# Exploring the Dynamics of Urban Sprawl Using GIS & RS Techniques and By Modeling Using CA-Markov Model in District Peshawar

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Urban sprawl is characterized by the unplanned and uneven expansion of built-up areas, driven by multiple processes and resulting in inefficient resource utilization. Pakistan, a rapidly developing country and the fifth most populous globally, faces significant challenges related to extreme population growth. Peshawar, the provincial capital of Khyber Pakhtunkhwa, has experienced substantial urbanization in recent decades, highlighting the need for detailed urban planning analyses. This study examines the urban sprawl in the Peshawar district from 2010 to 2020 and projects future trends up to 2030. It uniquely employs the CA-Markov model for forecasting urban sprawl, a method not previously used in this context. The research utilizes remotely sensed satellite data for three distinct periods (2010, 2015, and 2020) to analyze land use patterns. The Object-Based Image Analysis (OBIA) approach was employed to assess these patterns, while the CA-Markov Model was used in a GIS environment to predict land use and land cover (LULC) changes through to 2030. The study identifies two primary patterns of urban sprawl in Peshawar: ribbon sprawl along major roads and leapfrog sprawl at the city's periphery, reflecting trends common in major Pakistani cities. The analysis reveals a significant increase in urban areas, which expanded from 23% to 39% of the total area over the decade, while agricultural land decreased from 44% to 35%. To better understand these land use changes, the paper proposes a simulation method divided into two components: a quantitative forecast using the Markov model and spatial pattern simulation using the CA model. The CA-Markov model forecasts that by 2030, urban land will encompass 44% of the area, with significant conversions from barren and vegetated lands.

**Keywords:** Urban Sprawl, LULC, CA-Markov Model, Land Change Modelling.

**Introduction:**

Urban sprawl is a significant outcome of population agglomeration in urban areas (Cobbinah & Darkwah, 2016; Mosammam et al., 2017; Xu et al., 2019) [1][2][3]. It refers to the "unrestricted expansion of housing, commercial development, and roads over large areas of land, with minimal regard for urban planning" (Fouberg et al., 2012) [4]. As noted by Bhatta et al. (2010) [5], while definitions of sprawl may vary, there is broad agreement that urban sprawl is marked by unplanned and uneven growth patterns driven by various processes, leading to inefficient resource use. Urbanization, where populations migrate from rural areas to major cities, is a global phenomenon (Ali et al., 2017) [6], significantly altering land use and land cover patterns and impacting local ecosystems and vegetation (Herold et al., 2003; Liu & Lathrop Jr., 2002) [7][8]. Accurate data on urban growth is essential for municipalities in rapidly expanding urban and suburban areas to support urban planning, water and land resource management, market analysis, and service allocation.

Traditional surveying and mapping methods for estimating urban sprawl are often costly and time-consuming, making such data scarce, particularly in developing countries. This has led to increased interest in using GIS and remote sensing technologies for monitoring and mapping urban sprawl (Goetz, 2013) [9]. Remote sensing and GPS integration have greatly enhanced the accuracy of urban sprawl measurements. Airborne and satellite remote sensing provide precise data for tracking deforestation, land use changes, and ecosystem dynamics (Fu et al., 2013; Ligate et al., 2018) [10][11]. Geospatial techniques are invaluable for analyzing and forecasting urban growth on various scales (Lu et al., 2019; Hashem & Balakrishnan, 2015) [12][13].

Land use change models are essential for analyzing the drivers and impacts of land use dynamics and identifying patterns of urban sprawl. Models such as mathematical equations, spatiotemporal modeling, system dynamics simulation, statistical models, and various hybrid approaches, including the cellular automata–Markov chain (CA-Markov) model, are used to simulate and predict land use and land cover (LULC) changes. The CA-Markov model combines the spatial variation capabilities of the Cellular Automata (CA) model with the long-term predictive power of the Markov model. This hybrid approach has proven effective for assessing and simulating urbanization and landscape dynamics (Keshtkar & Voigt, 2016) [15]. The Markov model forecasts future land use based on current trends, while cellular automata detect geographic changes and predict future scenarios based on historical data (Rimal et al., 2018) [16].

Peshawar, the capital of Khyber Pakhtunkhwa Province in Pakistan, ranks as the most populous city in the region. In 1998, it housed approximately 33% of the total urban population of Khyber Pakhtunkhwa, and this share increased to 45% by 2017 (Census Report, 1998 & 2017). This research employs spatial techniques, including remote sensing and GIS, to investigate urban sprawl in Peshawar using Object-Based Image Analysis (OBIA) with satellite data from 2010, 2015, and 2020. The study also simulates future LULC scenarios and urban expansion for 2030 using the CA-Markov model.

