards, different unplanned and planned towns tended to expand and some new towns were started constructing. i.e. DHA in Multan. The growth of the Multan city is horizontally and it is more enhanced when compared to the nearby surrounding areas.

The phenomenon of urbanization increased more frequently in the time interval from 2017- 2021, with a growth rate of 5% to 9%, due to the construction of various towns and well-known societies. The proportion of built-up and bare land was greater than the vegetation as various towns and societies removed the vegetation cover in the year 2021, the replacement of vegetation with impervious areas and barren land. The settlement in 2001 was calculated as 2%, which further increased by 5% in 2017, and then from 2017 to 2021 it increased rapidly at the rate of 9%, shown in Figure 3.5 with the spatial-temporal growth of settlements increased from 2017 to onwards 2021.

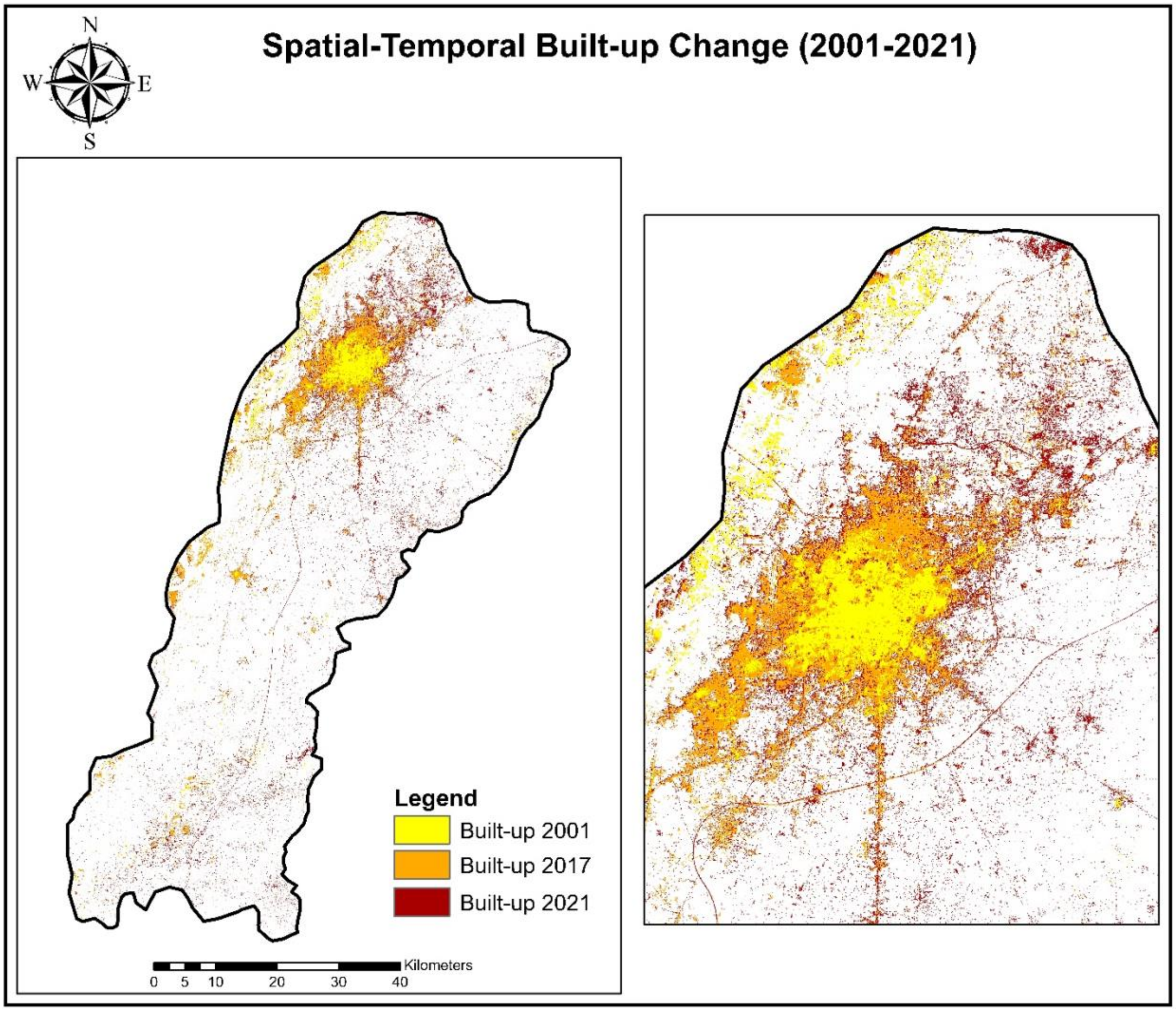

Figure 3.5: Change in Built-up Area from year 2001-2021

3.6 Spatial-Temporal Change in LULC

Change detection through satellite images is important as it shows how the features on the surface changed statistically and visually. The patterns of the different classes over time were spatially visualized to understand the features that change from one class to another.

Both the qualitative and quantitative assessment of spatial-temporal variations and changes in the LULC classes are done. A qualitative assessment of LULC changes is shown in Figure 3.6. The quantitative assessment of LULC changes from 2001 to 2021 is shown in Table 3.6. They are shown as the percentage of change for each year (2001, 2017, 2021). The classified analysis demonstrates the assessment of the impacts of urban sprawl on the different classes with the total gain in built-up areas by the replacement of barren land.

