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Quantifying and Predicting Urban Sprawl in Sargodha, Punjab: A Remote Sensing and MLP-Markov Chain Approach

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Abstract
Urbanization, the conversion of rural landscapes into built environments, has accelerated rapidly in developing nations. In Pakistan—where the 2017 census recorded a 36.44 urbanization proportion—medium-sized cities in Punjab play a pivotal role in this transition. This study examines urban growth in Sargodha City through three integrated components: (1) historical land-use/land-cover (LULC) analysis using remote sensing from 1998 to 2022; (2) future LULC prediction employing a Multilayer Perceptron–Markov Chain Analysis (MLP–MCA) model; and (3) a structured questionnaire assessing residents' perceptions of urbanization impacts. Landsat imageries were classified as quantifying LULC changes, revealing a ~5%—18% (between 1998—2022) rise in built-up area. The MLP–MCA model—calibrated with 10,000 iterations, 50% training/testing samples, static (aspect, slope, elevation) and dynamic (road proximity) variables—achieved 89.19% accuracy and a Kappa of 0.89. A stratified Likert-scale survey of 385 participants captured attitudes toward urban growth, land-use change, and associated socio-environmental effects. Results revealed that built-up area expanded from ~77 km² (5%) to ~278 km² (18%) (1998–2022) and is projected to reach 29% (~454 km²) of the study area by 2035 and 32% (~506 km²) by 2050, with hotspots in northwestern and southeastern sectors. Residents reported mixed sentiments: many acknowledged economic and infrastructural benefits, while concerns centered on environmental degradation, resource strain, and uneven planning. Awareness of urbanization metrics varied across demographic groups. Sargodha's transformation from an agrarian landscape toward a predominantly urban environment underscores an accelerating trend that—although currently below national average demands proactive planning. Integrating empirical LULC projections with local perceptions offers a comprehensive framework for sustainable urban management in medium-sized cities of Punjab.

Keywords: Urbanization Trend, Markov Chain Analysis, LULC Change, Prediction, Multi-Layer Perceptron, Spatial Analysis, Medium—sized cities.

1. Introduction

Urbanization is the process by which a growing population lives in urban regions, resulting in the growth and extension of cities. It is a continuous phenomenon with important implications for society, the economy, and the environment. This section thoroughly examines the history and importance of urbanization, highlighting its fundamental causes, consequences, and the need for in-depth research and analysis. Throughout human history, urbanization has been a trend[1]. But over the past century, urbanization has expanded significantly and quickly[2]. During the Industrial Revolution, technological developments and economic changes that concentrated industry and people in urban areas started a turning point in urbanization[3]. Understanding the historical background allows us to comprehend the origins of urbanization and how it has changed over time. The history and foundation of urbanization can be followed back to antiquated times and have been molded by different social, financial, innovative, and natural variables with no end in sight[4]. The twenty-first century is known as the urban century because, according to the United Nations (2018), more than half of the world's population lives in cities[5]. According to The Urban Age Project, the London School of Economics, urban growth has varied greatly across regions, with many African and Asian cities rapidly expanding since 1950, while urbanization has slowed in Latin America. Several cities projected to be among the largest by 2025 were small towns in 1950, reflecting stark contrasts in urban development trajectories. Pakistan is one of the most quickly urbanizing countries in South Asia[6]. According to the 2017 census, Pakistan's total population is ~207.68 million, with a population growth rate of ~2.40%. Pakistan is a highly urbanized country in South Asia, with an urbanization proportion of

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36.44. Urbanization is now accelerating more rapidly than ever, forming dense, interconnected networks of human settlements and infrastructure that concentrate, reproduce, and contest modern capitalism—defying earlier predictions of its decline[7].

Medium-sized cities in Pakistan can vary in population size, but according to the United Nations (UN), generally they fall within the range of 500,000 to 1 million residents[8]. Some of the prominent medium-sized cities in Punjab Pakistan include Bahawalpur, Sargodha, Sialkot, Sheikhupura, Rahim Yar Khan, Jhang, Sahiwal, Mianwali and Okara. The rapid growth of these cities can be attributed to several factors. Firstly, rural-to-urban migration has been a significant driver of urbanization. People from rural areas move to medium-sized cities in search of better economic opportunities, education, and healthcare facilities[9,10]. Secondly, industrialization and economic activities have also contributed to the urbanization of medium-sized cities. Many of these cities have developed as industrial hubs, attracting both labor and investment. Another trend in medium-sized cities is the expansion of housing schemes and real estate development. As more people migrate to these cities, there is an increased demand for housing. Education is another significant aspect of urbanization in medium-sized cities. These cities often have a higher concentration of educational institutions, including schools, colleges, and universities. This attracts students and professionals seeking quality education and research opportunities. As a result, there is a growing student population in these cities, which can have a positive impact on the local economy[11,12,13,14,15].

However, it's important to note that urbanization in medium-sized cities also comes with its set of challenges. One of the key challenges is ensuring that urban growth is sustainable and inclusive[15,16]. Sargodha was chosen specifically among other medium sized cities because it is a typical medium-sized city in Punjab, Pakistan, that is rapidly growing and diverse. This diversity makes it ideal for examining the urbanization process from a variety of perspectives. Sargodha is considered an urban area because of its higher population density than surrounding areas. In recent years, rapid urbanization has caused many problems, including the shifting of rural vegetative land into residential colonies, leading to severe LULC change due to the influx of people from surrounding areas[17,18]. The study's main aim is to thoroughly examine and comprehend the trends, dynamics, and socioeconomic aspects of urbanization in the context of Punjab's medium-sized cities, with a particular emphasis on Sargodha. By combining two approaches, a questionnaire-based assessment (see questionnaire APPENDIX—1) and the LULC change assessment using remote sensing and GIS analysis, the study hopes to accomplish this. LULC changes are significantly impacted by the urbanization process. Analyzing LULC changes is crucial for tracking trends and comprehending how urbanization affects the environment. Analysis of LULC changes can offer essential insights into the causes of urbanization, how urbanization affects the environment, and how well urban planning and management policies work. Urbanization is a significant cause of changes in land use and land cover. Hence the significance of LULC change in urbanization is considerable. Cities frequently encroach on nearby rural areas as they grow and expand, changing the land's usage and cover[19,20]. Promoting sustainable urban growth and safeguarding significant natural areas depend on understanding and tracking these changes.

With the recent development of remote sensing technologies, GIS technologies, and machine learning algorithms, approaches and methods for LULC change detection have become more complex. These techniques make it possible to map and track changes in LULC through time accurately and effectively. The classification of LULC has extensively used the Markov Chain model MLP as an urban growth model. Markov Chain analysis is a practical method for examining the likelihood of changes

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in LULC over time. This method can be used to model changes in land use and land cover, spot trends and patterns, and predict upcoming systemic changes. Markov Chain analysis is still useful for analyzing changes in land use and land cover, even if it has several drawbacks, especially in regions that are quickly urbanizing. MLP is a valuable technique for analyzing and predicting remote sensing data because it has been effectively applied for various LULC categorization applications[21,22,23,24,25]. By synthesizing the predictive capabilities of MLP and Markov Chain analysis with the contextual depth offered by questionnaire-based assessments, this integrative framework establishes a robust foundation for deciphering urbanization trends in medium-sized cities, exemplified through the case study of Sargodha City in Punjab, Pakistan. This study aims to use a combined strategy of LULC change detection and questionnaire-based evaluations to comprehensively examine and analyze the urbanization dynamics in medium-sized cities of Punjab, with an emphasis on Sargodha City, Pakistan. The following goals are the focus of the study:

i. To analyze the changes and dimensions of the built-up area along with urbanization as a significant scenario.
ii. To simulate and analyze LULC change for years 1998-2022, then to predict scenarios of future LULC changes quantitatively and spatially for 2035-2050.
iii. To analyze the study area's driving forces governing the land use changes and urbanization and their implications for planning.

2. Materials and Methods

2.1. Study Area

Among the various medium-sized cities situated in Punjab, Pakistan, this research is mainly centered on the city of Sargodha, Pakistan. Located on the dynamic floodplain of the Jhelum River, the district of Sargodha is a portion of the upper Indus plain. The region under investigation is located in Pakistan's Punjab province. The total area of District Sargodha is 5,854 km^2. The geographical coordinates of Sargodha district are between 31°34' N and 32°36' N, and 72°10' E and 73°18' E. The area between the Chenab and Jhelum rivers is known as Chaj Doab, and it includes the whole Sargodha district. Sargodha district is bordered by the following districts: Jhelum to the north, Mandi-Baha-Uddin and Hafizabad to the east, Chiniot and Jhang to the south, and Khushab to the west. Among Pakistan's major cities, Sargodha ranks 12th. Citrus fruits, wheat, and sugarcane are some of the most prominent agricultural products grown in District Sargodha. This area gets its nickname, "Citrus Capital of Pakistan," from the abundance of oranges and other citrus fruits grown there. Its transportation systems, healthcare facilities, and educational institutions are all well developed[17].(Figure 1).