**Study Area:**

Peshawar District, the capital of Khyber Pakhtunkhwa Province, covers an area of approximately 1,257 km² and is situated at an altitude of 311 meters above sea level. Historically significant, Peshawar was once a major center of Gandhara and has been ruled by various civilizations, including the Persians, Greeks, Buddhists, Kushans, Afghans, Mughals, Marathas, Sikhs, and British. The district is bordered by Charsadda District to the north, Nowshera District to the east, Khyber District to the west, Mohmand District to the northwest, and Kohat District to the south. Geographically, it extends from 33°44' to 34°15' north latitude and from 71°22' to 71°45' east longitude.

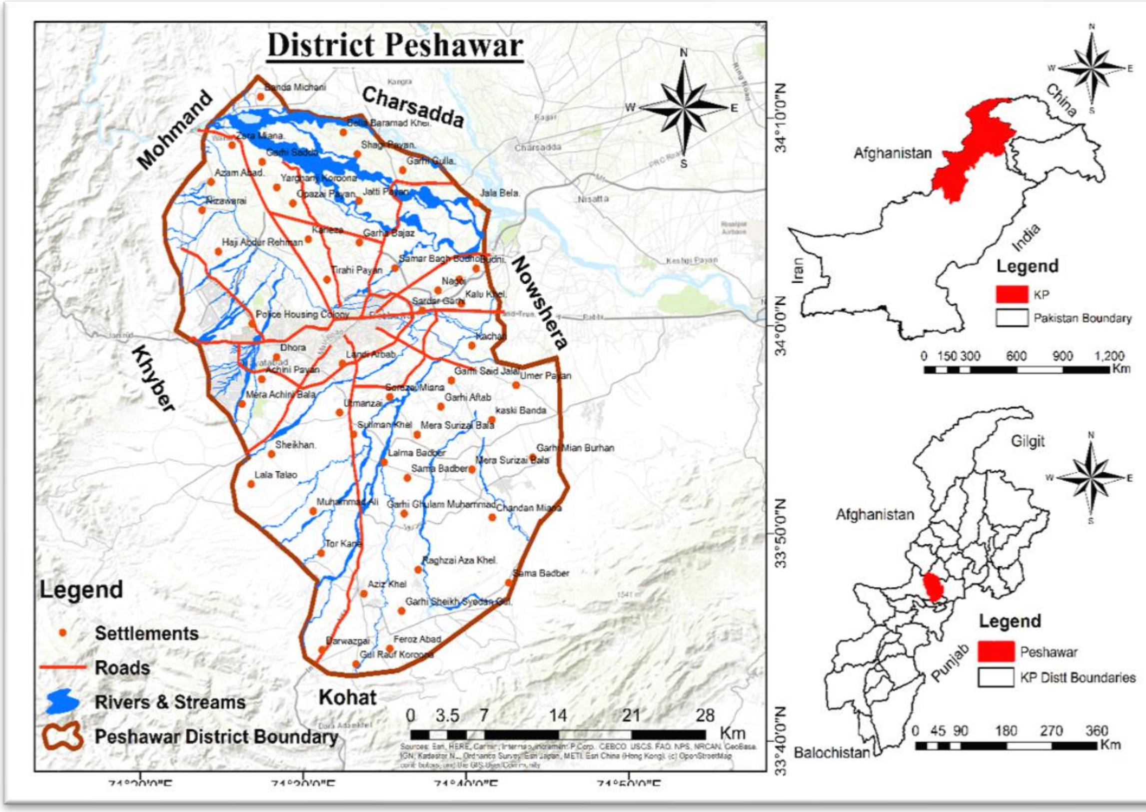


**Figure 1:** Study Area Map

**Objectives:**

- To find out the land use pattern of the study area.
- To examine the urban sprawl between 2010 and 2020 in the study area.
- To predict the future LULC change till 2030 by using the CA-Markov model in the study area.

**Data Sets:**

Cloud-free Landsat-7 ETM+ and Landsat-8 OLI satellite images, obtained from the USGS Earth Explorer (as listed in Table 1), were utilized for this study. These datasets were available at no cost, providing an efficient and economical means for multi-temporal monitoring and quantification of land use and cover changes. The satellite data were georeferenced and cropped to the study area boundaries. All data were projected using the UTM (Universal Transverse Mercator) Zone 42 North coordinate system.