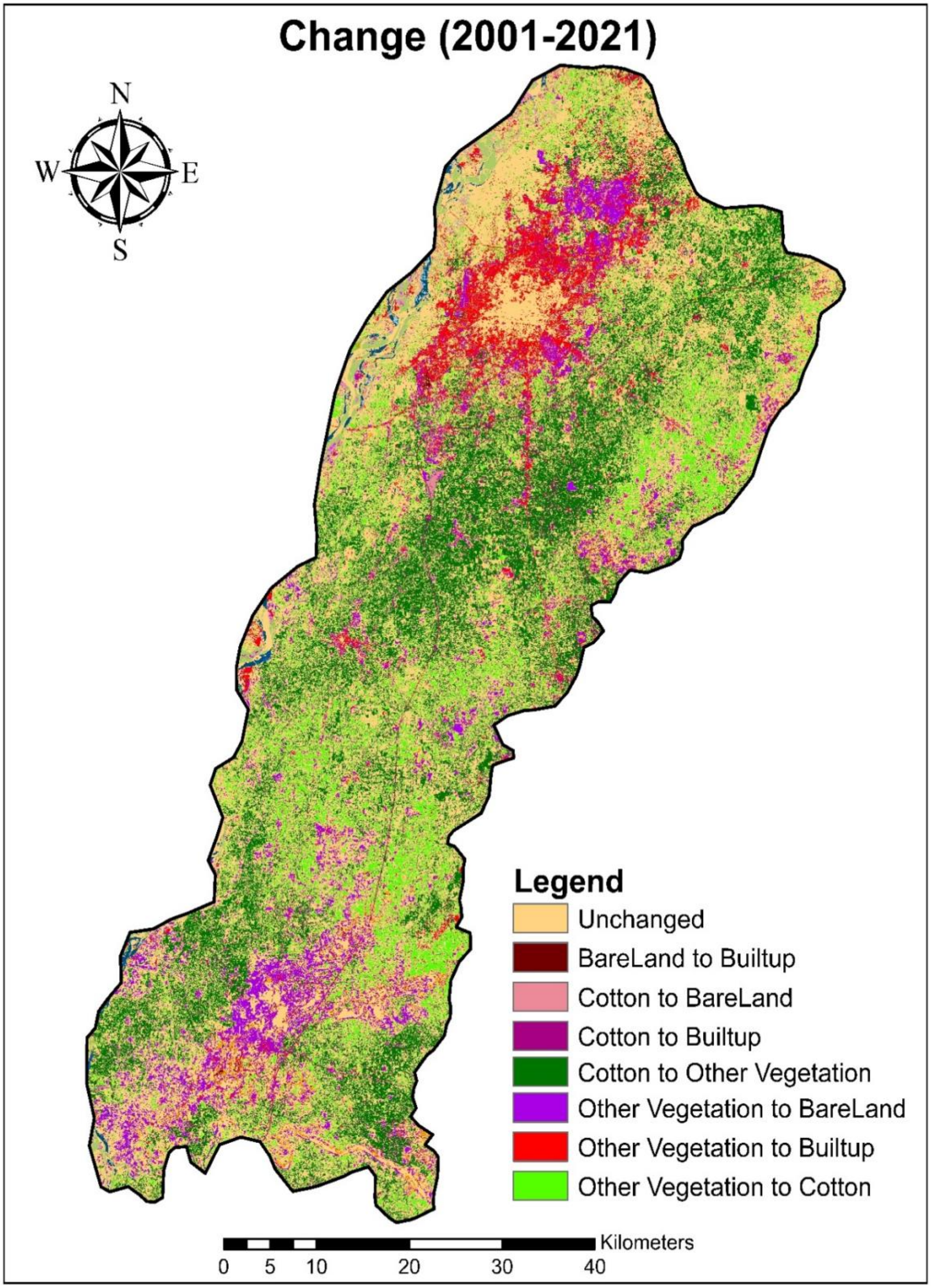

Figure 3.6: LULC Change Map (2001-2021)

Table 3.6: Change Detection of LULC (Positive Values = Gain, Negative Values = Loss)

LULC Classes	**2001-2017 (% change)**	**2017-2021 (% change)**	**2001-2021 (% change)**
Built-up	3	4	7
Water	0	0	0
Bare Land	1	2	3
Cotton	(-) 2	(-) 13	(-) 15
Other Vegetation	(-) 2	7	5

3.7 Change Detection in Built-up and Vegetation (2001-2021)

The analysis of the time-series LULC change detection show the variations and the transition of classes, where the notable change was detected in the built-up area with increasing growth, shown in Figure 3.7. A total of 83 Km^2 of built-up area was calculated in 2001 which increased up to 345 Km^2 in 2021. Whereas the other LULC classes i.e., vegetation, bare land, cotton, and water had significant variations with time, with the increase/decrease in different seasons observed. The graph in Figure 3.8 depicts a temporal vegetation change over different years.

A significant trend was observed in the graph that helps in determining the loss and gain in vegetation in different years. The trend graph was divided into three windows by the rate of change of the vegetation annually. The first window started in 2001, with a coverage of 2080 Km^2 area of vegetation. In the second window in the year 2017, major development of the different housing societies and towns started with the cutting down of trees and removal of vegetation by replacing the urban areas resulting in the decrease of vegetation to 2000 Km^2.

The third window in 2021, has significant phenomena of vegetative cover after the drop off till the year 2017 of 2000 Km^2, it again started growing and has a maximum covered area of 2290 Km^2 for the year 2021. This increase in the vegetation cover was due to the development of green belts, parks, and tree plantations within the developing housing societies.