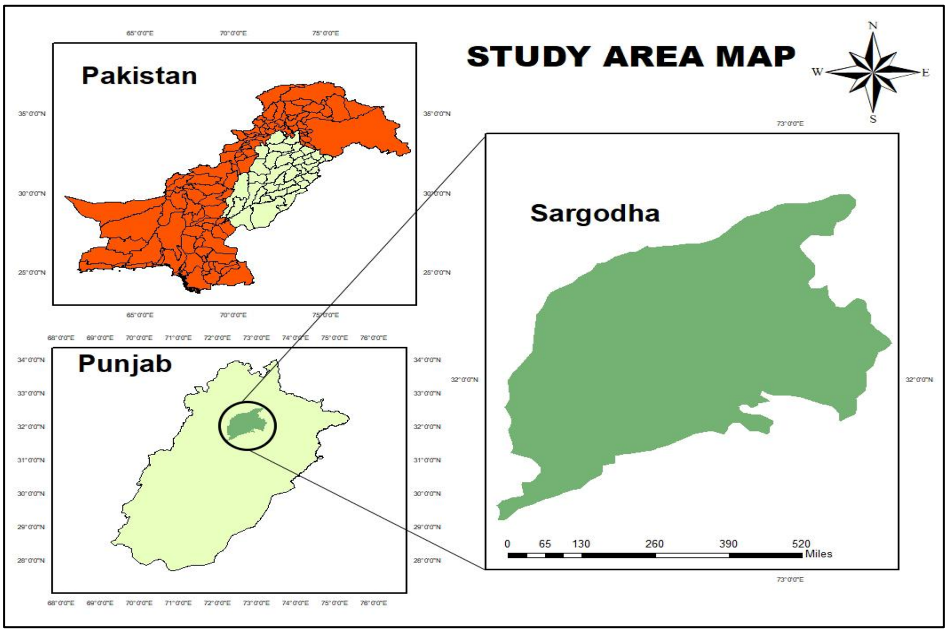

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Figure 1: Map of the Study Area.

2.2. Data Collection:

The study is carried out in two phases, i.e., LULC assessment and questionnaire-based assessment (see questionnaire, APPENDIX—1). This research is based on two types of datasets: satellite-based datasets and questionnaire datasets. The satellite-based data (remote sensing images) of the Sargodha city were downloaded from the United States Geological Survey (USGS) website (i.e., https://earthexplorer.usgs.gov/). Remote Sensing satellite images are preferred because their spatial, temporal, and spectral resolutions are more accurate and provide more authentic input for planning and mapping purposes. For this , the remotely sensed LANDSAT images of the years 1998, 2010, and 2022 were downloaded from the USGS website. The Landsat images of 1998 and 2010 were downloaded from LANDSAT 5, whereas the Landsat image of 2022 was downloaded from LANDSAT 8 (According to the image availability of these years). The ASTER DEM data was required to create the variables, i.e., elevation, slope and aspect, that are required for the prediction purpose in the Land Change Modular process. The DEM data is acquired from Earth Data of The National Aeronautics and Space Administration (NASA) (i.e., https://search.earthdata.nasa.gov/) (Table 1). The road networks are extracted from the Open Street Map according to the study area. This data is required to create distance from road variables. See Figure 2 for a brief methodological overview of this whole study.

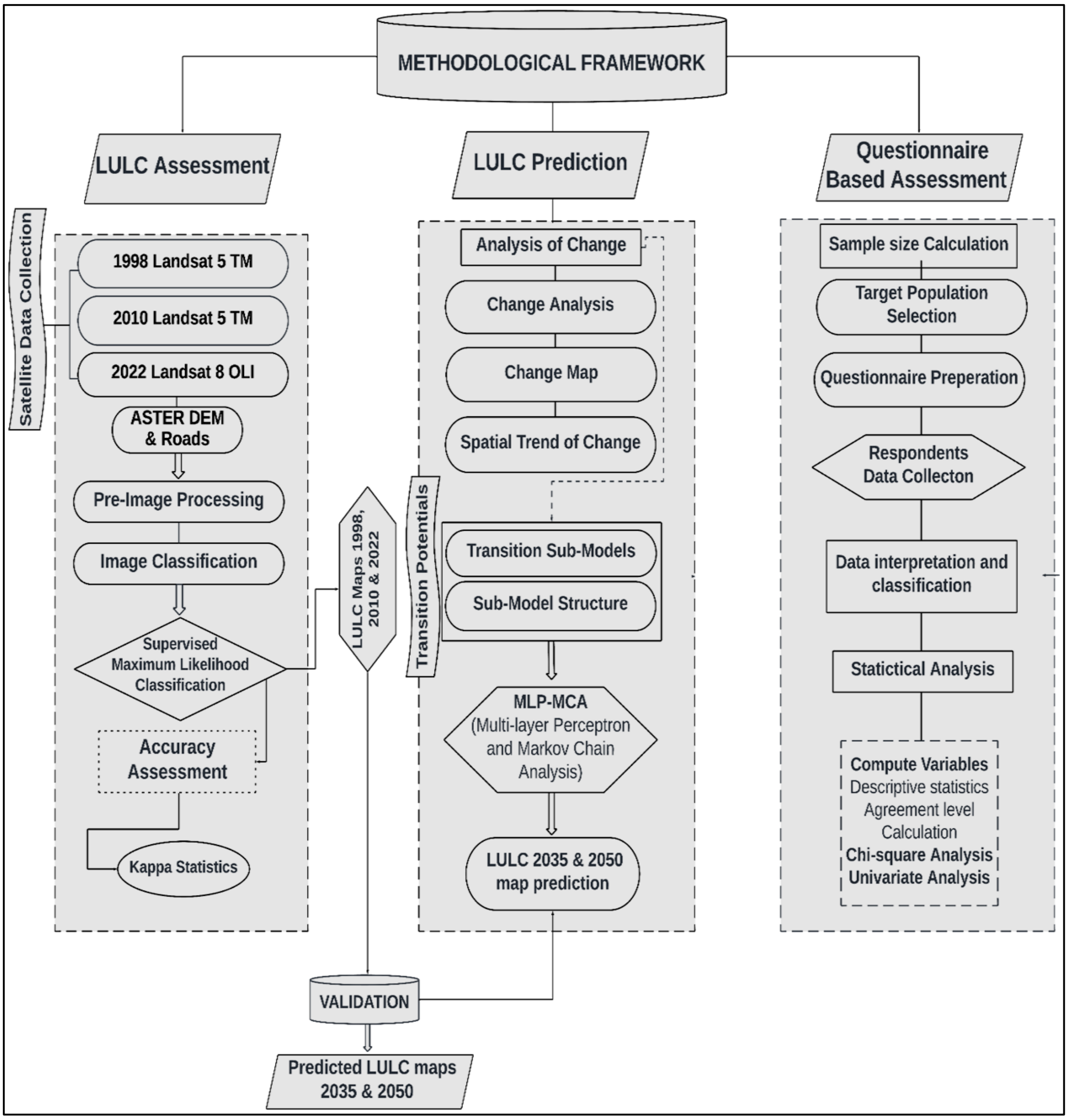

Figure 2: Flowchart showing a brief methodological overview of the study.

Table 1: Acquired Landsat Images

Years	Satellite	Date	Path	Row	Spectral Bands
1998	LANDSAT-5 TM (Thematic Mapper)	1998-03-29	150	038	Band 5, Band 4, Band 3
2010	LANDSAT-5 TM (Thematic Mapper)	2010-11-25	150	038	Band 5, Band 4, Band 3
2022	LANDSAT-8 OLI (Operational Land Imager)	2022-08-22	150	038	Band 5, Band 4, Band 3

