Journal of Geography and Social Sciences, 2020, 2 (2), 164-182.
http://www.jgss.com.pk

Original Article OPEN ACCESS

Land use/land cover change detection and prediction using the CA-Markov model: A case study of Quetta city, Pakistan

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ABSTRACT

Background: Land use/land cover changes are the results of rapid urban growth and human activities. The anthropological activities, such as growth in population, rapid urbanization, and fast economic advancement, have modified the surface of the earth, which causes change at a local level and worldwide. Therefore, LULC monitoring and modelling are important for sustainable urban development.
Objectives: The current study aims to detect changes in land use/ land cover from 1998-2018 and to predict changes for the year 2028 using the integrated Cellular Automata-Markov model in Quetta city, Pakistan.
Methods: Three temporal satellite imageries were used for the detection of changes during 1998, 2008, and 2018. Maximum Likelihood Classification techniques were used for classification and change detection, whereas, Cellular Automata-Markov integrated model was used for the prediction of 2028. The standard kappa coefficient was used for assessing the validity of the model.
Results: The result shows an increase (27.1km2) in the built-up area, while a decrease (15.4 km2) in open spaces and 11.7 Km2 in green areas from 1998 to 2018. Moreover, the Prediction result shows that the green area and open spaces would likely be decreased (2.7 km2) and 3.86 km2 from 2018 to 2028 respectively, whereas a slight increase (6.56 km2) in built-up is expected from 2018 to 2028.
Conclusions: This study concluded that Quetta city had witnessed LULC changes over the last 20 years. The current study revealed that the condition of green areas and open spaces are much precarious due to the rapid urbanization in the city. Whereas, the alarming increase in the built-up area creates many complications for the current and future planning process. The use of GIS and RS can be used effectively for detecting and predicting LULC changes. The present study can be used as a direction for other studies using projected LULC models.

ARTICLE HISTORY

Received: 3 Oct 2020
Accepted: 26 Dec 2020
Published: 31 Dec 2020

KEY WORDS

Change prediction;
Markov Chain;
Cellular Automata;
GIS and Remote Sensing;
Land use land cover change detection;
Quetta;

1. INTRODUCTION

Rapid urbanization is happening throughout the world, which leads to several urban-associated environmental and social problems (Khawaldah, 2016; Ridd & Hipple, 2006). Urbanization is caused by population growth and frequent anthological activities, such as industrialization and migration from rural to urban areas, which will lead to densification and urban sprawl (Sexton et al., 2013). These processes necessarily result in land use/land cover (LULC) change, affecting both the natural ecosystem and anthropogenic system (Gillanders et al., 2008). The anthropological activities have changed LULC at local and national levels through population growth, rapid/unplanned urbanization and economic growth

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(Hamad et al., 2018; Lambin et al., 2003; Singh et al., 2015). The change in LULC has been observing since first Landsat Satellite was launched in the 1970s (Bazai & Panezai, 2020; Hadeel et al., 2009; Rashed et al., 2005; Shirazi & Kazmi, 2014).

Knowledge about the land use/land cover has become progressively significant in the process of urban planning and management, especially to understand uncontrolled development, environmental degradation, loss of agricultural fields, and damage to biodiversity (Anderson, 1976; Bazai & Panezai, 2020). Consequently, information about land use/land cover changes over time is one of the significant parameters in the process of planning and managing land (Ramankutty & Foley, 1999). Therefore, monitoring and detecting LULC change is crucial to urban planners, government departments, hydrologists and environmentalists. Additionally, the prediction of future LULC change offers a framework of long-term measures for improved planning and management of resources (Fathizad et al., 2015). Therefore, the availability of reliable and updated land cover data is vital for monitoring, planning, and management programs (Muller & Middleton, 1994).

Remote Sensing and Geographic Information System (RS & GIS) is a dynamic technique to investigate and detect the variations in land use and land cover (LULC) (Mukhopadhaya, 2016). They are very effective and powerful tools and are increasingly used for assessing urban expansion and change detection analysis (Ghaffar, 2015). GIS provides a flexible environment for gathering, storing, analyzing, and displaying digital information important for LULC change detection (Reis, 2008). Furthermore, for the prediction studies, continuous data from Landsat imageries provide effective information that can be used as an input (Hamad et al., 2018). Markov Chain Analysis mostly used in terms of quantity of simulation of LULC change, and not able to get the variation degree of the land use forms from a spatial view (Halmy et al., 2015; Sklar & Costanza, 1991); whereas, Cellular Automata model has solid and powerful prediction capacity to show changes spatially and periodically (Yuan et al., 2015b). Therefore, the combine benefits of CA-Markov can be the best choice for LULC change prediction

Land use/land cover prediction models generally seek to detect where the change has been occurred or will possibly occur (Veldkamp & Lambin, 2001). With the development of remote sensing, satellite imageries are providing LULC information, spatial and temporal process, and simulation (Weng, 2002; Yuan et al., 2015a). There are several methods and techniques which can be used for modelling and predicting land-use/land cover change (Halmy et al., 2015; Overmars et al., 2003; Veldkamp & Lambin, 2001). Some of the empirical models for LULC change detection and simulation are cellular automata (CA) (He et al., 2005), Clue-s model (Zhan et al., 2007), Markov model (Guan et al., 2008), CA-Markov model (Akin et al., 2012; Wang et al., 2014), etc. These models help and support the preparation of land use planning and decision making (Guan et al., 2011; Halmy et al., 2015). However, several studies have used the CA-Markov and Markov chain model to predict and simulate land use/land cover change over various landscapes (Liping et al., 2018). For example, from central Florida, USA, Subedi et al. (2013) have used Spatio-temporal data to examine the appliance of Cellular Automata and Markov model to predict the changes in Saddle Creek drainage basin in Florida. Similarly, (Halmy et al., 2015) have used Markov-CA to predict changes in 2023 by inferring current dynamics. From Pahang state Malaysia, Rendana et al. (2015) have employed Cellular automata (CA) and Markov chain analysis to predict future land-use in the study area. Moreover, Hamad et al. (2018) also used a Cellular Automata (CA)-Markov chain model for the year 2023.