**Table 1:** Depicts the datasets used in this study.

| S. No | Satellite Sensors | Path | Row | Resolution | Year |
|---|---|---|---|---|---|
| 1. | Landsat-7 ETM+ | 151 | 36 | 30m | 2010 |
| 2. | Landsat-8 OLI | 151 | 36 | 30m | 2015 |
| 3. | Landsat-8 OLI | 151 | 36 | 30m | 2020 |

**Methodology:**

The workflow consisted of three primary steps: land use/land cover (LULC) classification, analysis of urban expansion, and modeling of future LULC scenarios. Figure 2 illustrates the comprehensive data processing workflow used in this study.

**Image Classification:**

The Object-Based Image Analysis (OBIA) method was employed for supervised classification of LULC for the years 2010, 2015, and 2020. The classification process involved multiresolution segmentation, which merges regions from individual pixels to larger segments based on user-defined homogeneity criteria, using a scale of 200. Following segmentation, new classes (barren, urban, agriculture, water) were created in the class hierarchy window. Sample points were selected and assigned to each class, and a new rule was appended to the process tree for classification. The final classified image was exported to ArcMap in vector (polygon) format. Subsequently, the vector data was converted to a raster file using the Polygon to Raster tool in Arc Toolbox. To facilitate a detailed examination of urban sprawl, the urban area was clipped from the entire vector-classified image.

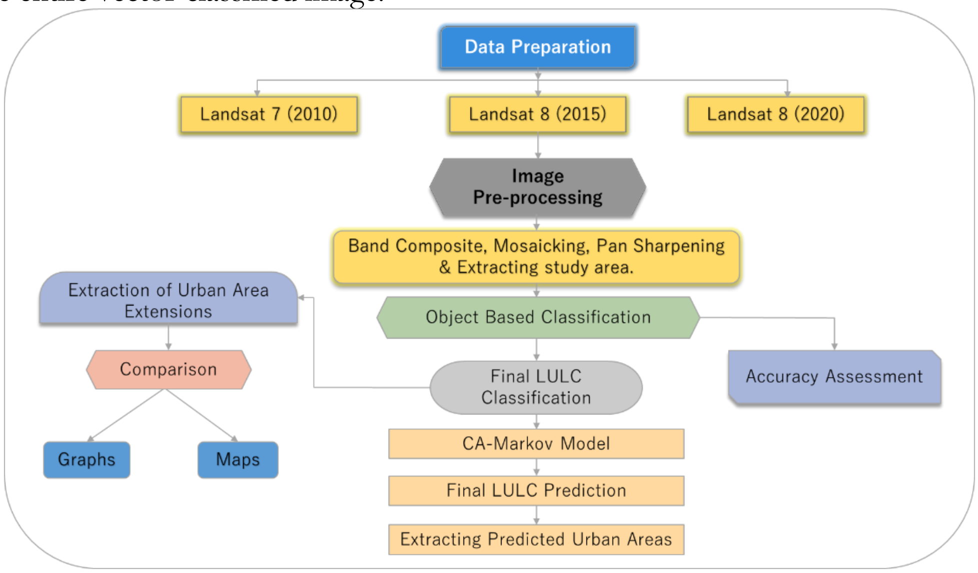


**Figure 2:** Methodology Flowchart.

**Ground Validation:**

No classification process is entirely accurate, making accuracy assessment crucial. For this study, a shapefile named "Reference" was created to assess classification accuracy, using the same coordinate system as the pre-classified image. This shapefile included two fields: "Land cover" (text) and "Class" (short integer). A total of 200 test points (50 per class) were manually assigned to their respective classes based on the classified image. The processing extent of the reference points matched that of the classified image. The reference points were then converted to a raster format using the Point to Raster tool, and their alignment was verified. The reference shapefile and the classified image were combined using the Combine tool, and any extra classes were removed with the Pivot tool. The attribute table was exported as a text file, and accuracy was calculated by dividing the number of correctly classified points by the total number of points. This process was repeated for each classified image.

**LULC Simulation:**

The Markov chain method is used to model land use changes over time, where each state depends on the previous one. It represents these changes through matrices, which detail the potential transitions between land use categories. The Markov chain equation utilizes land use distributions at the beginning (Mt) and end (Mt+1) of a period, alongside a transition matrix (MLc) that captures these changes. Cellular Automata (CA) are incorporated to add spatial detail to the model, providing a more granular view of land use changes.

In this study, Idrisi 15 and IDRISI 17.0 (Selva edition) were used to integrate CA with the Markov model (Figure 3). Land use classes were prepared in ArcGIS 10.5, converted to TXT format using the Raster to ASCII tool, imported into IDRISI, and converted to RST files. For simulation purposes, the study area was divided into regular grids, with each grid considered a cell. Each cell could represent one of four states: agricultural land, urban land, water body, or barren land. A 5 x 5 contiguity approach was used for defining neighborhood extensions.

