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Research article

Quantifying sustainable urbanization by predictive modeling for better agricultural management: A case study in the South Asiatic Region

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A B S T R A C T

Global population growth and uncontrolled are creating threats to agricultural land. To address urbanization, proactive planning is required. Land use and land cover (LULC) classification maps for 2002–2022 were analyzed using remote sensing (RS) and geographic information systems (GIS) in Sahiwal, Punjab, Pakistan. Idrisi's Cellular Automata (CA)–Markov model was used to predict future scenarios. The results showed that urbanization was rapidly accelerated in large LULC changes that were unpredictable. In particular, the urbanized area increased by 234.7 km^2 (91 %) from 22.83 km^2 in 2002 to 257.53 km^2 in 2022, with a reduction of 656.05 km^2 (52 %), from 1252.52 km^2 in 2002 to 596.47 km^2 in 2022, of agriculture land. About 17.05 km^2 of land was lost to urbanization; however, a large portion of CA 251.75 km^2 was absorbed due to careless urban growth. The CA-Markov projection revealed that from 2022 to 2042, agriculture will experience the largest net change, losing about −226.09 km^2 of land. However, the projected results showed that the urban class will be expanded up to 450.23 km^2 and will gain approximately 192.7 km^2 in 2042. The overall findings show that it is possible to manage outcomes quantitatively and control haphazard and unplanned urban sprawl by putting forward a comprehensive master plan.

1. Introduction

Increasing density leads to denser urban settlements in dispersed rural settlements [1]. The world population in cities is expected to reach about 67.2 % by 2050 [2,3]. During the last 30 years, urbanization accelerated much faster than global urbanization (80 %), compensating for the population growth (52 %) studied by Liu [4]. Similarly, with an average growth rate of 180 %, urbanized areas will expand from 65,000 km^2 in 2000 to 186,000 km^2 in 2030 [5]. The progressive and uncontrolled expansion of urbanization around the world is reshaping the entire planet [6]. In recent decades, rapid urban expansion has been attributed primarily to population and economic expansion [7], environmental changes due to urbanization [8], and socioeconomic changes [9]. Besides, LULC changes are greatly accelerated by intensified anthropocentric processes [10]. As such, the shift from natural to artificial covers has detrimental

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social and ecological effects and raises serious concerns about ecology, safety, housing, and human life [11,12]. The urban growth increased the pressure on agricultural land (70 %) and forests (9 %). For example, agricultural areas made up 36.1 % of Turkey's rural areas in 1988, but this percentage dropped to 30.8 % in 2016 [13]. Approximately 40 million acres of agricultural land have been abandoned for housing during the past 30 years. Despite its positive effects in some developing countries, urbanization is generally unfavorable and has negative outcomes in others [14]. Natural ecosystems are degraded as a result of urbanization. The environment has been affected by altered land use [15], loss of biodiversity worsening [15,16] air quality, and eventually climate change [17]. In addition, the effect of the heat island has increased [18–20] and air pollution has also increased [1,21,22]. Recent research has emphasized the importance of organic fertilization and sustainable agricultural ecosystems using eco-friendly techniques [23,24]. The green revolution for sustainable development has been an emerging technology in developing countries and has required specific managerial aspects [25], and stakeholders' pressures in terms of regulatory pressures [26]. The function and structure of the urban ecosystem have been destroyed as a result of these conditions, and appropriate land management practices, modeling, mapping, and future predictions are imperative to cope with this serious problem [14].

The CA-Markov model successfully integrates with GIS and remote sensing, enabling dynamic spatial modeling of LLU using transformations. This method was used to study and quantify urban expansion and landscape change, with predictions of declining land use and wetlands. In Pakistan, urban land is continuously engulfing rural land, and this study focuses on land configuration using geospatial tools and measuring land change over the last 20 years. The changes in this model are governed by local rules established by the CA spatial filter or suitability maps [15,16]. Stochastic models that involve interacting spatial and temporal dynamics [17–19]. Urban expansion and landscape change have been studied and quantified using this method [20]. Based on its current rate, the Markov model forecasts land use's future state [21]. For example, based on the predictions of LULC for 2035 [22], found that a decrease in agriculture will be followed by an increase in barren land in Daqahlia, Egypt [27]. Similarly, as indicated by the Markov Chain analysis, 20 % increase in built-up areas in Doha, Qatar [23]. Corner [24] revealed that for the decades 1990, 2000, and 2011, the buildings and the bare soil in Dhaka, Bangladesh, indicate an increasing trend, whereas the agricultural land has declined [24]. The prediction of the MCA technique 2020–2030 for Mumbai, India, showed similar trends of decreasing forest lands and wetlands [25]. In