In Pakistan, numerous studies have been conducted on Land-use/ land cover modelling using various models, such as Markov chain, Cellular automata, Multilayer Perceptron. Masud et al. (2016) have revealed a massive increase in the built-up area in Sahiwal Tehsil, Punjab, and would likely increase further in the projected the year 2019. The results from the study of Mannan et al. (2019) showed that forest land decreased from 40936.77 ha to 36709.23 ha, agricultural land increased from 4220.46 to

10374.64 ha, Whereas the built-up area increased from 1497.60 to 5395.12 ha. The results of the study conducted in the capital city of Punjab (Lahore) by Bhatti et al. (2015) shows a great increase of 47% in 1999 to 57% in 2011 while the predicted results of multilayer perceptron neural network (MLP model) indicates an increase in a built-up area and decrease in agriculture area from 2021 to 2035. However, Imran and Mehmood (2020) showed that rapid development in the residential sector has increased temperature by 6 °C and decreased the vegetation cover by 9%. Moreover, a 3 % decrease in vegetation cover by 2035 may occur in the future. Similarly, the result from the study of the Ullah et al. (2019) showed that the built-up area had the highest mean LST compared to other classes. Whereas an increase of 12.48% & 14.65 in LULC may occur in 2032 and 2047, respectively. Another study conducted by Samie et al. (2017) in Punjab shows a massive increase in built-up and cultivated and decrease in water and grassland. Ullah et al. (2019) conducted a study in the lower Himalayan region, Pakistan, the results show 5.75% increase in the built-up area while vegetation decreases to 9.88% (1990-2017) while the results of predicted models show built-up area would be increased to 12.48% and 14.65% in 2032 and 2047. There is a deficiency of literature that has conducted land use/land cover change detection and prediction in Balochistan, as well as in Quetta. Only two studies have been conducted earlier in Balochistan on land use/ land cover change detection. Khan and Qasim (2017), have studied spatiotemporal dynamics of LULC in District Pishin, Balochistan; whereas, Bazai and Panezai (2020) have assessed urban sprawl and land-use change dynamics in Quetta city, Balochistan. To the best of the authors' knowledge, not a single study is existing on LULC change prediction and the application of the CA-Markov model in Quetta city as well as in Balochistan. The current study aims to detect changes in land use/ land cover from 1998-2018 and to predict changes for the year 2028 using the integrated CA-Markov model in Quetta city, Pakistan.

2. METHODS

2.1 Study design

The current study follows the case study design, and integrated GIS and RS technologies were used for classification, of satellite imageries. These imageries were used to detect the change in different land use/land cover classes from (1998-2018). Afterwards, CA-Markov models were applied to predict future change in these classes.

2.2 Setting

Quetta city (Figure 1) is the provincial capital city of Balochistan, Pakistan (Bazai & Panezai, 2020). Quetta city ranks as the 10th most populous city of Pakistan. (Pakistan Bureau of Statistics, 2017). The population of Quetta city has grown by 78.6 percent from 0.56 million in 1998 to 1 million in 2017 (Pakistan Economic Survey, 2017-18). The geographical location of the city is 29° 48′ N to 30° 27′ N latitude and 66° 14′ E to 67° 18′ E longitude (Ainuddin & Routray, 2012). The city is bounded in the north by Pishin district, northeast by Ziarat district, east by Harnai district, and west by Afghanistan, south by Mastung district, whereas, Nushki district is situated in the south-west (PAIMAN & USAID, 2009). Quetta, a bowl-shaped valley, is bounded by limestone slopes of Chiltan, Takattu, Zarghoon and Lamrdar ranges (Khan et al., 2010). It extended on 2,653 km^2 area (Planning & Development Department & UNICEF, 2011).

2.3 Data sources and collection

Three temporal satellite imageries (Landsat Path-153 and Row-039) with ten years intervals during 1998-2008 and 2018 were downloaded from USGS having a 30m resolution (United States Geological Survey, 2019). The detail of these imageries is shown in table 1. The shape files (roads, railway track, and country boundary) were downloaded from Open Street Map. This study used the 2017 boundary of Quetta city for the current study, and the shape file of the boundary was taken from the Pakistan Bureau of Statistics, Regional Office, Quetta.

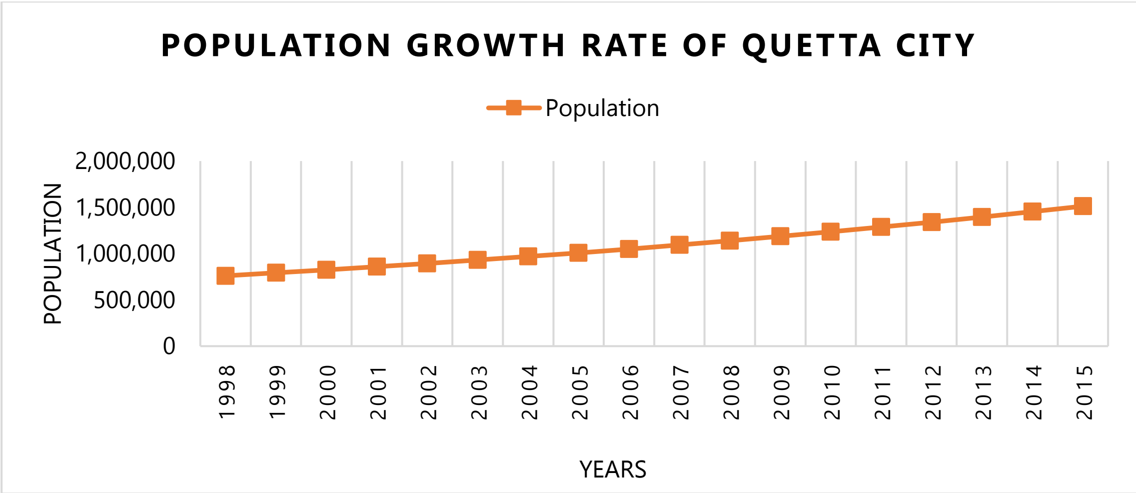

Figure 1. Population growth rate of Quetta city

Source: Pakistan Emergency Situation Analysis - District Quetta April 2015 (ALHASAN SYSTEMS, 2015)