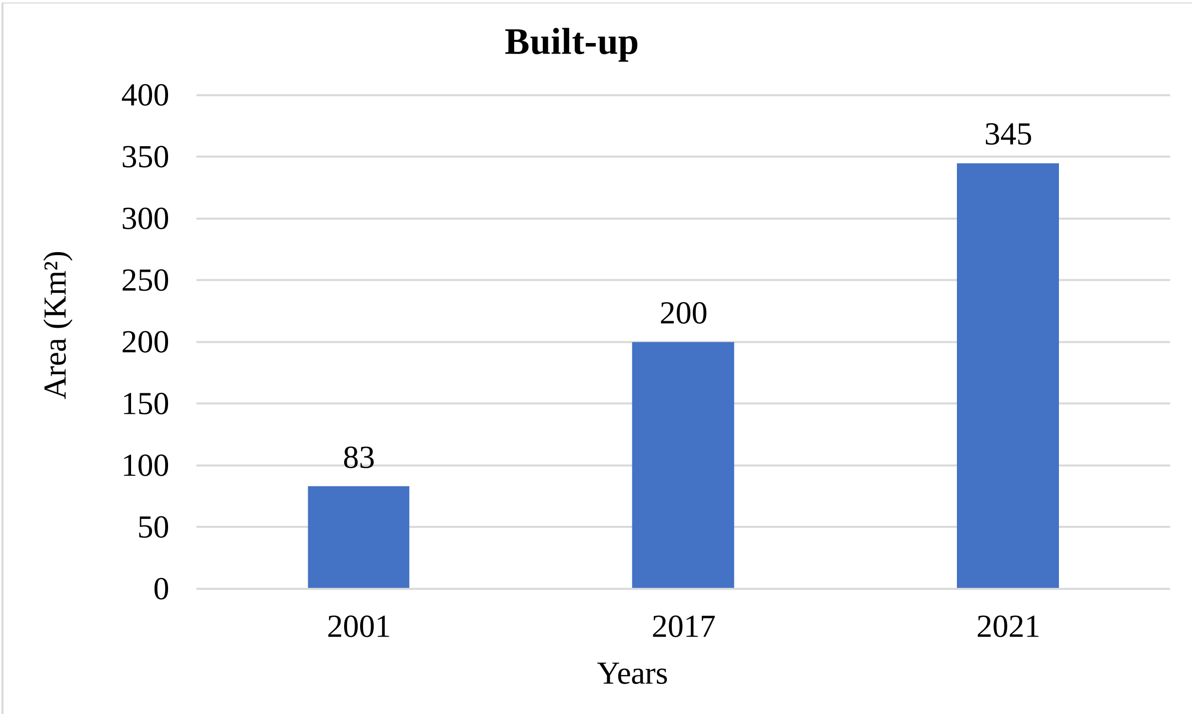

Figure 3.7: Trend Analysis of Built-up

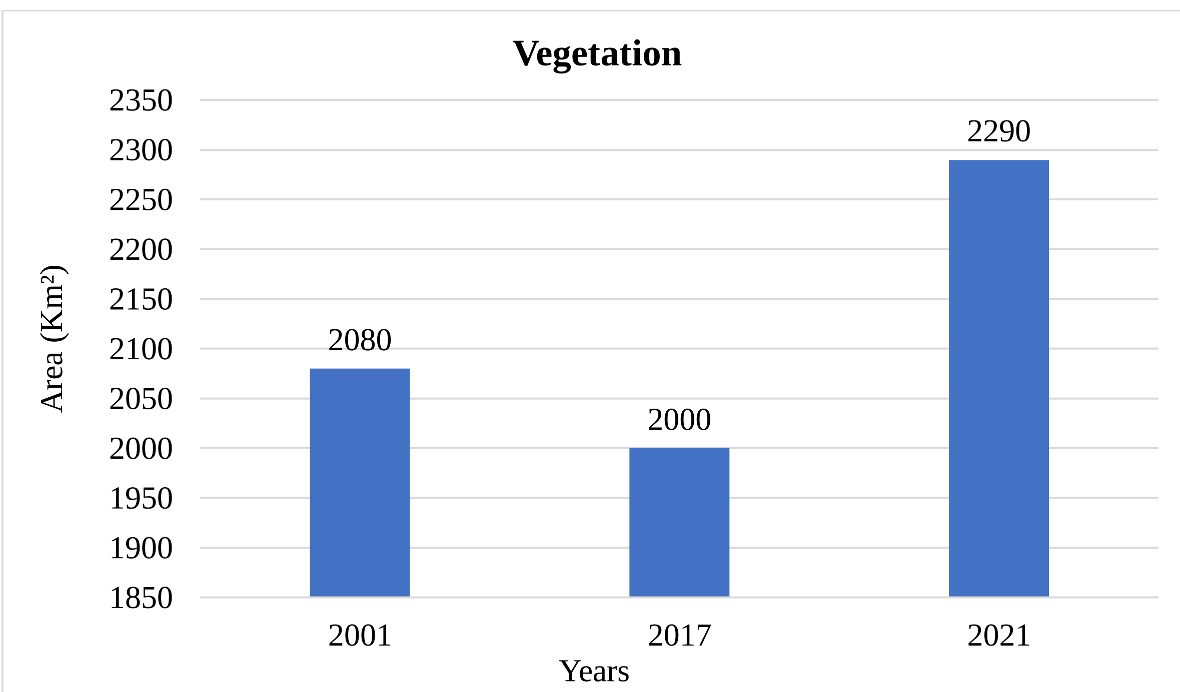

Figure 3.8: Trend Analysis of Vegetation

3.8 Time Series Analysis of Cotton Areas

The major focus of this study is on the status of cotton crops over the study periods. Multan district is well-known for its outstanding agricultural production, particularly cotton and mango. Cotton is the major source of support for the textile sector of the country. Urbanization in the district is rising constantly and affecting the vegetation including major crops like cotton. In the past two decades, cotton had an immense downfall. From the year 2000-2021, urban growth negatively affected the growth of cotton. Some other LULC classes also affected the growth of cotton like an increase in bare land or an increase in the growth of some other crops in the district. The trend analysis of cotton crop areas shows that it is continuously decreasing. In 2001, the cultivated cotton crop area was 1467 Km^2 which reduced to 1400 Km^2 in 2017 and further reduced to 900 Km^2 till 2021. Figure 3.9 shows the downfall trend of cotton crop in the Multan district.

3.8.1 Conversion of Cotton-Grown Areas to Built-up Analysis

This study is about how the increasing urban trends are affecting the agricultural land in the Multan district mainly focusing on the cotton crop, so we analyzed the impacts of urbanization on the cotton crop. Figure 3.10 shows how much cotton crop area has been converted to built-up in the past two decades. From 2001 to 2017, 10 Km^2 of cotton areas were converted into a built-up area and from 2017 to 2021, it increased up to 25 Km^2.

The analysis show that 2% out of total affected cotton cropped areas is due to urbanization in the Multan city. Here are some factors affecting the cotton yield in the district. Cotton is a weather sensitive crop and difficult to manage as compared to other crops. Its picking is not in one go rather it has different stages. Cotton is prone to White Fly attack. In recent years, people have shifted towards maize crop instead of cotton due to the input costs, difficult management and low yield. Cotton requires moderate rain at its early growth stages and dry weather after flowering but shifts in rainfall patterns can affect the cotton crop areas. Figure 3.11 shows the spatial-temporal changes in cotton crop areas.