The transition rule, essential to the Markov-CA model, drives the transformation of land use patterns based on changes in cellular states. CA filters, which are adjustable according to adjacent cellular states, help in defining spatial weights. The standard 5 x 5 contiguity filter was used as the default neighborhood definition, with the number of CA iterations set at 100 to simulate the landscape spatial pattern for 2030. The Markov-CA model was used to simulate both spatial and temporal changes in urban land use, employing real data for parameterization and transition rules. After validating its accuracy, the model also provided predictions for future land use trends.

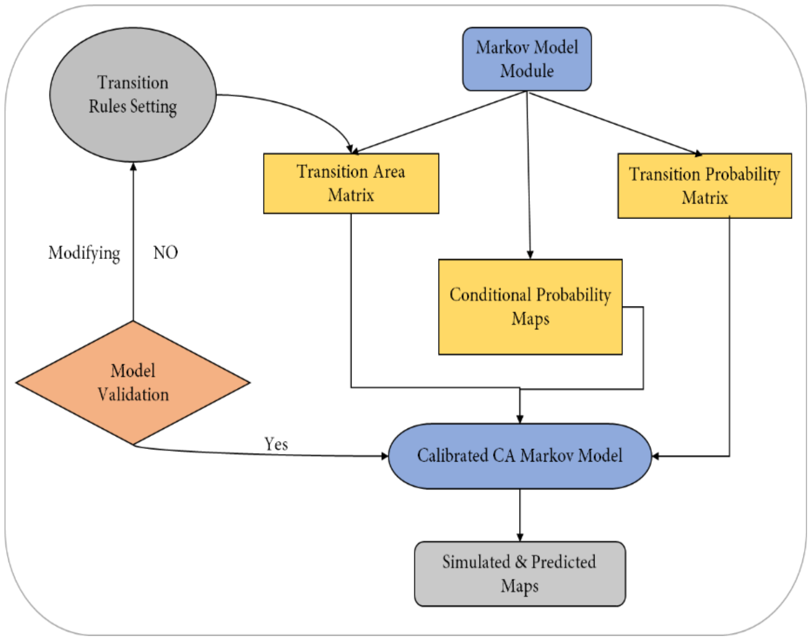


**Figure 3:** Flow Chart of CA-Markov Methodology

**Results and Discussion:**

**LULC Change:**

In the study area, four land use/land cover (LULC) classes were identified: barren, urban, vegetation, and water (Figure 4). The accuracy assessment results revealed overall classification accuracies of 89%, 91%, and 91% for the years 2010, 2015, and 2020, respectively. The corresponding kappa coefficient values were 0.86, 0.90, and 0.89 for these years. Table 2 illustrates the spatial-temporal changes in land cover, specifically highlighting the decrease in agricultural cover and the increase in urban land within District Peshawar. The land cover is categorized into four classes—barren, urban, agricultural, and water—across three distinct time points. The data indicate a clear trend of expanding built-up areas and a corresponding reduction in agricultural land over the studied period. The accompanying graph visualizes the overall changes in land cover over the past decade.