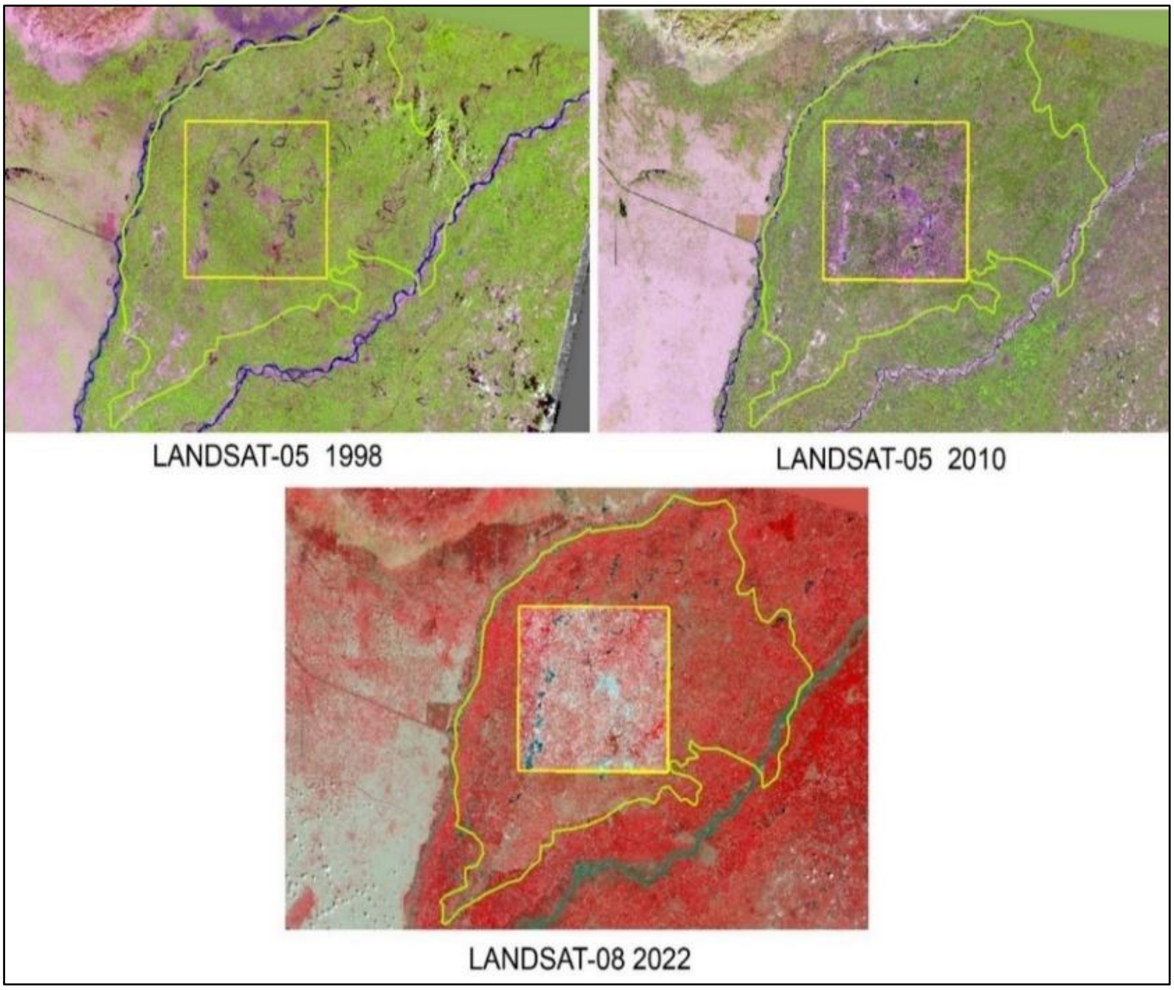

Figure 3: Image pre-processing of years 1998, 2010 and 2022

2.3. Pre-image Processing:
With layer stacking, different bands from the identical sensor were combined to create a single multiband image. The downloaded satellite images were processed. In ArcGIS software, layer stacking, and clipping of study area were performed on each dataset of LULC images. Then these datasets were referenced in the UTM projection (Universal Transverse Mercator), and the WGS (World Geodetic system) was applied according to the location of the country, as WGS_1984_UTM_43N. By using appropriate band combinations, the FCC (false color composite) was generated this FCC was required to select the training samples. The training samples were generated separately for each LULC class and analysis[17,18] (Figure 3).

2.4. Selection of Training Samples:
The creation of a training set was done using the training data gathered in step one for the map of each year 1998, 2010 and 2022. To accurately represent the spectral properties of each class, the training set should have enough samples[23]. To do the image classification process, the training samples were generated separately for each LULC class for satellite images of the years 1998, 2010, and 2022. Only four land use categories are employed. Built-up, Water bodies, Barren land and Agricultural land. These four categories were considered because other categories like snow tundra, forest range, etc. are not present by nature in the study area. Because the primary focus is to simulate the land use land cover change with urbanization (as the main driving factor or cause), only these four land use categories were enough[17,18].

2.5. Creating Signature files & Supervised Maximum likelihood classification:
This method involves categorizing the pixels in the satellite imagery into distinct land cover classes by training a classification algorithm using reference data or ground truth samples. After selecting training samples, signature files were generated to proceed with supervised maximum likelihood classification (SMLC). The SMLC approach is frequently employed in urban settings for LULC assessment[26]. The SMLC technique calculated these statistics to determine the likelihood that a pixel belongs to a particular land cover class for the years 1998, 2010, and 2022. The SMLC method is trained with the training set and the projected class statistics[17]. Based on the calculated statistics, the algorithm determined the likelihood value distribution of the

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spectral metrics for each land cover class[27]. Each pixel for each LULC class type is given a probability based on the information provided by the maps of the years 1998, 2010, and 2022[28] (Figure 4).

2.6. Accuracy Assessment of LULC:

The Supervised Maximum Likelihood Classification (MLC) for LULC evaluation must undergo an accuracy assessment, a critical stage for determining its worth[29,30]. This procedure was useful in LULC maps for 1998, 2020, and 2022. After the classification process of these satellite images, the "*Confusion Matrix approach*" is applied to check the accuracy of the whole classification. This assessment computed all user, producer, overall accuracy, and Kappa statistics for LULC maps of 1998, 2010, and 2022. The designated map is compared to reference data or ground truth samples to assess the classification's accuracy. The confusion matrix approach allowed the estimation of several accuracy measures, including user, producer, overall accuracy, and Kappa statistics[31] (Table 2).

2.7. Area Statistics of Classified LULC Maps for the years 1998, 2010 and 2022:

The following table presents the Area Statistics for Classified Land Use and Land Cover (LULC) Maps for three distinct years: 1998, 2010, and 2022[17,18]. It offers explanations for the changing landscape of a particular area. In 1998, most of the land was devoted to agricultural purposes, covering 62% of the total area, while built-up areas, water bodies, and barren land comprised smaller percentages. Interestingly, agricultural land decreased in the following years, and built-up land increased (Table 3).

2.8. Change Detection of LULC maps:

Through supervised Maximum Likelihood Classification and cross-tabulation for the periods 1998–2010, 2010–2022, and 1998–2022 (see Tables 4–6), LULC change detection shows a pronounced urbanization trend—built-up areas grew from ~77 km² in 1998 to ~146 km² in 2010 and ~279 km² by 2022—while agricultural land steadily declined (from ~968 km² to ~734 km² and then ~679 km²). Water bodies and barren land exhibited smaller, more variable shifts, and the reliability of these findings is supported by accuracy assessments[32,33,34].

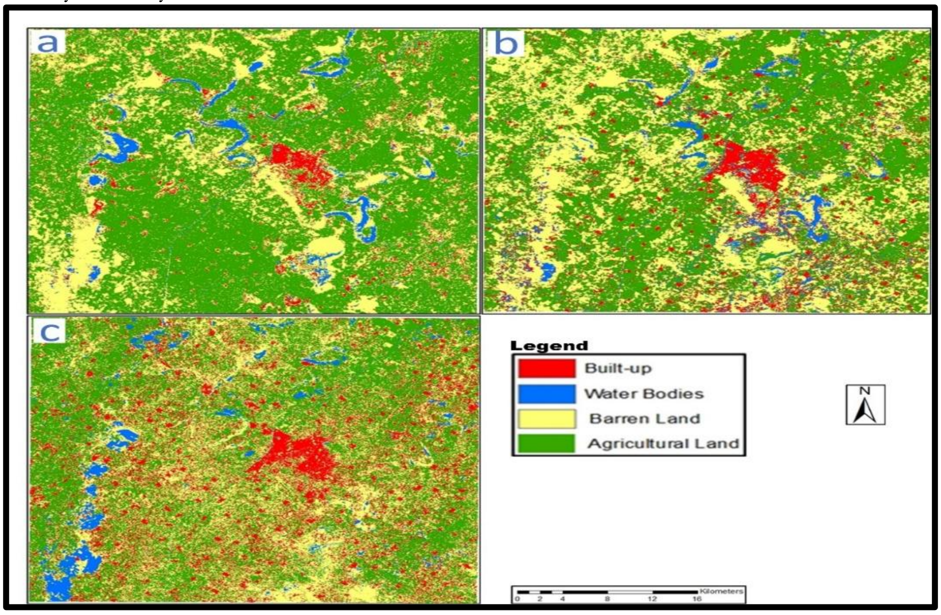

Figure 4: Classified images of LULC Change of Sargodha: (a) 1998, (b) 2010, (c) 2022.