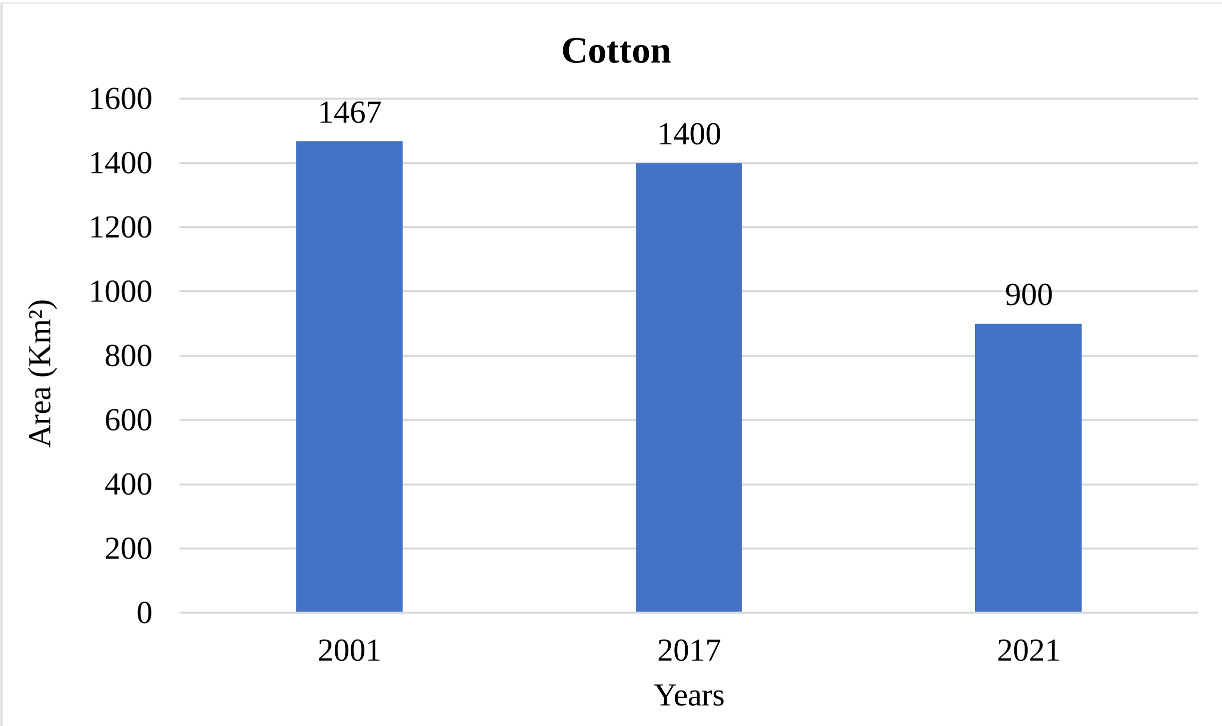

Figure 3.9: Trend Analysis of Cotton Crop

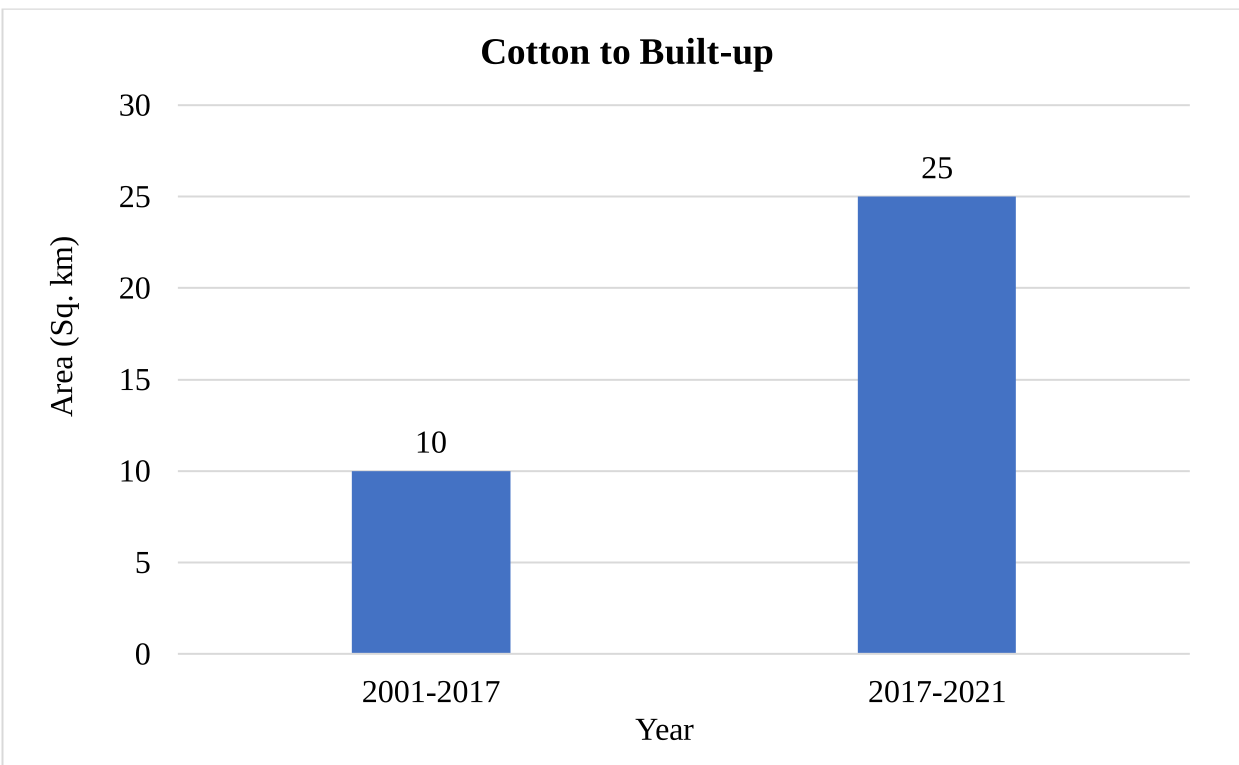

Figure 3.10: Conversion of Cotton Grown Areas to Built-up Graph

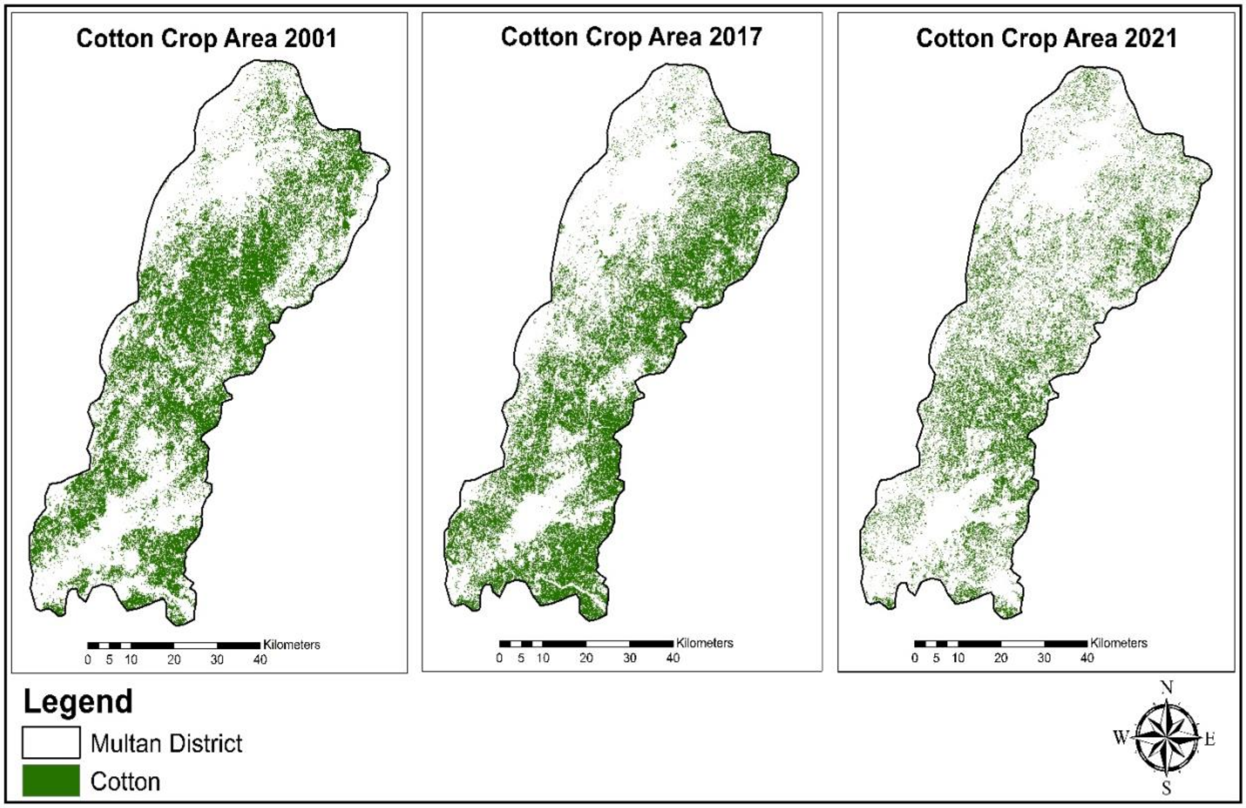

Figure 3.11: Spatial-temporal Analysis of Cotton Crop Areas

3.9 Prediction of LULC for Year 2031

The CA-ANN model used in QGIS 2.8.3 with the installation of the plugin Modules for Land Use Change Evaluation (MOLUSCE) 3.0.13 (Muhammad et al., 2022). The MOLUSCE plugin is designed for LULC change analysis and future prediction. It has some modules and functions which includes, an input module, area change analysis, modeling methods, validation, and simulation.

MOLUSCE uses raster data and other spatial data as input. For correlation analysis, evaluating the correlation module uses three techniques namely Pearson's correlation, Cramer's coefficient, and Joint information uncertainty. The area changes module generates class statistics and transition matrix tables. There are four different algorithms, Artificial Neural Network (ANN), Multi Criteria Evaluation (MCE), Weights of Evidence (WoE), and Logistic Regression (LR) to model transition potential. The Cellular Automata Simulation module is used to simulate future prediction maps.

The Artificial Neural Network algorithm has five inputs which are used to generate the output. These inputs are neighborhood, learning rate, momentum, hidden layers, and maximum iterations. Neighborhood is the total number of neighbor pixels around the current pixel. Maximum iteration numbers, learning rate, and momentum are the parameters of learning. One iteration is a complete pass through the entire dataset. Large values of momentum and learning rate means fast learning, but the learning process would be unstable (spikes on the graph). Small values of momentum and learning rate mean slow but stable learning. Hidden layers have a number of neurons. N^1 is the number of neurons in 1st hidden layer, N^2 is the number of neurons in the 2nd hidden layer, and so on.

The outputs are graph area, delta overall accuracy, minimum validation overall error, and current validation kappa. The graph area has training and validation learning curves. The training curve (green curve) gives an idea of how well the model is learning and the validation curve (red curve) gives an idea of how well the model is generalizing. The gap between the training and validation curve shows that the model is overfitting.

The graph also has minimum and maximum values of 0.1 to 0.4 at the y-axis. These values represent the error rate matrix. It tells the model's performance during training. Minimum values indicate that model performance is improving over time while higher values indicate the overfitting of the model. These values are helpful in the decision-making process of neural networks. The graph of the model is shown in Figure 3.13.

The delta overall accuracy is the difference between initial and final accuracy after training. It represents the performance of the model over time. A higher final accuracy value indicates an improvement in overall accuracy. Min. validation overall error is the lowest error rate achieved by the model during the validation process. It is calculated based on the mean square error or mean absolute error. The model is trained so that this error is reduced and the model can perform well on unseen data. In this study, min. validation overall error value is 0.063 which indicates the good performance of the model.