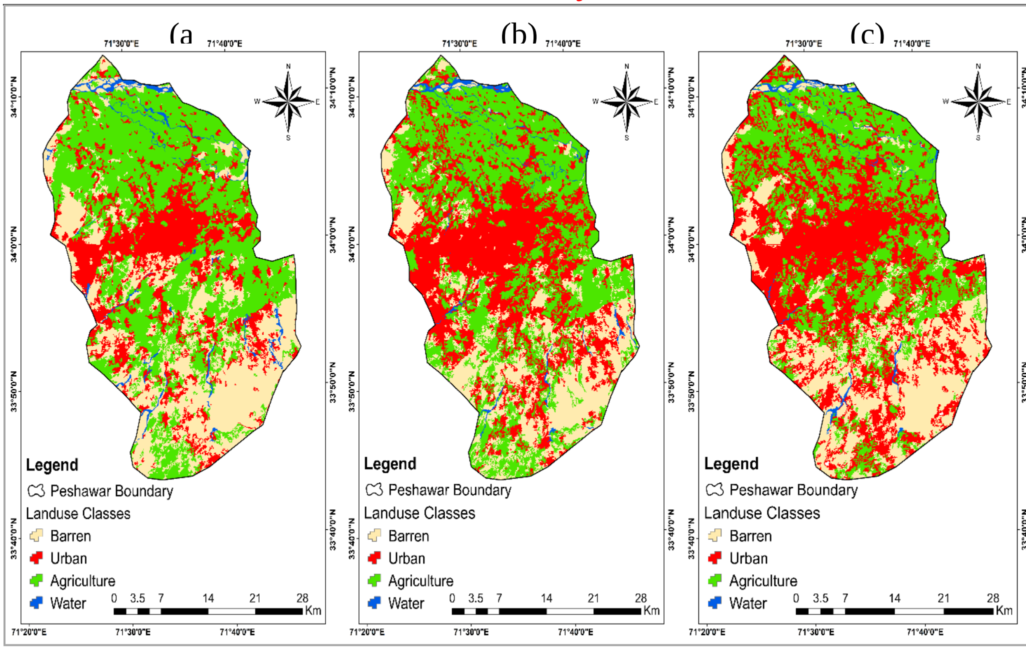


**Figure 4:** LULC map of Peshawar in (a) 2010, (b) 2015, and (c) 2020

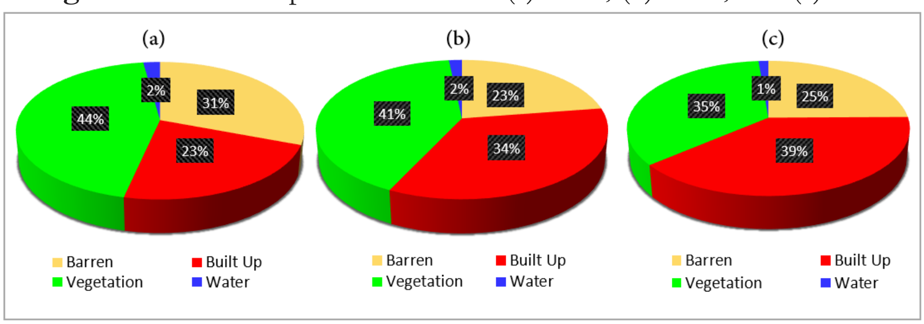


**Figure 5:** Pie Chart of LULC Peshawar in (a) 2010, (b) 2015, and (c) 2020

Peshawar has taken an unexpected geographical shape now. There is no restriction on the development of urban land in this area. Recently, urban expansion has been more prominent in the central direction of direction during the previous years. Peshawar has faced rapid urban sprawl during the last ten years.

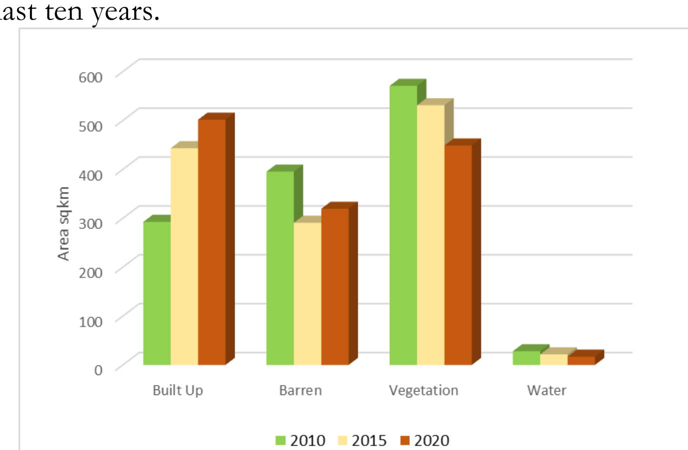


**Figure 6:** Graph displaying the Spatial-Temporal Changes of LULC of Peshawar from 2010-20

**Table 2:** Spatial-Temporal Change of Land Use Land Cover Peshawar from 2010-20

| Land Use Classes | Area (sq. km) 2010 | Area (sq. km) 2015 | Area (sq. km) 2020 |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **Barren** | 395.4366 | 290.8854 | 319.4127 |
| **Urban** | 292.6656 | 443.3283 | 501.6105 |
| **Agriculture** | 570.8475 | 531.1305 | 448.7364 |
| **Water** | 28.0647 | 21.6657 | 16.8525 |

**Urban Sprawl:**

The rapid expansion of built-up areas in Peshawar from 2010 to 2020 highlights a significant lack of effective land use management. The predominant preference for construction among residents has led to a noticeable impact on agricultural land. The absence of government regulations or restrictions on construction and site selection has allowed for unchecked urban growth, often disregarding optimal planning and site selection principles. This unregulated expansion has resulted in urban sprawl extending in nearly every direction from the city center. The following maps and graphs provide a clear visualization of this growth over the past decade.