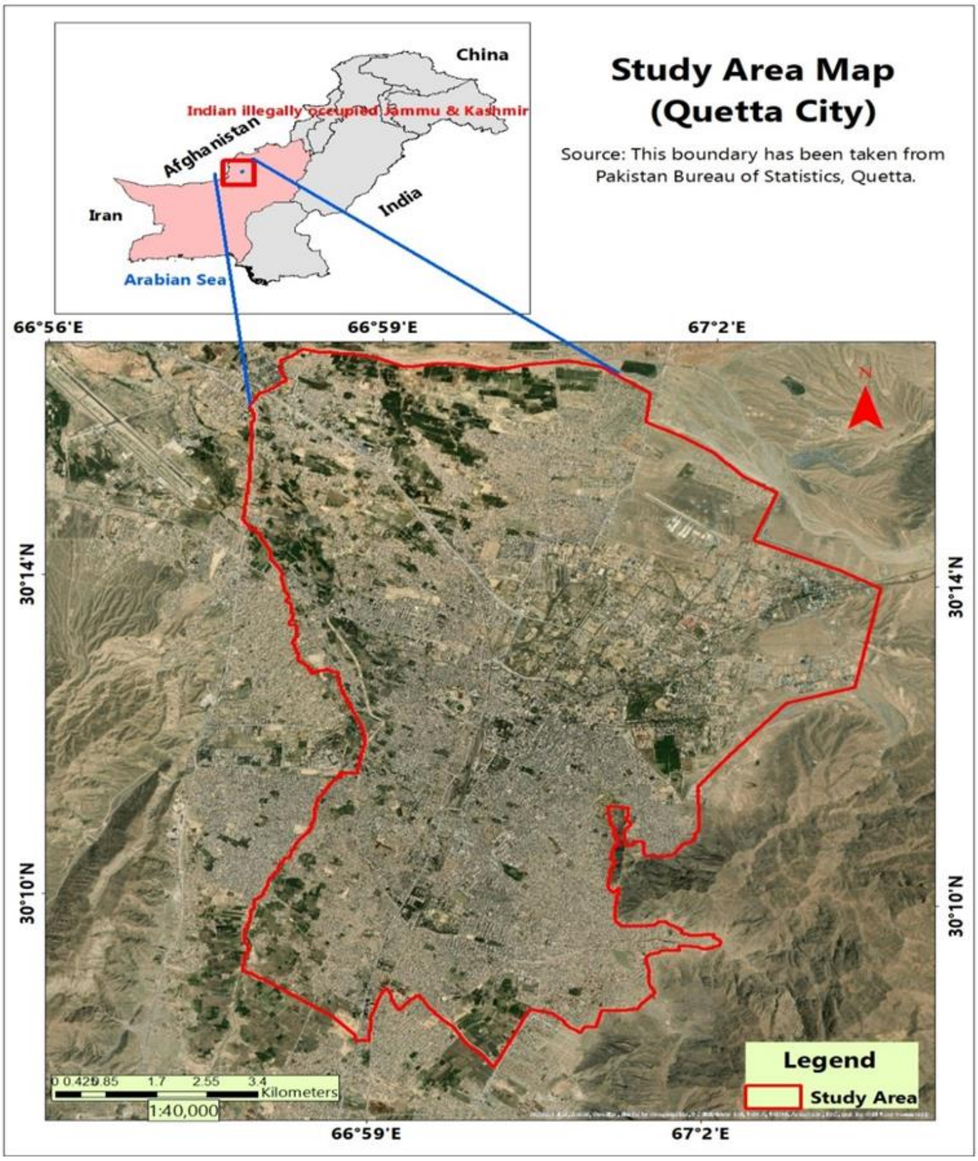

Figure 2 Study area map

2.4 Data analysis methods

In the current study, the downloaded multi-temporal remote sensing images were processed through different phases to detect and predict the Spatio-temporal changes in LULC of Quetta city Balochistan, Pakistan. In the first phase, the imageries were classified using the maximum likelihood supervised classification (MLC) method in Arc GIS 10.4 for generating LULC maps for the years 1998, 2008, and 2018. In the second phase, LULC change detection analysis was conducted. In the third phase, the transition probability matrix was generated using the "Markovian transition estimator tool" in IDRISI Selva, and the "multi-criteria evaluation model" (MCE) was used for the making of transition probability maps (Mukhopadhaya, 2016). Furthermore, the result of both above-mentioned tools was used in the CA-Markov integrated model for the LULC change prediction for the year 2028.

2.4.1 Pre-processing of imageries

The satellite imageries were taken from two different sensors (Landsat TM and Landsat OLI). The downloaded multi-temporal remotely sensed imageries were then passed through different processes for further analyses. The map projection of the satellite imageries was set as Universal Transverse Mercator (UTM), Zone 42 N, and the Datum was set to World Geodetic System (WGS) 1984. Using band composite tool, all multi-band raster imageries (1998, 2008, and 2018) were converted into a single raster dataset using ArcGIS 10.4. An image enhancement tool was also applied to making imageries more enhanced. The study area was cropped from all imageries using ''extract by mask tool'' in ArcGIS using the 2017 boundary of Quetta city.

Table 1 Details of Landsat imageries used in this study

Sr. No.	Acquisition date & year	Path/ Row	Satellite sensor	Resolution (m)	Cloud Cover (%)	Number of Bands	Format
1	7/24/1998	153/039	LANDSAT_5-TM	30	Less than 10	7	Geo TIFF
2	7/19/2008	153/039	LANDSAT_5-TM	30	Less than 10	7	Geo TIFF
3	7/15/2018	153/039	LANDSAT_8 (OLI_TIRS)	30	Less than 10	11	Geo TIFF

Source: Imageries taken from USGS Explorer

2.4.2 Image processing/ LULC classification

The three LULC classes (green areas, open spaces and built-up areas) were identified for the classification of imageries in the current study (Table 2). Ninety (90) training samples were selected for three LULC classes and 30 training samples were selected for each class. Moreover, the supervised Maximum Likelihood Classification (MLC) was applied to classify satellite imageries. MLC is the most widely used method of classification.