Current validation kappa is calculated for a machine learning model based on its performance on a validation dataset. It is used to assess the agreement between predicted and actual values of the model. Higher kappa values indicate better agreement between predicted and actual values. In this study, the kappa value is 0.83 which is good. The output values are shown in the Table 3.8.

Multi Criteria Evaluation (MCE) algorithm is a decision-making process that evaluates and ranks alternatives based on multiple criteria. It is often used for spatial decision-making, such as site selection, land use planning, or environmental impact assessment. Key components of MCE are criteria identification, criteria weighting, standardization, aggregation, evaluation, and ranking.

Weights of Evidence (WoE) algorithm transforms categorical variables into continuous variables, making them more suitable for models that require numerical input, like logistic regression. It is helpful in credit scoring and risk modeling, which helps assess the predictive power of categorical variables.

Logistic Regresssion (LR) is used for binary classification tasks, where the goal is to predict the probability of one of two possible outcomes based on input features. Despite its name, logistic regression is a linear classification model rather than regression. It includes two inputs which are maximum iterations and neighborhood. Outputs are pseudo-R-squared values, coefficients, standard deviation, and P-values.

The first step of the model training was to input the data, which the model learned, to simulate data and measure the transition analysis from the initial to the final year. At the initial stage of model training, it was trained for two datasets; the input LULC data of 2001 and 2017. The CA-ANN model generated the change table and change map first to predict the year 2021 later. The least change ranges between 0-4 km², the moderate 10-16 km², and the highest between 21-24 km². The change map is shown in Figure 3.12 and the change statistics are shown in Table 3.7.

After the change map generation, the model simulated the predicted map of already classified LULC for the year 2021. The predicted LULC map was then compared with the already classified LULC map to evaluate and validate the percentage of correctness which was 83%. In the classified LULC 2021, built-up area was 345 km² and in model predicted LULC 2021, it was 361 km². It means model predicted 1% more built-up than the classified LULC 2021. Water was 55 km² in classified LULC and 47 km² in predicted LULC. Bare land was 200 km² in classified LULC and 367 km² in predicted LULC. The model predicted 5% more bare land than the classified LULC. Cotton is 900 km² in classified LULC and 797 km² in predicted LULC. Other vegetation is 2290 km² in classified LULC and 2218 km² in predicted LULC. The comparison of classified and predicted LULC maps is shown in Figure 3.14. Quantitative LULC changes between both the maps were also generated and shown in Table 3.9.

Once the model was trained and validated on already classified LULC, the prediction for the required year 2031 was done. According to the model prediction, the urban area would further increase to 405 Km² and bare land to 240 Km² while, cotton will be decreasing to 855 Km² and other vegetation including forest, shrubs, and other crops up to 2253 Km² in the year 2031. The predicted LULC map is shown in Figure 3.15. The predicted changes in area for the year 2031 is shown in Table 3.10.