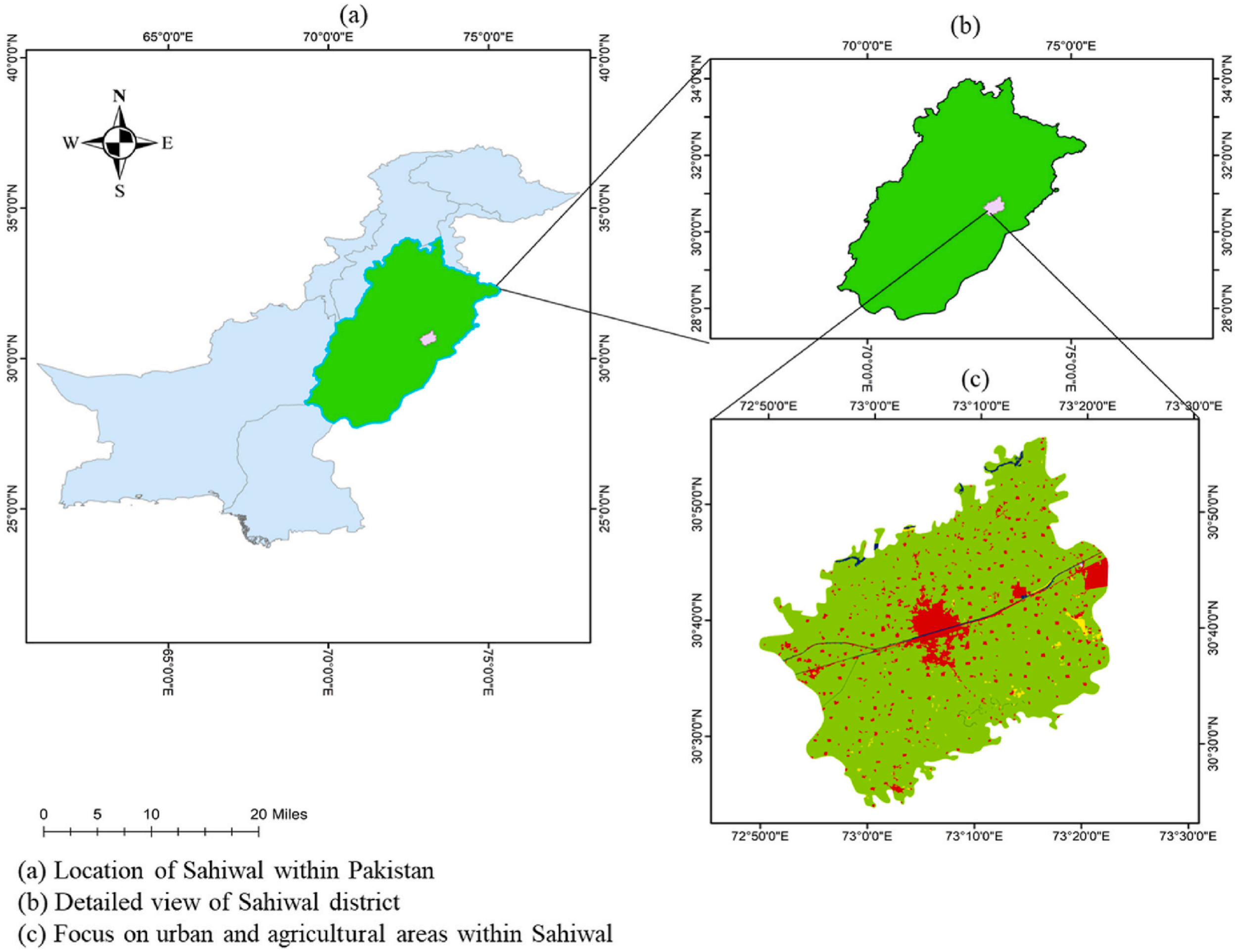

Fig. 1. A description of the study area's geography.

Karachi, Pakistan, Baqa conducted LULC dynamics for the years 1990, 2000, 2010, and 2020 [20]. As predicted by the CA-Markov model, the total urban area in 2030 could grow to 652.59 km^2. Several studies have been conducted for the LULC mapping of various regions of the globe at different time periods [26,28–31].

According to the World Bank [32], 60 % of Pakistan's population lives in rural areas and 45 % of them are depend on agriculture. Pakistan's urbanization will lead to living in urban cities by 2025 as a result of rapid urbanization [3]. In making decisions, it is important to know the past, present, and future growth of LULC. In studies on urban expansion and the evaluation of changes in LULC, modern RS methods and GIS integration are effective tools for spatial analysis of the data [29,30]. By using RS data to monitor the urbanization of land cover in Ethiopia [27,31,33–40]. Similarly, wetlands loss has increased twofold in the last 20 years based on RS data [15,41–44]. Furthermore, using remote sensing data, Beijing has converted approximately 50 % of its cultivated land into urban areas [16,]. Pakistan's compact city development potential was evaluated by Ref. [17], using GIS resulting in decreased, vegetation and agriculture between 2021 and 2035 [18]. In Pakistan, urban land is continuously engulfing rural land; therefore, this study focuses primarily on the pattern of land using geospatial tools and measuring the change in land over the past 20 years [45–50]. There is still a lack of sufficient literature on urban expansion in Pakistan. Currently, there has been no research on addressing urban expansion in Sahiwal, Punjab, Pakistan, to the best knowledge of the authors.

For the China-Pakistan Economic Corridor (CPEC) study in Sahiwal, Punjab, will improve the quality of life of residents of the province [50,51] and result in significant changes in land use [52–54].

The study highlights the importance of understanding past, present, and future growth of UTLC in developing countries, especially in regions like Pakistan. The main objectives of the current study are: (1) Using satellite data from 2002 to 2022, this study attempts to thoroughly examine the temporal and spatial dynamics of urban growth in Sahiwal, Punjab, Pakistan. (2) CA-Markov models were used to simulate the city's urban growth, land use planning, and future LULC scenarios for the year 2042. (3) To help local governments and policymakers to make sustainable plans for future land use and urban development to achieve innovative green goals.

2. Materials and methods

2.1. Study site

In Pakistan, Sahiwal is the second-most populous city. Lahore and Multan are 180 km away from Sahiwal, which lies between these two cities. It lies from 30° 39′ 51.84″ N to 73° 06′ 29.88″ E (Fig. 1). Agriculture and cattle farming are the main occupations. Pakistan's latest census estimates Sahiwal's population was 2.52 million in 2017, with an area of 3201 km^2 and a population density of 785.1/km^2 [55]. About 79.5 % live in rural areas, whereas about 20.5 % live in urban areas with an annual population change of 1.6 %. Because of the implementation of the CPEC coal power project, Sahiwal faces subsequent urbanization and mass destruction.

2.2. Data collection

The data was collected sequentially using a structured questionnaire and interviews (first by questionnaire and then by in-depth interviews). These studies involved participants from Sahiwal, Punjab, Pakistan. An in-depth interview and a questionnaire were prepared for data collection. At least 500 participants participated in the CPEC initiative using the structured questionnaire, regardless of their age, sex, or educational status. At the beginning of the survey, the respondents were informed that the survey was a voluntary effort and that their information would help complete the study. In emerging economies, especially Pakistan, structured questionnaires are the most effective for collecting data. Sahiwal's selected regions received 500 questionnaires. The current coal power project is constructed under the initiatives of the CPEC in this region. The results of the structured questionnaire should be articulated in a more meaningful manner after they have been completed; we conducted an interview with various participants regarding the impact of CPEC on urbanization, poverty alleviation, job creation, ease of life, and biodiversity. SPSS 25.5 and a Sigma plot were used to present the data collected from the interviewee and questionnaire.

2.3. Analyzing and image processing data

To monitor the dynamic changes of the land, expansion, and identification of urbanization from 2002–2022, ENVI, Erdas Imagine, and, above all, ArcGIS 10.5 were used. The United States Geological Survey (USGS) Earth Explorer published the RS data to assess LULC changes and urban expansion [56]. ArcGIS 10.2.2 software was used to detect LULC changes. An online portal provided by the US Geological Survey (USGS) was used to acquire three satellite images for free. Landsat data (L1T) level one terrain corrected by USGS were processed and provided using WGS84 geodetic datum, Universal Transverse Mercator projection (UTM, Zone 42N). A multi-temporal Landsat product with cloud-free data (TM, ETM+, OLI-TIRS) was downloaded for 2002, 2012, and 2022 (Table 1). In

Table 1
Description of Landsat images utilized in the current study.

Acquisition date	Sensor	Resolution	Path/Row	Cloud cover (%)
2002-01-21	LANDSAT 5 TM	30 m	149/39	1.78
2012-12-08	LANDSAT 7 TM	30 m	149/39	4.00
2022-10-17	LANDSAT 8 OLI	30 m	149/39	5.72

this study, we used an interval of ten years between two temporal points. Satellite images were further processed in ArcGIS and Google Earth Pro. Images with multiple bands are combined into a single raster data set for all three years, 2002, 2012, and 2022, using the band composite tool in ArcGIS 10.2.2. Image enhancement was also done in ArcGIS. Using ENVI 5.3 software, Landsat 7 ETM + satellite images have been corrected for scan line errors. Detailed information on the acquired data is presented in Table 1. To simulate the LULC scenario, the CA-Markov model was trained using road network data.