Table 2 Land use/ land cover classes and description

Classes	Description
Green Area	Natural vegetation, trees, parks, gardens, grassland and playgrounds having grass.
Open areas	Areas with no vegetation cover, sand, barren land,
Built-up land	This includes: residential, industrial, Roads Services, mixed urban or built-up Area

Source: (Bazai & Panezai, 2020; Hyandye & Martz, 2017)

2.4.3 Accuracy assessment

This study used the Kappa coefficient for accuracy assessment. Kappa coefficient is used commonly to evaluate the accuracy of the classification of satellite imagery (Yuan et al., 2015b). The accuracy assessment is carried in terms of the user's accuracy, producer's accuracy, and overall accuracy (Bazai & Panezai, 2020; Liping et al., 2018) (See Table 6).

2.4.4 Methodology adopted in the current study

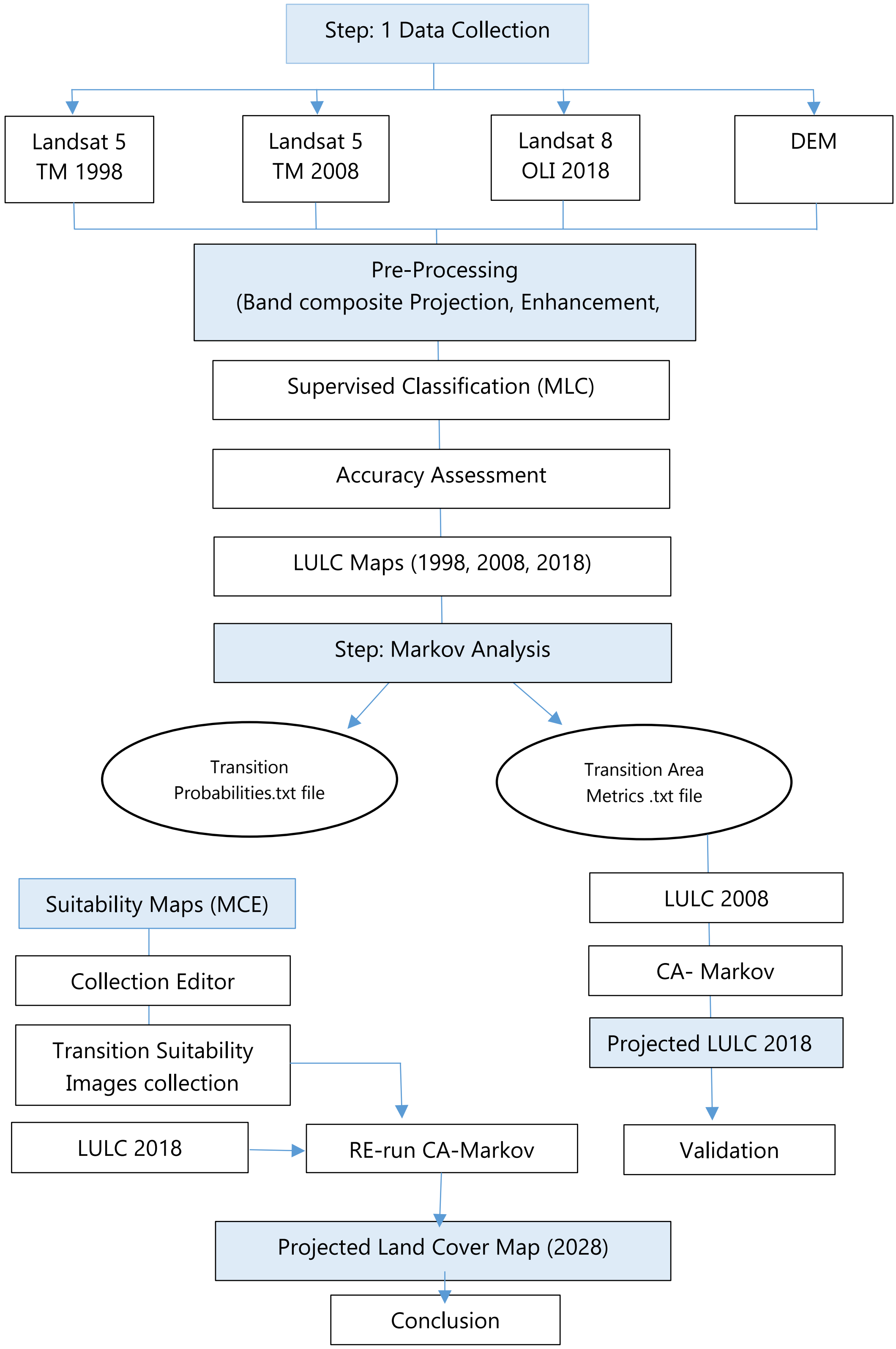

Figure 3 Methodological flow chart

2.4.5 Preparation of suitability maps

The suitability maps are the requirement of using Cellular Automata. These maps were generated using Multi-Criteria Evaluation (MCE) and Fuzzy membership function, which determined the status of change, represent the possibility of change of pixel from one category to another or remain unchanged (Rimal et al., 2017). The MCE is a widely used method for assessing and aggregating weighted maps (Criterion) composed of experts understanding and influence of the factor LULC (Hyandye & Martz, 2017). In this study, suitability maps were generated using the factors responsible (slope, digital elevation model and road distance) for LULC change and distribution (Hyandye et al., 2015; Rimal et al., 2017). The detail about factors is mentioned in Table 3. The steps are given in figure 3 for making suitability maps.