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Table 2: Accuracy Assessment of LULC Maps for years 1998, 2010 and 2022

Years	**1998**		**2010**		**2022**	
LULC Class	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**
Built-up	100	100	87.5	93.33	91.66	91.66
Water	100	85.71	87.5	87.5	90	100
Barren Land	85.71	85.71	90	90	87.5	87.5
Agricultural Land	83.33	90.90	83.33	71.42	90	81.81
Overall Accuracy	0.9000		0.875		0.9000	
Kappa Coefficient	84.68%		90%		87%	

Table 3: Area Statistics of Classified LULC Maps of the Years 1998, 2010 and 2022

Classes of Classified maps	**1998**		**2010**		**2022**	
	Area (km²)	**%**	**Area (km²)**	**%**	**Area (km²)**	**%**
Built-up	77.1717	5	145.851	9	278.814	18
Water	48.4782	3	69.5655	4	56.1233	4
Barren Land	463.5380	30	608.2562	39	543.927	35
Agricultural Land	968.276	62	733.789	47	678.607	44

Table 4: Change Detection in LULC during 1998-2010

Years	**1998**		**2010**		**Change 1998-2010**	
LULC Classes	**Area**	**%**	**Area**	**%**	**Area**	**%**
Built-up	77.1717	5	145.851	9	-68.6793	-4
Water	48.4782	3	69.5655	4	-21.0873	-1
Barren Land	463.5380	30	608.2562	39	-144.7182	-9
Agricultural Land	968.276	62	733.789	47	234.487	15

Table 5: Change Detection in LULC during 2010-2022

Years	**2010**		**2022**		**Change 2010-2022**	
LULC Classes	**Area**	**%**	**Area**	**%**	**Area**	**%**
Built-up	145.851	9	278.814	18	-132.99	-9
Water	69.5655	4	56.1233	3	13.4422	1
Barren Land	608.2562	39	543.927	35	64.3292	4
Agricultural Land	733.789	47	678.607	44	55.191	3

Table 6: Change Detection in LULC during 1998-2022

Years	**1998**		**2022**		**Change 1998-2022**	
LULC Classes	**Area**	**%**	**Area**	**%**	**Area**	**%**
Built-up	77.1717	5	278.814	18	-201.6423	-13
Water	48.4782	3	56.1233	4	-7.6451	-1
Barren Land	463.5380	30	543.927	35	-80.389	-5
Agricultural Land	968.276	62	678.607	44	289.669	18

2.9. LULC Maps Conversion and Variables Preparation:

LULC Maps of the years 1998, 2010 and 2022 were reclassified to give the same number of IDs, and then for further processing, these LULC maps were converted into the ASCII format with the same row and column values, spatial reference, cell size, pixel depth and pixel type (Table 7).

For the preparation of variables, all the tiles of ASTER DEM were mosaicked, and the study area was extracted from it. Then the variables, i.e., Aspect, Slope, and Elevation were created from the DEM. The shapefile of roads was exported from the Open Street Map, from which the study area roads were extracted, and distance from roads was created using the Euclidean Distance Tool in ArcGIS software. In order to do further processing in TerrSet software, all the variables were converted into ASCII format with the same row and column, spatial reference, cell size, pixel depth and pixel type. The LULC maps and the variables were converted into ASCII Format to run further in TerrSet Software where the Arc-info raster ASCII was formatted to IDRISI with spatial reference UTM_43N and these were converted from real to integer data type[35,36] (Figure 5).

Table 7: Details of LULC maps converted into ASCII format

LULC Maps	Cell Size	Column	Row	Spatial Reference	Pixel Depth	Pixel Type
1998	30	1349	1299	WGS_1984_UTM_Zone_43N	8-Bit	unsigned integer
2010	30	1349	1299	WGS_1984_UTM_Zone_43N	8-Bit	unsigned integer
2022	30	1349	1299	WGS_1984_UTM_Zone_43N	8-Bit	unsigned integer

2.10. LCM-Driven LULC Change Forecast

Markov chains adhere to stochastic process models that delineate the probability of one variable (e.g., Slope or LULC) transitioning to another (e.g., roadways) within a certain time frame[37]. The Land Change Modeler (LCM) facilitated the analysis of land-cover change and the simulation of future scenarios by combining multilayer perceptron neural networks with Markov chain matrices to evaluate transition potentials (e.g., barren to built-up, agricultural to built-up) utilizing both static (slope, elevation, aspect) and dynamic (distance from roads) factors. It produced spatial trend graphs for the periods 1998–2010, 2010–2022, and 1998–2022, indicating a climb of built-up expansion in central regions, and generated Markov probability matrices[38] for 2035 and 2050—demonstrating an increase in built-up persistence from 0.636 to 0.795—and associated area projections[39,40,41] (Figure 5 & Table 8—9).

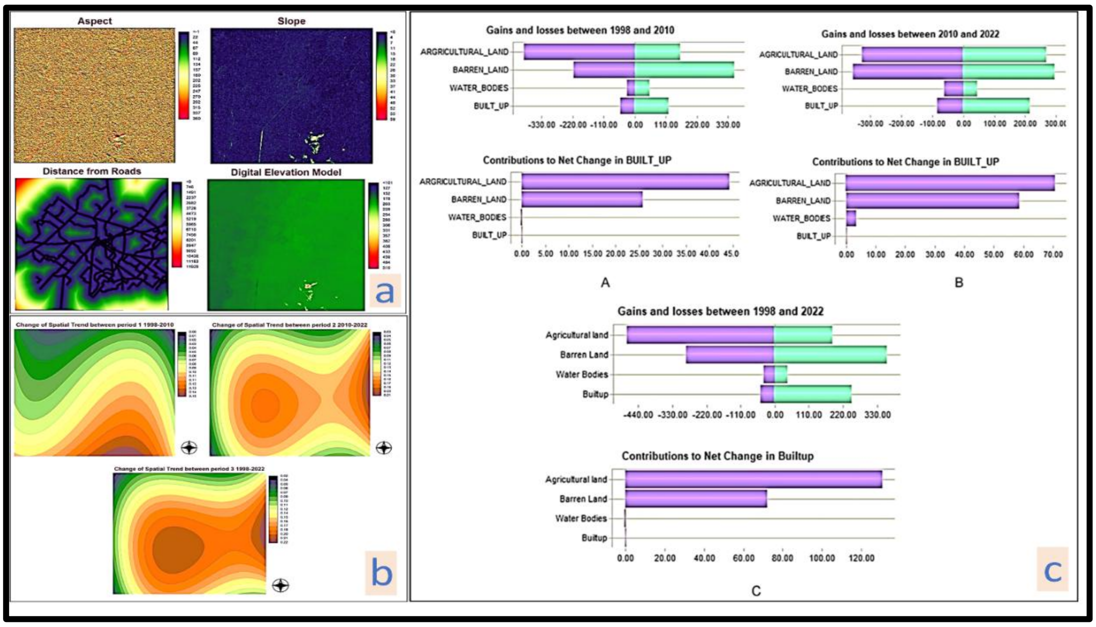

Figure 5: Data preparation for land use prediction: (a) Vital Variables for Prediction, (b) Change of Spatial Trend, (c) Transition Potential Modeling according to the gain and losses and contributions to net change in built-up from Period 1 (1998-2010) "A," Period 2 (2010-2022) "B," and Period 3 (1998-2022) "C."

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Table 8: Markov Conditional Probability Matrix for year 2035				
LULC classes	**Built-up**	**Water bodies**	**Barren land**	**Agricultural land**
Built-up	0.6360	0.0207	0.1853	0.1580
Water bodies	0.0260	0.5449	0.3256	0.1036
Barren land	0.1329	0.0469	0.5992	0.2210
Agricultural land	0.0986	0.0023	0.2193	0.6799

Table 9: Markov Conditional Probability Matrix for year 2050				
LULC classes	**Built-up**	**Water bodies**	**Barren land**	**Agricultural land**
Built-up	0.7950	0.0360	0.2976	0.2713
Water bodies	0.0818	0.2488	0.4590	0.2104
Barren land	0.2079	0.0656	0.3833	0.3432
Agricultural land	0.1710	0.0138	0.3351	0.4801

2.11. Data Collection through Field Survey

In addition to mapping LULC changes for 1998, 2010, and 2022, a structured questionnaire survey was conducted—separate from the geospatial analysis—to capture residents' insights on urbanization in Sargodha. Focusing on built-up land as the key indicator of urban growth, the survey targets local residents, real-estate developers, and academic experts to provide diverse perspectives on land-use changes. Comprised of seven sections—demographics; perceptions of urbanization and its environmental impacts; views on Sargodha's urban growth; awareness of LULC change detection; personal experiences with land-cover change; perceptions of land-use dynamics; and drivers of urbanization—the questionnaire uses a five-point Likert scale to quantify responses. A sample of 385 respondents (determined via EPI Info) was surveyed, and their responses were analyzed in SPSS using descriptive statistics and chi-square tests. This mixed-methods approach combines quantitative mapping with community perceptions to inform sustainable urban planning and policy[42,43,44,45].