The other deriving factors than classified data were also fetched into the model as initial data to enlarge the performance and accuracy of the model like DEM, roads and rivers, etc.

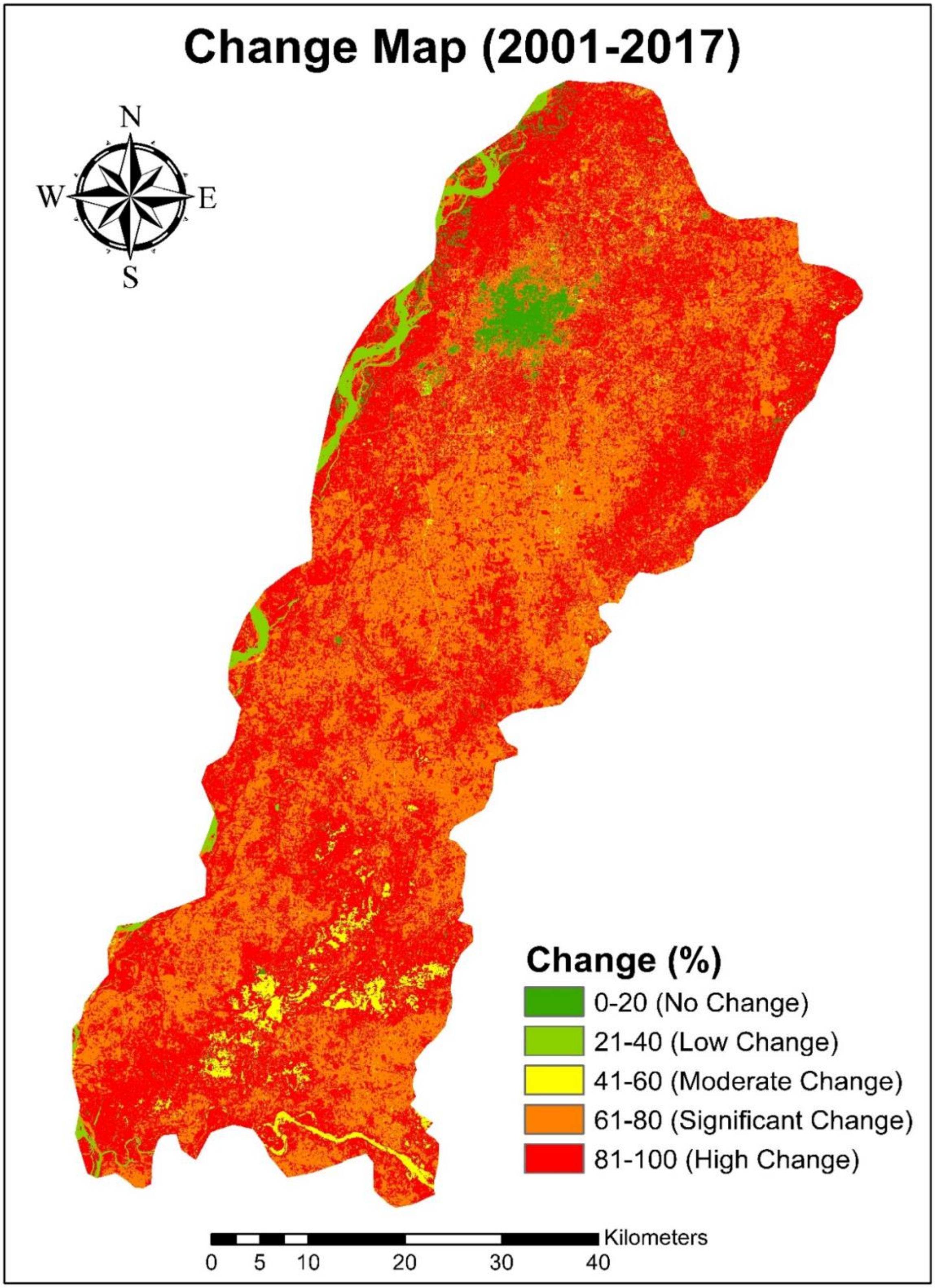

Figure 3.12: Change Map of LULC (2001-2017) Simulated by Model

Table 3.7: Area Change of LULC Simulated by Molusce Tool

Class Name	2001 (Km^2)	2017 (Km^2)	Change (Km^2)
Built-up	83	200	117
Water	70	60	-10
Bare Land	90	130	40
Cotton	1467	1400	-67
Other Vegetation	2080	2000	-80
Total	3790	3790	157

Table 3.8: Artificial Neural Network Training Statistics

1	Max. Iterations	1000
2	Hidden Layers	10
3	Momentum	0.050
4	Overall Accuracy	0.022
5	Min. Validation Overall Error	0.063
6	Current Validation Kappa	0.83