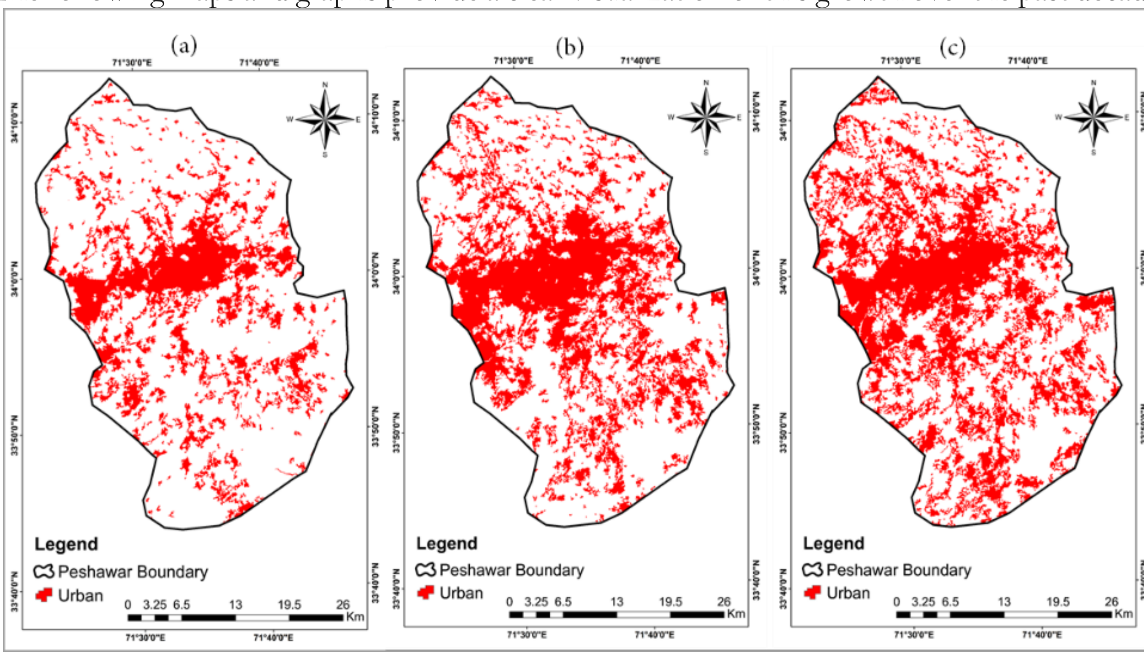


**Figure 7:** Urban Map of Peshawar in (a) 2010, (b) 2015, and (c) 2020

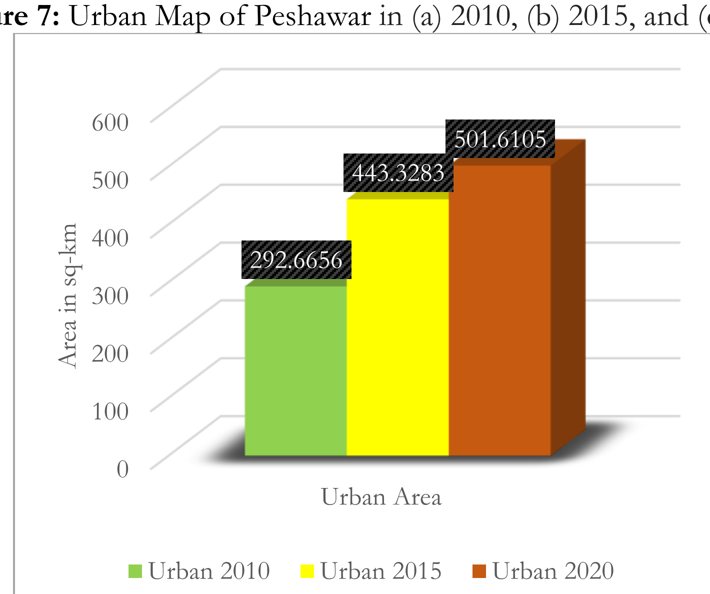


**Figure 8:** Graph displaying Urban Change in Peshawar from 2010-20

**CA-Markov Model Outcomes:**

After running the CA-Markov model, transition potential maps were generated. The simulated maps for Peshawar District in 2030 indicate a continued expansion of built-up land, as it progressively encroaches upon and displaces other land uses.