2.4. Image classification and accuracy assessment

Land use data are identified using image classification to detect changes over time. To classify, ArcGIS v10.5 software was used in conjunction with the supervised classification algorithm method, including urban, agricultural, barren, water bodies, and forests, as shown in Table 2. The study region focused primarily on expanding urban areas, keeping in mind its main objective. The best pixel-based classification algorithm is the supervised classification algorithm [57]. Hyper plane-based classification algorithm optimizes class separation over other traditional classification algorithms [58]. In this study, an error matrix and a confusion matrix are used in this study to assess accuracy. Each LULC type predicts the number of pixels as a percentage. Producer accuracy consistency is the percentage of pixels classified correctly for each land use type based on the total number of pixels classified. The Kappa coefficient and the suitability of the images for analysis determine the agreement of the classified map. To solve the problem of mixed pixels after classification, a polygon-based editor tool was used to modify the classified raster. This means that the polygons were drawn correctly on all images for these training samples. To assess the classification and precision of the training samples, approximately 2000 samples were collected in the study areas. However, in the accuracy assessment, 70 % of the samples were used for classification and 30 % for calculating the kappa statistics and overall accuracy. To calculate the accuracy of a pixel, the accuracy of the user can be calculated by an equation (1) [59].

$$User\ accuracy: = \frac{Number\ of\ the\ correctly\ classified\ pixels\ in\ each\ category}{\text{Total number of correctly classified pixels in that category (the row total)}} \times 100 \tag{1}$$

This indicator shows the percentage of the ground class that has been corrected by the producer. It is calculated using the proportion of classified reference pixels in image correct pixels in equation (2) [60].

$$Producer\ accuracy: = \frac{Number\ of\ the\ correctly\ classified\ pixel\ in\ each\ category}{\text{Total number of correctly classified pixels in that category (the Column total)}} \times 100 \tag{2}$$

The Kappa value represents the final level of accuracy between a classified map and a ground reference map. Eq. (3) specifies the Kappa coefficient (K). To determine the image accuracy, 200 points were used.

$$\text{Kappa coefficient} = \text{N} \sum\nolimits_i^m \text{xii} - \sum \text{m i (xi + x + i)} / \sum \text{m i (xi + x + i)} \ldots. \tag{3}$$

In Eq. (3), In the confusion matrix, N represents the number of pixels used for accuracy assessment, m represents the number of rows, X_i+ is the total number of pixels in the i-th row, Xii is the number of pixels in the i-th row in the i-th column, X + i is the total number of pixels in the i-th column.

The selected images (2002, 2012, and 2022) were all processed using this method. Then the built-up and non-built-up areas were calculated in ArcGIS.

The symmetry of each LULC in the study is determined as

$$A_{ic} = A_{it2} - A_{it1} \ldots \ldots \ldots \ldots \tag{4}$$

The rate of change/year for each LULC for a given time period is deliberated as

$$A_{ir} = A_{ic}/(t_2 - t_1) \ldots \ldots \ldots \ldots \tag{5}$$

where A_{it1} and A_{it2} signify the total area of the LULC type i at times t_1 and t_2; A_{ic} is the changing area of the i-th type in a given time; and A_{ir} is the change rate/year for each LULC type from time t_1 to time t_2.

2.5. Markov chain analysis for predicting LULC change in Sahiwal

A program called IDRISI Selva 17.0 is certified to process images and provide geographic information (Clark Labs, USA), a display

Table 2
LULC classes in Sahiwal city from the field survey.

Classes	Description
Urban	Area such as rural residential areas, industrial, roads settlements, and other construction areas
Agriculture	Cultivated crops land, cultivated land, urban agricultural land, fallow fields, paddy fields and irrigated land
Vegetation	Trees, shrub land, semi-natural vegetation, playground, grassland, garden and vegetation area
Barren land	Bare land, bare soil, bare rock, some debris and other building but uncompleted land
Water	River, lake, hydraulic structures, ditches, and swamps
Uncultivated land	Forest land, park green space and protective greenbelt

system with about 300 modules [56]. Based on the Cellular-Automata-Markov Chain (CA-Markov Chain) model of IDRISI's Selva v_17.0, the LULC distribution of 2042 was predicted [61]. A Markov chain describes the probability of a change in land use or state using a transition probability matrix. An analysis of land use changes between dates was used to create a probability transition matrix. For mapping spatial dispersal to the predicted urban growth, CA was suggested [62,63]. This matrix is the outcome of setting a proportional error during the crossing between images. An indicator of how close two maps of the same situation are to each other is the Kappa-Agreement Index (KIA) of 2002, 2012, and 2022, which was used to assess the forecast performance for 2042. Therefore, the KIA was used to compare the LULC map of supervised classification with the modeled map for 2042 in order to assess the performance of the CA-Markov in predicting LULC changes. The classification process produces transition probability maps that are then used to project potential changes between two specified times. The transition probability has the following mathematical expression:

$$\sum_{I=1}^{m} Pij = 1 i = 1, 2 \ldots . m$$

$$P = (Pij) = \begin{matrix} P11 & P12\ldots & P1m \\ P21 & P12 & P2m \\ Pm1 & Pn2 & Pmm \end{matrix}$$

where, Pij is the likelihood that one land use will change into another, m is the type of land use in the area under study, and the Pij values fall between 0 and 1. Cellular automata and Markov are combined to create CA-Markov, which simulates the evolution of the pixel-represented geographic area. The transition function for the study area was calculated using the difference between 2002 and 2022. After that, CA-Markov projected the land cover for 2042 using this transition function.

3. Results

3.1. Accuracy assessment of LULC maps

The study presents classified images of land use patterns in Sahiwal, Punjab, focusing on urbanization, agriculture, vegetation, and water bodies. The classification accuracy is 85 %, with a higher score useful for predicting future expansions. The overall classification accuracies were 87.68 %, 84.12 %, and 89.21 % for 2002, 2012, and 2022, meeting the 80 % rule of OA. The kappa coefficient values were greater than 80 %. Using the classified map, we can predict the growth of urban areas based on the study's accuracy level.

3.2. Urban Land Expansion

LULC have changed dramatically in their study area over the last two decades (Table 3). A total of three land cover maps were created for the period 2002–2022, illustrating the trend of urban expansion in Sahiwal, Pakistan (Fig. 2). In Sahiwal, land use changed significantly between 2002 and 2022, and the most notable change was the rapid expansion of urban areas (Fig. 2). Among the land cover classes, agricultural and urban land were the most prevalent LULC types (Fig. 2). It is worthy of note that urban expansion was continuously increased at the cost of agricultural land throughout the two decades (Fig. 3). A significant portion of the existing agricultural ecosystem was destroyed by extremely unplanned rapid urban expansion in 2022, subsequently altering the land-use transition in Sahiwal (Figs. 2 and 3). Urban and uncultivated land areas increased between 2002 and 2022, while agricultural and barren land areas decreased (Table 3).