Table 3 Criteria development data sources

Criteria	Criteria sources data	Data Source
Elevation	DEM	USGS
Slope	DEM	USGS
Road distance	GIS Data	Open Street Map

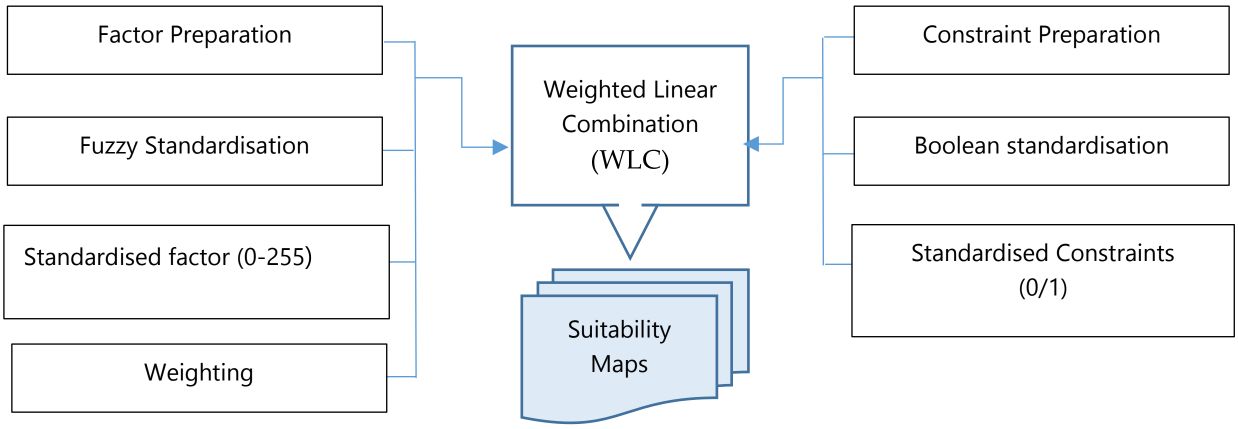

Figure 4 Steps for generating suitability maps

2.4.6 LULC change Prediction

This study used the CA-Markov combined approaches for predicting future LULC in Quetta City for the year 2028. The CA-Markov model is a combination of two different techniques: Cellular Automata and Markov. CA-Markov model is a useful and simple method for projecting future LULC based on changes observed in the past (Borana & Yadav, 2017; Mukhopadhaya, 2016; Yirsaw et al., 2017). The processes were performed in IDRISI Selva 17.0. To run this model, firstly, it required some inputs, including LULC maps, which were extracted using ArcGIS 10.4 for the years 1998, 2008 and 2018. Secondly, it required the transition probabilities and transition area, which were generated using the Markov model in IDRISI Selva (Hadi et al., 2014; Pontius & Malanson, 2005). The results obtained from the second step contain several pixels, which are expected or supposed to change through a certain period from one class to another class. The third and last requirement was suitability images, which were obtained using MCE and Fuzzy membership function. The tabular data of the Markov model combined with Suitability maps utilizing 5+ five contingency filter to predict LULC map of 2028 (Borana & Yadav, 2017; Halmy et al., 2015; Yuan et al., 2015b).

2.4.7 Validation of simulated LULC

The validation of the model is a significant part of any prediction-based studies. Kappa index is frequently used for checking the accuracy of the model in many studies (Kamusoko et al., 2009; Liping et al., 2018; Mukhopadhaya, 2016; Yuan et al., 2015b). In this study VALIDATE model was used in IDRISI selva to compare the predicted 2018 LULC with actual 2018 LULC to assess the accuracy of the model (Kamusoko et al., 2009; Liping et al., 2018; Mukhopadhaya, 2016; Yuan et al., 2015b). The validation result is shown in Table 9.

3. RESULTS

3.1 LULC classification and change detection

The MLC supervised technique was used for the classification of all three imageries for the years (1998, 2008, and 2018). Three classes were selected for each imagery for classification. The detail of these classes is mentioned in Table 2. The statistic shows an overall massive increase in built-up area and decrease in green areas and open spaces from 1998 to 2018. In 1998 the green area was 22.15 km² (23.32%), open spaces were 31.09 km² (32.73%), and the built-up area was 41.76 km² (43.96%). The classification results of 2008 show that the green area was 18 km² (18.95%), open spaces were 19 km² (20%), and the built-up area was 58 km² (61.05%). Whereas in 2018, the green area was 10.45km² (11%), open spaces were 15.69 km² (16.52%), and the built-up area was 68.86 (72.48 %) of all area. The statistical detail for each year is given in Table 4. The statistics show that the overall decrease in green areas and open spaces are (11.7 km², 52.8%), (15.4 km², 49.5%) respectively and the built-up areas have been increased (27.1 km², 64.9%) from 1998 to 2018. These changes can be seen through maps in Figure 5 and Figure 6, showing LULC classification for the years 1998, 2008, and 2018.