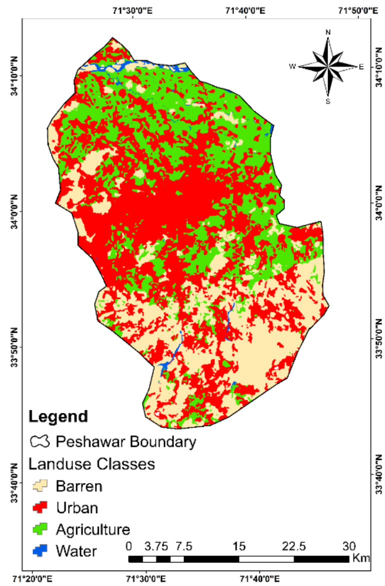


**Figure 9:** Peshawar 2030 LULC Predicted Map

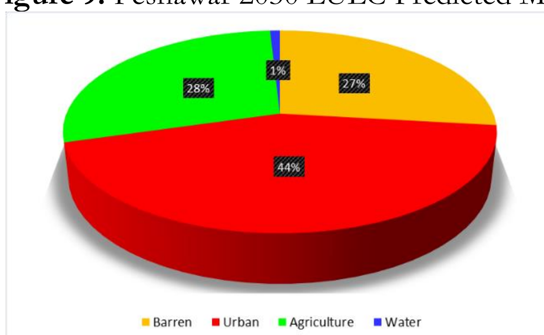


**Figure 10:** Pie Chart Showing Area Covered by Land Use Classes in Percentage, Peshawar 2030

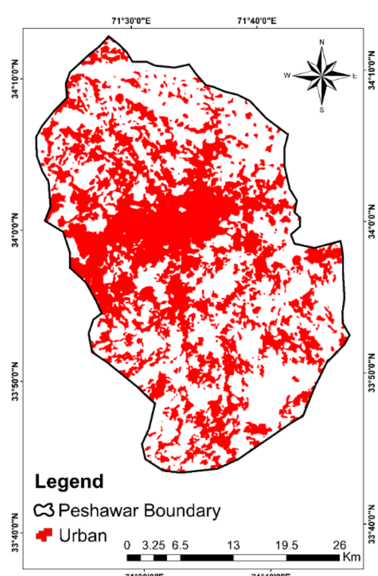


**Figure 11:** Predicted Urban Map of Peshawar 2030

The research aimed to simulate urban sprawl in the Peshawar district. To achieve this, urban areas were distinguished from non-urban areas. The CA-Markov model simulation for 2030 predicts that urban land will expand to cover 44% of the district, converting areas previously classified as barren land and vegetation. This represents a 6% increase in urban land compared to 2020.