The study area is primarily affected by urbanization, which is expected to occur at a faster rate than previously anticipated. The total studied area was found to be 1645.71 km^2. During the year 2002, the largest area of land used for agriculture was 1252.52 km^2, which fell to 596.47 km^2 in 2022 (Table 3). By 2022, the urban area will reach 257.53 km^2, up from 22.83 km^2 in 2002. Urban surface change dynamics increased by 234.7 km^2 between 2002 and 2022, agriculture lost −656.05 km^2, vegetation lost about −95.84 km^2 of area; barren land gained about 15.45 km^2, water bodies gained about 279.86 km^2, and uncultivated land gained about 221.82 km^2 (Table 3). Furthermore, water bodies may experience a blatantly abnormal phenomenon in 2022, which left Sahiwal in the top three of the worst-hit flood areas. The summer's concentrated heavy rains caused the serious flood that led to the plunge. Large areas of farmland were inundated by the breakwaters of many lakes.

Table 3
Areal changes in each LULC classes in Sahiwal City.

LULC Classes	Area (km^2)		2022	Change rate (km^2/10 yrs)	2002–2022
	2002	2012		2002–2012	
Urban	22.83	138.82	257.53	115.99	234.7
Agriculture	1252.52	605.68	596.47	−646.84	−656.05
Vegetation	128.92	596.7	33.08	467.78	−95.84
Barren land	81.83	70.25	97.28	−11.58	15.45
Water	16.64	82.62	296.5	65.98	279.86
Uncultivated land	142.97	151.56	364.79	8.59	221.82

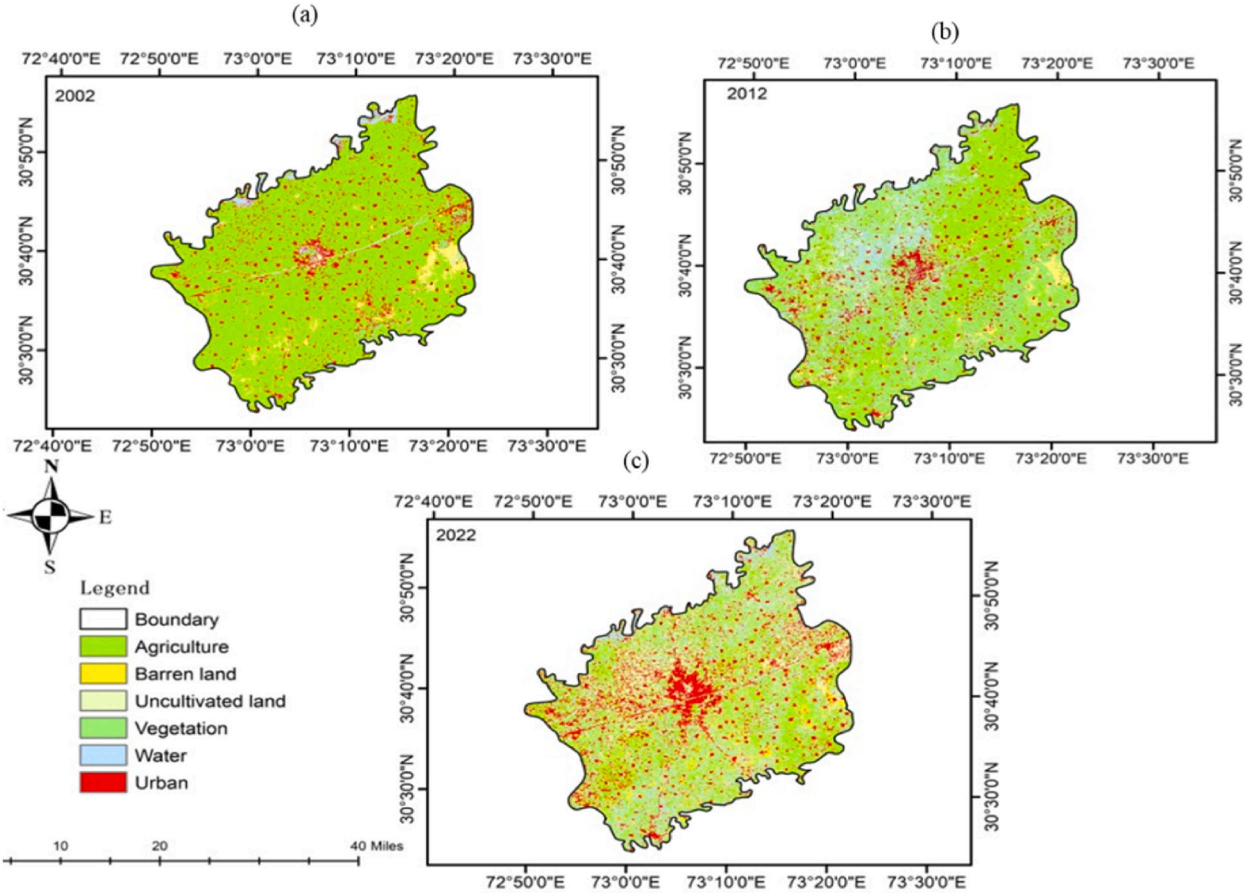

Fig. 2. 2002–2022 LULC map of Sahiwal city A labels "(a)," "(b)," and "(c)" to represent the years 2002, 2012, and 2022, respectively.

3.3. Urbanization mode of different land consumption

Fig. 4 shows the land use conversion for the years 2002–2022. Land use conversion data from 2002 to 2022 reveal a significant increase in urbanization over the past 20 years. Urbanized areas increased by 234.7 km^2 (91 %), indicating a significant increase in urban extent. However, urban sprawl has also reduced the amount of land suitable for agriculture by 52 %. In other words, over the last 20 years, the urban scope has increased by a factor of three, which is a significant sign of urbanization (Fig. 3). In addition to the advantages, urban sprawl also directly reduced the amount of land that could be used for agriculture, which fell by 656.05 km^2 (52 %) as shown in Table 3.

Over the past 20 years, urbanization has facilitated certain conversions (Fig. 3). There were 132.56 km^2 of agricultural land converted into urban land. Comparatively, fewer other land uses were converted into urban land (Fig. 3). Land gains and losses in urban areas over time, approximately 17.05 km^2 of area was lost by urbanization, whereas a significant amount of area CA 251.75 km^2 (Fig. 5).