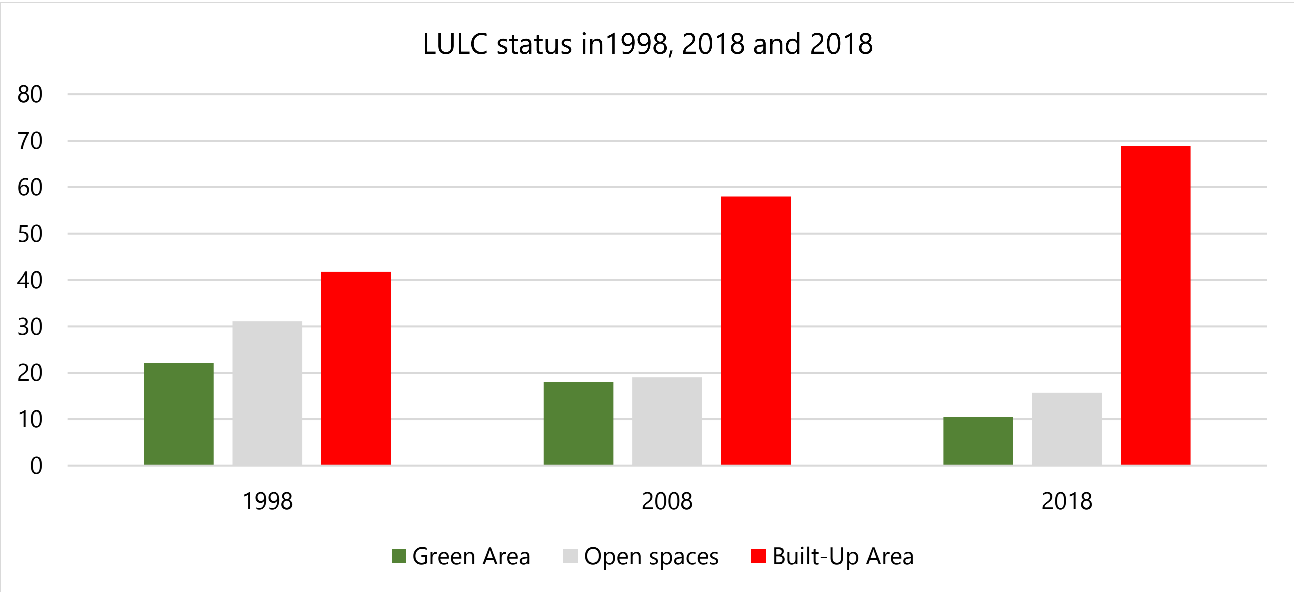

Figure 5 shows the status of LULC in three different periods

3.2 LULC change detection from 1998 to 2008

The change detection analysis shows the significant changes in all three classes from 1998 to 2008. The built area had significantly increased from 41.7 km2 in 1998 to 58 km2 in 2008. The increase observed in this class was 16.2 km² (46.20%) in the said period. While the open spaces were decreased from 31.09 km² in 1998 to 19 km² in 2008. The decrease detected in this class was 12 km² (38.89%). Moreover, the green area was decreased from 22.15 km² in1998 to 18 km² in 2008. The change detected in this class was 4.15 km² (18.74%). The details are given in Figure 8.

3.3 LULC change detection from 2008 to 2018

The change detection statistics from 2008 to 2018 revealed considerable changes in all three classes. The built area had considerably increased from 58 km^2 in 2008 to 68.86 km^2 in 2018. The increase witnessed in this class was 10.86 km² (18.72%) in the above-mentioned period. While the open spaces were decreased from 19 km^2 in 1998 to 15.69 km^2 in 2008. The decrease detected in this class was 3.31 km² (17.42%). Moreover, the green area was decreased from 18 km^2 in1998 to 10.45 km^2 in 2008. The change detected in this class was 7.55 km² (41.94%). The details are given in Figure 8.

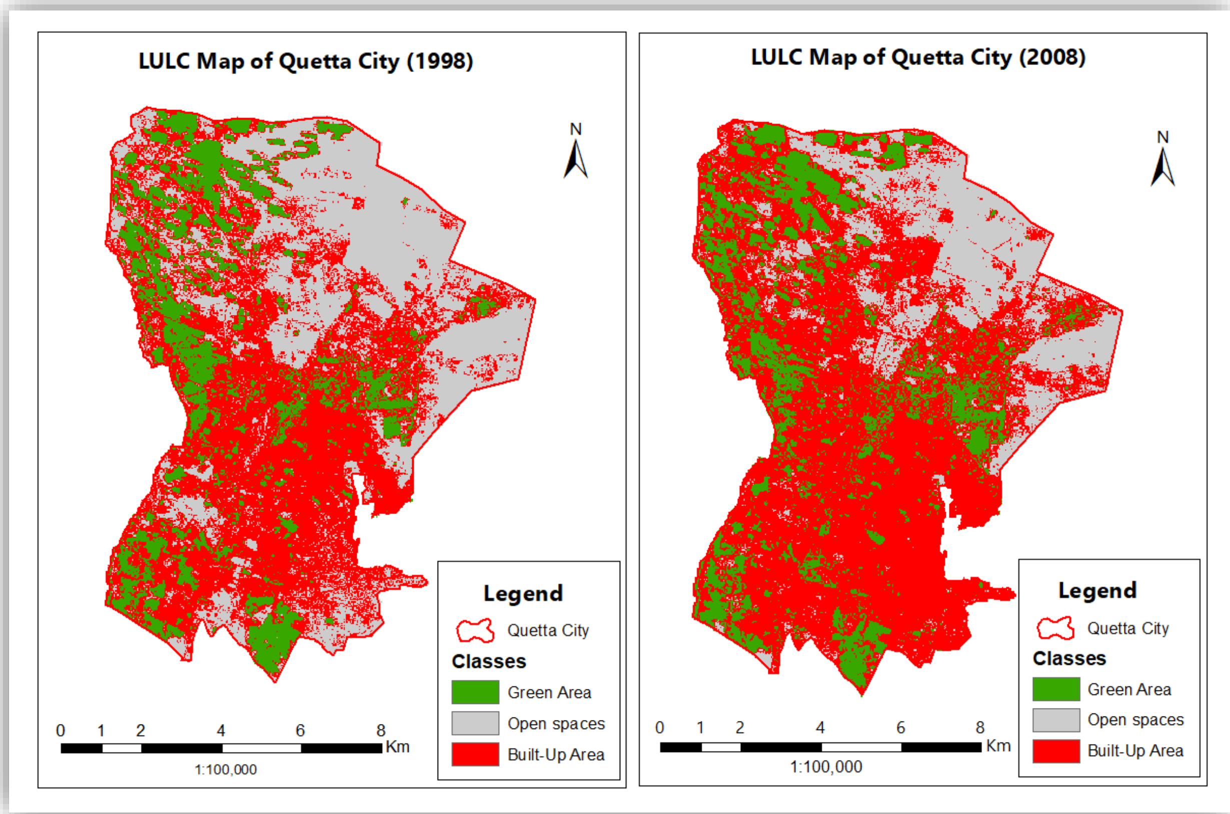

Figure 6 Showing LULC maps of 1998 and 2008

Table 4 LULC areas of 1998, 2008 and 2018

Land use classes	1998		2008		2018	
	Area/Km²	Area %	Area/Km²	Area %	Area/Km²	Area %
Green area	22.15	23.32	18	18.95	10.45	11
Open spaces	31.09	32.73	19	20	15.69	16.52
Built-up area	41.76	43.96	58	61.05	68.86	72.48
Total	95	100	95	100	95	100

Table 5 Change detection analysis for the years 1998, 2008 and 2018

Land use classes	Change detection b/w 1998-2008		Change detection b/w 2008-2018		Change detection b/w 1998-2018	
	Area/Km²	Area %	Area/Km²	Area %	Area/Km²	Area %
Green area	-4.15	-18.74	-7.55	-41.94	-11.7	-52.82
Open spaces	-12.09	-38.89	-3.31	-17.42	-15.4	-49.53
Built-up area	16.28	46.20	10.86	18.72	27.1	64.89