3. Results and Insights

3.1. Urbanization Assessment based on Built-up Results:

The assessment of LULC changes, specifically focusing on the expansion of built-up areas, yielded significant insights into the urbanization trends in this selected medium-sized city of Punjab. The analysis of LULC data from 1998 to 2010 revealed an expansion of built-up areas by approximately 145.85 square kilometers, constituting 9% of the total study area. This initial period marked a moderate level of urbanization. Subsequently, from 2010 to 2022, the built-up area further increased to 278.814 (18%) square kilometers (Figure 4). This nearly doubled expansion highlighted a substantial acceleration in urbanization during this period (Table 3—6). Utilizing the Multilayer Perceptron (MLP) and Markov Chain Analysis (MCA) approach, the study predicted the future built-up area expansion. To do so, the LCM session was executed, which showed the change analysis, transition potentials, and prediction segment[46]. This procedure was done separately for all the 3-time periods. The gain and loss and contributors to net change in built-up for periods 1, 2, and 3 were observed, based on which change maps were generated, which showed all the transitions within the study area. Further, the spatial trend of change was mapped

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42 "Questionnaires and Surveys," in *Research Methods in Intercultural Communication*, 1st ed., by Tony Johnstone Young (Wiley, 2015), https://doi.org/10.1002/9781119166283.ch11.

43 David A. Butler et al., "Analysis Methods and Descriptive Statistics," in *Assessment of the Department of Veterans Affairs Airborne Hazards and Open Burn Pit Registry* (National Academies Press (US), 2017).

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45 Sureiman Onchiri, "Conceptual Model on Application of Chi-Square Test in Education and Social Sciences," *Educational Research and Reviews* 8, no. 15 (2013): 1231.

46 Bhavna Singh et al., "Monitoring of Land Use Land Cover Dynamics and Prediction of Urban Growth Using Land Change Modeler in Delhi and Its Environs, India," *Environmental Science and Pollution Research* 29, no. 47 (2022): 71534–54, https://doi.org/10.1007/s11356-022-20900-z.

for each period 1 (1998-2010), 2 (2010-2022), and 3 (1998-2022) by taking three orders of polynomial, which showed the appropriate change trend pattern. The trend was mapped from all classes (i.e., Water Bodies, Barren Land, and Agricultural land) to the Built-up class, which showed the built-up transition more intense from the middle region of the study area. Then the transition sub-models were created, and only two major transitions were considered according to the objectives of the study: Barren land to built-up and agricultural land to built-up, which were grouped within a single name as Built-up, which was evaluated by taking Evidence likelihood as the variable transformation utility. Aspect, slope, elevation, and distance from the road area were taken as variables for the transition sub-model Structure. Aspect, slope and elevation area were taken as the static variables. In contrast, distance from roads was taken as the dynamic variable because the population and development along the road's sides fluctuated over time (Figure 5).

Multilayer Perceptron was run with 10000 iterations by taking 1000 sample sizes per class with a ratio of 50% training and 50% testing RMS (Root mean Square), which referred to the error or loss measurement used to measure the discrepancy between the MLP's predicted output and the actual target output[47,48]. The resultant MLP shows an 89.19% accuracy rate. The change prediction is done by using the Markov Chain[46]. To get valid results, This MLP-MCA procedure was initially applied to period 1 (1998-2010) to predict the LULC change patterns in 2022 by using the LULC maps of 1998 and 2010. Then, the same process was applied to period 3 (1998-2022) LULC maps to predict the map of the years 2035 and 2050 using the MLP-MCA approach. For the validation, the predicted LULC map of 2022 was compared with the supervised LULC map of 2022 utilizing the kappa statistics. The overall observations showed 0.89 kappa agreement between the observed LULC map and the predicted LULC map, which shows the successful prediction (Figure 5 & Table 2 & Table 8—9).

The results indicated a projected built-up area of ~454 square kilometers for the year 2035, constituting approximately 29% of the total study area. Additionally, for the year 2050, the predicted built-up area is ~506 square kilometers, accounting for approximately 32% of the total study area. The model also predicted that the most significant increase in urban area will occur in the north-eastern-western and southeastern-western parts of the city (Figure 6 & Table 10). Comparing the predicted built-up expansion percentages with the overall urbanization trend in Pakistan, which stands at 36.4%,[49] several insights emerge:

• **Current Urbanization Trend**: The study's findings suggest that the current urbanization trend in the studied medium-sized cities of Punjab is relatively lower than the national average. The built-up expansion percentages for both 2035 (29%) and 2050 (32%) fall below the country's average urbanization rate of 36.44[43].

• **Accelerated Urbanization**: While the projected urbanization rates in the studied city remain below the national average, the rapid increase in built-up areas over the years indicates an accelerating trend. The jump from 5% in 1998–2010 to 32% by 2050 underscores the swift pace of urban development and raises concerns about its potential impacts[50].

• **Potential Future Trajectory**: The predicted built-up area for the years 2035 and 2050 suggests that these medium-sized cities could experience an upward trajectory in terms of urbanization or urban Sprawl. The trends imply that urbanization is likely to continue expanding, albeit at rates slightly below the national average[51].

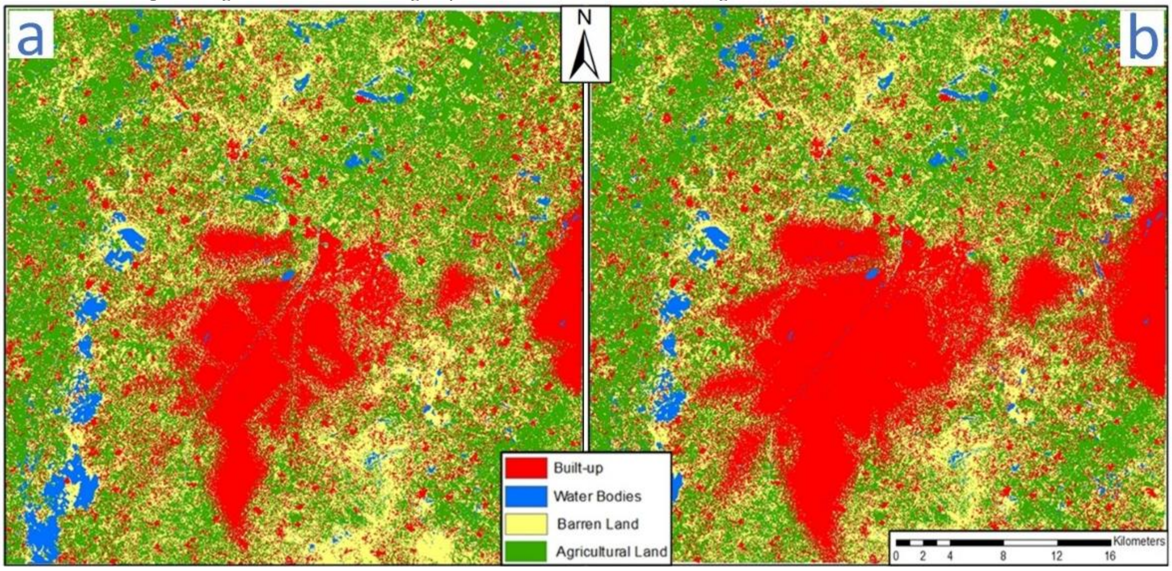

Figure 6: Predicted LULC images of year 2035 and 2050: (a) 2035 & (b) 2050.

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Table 10: Area statistics of Predicted LULC of Years 2035 and 2050

LULC classes	Predicted 2035		Predicted 2050	
	Area (km²)	Area (%)	Area (km²)	Area (%)
Built-up	453.8154	29%	506.2529	32%
Water bodies	56.6919	4%	53.6922	3%
Barren land	471.5006	30%	454.3724	29%
Agricultural land	601.4655	38%	569.1562	36%
Total	1583.47	100.00	1583.47	100.00

3.2. Urbanization Trends and Public Opinion:

The questionnaire data was analyzed to understand respondents' experiences, perceptions and knowledge of urbanization trends and drivers' impacts. (Please refer to the questionnaire at the end in Appendix—1 to understand the results given here). The Likert-scale questionnaire responses of 385 Sargodha residents revealed their views on urbanization and its effects, challenges, and drivers. Ordinal measure data was ranked or ordered, so it was not normally distributed. Descriptive statistics' median and mode measures of central tendency were best for such data. In tables 2.1—2.3 (Appendix—2), the percentage frequency distribution and level of agreement of responses in each category were calculated separately for each variable of each section. Additionally, chi-square analysis was done. The choice of such statistics helped determine respondents' attitudes or responses to urbanization (perception and impact), LULC change (knowledge and awareness), experience with urbanization, perception of LULC change, and the driving forces governing land use changes and urbanization. The findings illuminate Sargodha's complex urban growth dynamics and their effects on the environment, society, and economy. The questionnaire-based assessment's main findings are:

Across six thematic sections, respondents reported that urbanization in Sargodha has driven higher population density, agricultural-land conversion, infrastructure growth, informal settlements, and ecosystem impacts—though overall perceptions on environmental consequences were both neutral and in favor. Views on urbanization's benefits and challenges varied, with many recognizing economic and social gains despite limited familiarity with specific urbanization indices. Awareness of LULC change-detection methods ranged from well-informed to unfamiliar, and most participants personally witnessed land-cover shifts—especially agricultural to built-up conversions—and their effects on food production, connectivity, and open spaces. Finally, they pinpointed key drivers of change—social services availability, population pressure, development projects, and infrastructure quality—underscoring the multifaceted forces shaping Sargodha's urban expansion.