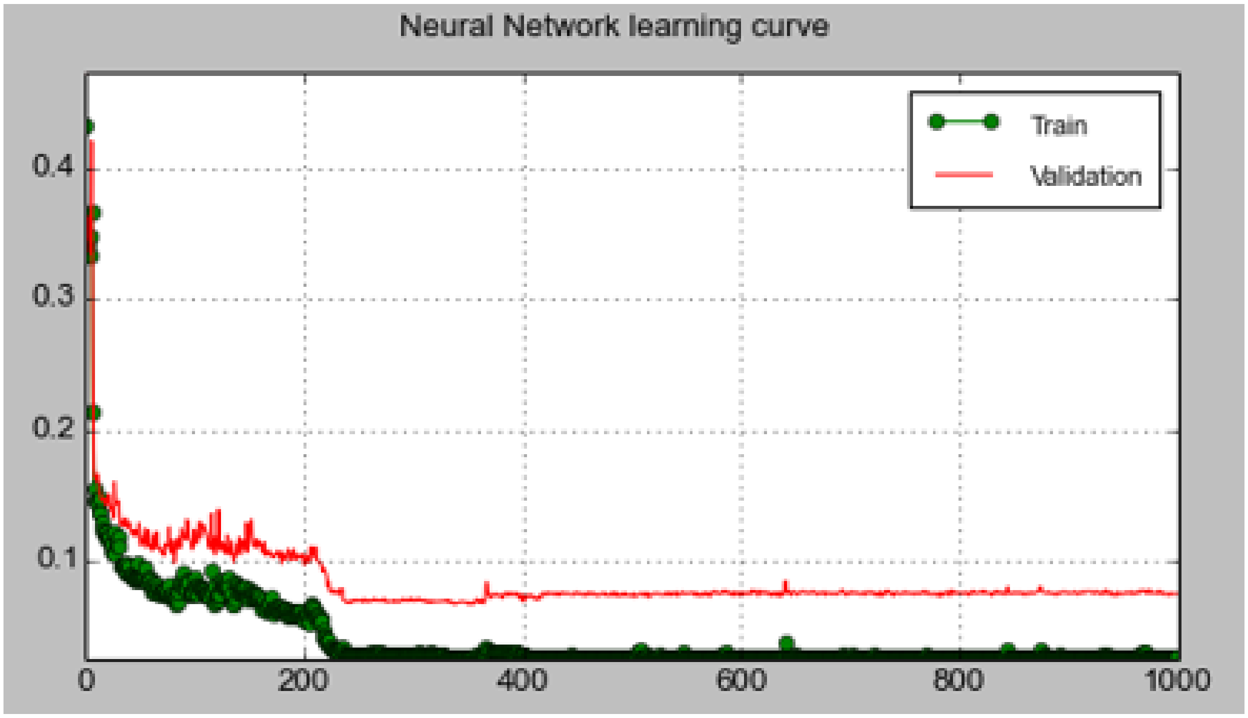

Figure 3.13: Model training with input data as LULC

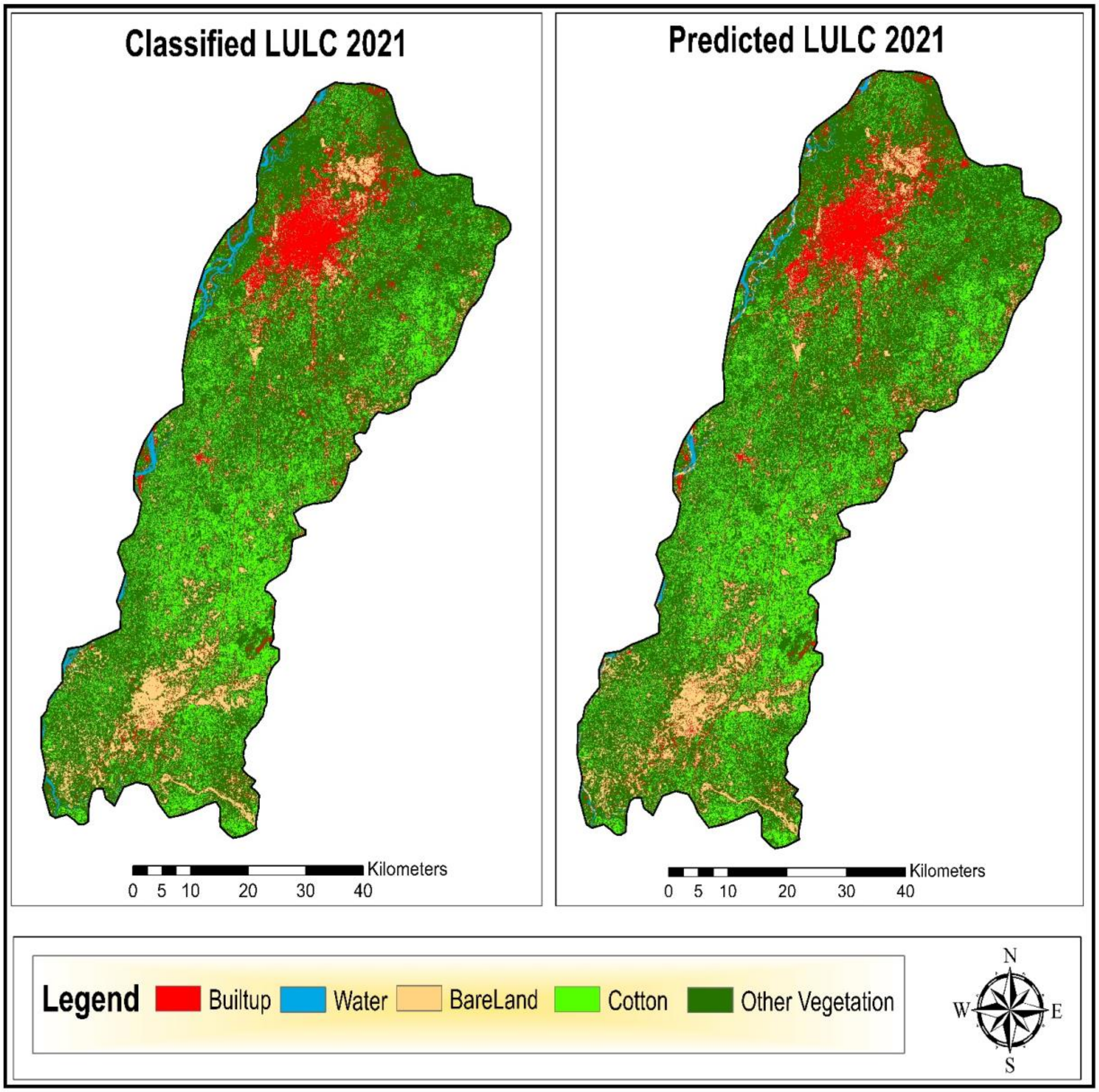

Figure 3.14: Model Validation by Comparison of Classified LULC 2021 and CA-ANN Predicted LULC 2021

Table 3.9: Comparison of Classified LULC 2021 and Predicted LULC 2021

LULC Class	**Classified LULC 2021**		**CA-ANN Predicted LULC 2021**	
	Km²	**%**	**Km²**	**%**
Built-up	345	9	361	10
Water	55	2	47	1
Bare Land	200	5	367	10
Cotton	900	24	797	21
Other Vegetation	2290	60	2218	58
Total	3790	100	3790	100