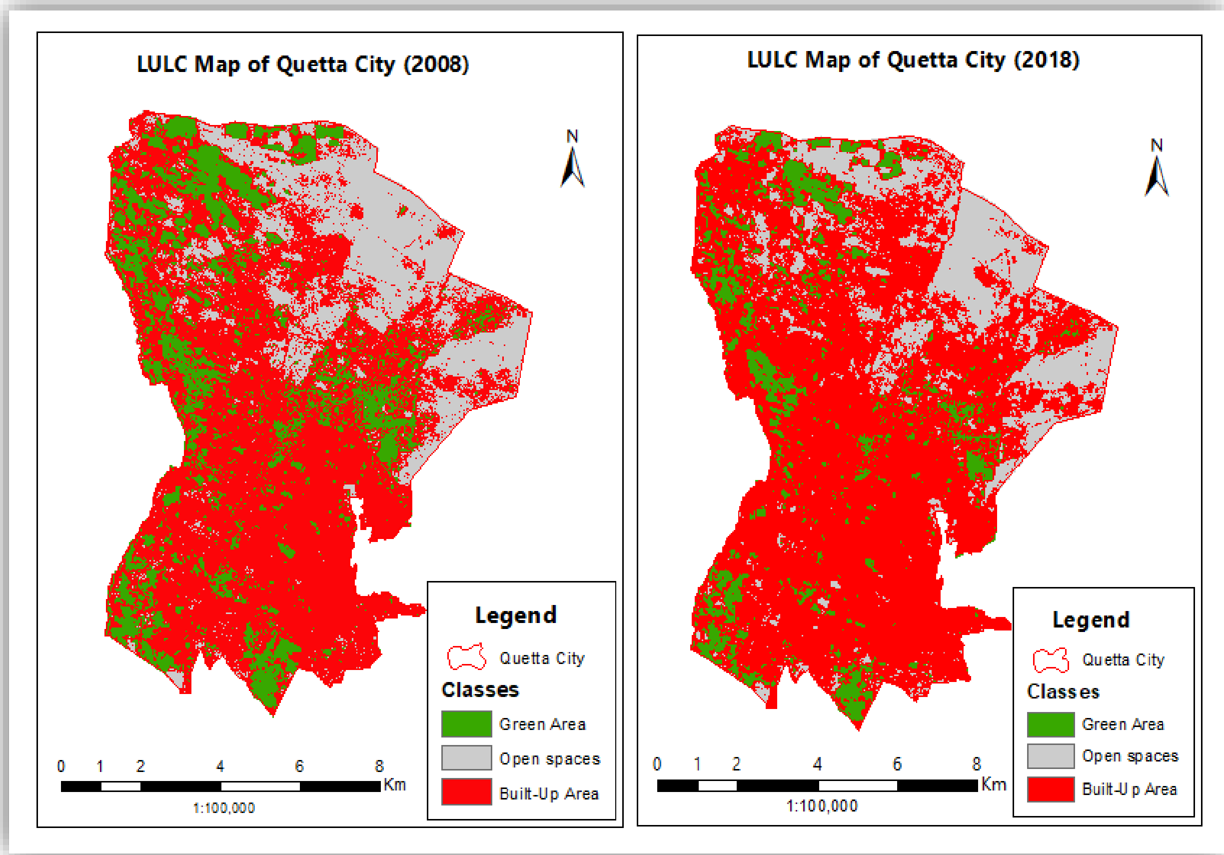

Figure 7 Showing LULC maps of 1998 and 2008.