3.4. Markov transition analysis

Based on land use conditions in Sahiwal, Punjab, Pakistan, between 2002 and 2022, Land use types were calculated using the Markovian process transition probability matrix (Table 4). There are 0–1 values in the land use transition probability matrix. Vertical or horizontal transitions are more likely to occur when a value is closer to 1 than when it is farther from 1. Land in urban areas has a probability of 0.5857, whereas agricultural land has a probability of 0.4161 (Table 4). In comparison to other land use patterns, vegetation, and barren land are the most unstable. Over the course of the research period, changes occurred both in the increase and decrease of localities (Table 4). The probability of converting agricultural land to agricultural land is 0.41, agricultural land to barren land is 0.04, agricultural land to uncultivated is 0.22, agricultural land to vegetation is 0.01, and agricultural land to urban is 0.10, and so on. Changes occurred across localities, with the highest probability of conversion from non-cropland to urban land being 0.58. A GIS framework was used to calculate the transition probability (Table 4).

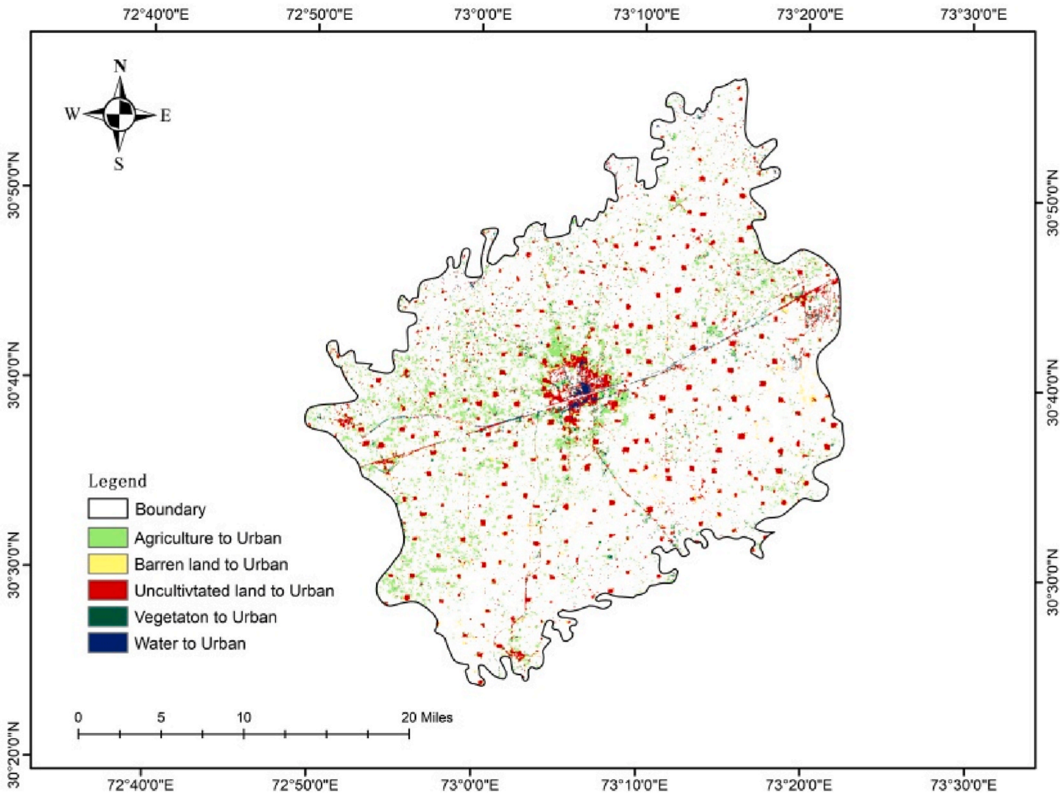

Fig. 3. Dynamics tends of urban expansion and various LULC covers to urban from 2002 to 2022 in Sahiwal.

3.5. Prediction of LULC for 2042

Using the transition area matrices, we use the CA-Markov model to forecast land use in 2042 for Sahiwal city (2002–2022) as shown in Fig. 6, and LULC (Table 5). The net change in agriculture is the biggest, and it will lose about −226.09 km^2 from 2022 to 2042 (Table 5) (see Table 6).

CA-Markov model was used to predict land use and land cover in Sahiwal city from 2002 to 2022. The largest net change was recorded in agriculture, which lost about −226.09 km2 from 2022 to 2042 (Fig. 6 and Table 5). The model predicted an average KIA of 0.83 for urban areas and 0.91 for agriculture, with a relative error of less than 5 % in land use patterns (Fig. 6).

In 2042, the CA-Markov model was used to project land use and land cover (Fig. 7). The average KIA predicted for urban and agriculture using CA-Markov calculations was 0.83 and 0.91, respectively. There was a strong agreement between the validation results and the simulation map. LULC maps in the study area can be simulated with the CA-Markov model based on kappa values. There is a relative error of less than 5 % in land use patterns, with the exception of urban land, and agriculture land in particular has an absolute error of less than 0.3 %. Kappa indicates moderately high agreement between actual and predicted LULC (Fig. 8).

3.6. Structural questioner and interview results

The study investigated the areas selected by Sahiwal to understand local perceptions of community economic development (CPEC) as shown in Appendix 1 and Fig. S1.

3.6.1. Structural equation modeling

The model was estimated using structural equation modeling through AMOS 21 (8). Model fit indices indicated that all cutoffs were met; CMIN/DF = 2.058 showed perfect fit with all cutoffs, which is less than 3, GFI = 0.88, AFGFI = 0.85, CFI = 0.93, TLI = 0.92, NFI = 0.0.88, RMR = 0.021, and RMSEA = 0.059) were in the acceptable range (Saad et al., 2020). Table 7 shows that CPEC significantly affects poverty alleviation ($\beta = 0.201, p < 0.05$). It was found that CPEC would significantly improve opportunities in the area [57]. But CPEC has no influence on quality of life ($\beta = 0.029, p > 0.05$) and also an insignificant influence on biodiversity ($\beta = 0.004, p > 0.05$), respectively. These findings are different - [58] because they claim CPEC as a game-changer and driver of quality life. However, our findings also describe that CPEC would influence quality of life and enhancement indirectly through the building and advancement of infrastructure. Building the CPEC has a significant influence on urbanization ($\beta = 0.369, p < 0.05$). Our findings are in line with [57], who claimed that CPEC improve infrastructure and build in deprived areas. Urbanization has a significant influence on poverty