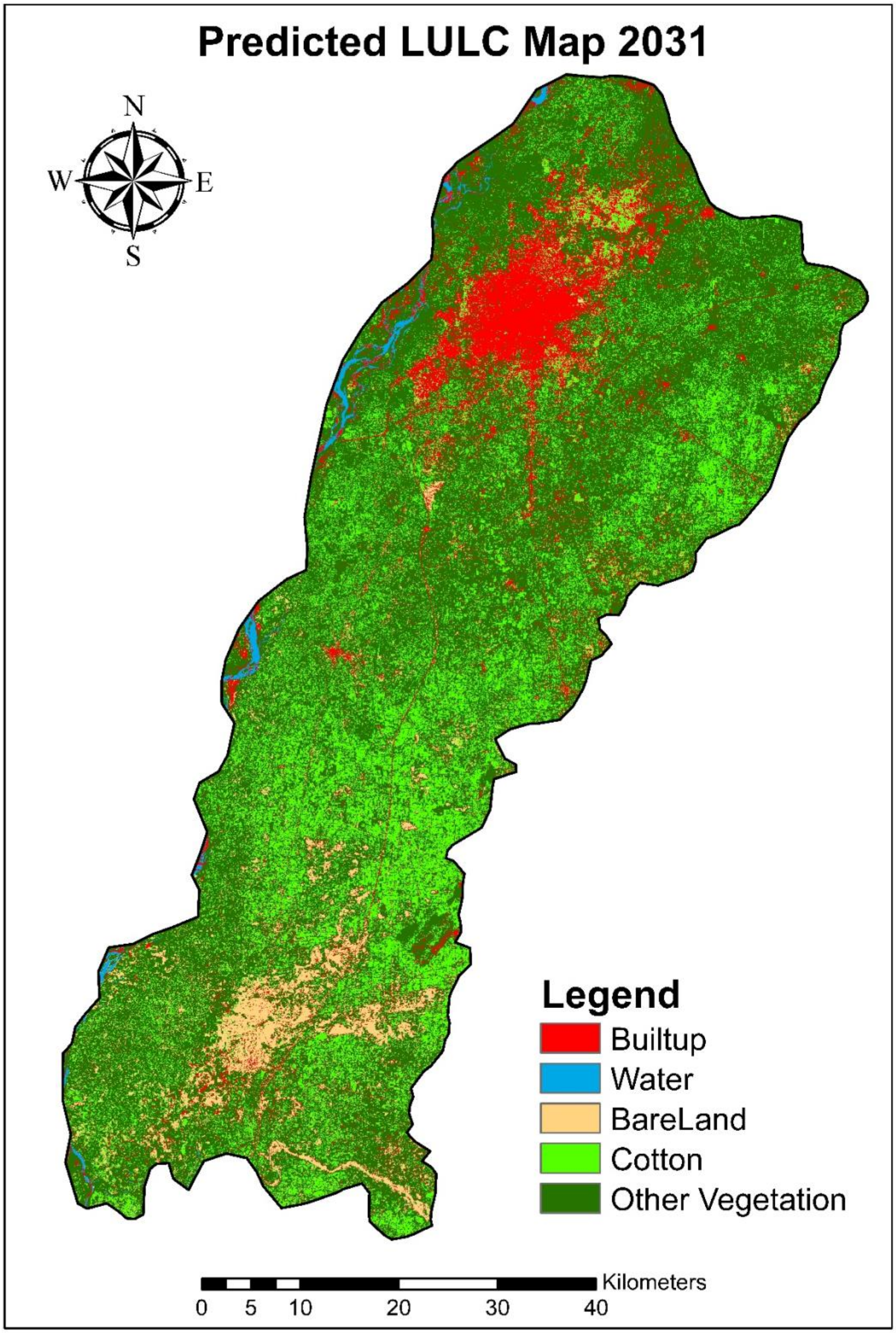

Figure 3.15: Predicted Map of LULC 2031

Table 3.10: Comparison of LULC 2021 and Predicted LULC 2031

LULC Class	**Classified LULC 2021**		**CA-ANN Predicted LULC 2031**	
	Km^2	**%**	**Km^2**	**%**
Built-up	345	9	405	11
Water	55	2	37	1
Bare Land	200	5	240	6
Cotton	900	24	855	23
Other Vegetation	2290	60	2253	59
Total	3790	100	3790	100

CHAPTER 4

CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

The research is conducted on the impacts of urbanization on agricultural areas in the Multan district for the past two decades (2001-2021). Supervised classification using the maximum likelihood algorithm is applied for temporal LULC classification. In this study, Landsat-7, and Sentinel-2 are used for the years 2001, 2017, and 2021 respectively.

The classified map of Landsat-7 for the year 2001 has an overall accuracy of 80% due to its coarse resolution. For the years 2017 and 2021, classification results based on the Sentinel-2 imagery, overall accuracy are 88% and 84% respectively. These results showed that Sentinel imagery gives better insights to differentiate the LULC classes than Landsat-7 data.

The time-series LULC classification maps indicated the temporal variations of the different classes in the district. The transition of multiple features revealed that the main factor of reduction in agricultural land was the increase in the settlements and impervious surfaces i.e., built-up class. The main causes of the urban expansion are the migration of people from the surrounding areas towards the city for multiple socioeconomic activities and the development of new housing societies. Due to this, the population has increased with the increase in urbanization.

This means that the agriculture in the surrounding of the Multan urban area has decreased due to the continuous urban growth in the city. The built-up area has been increased up to 7% from 2001-2021. While cotton cropped areas reduced to 15%, bare land increased to 3% and other vegetation including orchards, seasonal crops, forest, and grass has been increased to 5%. The reduction in cotton crops is mainly due to urban growth.

The research aimed to develop a methodology for the spatial and statistical analysis of LULC, correlated urban growth with the vegetation specifically cotton crop to find the effect of built-up area on cotton crop. Built-up area is negatively correlated with the cotton crop. Another focus of the research was on the measurement of future LULC to find the trends of the cotton crop growth.

The second objective was to predict LULC for the year 2031. For this purpose, the CA-ANN model is applied in QGIS. Two already classified LULC images (2001, 2017) are used as an initial and final input along with spatial variables. A change map is generated by the model and the output change has been classified in to three three class , i.e., least (0-4 Km^2), medium (4-4 Km^2), and the high (21-24 km^2).

A predicted LULC map for the year 2031 is generated by the model, based on the past trends of LULC changes. According to the predicted map, the predicted changes form 2021-2031 would be that the built-up area will increase by 60 Km^2 from 2021, bare land by 40 Km^2, while cotton crops will reduce to 45 Km^2 and other vegetation including crops, shrubs, and orchards, will reduce about 37 Km^2.

4.2 Recommendations

Spatial-temporal analysis shows that there is an obvious agricultural loss. Future predictions also show the loss of agriculture with the increase of built-up areas. To protect the agricultural sector from decline, there is a dire need for sustainable urban planning, management, and the timely implementation of policies. Remote sensing and GIS are advanced technologies that are used in this study and MDA can use these technologies for the monitoring of the urban development and thus would be easy for urban planning. The local bodies should invest in green areas in the most populated areas. It will also improve the environment.

The administrative bodies in the agriculture sector should be more focused on the growth of cotton crops because it support the textile industry of the country. Remote sensing and GIS should be used also in the agriculture sector for crop yield monitoring. There must be a smart approach to vertical buildings instead of horizontal buildings to avoid loss of the prime agricultural land. Moreover, there should be strong communication between the urban development authorities and the agriculture sector administration which would be helpful in the protection of agriculture and the controlled urban sprawl.

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