3.2.1. Chi-Square & Univariate Survey Analyses

Chi-square analyses across all thematic sections (Perceptions of Urbanization Impacts, Urbanization in Sargodha, LULC Change Awareness, Personal Experience, LULC Perception, and Driving Forces) yielded highly significant associations (χ^2 ranging from 119.894 to 310.322 with $p < 0.001$), confirming that respondents' views differ systematically across variables (Table 11). Univariate analysis of demographics (n=385) showed respondents were relatively young (Age M=2.65, SD=1.10), predominantly male (Gender M=1.30, SD=0.46), and moderately educated (Education M=2.22, SD=0.68) (Table 12). Univariate analysis of thematic perceptions revealed moderately positive views across all sections: urbanization processes and environmental impacts (M=3.97, SD=0.27), urbanization in Sargodha City (M=3.31, SD=0.33), LULC change awareness (M=2.89, SD=0.51), personal experience with LULC change (M=2.95, SD=0.56), perceptions of land use/cover change (M=3.23, SD=0.33), and drivers of urbanization (M=3.21, SD=0.32), with low to moderate variability indicating consistent responses (Table 13).

Table 11: Chi-square Analysis Test Statistics

Variables/Sections	Chi-Square	df	Asymp. Sig.
Perception of Urbanization Process and its Environmental Impact	310.322a	16	.000
Perception of Urbanization in Sargodha City	288.691b	20	.000
Knowledge and Awareness of LULC Change Detection	212.345c	13	.000
Experience with Urbanization and LULC Change	119.894d	15	.000
Perception of Land Use and Land Cover Change	160.416e	14	.000
Driving forces governing the land use changes and urbanization	290.010a	16	.000

Table 12: Univariate Analysis of respondents with respect to Age, Gender And Education (Section 1)

Sr. No	Variables	Mean	St. Deviation
1	Age	2.65	1.101
2	Gender	1.30	0.459
3	Education	2.22	0.684

Table 13: Univariate Analysis of Respondents			
Sections	**Mean**	**St. Deviation**	**Total Respondents**
Perception of Urbanization Process and its Environmental Impact	3.9694	0.27204	385
Perception of Urbanization in Sargodha City	3.3117	0.33131	385
Knowledge and Awareness of LULC Change Detection	2.8873	0.51018	385
Experience with Urbanization and LULC Change	2.9515	0.55963	385
Perception of Land Use and Land Cover Change	3.2291	0.33210	385
Driving forces governing the land use changes and urbanization	3.2092	0.31832	385

4. Discussion and Conclusions

In this Research study, the urbanization trend in Sargodha, Pakistan, is evaluated[17,18,47] using a combination of public perception surveys through questionnaire analysis[52] (see questionnaire—APPENDIX—1), LULC change analysis, and future prediction of LULC classes, especially the built-up class, to assess the future built-up expansion, which represents the urbanization trend using the cutting-edge analytical methods like Multilayer Perceptron and Markov Chain analysis[53]. The goal was to develop an awareness of the dynamic interaction between LULC changes and public perceptions of urbanization and its effects. As a result, the MLP-MCA strategy to anticipate LULC changes has resulted in significant results, providing essential insights into the dynamics of urban development and transformation across time. The investigation across three different periods provided a thorough understanding of the study area's changing trends, transition potentials, and prediction stages. The detailed examination of gain, loss, and contributors to net change in the built-up areas for each period has resulted in accurate change maps, highlighting intricate transitions within the landscape. The spatial trend analysis, facilitated by polynomial orders, has effectively captured the evolving change patterns across the years. To be precise, our land-cover analysis paints a clear picture of rapid urban expansion in this medium-sized Punjab city. Between 1998 and 2010, built-up area grew from roughly ~77 km² to ~146 km² (9% of the study region), then surged to ~279 km² (18%) by 2022—an almost two-fold acceleration in the second period. A study in 2017 by Riaz et al. was in line with our findings and reported built-up change in Sargodha upto 19% during 1992—2015[47]. Two studies in 2023 by Farooq et al. nearly confirmed or slightly disagreed with our finding and reported that Sargodha built-up increased upto 13% from 1993—2023[17,18]. Another study reported a ~16% increase from 1987—2017[54] (Figure 6 & Table 10).

Our MLP–Markov chain model, validated with a $\kappa = 0.89$ agreement against the 2022 map and achieving 89.2% classification accuracy, projects that built-up land will reach about ~454 km² (29%) by 2035 and ~506 km² (32%) by 2050. These figures remain below Pakistan's national urbanization rate (36.44), but the steep rise—from 5% built-up in 1998–2010 to 32% by mid-century—signals an unmistakable acceleration that will concentrate most growth along the city's northeast and southeast peripheries. Other studies also highlight this alarming surge of built-up land, e.g., research based in Peshawar, Pakistan, by Tariq and Mumtaz (2023), revealed upto ~30% built-up increase up till 2054[55]. Another study in Raya, northern Ethiopia, by Gidey et al. (2017) (LULC: 1984—2015) reported that ~48% of built land increased until 2033[56]. Even a Karachi, Pakistan–based study reported the built-up area's explosive increase of to ~111% until 2030[57] (Figure 6 & Table 10).

Particularly noteworthy is the intensified transition to built-up areas, notably concentrated in the middle region of the study area, which reflects the changing dynamics of development in response to various factors. The development of transition sub-models, explicitly focusing on critical transitions like barren land and agricultural land to built-up areas, has provided a targeted understanding of how these changes occur[54]. Aspect, slope, elevation, and distance from roads have been adeptly utilized as variables, with the dynamic variable of road proximity capturing the variable population and developmental trends along these corridors. Utilizing the Multilayer Perceptron with rigorous iterations and well-structured training and testing datasets has demonstrated its efficacy in predicting LULC changes with a commendable accuracy rate of 89.19%[45,50]. The combination of MLP-MCA methodology, meticulous variable selection, and accurate validation techniques has enabled us to confidently

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predict LULC changes, providing an invaluable tool for urban planners, policymakers, and researchers. The predicted LULC Maps shows a massive increase in built-up for the years 2035 and 2050, which shows the expansion of the central city towards Lahore Road, Faisalabad Road, and along the surroundings of the central city. This expansion in the city can be assumed to be accurate towards the Lahore Road side, as there is a significant gap between the central city and Lahore Road, because for now there is a rapid development due to the private universities and colleges, i.e., the University of Lahore, Superior University, Niazi Medical and Dental College, Punjab college etc., therefore, the trend of population development and urban expansion is seen more significantly on that side. On the other hand, Faisalabad Road is also developed and will develop more, as shown in the prediction results (Figure 6 & Table 10). The agricultural and barren land may decrease, and water will increase and decrease because there are many fish farms, as most of the area of Sargodha is barren and salinized; therefore, people make fish farms, and there is a change increase in that business. Therefore, urbanization may also increase as the built-up increases in the future. This research enhances our understanding of urban dynamics and contributes to more informed decision-making for sustainable development in the years to come[17,18,58,59,60,61,62].

Our community survey (n=385) complements these spatial trends with equally revealing attitudes. Chi-square tests across six themes—from perceptions of environmental impacts to knowledge of LULC change—were all highly significant (χ^2 between ~119 and ~310, $p < 0.001$), confirming that demographic groups view urbanization differently. Univariate summaries show our respondents are relatively young (Age M=2.65, SD=1.10), predominantly male (Gender M=1.30, SD=0.46), and moderately educated (Education M=2.22, SD=0.68). They hold moderately positive views on urbanization's processes and impacts (means ~3.3–4.0 on a 5-point scale), display fair awareness of LULC detection methods (M=2.89, SD=0.51), and report varied direct experiences with land-cover change (M=2.95, SD=0.56). Importantly, they consistently identify population pressure, infrastructure development, and social-service availability as the key drivers behind Sargodha's evolving landscape. Together, these spatial and social insights underscore both the momentum of urban growth and the community's nuanced understanding—critical considerations for crafting informed, sustainable urban policies[17,18,47,63,64,65,66](Table 11—13). Respondents expressed varying degrees of agreement with statements about urbanization in Sargodha. While many believed that urbanization was a significant problem within the studied area, not all were aware of the research area's urbanization indices. The perception of the environmental benefits of urbanization, its economic advantages, and societal benefits also varied. Most participants agreed that Sargodha has experienced increasing urbanization in recent years, leading to land use/cover changes[17,18]. The perception of the city's urbanization rate being alarming and its economic opportunities benefiting from urbanization was mixed. Furthermore, participants widely agreed that urbanization has had a negative impact on the availability of green spaces while also contributing to infrastructural development[67,68,69]. Participants demonstrated varying levels of familiarity with detecting changes in land use/cover and remote sensing techniques used for assessment. While some were aware of studies on LULC change in Sargodha, others needed to familiarize themselves with remote sensing techniques. Interestingly, there was a mixed response regarding whether LULC change is the root cause of urbanization. People direct experiences with urbanization and LULC change in Sargodha were diverse. Many had witnessed the shift of agricultural land to urban neighborhoods and had personally observed land use/cover changes during their time in the city. The conversion of agricultural land to urban areas was believed to have influenced local food production and impacted accessibility and connectivity within the city. Respondents also agreed that the growth of urban areas had led to the displacement of native