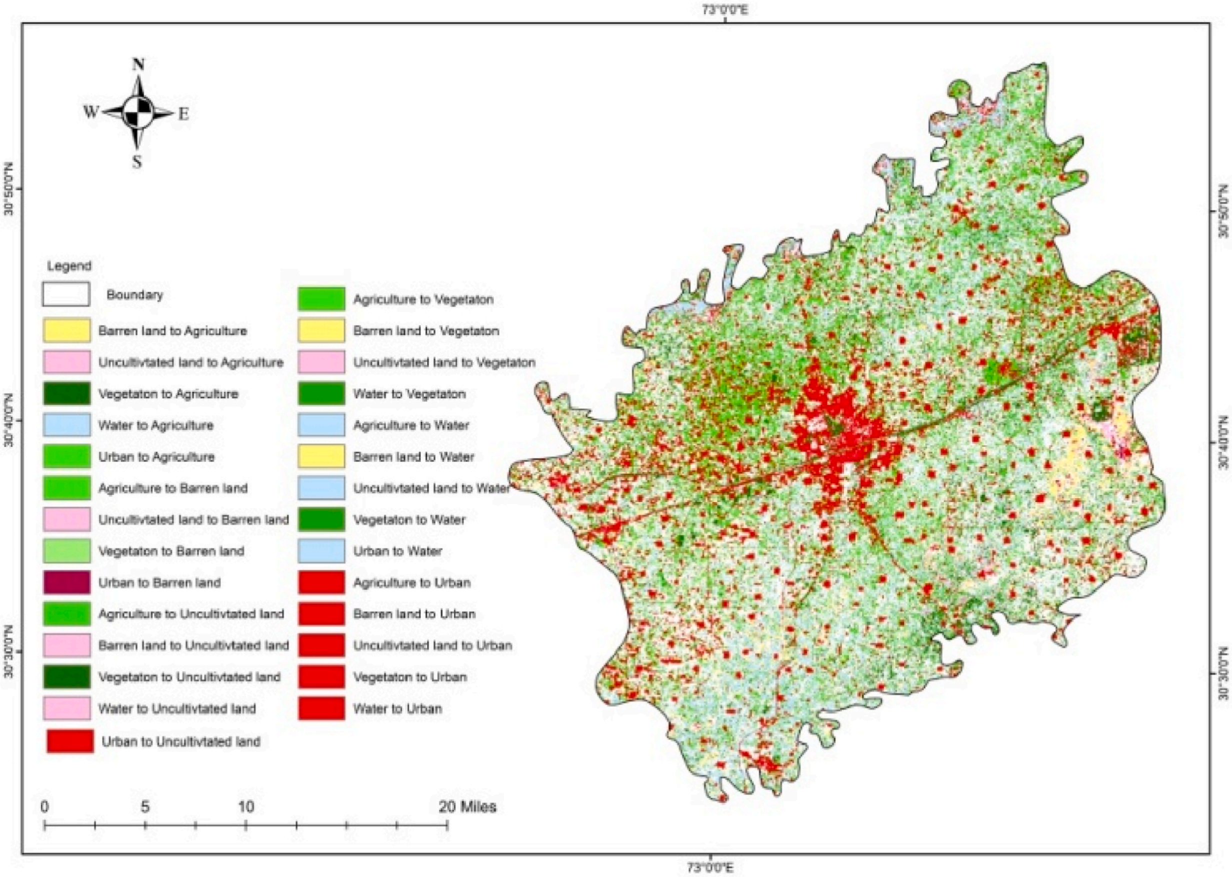

Fig. 4. Changes in different land use conversion classes in Sahiwal from 2002–2022.

alleviation ($\beta = 0.399$, $p < 0.05$), quality of life ($\beta = 0.166$, $p < 0.05$), and biodiversity ($\beta = 0.346$, $p < 0.05$), respectively.

The indirect influence of CPEC on poverty alleviation is significant ($\beta = 0.147$, $p < 0.05$), and the direct influence also remained significant. CPEC was predicted to improve living standards for the poor and advance infrastructure in deprived areas.

The correlation matrix is shown in Table 7. There is a significant positive relationship between CPEC and urban development, according to the results ($r = 0.411$, $p < 0.05$), moderately correlated with poverty alleviation ($r = 0.393$, $p < 0.05$), and weakly correlated with biodiversity ($r = 0.143$, $p < 0.05$). However, the relationship of CPEC with quality of life is insignificant ($r = 0.098$, $p > 0.05$). Urbanization is significantly related to poverty alleviation ($r = 0.517$, $p < 0.05$), quality of life ($r = 0.186$, $p < 0.05$), and biodiversity ($r = 0.371$, $p < 0.05$). CPEC development and perceived community benefits and opportunities were found to be moderately and weakly correlated in previous studies [53]. Additionally, all correlation values in the sample data are below the 0.80 cutoff ranges, so there is no multicollinearity issue.

4. Discussion

Rapid urbanization is having a significant impact on land cover, transforming agricultural and vegetation land into urban areas [12]. By converting agricultural and vegetative land into urban areas, the trend toward urbanization promotes urban growth [20]. A GIS-based map helps identify issues and potential future growth directions. Sahiwal city in Punjab has seen a significant increase in urban area between 2002 and 2022, while agricultural and vegetation cover has decreased significantly. Similar trends have been observed in Quetta, Balochistan and Karachi city. The loss of vegetation cover has led to health and environmental problems [13,64]. The findings of this study, which are consistent with previous studies, showed significant changes in urban areas of Sahiwal city, Punjab [65]. Similar to this, the findings of our study showed that the agricultural cover in the study area suffered a significant loss [66, 67]. These results are consistent with earlier research on urban expansion and changes in LULC in different Pakistani cities. In addition, a reduction of a third in open spaces in Sahiwal city between 2002 and 2022 in this study. These results support earlier research in significant Pakistani cities such as Karachi and Peshawar [66]. Recently, Sun [68], emphasized on the influence of economic growth and environmental technologies on large population transformation.

From 9.55 km^2 in 1986 to 21.45 km^2 in 2015 in Awka, a town in Nigeria, the urban area increased over time, similar to our research. As a result, vegetation lost about 12.29 km^2 between 1986 and 2015, falling from 33.69 km2 to 21.41 km^2 [69]. Bangladesh's