**Transition Graphs:**

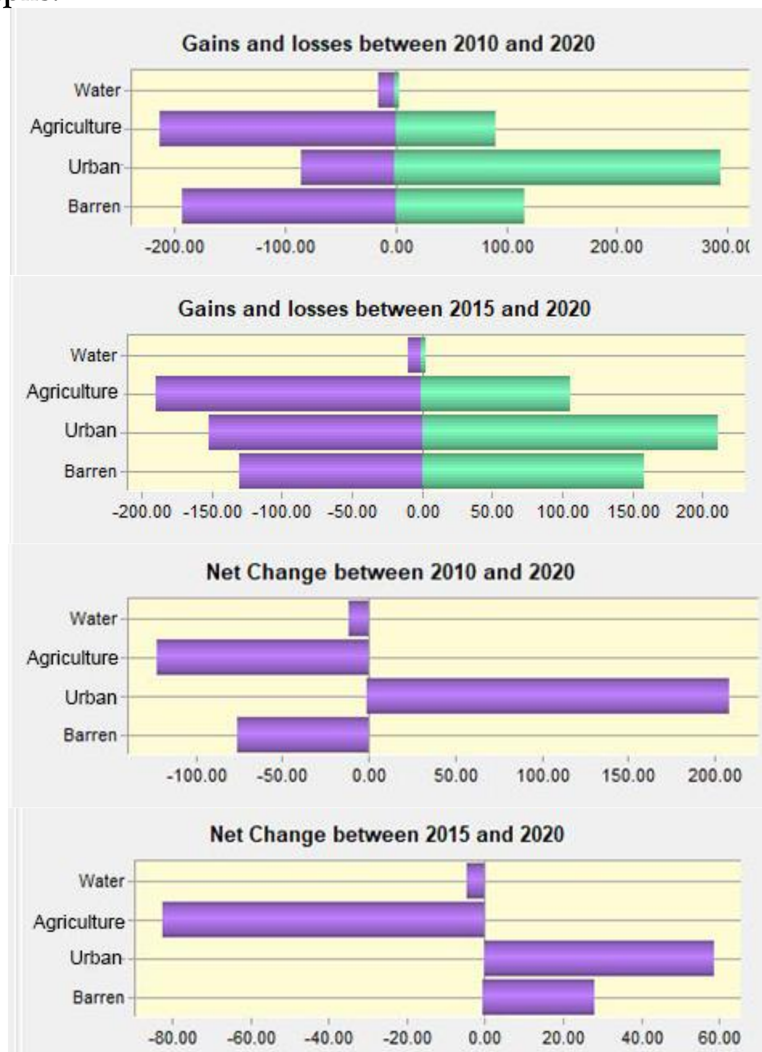


**Figure 12:** Transition Graphs

From the figure, there are significant changes and transitions among various land use/cover classes from 2010 to 2020. The main changes and transitions are among agricultural land, vegetation, and built-up areas.

**Table 3:** Expected Transition Change

| Cells in | Expected to Transition to | | | |
|---|---|---|---|---|
| | Barren | Agriculture | Urban | Water |
| **Barren** | 96730 | 156490 | 98595 | 3088 |
| **Agriculture** | 149812 | 245253 | 157625 | 4601 |
| **Urban** | 132278 | 214471 | 147832 | 4015 |
| **Water** | 5122 | 7612 | 5212 | 779 |

**Table 4:** Probability of Changing

| Given | Probability of Changing to | | | |
|---|---|---|---|---|
| | Barren | Agriculture | Urban | Water |
| **Barren** | 0.2726 | 0.4409 | 0.2778 | 0.0087 |

| | | | | |
|---|---|---|---|---|
| **Agriculture** | 0.2688 | 0.4401 | 0.2828 | 0.0083 |
| **Urban** | 0.2653 | 0.4301 | 0.2965 | 0.0081 |
| **Water** | 0.2736 | 0.4065 | 0.2783 | 0.0416 |

**Findings and Recommendations:**

**Findings:**

- In 2010, the urban area was 292.6656 Sq.km.
- In 2015, the urban area extended to 443.328 Sq.km. This means an 11% increase in urban areas from 2010 to 2015.
- In 2020, the urban area extended to 501.610 Sq.km. This means a 16% increase in urban areas from 2010 to 2020 and a 5% increase from 2015 to 2020.
- The CA-Markov Model predicts that by 2030, 44% of the total area will be covered by urban areas in Peshawar.

**Discussion:**

This study leverages GIS and remote sensing techniques in conjunction with the CA-Markov model to examine and project urban sprawl in District Peshawar. The analysis reveals substantial urban expansion over the past decade, with forecasts indicating continued growth if current trends persist. Prior research on urban sprawl in Peshawar, such as studies by Raziq et al. (2016) [17] and Mehmood et al. (2016) [18], focused on historical data to document significant urban growth from 1990 to 2011. However, these studies did not extend into predictive modeling. This research incorporates the CA-Markov model to simulate future urban expansion scenarios, providing not only a confirmation of historical trends but also a forward-looking perspective on urban growth dynamics.

**Conclusion:**

The rapid increase in urban sprawl presents significant challenges, including the loss of agricultural land and environmental degradation. Expanding urban areas contribute to traffic congestion and urban heat islands, particularly in developing countries, which can lead to severe socio-cultural and environmental costs. The study highlights the detrimental effects of urban expansion on barren and agricultural lands, with resulting impacts on natural water sources due to increased pollution. The projections made using the CA-Markov model underscore the urgency of proactive urban planning and policy-making in District Peshawar. Anticipated growth may strain existing infrastructure and resources, necessitating strategic measures for sustainable development. To address these challenges, planners and policymakers should consider enhancing public transportation, preserving green spaces, and implementing effective zoning regulations to manage urban growth more effectively.

**Recommendations:**

Recent economic growth has created enormous problems in urban management matters, where urban expansion occurs without any concern for environmental impact. Rapid urbanization and intensive land-use conflicts are occurring at an alarming rate in some developing countries. Therefore, the simulation and prediction of urban growth is important for urban planners to formulate sustainable development strategies. Besides, this helps them to predict land demands in order to provide enough infrastructure for the inhabitants. By considering various responsibilities, District Peshawar can increase its green spaces. The incorporation of an active green area's strategy should be considered as a basic element in spatial and temporal planning of the District. Such strategies can be formulated by involving various administrative departments, scientists, cultural and social groups along with general public.

This research represents a significant advancement in understanding and predicting urban sprawl in District Peshawar using GIS, remote sensing, and CA-MARKOV modeling techniques. By providing a predictive framework, offering valuable insights for urban planners and policymakers aiming to foster sustainable urban development. Future research building on these findings can further enhance the ability to manage and plan for urban growth effectively.

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