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communities[70,71]. Respondents generally concurred that they had noticed land use and land cover changes in their neighborhoods due to urbanization. Changes in land use were perceived to have led to a decrease in agricultural land, and changes in land cover were seen as contributing to the loss of forests and green spaces[72]. Furthermore, participants acknowledged that these changes had affected natural ecosystems[73], altered urban aesthetics[74], and influenced the region's microclimate and urban heat island effect[75,76]. Most of the people identified various driving forces behind land use changes and urbanization. The availability of social and community services, population density, development of residential and commercial areas, accessibility of vacant land, presence of well-maintained infrastructure, and availability of essential services such as water, electricity, and recreational facilities were all considered factors influencing urban expansion and land use patterns. In conclusion, analyzing responses from the urban residents' questionnaire in Sargodha City provides valuable insights into the complex dynamics of urbanization and LULC change within this specific urban context. The statistical analysis, including the chi-square tests, underscores the robustness and significance of these findings. The wide range of perceptions, experiences, and opinions underscores the need for nuanced approaches to urban planning and development that consider both the benefits and challenges associated with urban growth[56,57,58,77].

In closing, our integrated analysis of satellite-derived LULC maps and community survey data paints a cohesive picture of a city in swift transition. Between 1998 and 2022, built-up land more than tripled—rising from 5%—9% to 18% of the study area—with the sharpest gains concentrated along major road corridors and in the city's core. Our MLP–Markov model, validated with an 89 % accuracy and $\varkappa = 0.89$, projects that by 2050 nearly one-third of the landscape will be urbanized—well below the national average but indicative of an accelerating local trend. Equally telling, our questionnaire of 385 residents confirmed that Sargodha's urban expansion is reshaping livelihoods and perceptions alike: people report firsthand losses of agricultural plots, pressure on services, and mixed feelings about environmental trade-offs, yet they consistently identify population growth, infrastructure investment, and social-service availability as the main drivers. Together, these findings demonstrate the value of proactive planning: if managed wisely—through targeted zoning, investment in green infrastructure, and community-driven decision-making—Sargodha can harness its growth to improve living standards while safeguarding its remaining farmlands and ecosystems. Future work should explore finer-scale scenario modeling and deepen stakeholder engagement to ensure that urbanization benefits everyone.

5. Author Contributions

Conceptualization, S.A.A.N., and L.A.W.; Data curation, U.K.N., S.A.A.N., and L.A.W.; Investigation, S.A.A.N., and U.K.N.; Methodology, S.A.A.N., L.A.W., and U.K.N.; Resources, S.A.A.N., L.A.W., M.N.M., and U.K.N.; Software, S.A.A.N. and U.K.N.; Supervision, S.A.A.N., and L.A.W.; Validation, S.A.A.N., L.A.W., and M.N.M.; Visualization, S.A.A.N., and U.K.N.; Writing—original draft, S.A.A.N., L.A.W., and U.K.N.; Writing—review and editing, S.A.A.N., M.N.M., L.A.W., and U.K.N. All authors have read and agreed to the published version of the manuscript.

6. Funding

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7. Ethical Approval:

This study received an ethical approval from the Ethical Review Committee of Government College University Faisalabad, Pakistan (Notification No: Ref. No. GCUF/ERC/305—Dated: 11 August 2023). Before asking the questions, we explained the survey purpose and process to each participant, and we asked for their permission. Only after they clearly agreed and gave their consent did we proceed with the questionnaire.

8. Data Availability Statement

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[74] Montanye, Erica, "Urban Dwellers Experiences Regarding Loss of Natural Environments Due to Rapid Urbanization" (Walden University ProQuest Dissertations & Theses, 2017), https://www.proquest.com/openview/0c6b135a8bf5a03b71e506f7da3ad41d/1?pq-origsite=gscholar&cbl=18750.

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The geospatial and statistical data analyzed in this research are not publicly posted. However, you're welcome to contact the corresponding author, and the data will be shared upon reasonable request.

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10. Conflicts of Interest
The authors declare no conflict of interest.

<u>APPENDIX—1</u>
SURVEY QUESTIONNAIRE
Quantifying and Predicting Urban Sprawl in Sargodha, Punjab: A Remote Sensing and MLP-Markov Chain Approach.
Section 1: Participant Information
- **Please enter your age:**

18-25 **b)** 26-35 **c)** 36-45 **d)** 46-55 **e)** 56 and up
- **Please specify your gender:**

Male **b)** Female **c)** Would rather not say
- **Please provide the following information about your educational background:**

a) High school diploma or equivalent **b)** bachelor's degree **c)** Master's degree **d)** PhD or equivalent
- **Location: Latitude ……………. Longitude………………**

Please rate how much you agree or disagree with the following statements:
Section 2: Perception of Urbanization Process and its Environmental Impact

Sr.	Questions	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
1	The population density in urban areas has increased as a result of urbanization.					
2	Agricultural land has been converted into residential or commercial districts as a result of urbanization.					
3	Urbanization has resulted in the increase of urban infrastructure (such as roads and buildings).					
4	The need for housing and real estate development has increased as a result of urbanization.					
5	Urbanization has changed the socioeconomic dynamics of urban regions.					
6	Urbanization has contributed to the emergence of informal settlements and slums.					
7	Noise pollution in urban areas has been exacerbated by urbanization.					
8	Urbanization has led to the loss of natural habitats for plants and wildlife.					
9	Cities' energy consumption patterns have been influenced by urbanization.					
10	Urbanization has influenced the local climate and weather patterns.					

Section 3: Perception of Urbanization in Sargodha City

Sr.	Questions	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
11	In the studied area Sargodha, urbanization is a significant problem.					
12	I am aware of the research area's urbanization indices.					
13	The environmental benefits of urbanization are substantial.					
14	Increasing urbanization benefits the economy.					
15	Urbanization is beneficial to society.					
16	Sargodha has seen increasing urbanization recently.					
17	I've noticed changes in land use/cover in Sargodha over time.					
18	Sargodha's urbanization rate is alarming.					
19	Sargodha's economic opportunities have benefited from urbanization.					

20	Urbanization has had a negative impact on the availability of green spaces in Sargodha.					
21	The growth of urban areas in Sargodha has resulted in increasing infrastructural development.					

Section 4: Knowledge and Awareness of LULC Change Detection

Sr.	**Questions**	**Strongly Disagree**	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
22	I am familiar with the concept of detecting changes in land use/cover.					
23	I am aware of remote sensing techniques used to assess changes in land use/cover.					
24	I am aware of studies conducted in Sargodha on changes in land use and land cover.					
25	I am familiar with remote sensing techniques for detecting land use/cover changes.					
26	I believe that LULC change is the root cause of urbanization.					

Section 5: Experience with Urbanization and LULC Change

Sr.	**Questions**	**Strongly Disagree**	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
27	In Sargodha, I witnessed the shift of agricultural land to urban neighborhoods.					
28	I have directly experienced land use/cover changes during my tenure in Sargodha.					
29	The conversion of agricultural land to urban areas in Sargodha has influenced local food production.					
30	Land use/cover changes have impacted accessibility and connectivity inside Sargodha					
31	The Sargodha city built-up has restricted the availability of open spaces.					
32	The urbanization process in Sargodha has resulted in the displacement of native community					

Section 6: Perception of Land Use and Land Cover Change

Sr.	**Questions**	**Strongly Disagree**	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
33	I have noticed land use and land cover changes in my neighborhood due to urbanization.					
34	Land use changes have resulted in a decrease in agricultural land in metropolitan areas.					
35	Changes in land cover have resulted in the loss of forests and green spaces.					
36	Changes in land usage have led to the growth of built-up regions.					
37	Changes in land cover have altered natural ecosystems and wildlife habitats.					
38	Changes in land use have impacted the availability of open places for recreational activities.					
38	Changes in land cover have altered the microclimate and urban heat island effect.					
40	Changes in land use have had an impact on groundwater recharge and water management in metropolitan areas.					
41	Land cover changes have altered the region's visual aesthetics and scenic splendor.					

Section 7: Driving forces governing the land use changes and urbanization

Sr.	Questions	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
42	The availability of social and community services has affected land use patterns.					
43	The increase in population density has led to changes in land use patterns.					
44	The development of residential areas has contributed to urban expansion in Sargodha City.					
45	The expansion of commercial and business zones has driven urbanization.					
46	The availability of vacant land has influenced land use decisions in the study area.					
47	The presence of well-maintained roads and highways has driven urban expansion.					
48	The accessibility of water supply and sanitation services has impacted land use patterns.					
49	The availability of electricity and power supply has contributed to urban growth.					
50	The presence of recreational and community facilities has driven urbanization.					