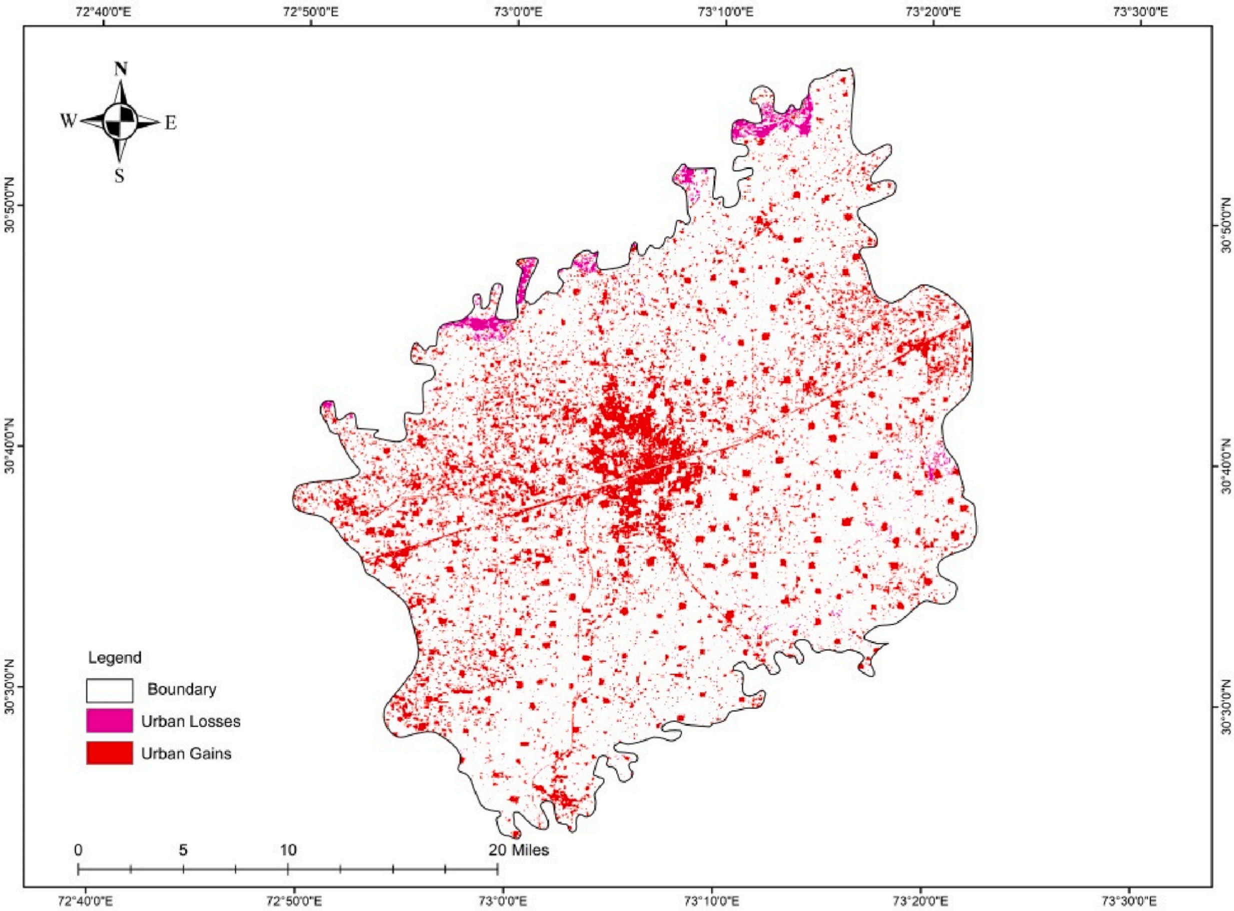

Fig. 5. Dynamics variations of urban loss and urban gain from 2002 to 2022.

Table 4
Markov transition probabilities matrix for the periods 2002–2022.

Classes	Agriculture	Barren land	Uncultivated land	Vegetation	Water	Urban
2002	2022					
Agriculture	0.4161	0.0441	0.2224	0.0188	0.1927	0.1058
Barren land	0.2321	0.3056	0.1449	0.0124	0.1482	0.1569
Uncultivated land	0.1166	0.0595	0.1567	0.0102	0.0713	0.5857
Vegetation	0.2799	0.0497	0.3439	0.0189	0.1708	0.1369
Water	0.0751	0.0369	0.2428	0.2407	0.1061	0.2985
Urban	0.0992	0.0659	0.1548	0.0281	0.3991	0.2528

five major cities' total built-up area increased by 468 % from 2356 ha in 1973 to 13,435 ha in 2014, while agricultural land and vegetation cover decreased respectively by 20.77 % and 61.91 % [70]. According to another study, approximately 50 % of Dhaka's land cover will become urban areas, with vegetation being more negatively affected than other land cover classes [71]. The findings of this study, which are consistent with those of previous studies [69–72], indicate that there have been noticeable changes in urban and vegetative land cover characteristics. Beijing is one example of a city where cultivable land is being used more and more for urban built-up areas [73]. A similar pattern of change could be anticipated in Hyderabad, India, where irrigated croplands were converted into an urban area in the year 2040. The use of such land increased the Sahiwal real estate market, which was also seen in Hyderabad, India, and increased prices in residential and commercial areas [74]. Parallels, the city of Sierra Leonean in Syria has seen an increase in the trend towards urban areas and agricultural land [75]. Taken together, a superb multi-lane network of roads constructed by CPEC to an international standard in Sahiwal could be the main contributing factor towards extreme urbanization. In 2002, all roads were 792 km long and in 2018, they were 1309 km long. Furthermore, the CPEC projects offered better employment opportunities and housing, as well as high-quality education to many people from other cities and provinces in the country. Infrastructural development and industrial growth are responsible for this growth and increase in economic potential of the region [76].

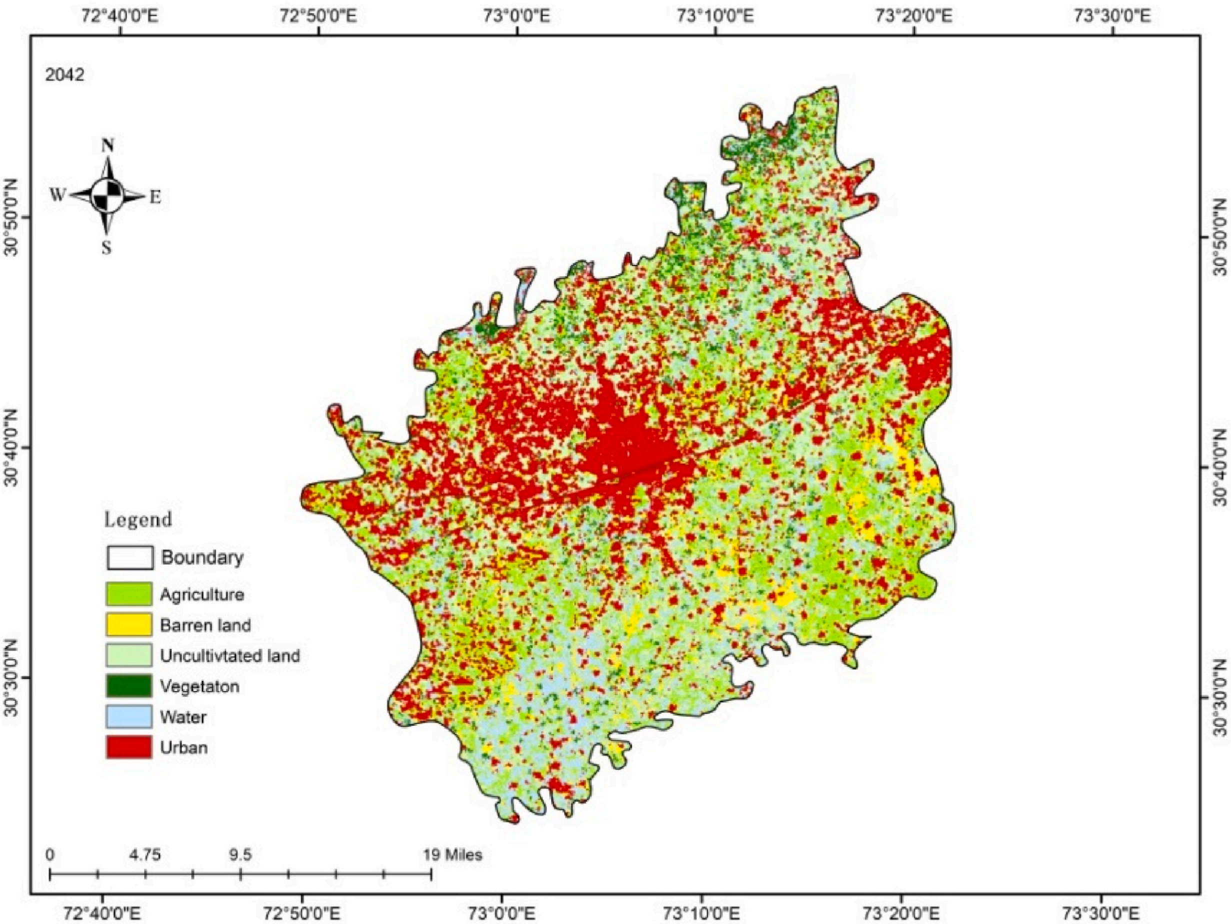

Fig. 6. LULC prediction cover map results for Sahiwal city in 2042.

Table 5

Predicted LULC changes for Sahiwal city in 2042.

LULC Classes	Area (km^2)	Change	
	2022	2042	km^2
Agriculture	596.47	370.38	−226.09
Barren land	97.28	107.28	10
Uncultivated land	364.79	327.20	−37.59
Vegetation	33.08	95.35	62.27
Water	296.56	295.27	−1.29
Urban	257.53	450.23	192.7

Table 6

Direct and indirect effects of CPEC and urbanization on various studies.

Factors	Direct effect	Indirect effect	Total effect
CPEC– Poverty alleviation	0.201**	0.147**	0.348**
CPEC– Quality of life	0.029	0.061**	0.091
CPEC-Biodiversity	0.004	0.128*	0.132*
CPEC- Urbanization	0.369**	–	0.369**
Urbanization- Poverty alleviation	0.399**	–	0.399**
Urbanization- Quality of life	0.166**	–	0.166**
Urbanization- Biodiversity	0.346**	–	0.346**

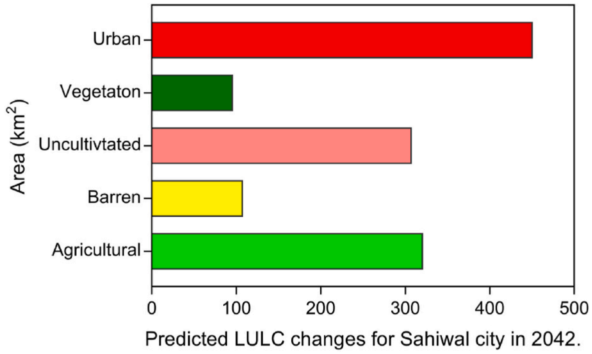

Fig. 7. Anticipation of different LULC changes in Sahiwal city for 2042.

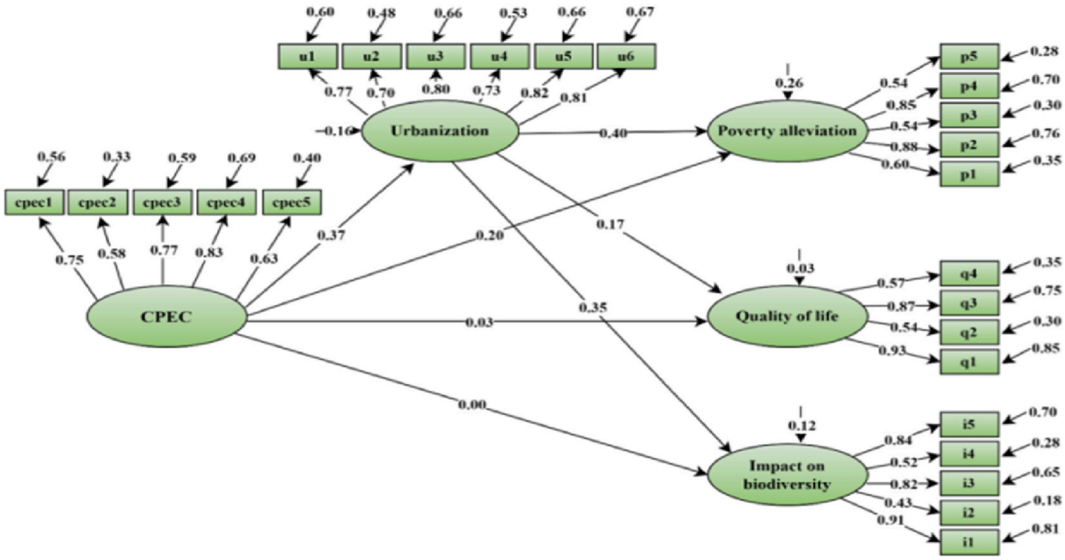

Fig. 8. Structural model estimation.

Table 7
The correlation matrix between studied variables.

Variables	CPEC	Urbanization	Poverty alleviation	Quality of Life	Biodiversity
CPEC	1				
Urbanization	0.411**	1			
Poverty alleviation	0.393**	0.517**	1		
Quality of Life	0.098	0.186**	0.187**	1	
Biodiversity	0.143*	0.371**	0.307**	0.179**	1

Note = **p value less than 0.005, *p value less than 0.05.

An analysis of land use patterns in Sahiwal, Pakistan, was conducted using Cellular Automata Markov Chain models showing that urban areas increased while vegetation and water cover decreased between 2002 and 2022, in line with previous research [20]. This conclusion is consistent with global predictions that urbanization will result from the continued growth of people at the expense of green space [21,30]. The study did not, however, consider the potential negative impacts of these changes on global and regional climate. Researchers should examine how land changes will affect regional climate in the future. For better agricultural management, an approach of agricultural courses for soil conservation and time series investigation can be used for further assessment of climate changes [77,78]. There is limited explanation of the model validation process about predictions for previous years (e.g., using data from 2002 to predict 2012) were tested against observed data (2022) as discussed by researchers [79,80], can be considerable for further research studies.

5. Conclusions

The study reveals environmental problems in Sahiwal city due to haphazard management issues. Urban areas increased by 234.7 km^2 between 2002 and 2022, while agricultural areas lost more than 656.1 km^2. Road construction and urbanization played an important role in this decline. The study's conclusions exposed flaws in urban planning and management procedures. The study recommends strengthening the capacity of responsible departments to control urban growth and using geospatial technologies to track urban sprawl. Policy proposals include reducing agricultural land losses, improving institutions and increasing investments in green technologies.

CRediT authorship contribution statement

Kashif Ali: Writing – original draft, Data curation, Conceptualization. **Jawad Ali Shah:** Writing – review & editing, Investigation. **Saif Ullah:** Writing – review & editing. **Syed Turab Raza:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Data availability statement

The data will be available on demand.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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