APPENDIX—2

SECTION 2 Perception of Urbanization Process and its Environmental Impact According to level of Agreement

Variables	V/1			V/2			V/3			V/4			V/5		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	1	.3	.3	2	.5	.5	5	.5	.5	20	5.2	5.2	2	.5	.5
Disagree	3	.8	1.0	8	2.1	2.6	9	2.1	2.6	57	14.8	20.0	8	2.1	2.6
Neither Agree nor Disagree	25	6.5	7.5	2	.5	3.1	11	.5	3.1	145	37.7	57.7	126	32.7	35.3
Agree	175	45.5	53.0	264	68.6	71.7	198	68.6	71.7	121	31.4	89.1	145	37.7	73.0
Strongly Agree	181	47.0	100	109	28.3	100	162	28.3	100	38	9.9	99.0	104	27.0	100
TOTAL	385	100		385	100		385	100		385	100		385	100	

Variables	V/6			V/7			V/8			V/9			V/10		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	16	4.2	4.2	4	1.0	1.0	1	.3	.3	6	1.6	1.6	3	.8	.8
Disagree	33	8.6	12.7	11	2.9	3.9	4	1.0	1.3	6	1.6	3.1	2	.5	1.3
Neither Agree nor Disagree	45	11.7	24.4	155	40.3	44.2	123	31.9	33.2	121	31.4	34.5	130	33.8	35.1
Agree	225	58.4	82.9	80	20.8	64.9	139	36.1	69.4	148	38.4	73.0	136	35.3	70.4
Strongly Agree	66	17.1	100	135	35.1	100	118	30.6	100	104	27.0	100	114	29.6	100
TOTAL	385	100		385	100		385	100		385	100		385	100	

SECTION 3: Perception of Urbanization in Sargodha City According to level of Agreement

Variables	V/1			V/2			V/3			V/4			V/5			V/6		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	2	.5	.5	38	9.9	9.9	35	9.1	9.1	75	19.5	19.5	75	4.2	4.2	16	4.2	4.2
Disagree	10	2.6	3.1	32	8.3	18.2	69	17.9	27.0	98	25.5	44.9	98	8.6	12.7	33	8.6	12.7
Neither Agree nor Disagree	133	34.5	37.7	156	40.5	58.7	126	32.7	59.7	86	22.3	67.3	86	11.7	24.4	45	11.7	24.4
Agree	138	35.8	73.5	46	11.9	70.6	118	30.6	90.4	82	21.3	88.6	82	58.4	82.9	225	58.4	82.9
Strongly Agree	102	26.5	100	113	29.4	100	36	9.4	99.7	44	11.4	100	44	17.1	100	66	17.1	100
TOTAL	385	100		385	100		385	100		385	100		385	100		385	100	

Variables	V/7			V/8			V/9			V/10			V/11		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	10	2.6	2.6	205	53.2	53.2	27	7.0	7.0	19	4.9	4.9	27	7.0	7.0
Disagree	27	7.0	9.6	103	26.8	80.0	47	12.2	19.2	12	3.1	8.1	21	5.5	12.5
Neither Agree nor Disagree	28	7.3	16.9	54	14.0	94.0	116	30.1	49.4	53	13.8	21.8	106	27.5	40.0
Agree	258	67.0	83.9	17	4.4	98.4	111	28.8	78.2	247	64.2	86.0	148	38.4	78.4
Strongly Agree	62	16.1	100	6	1.6	100	84	21.8	100	54	14.0	100	83	21.6	100
TOTAL	385	100		385	100		385	100		385	100		385	100	

Tables 2.1: Section 2 and 3 Level of Agreement

SECTION 4: Knowledge and Awareness of LULC Change Detection

Variables	V/1			V/2			V/3			V/4			V/5		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	34	8.8	8.8	34	8.8	8.8	82	21.3	21.3	67	17.4	17.4	74	19.2	19.2
Disagree	64	16.6	25.5	59	15.3	24.2	104	27.0	48.3	111	28.8	46.2	90	23.4	42.6
Neither Agree nor Disagree	108	28.1	53.5	111	28.8	53.0	98	25.5	73.8	125	32.5	78.7	117	30.4	73.0
Agree	133	34.5	88.1	123	31.9	84.9	74	19.2	93.0	80	20.8	99.5	91	23.6	96.6
Strongly Agree	46	11.9	100.0	58	15.1	100.0	27	7.0	100.0	2	.5	100.0	13	3.4	100.0
TOTAL	385	100.0		385	100.0		385	100.0		385	100.0		385	100.0	

Section 5: Experience with Urbanization and LULC Change

Variables	V/1			V/2			V/3			V/4			V/5			V/6		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	41	10.6	10.6	25	6.5	6.5	47	12.2	12.2	110	28.6	28.6	41	10.6	10.6	48	12.5	12.5
Disagree	64	16.6	27.3	43	11.2	17.7	95	24.7	36.9	61	15.8	44.4	88	22.9	33.5	83	21.6	34.0
Neither Agree nor Disagree	143	37.1	64.4	69	17.9	35.6	113	29.4	66.2	110	28.6	73.0	127	33.0	66.5	149	38.7	72.7
Agree	125	32.5	96.9	198	51.4	87.0	126	32.7	99.0	88	22.9	95.8	118	30.6	97.1	105	27.3	100.0
Strongly Agree	12	3.1	100.0	50	13.0	100.0	4	1.0	100.0	16	4.2	100.0	11	2.9	100.0	0	0	0
TOTAL	385	100.0		385	100.0		385	100.0		385	100.0		385	100.0		385	100.0	

Tables 2.2: Section 4 and 5 Level of Agreement

SECTION 6: Perception of Land Use and Land Cover Change According to level of Agreement

Variables	V/1			V/2			V/3			V/4			V/5			V/6			V/7			V/8			V/9		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	18	4.7	4.7	29	7.5	7.5	101	26.2	26.2	3	29.4	29.4	113	29.4	29.4	37	9.6	9.6	0	0	0	4	1.0	1.0	0	0	0
Disagree	28	7.3	11.9	102	26.5	34.0	75	19.5	45.7	1	14.3	43.6	55	14.3	43.6	95	24.7	34.3	0	0	0	5	1.3	2.3	0	0	0
Neither Agree nor Disagree	88	22.9	34.8	136	35.3	69.4	102	26.5	72.2	157	29.4	73.0	113	29.4	73.0	119	30.9	65.2	157	40.8	40.8	157	40.8	43.1	153	39.7	39.7
Agree	219	56.9	91.7	116	30.1	99.5	84	21.8	94.0	203	23.1	96.1	89	23.1	96.1	131	34.0	99.2	228	59.2	100.0	195	50.6	93.8	204	53.0	92.7
Strongly Agree	32	8.3	100.0	2	.5	100.0	23	6.0	100.0	21	3.9	100.0	15	3.9	100.0	3	.8	100.0				24	6.2	100.0	28	7.3	100.0
TOTAL	385	100.0		385	100.0		385	100.0		385	100.0		385	100.0		385	100.0		385	100.0		385	100.0		385	100.0	

SECTION 7: Driving forces governing the land use changes and urbanization According to level of Agreement

Variables	V/1			V/2			V/3			V/4			V/5			V/6			V/7			V/8			V/9		
Level of agreement	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V	F	V.P	C.V
Strongly Disagree	90	23.4	23.4	1	.3	.3	6	1.6	1.6	19	4.9	4.9	43	11.2	11.2	44	11.4	11.4	38	9.9	9.9	3	.8	.8	4	1.0	1.0
Disagree	139	36.1	59.5	1	.3	.5	24	6.2	7.8	61	15.8	20.8	90	23.4	34.5	93	24.2	35.6	137	35.6	45.5	25	6.5	7.3	23	6.0	7.0
Neither Agree nor Disagree	66	17.1	76.6	163	42.3	42.9	120	31.2	39.0	128	33.2	54.0	133	34.5	69.1	117	30.4	66.0	104	27.0	72.5	127	33.0	40.3	151	39.2	46.2
Agree	56	14.5	91.2	216	56.1	99.0	203	52.7	91.7	138	35.8	89.9	110	28.6	97.7	111	28.8	94.8	77	20.0	92.5	132	34.3	74.5	179	46.5	92.7
Strongly Agree	34	8.8	100.0	4	1.0	100.0	32	8.1	99.7	39	9.6	99.5	9	2.3	100.0	20	5.2	100.0	26	6.8	99.2	98	25.5	100.0	28	7.3	100.0
TOTAL	385	100.0		385	100.0		385		100.0	385			385	100.0		385	100.0		335	100.0		385	100.0		385	100.0	

Tables 2.3: Section 6 and 7 Level of Agreement