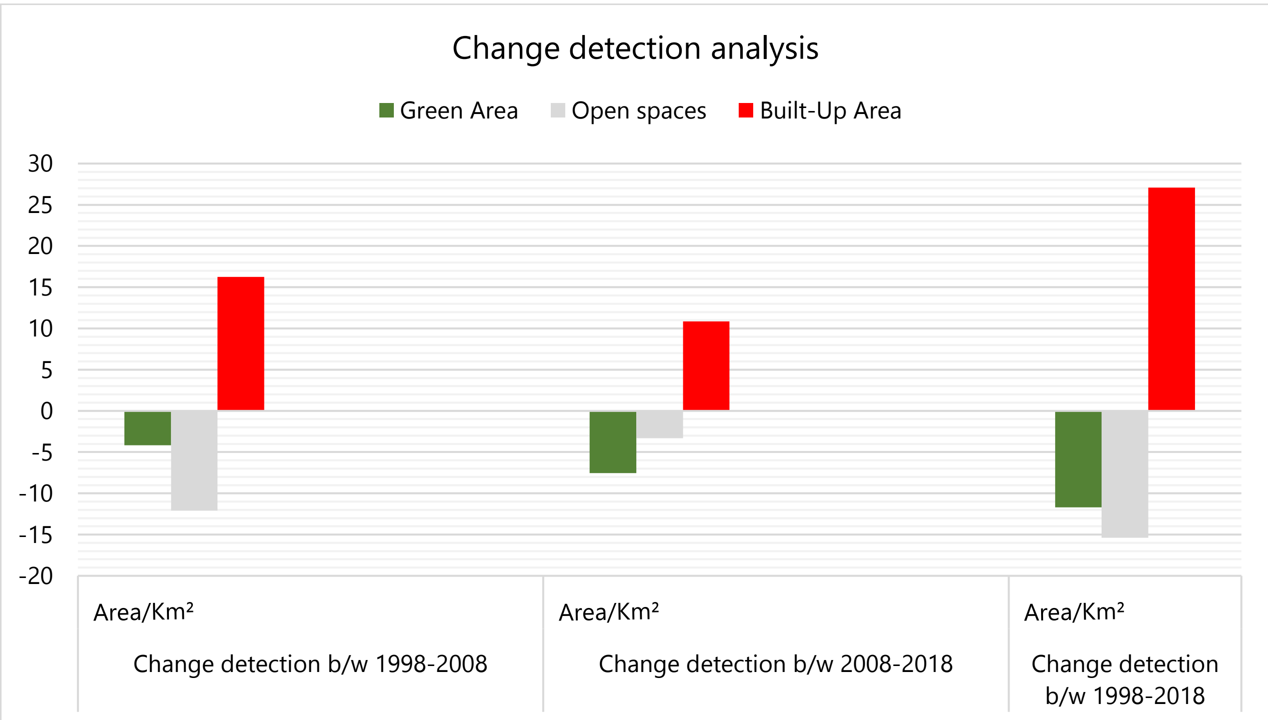

Figure 8 Change detection analysis

Source: Authors' calculations

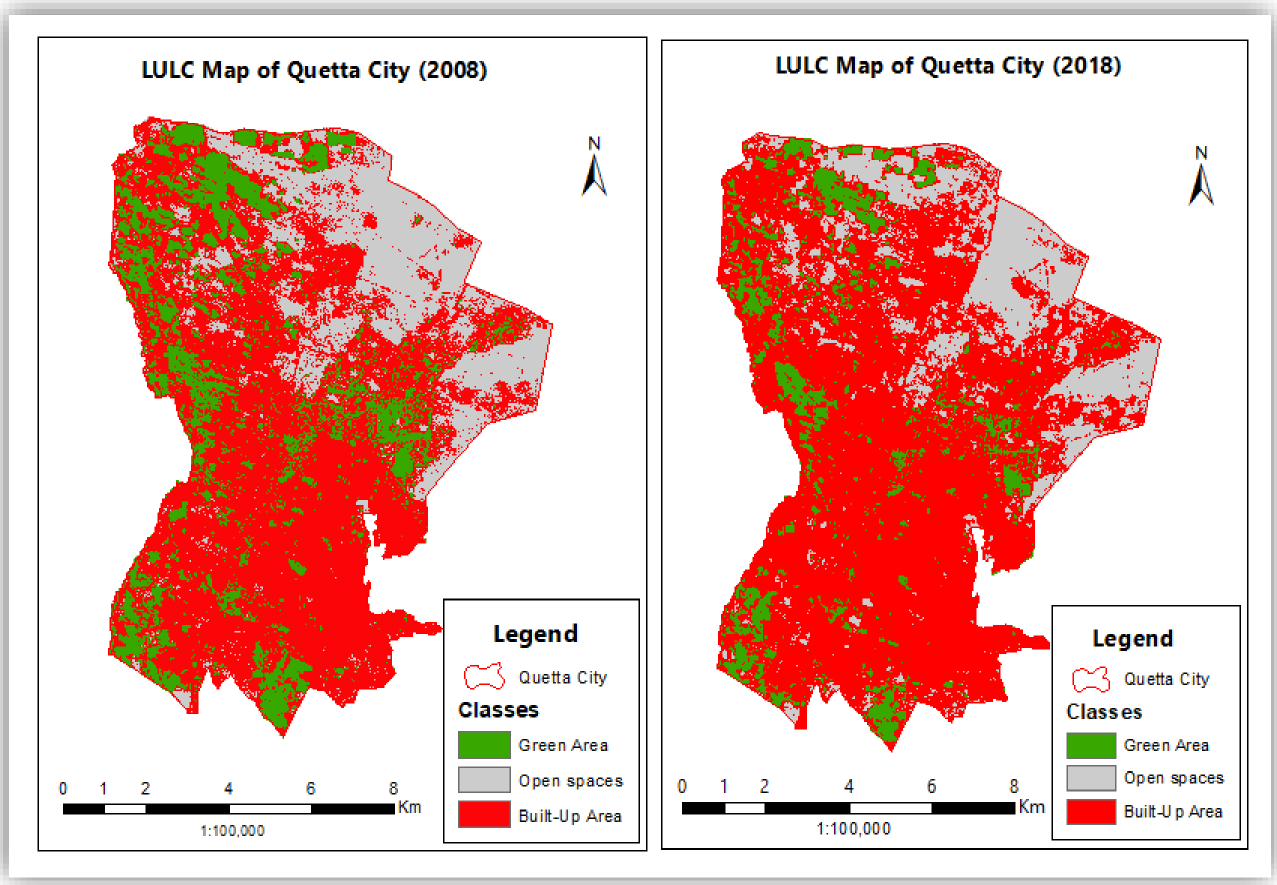

Figure 9 LULC Map of Quetta City

Accuracy assessment

Global Positioning System (GPS) survey was conducted to check the accuracy of classification using ArcGIS 10.4. Thirty (30) ground controlling points were taken for each class randomly for all three datasets. The error matrix was used to calculate the producer's accuracy, user's accuracy, and kappa coefficient to check the accuracy of the LULC classification of each year (1998, 2008, and 2018). The result shows that the overall accuracy of 1998 classification was 0.85, 2008 was 0.88, and 2018 was 0.85, which was high than Anderson's standard 0.85 or 85% (Khawaldah, 2016; Liping et al., 2018). The detail of the accuracy assessment is given in Table 6.

Table 6 Accuracy assessment values

LULC Classes	1998		2008		2018	
	Producer's	User's	Producer's	User's	Producer's	User's
Green area	100	96.77	93.33	93.33	93.33	93.33
Open spaces	87.5	84.85	83.33	83.33	83.33	83.33
Built-up Area	83.33	89.29	86.67	86.67	86.67	86.67
Overall accuracy (%)	90		88		90	
Kappa Coefficient	0.85	0.82	0.85	0.85	0.82	0.85

Source: Authors' calculations

3.4 LULC Change Prediction

The result shows that the Green area was 22.15 km² (23.15%) in 1998, which decreased to 10.45 Km² (11%) in 2018. The overall (-53 %) change has occurred from 1998 to 2018, and after ten years, i.e., in the year 2028, it would have decreased further by 25.84% (7.75 Km², 8%). The open spaces were 31.09 Km² (32.73%) in 1998 and decreased to 15.69 Km² (16.52%) in 2018, which shows a -49.53% change in a particular period. The CA-Markov result shows, open spaces would have decreased by 24.60% in 2028, which would be 11.83 Km² (12.45%) of the total area. The massive increase (27.1 Km², 64.89%) has been occurred in the built-up area from 1998 to 2018. Whereas, the predicted result shows that the built-up area would have increased by 6.5 km² (9.53%) in the next ten years, i.e., 2028

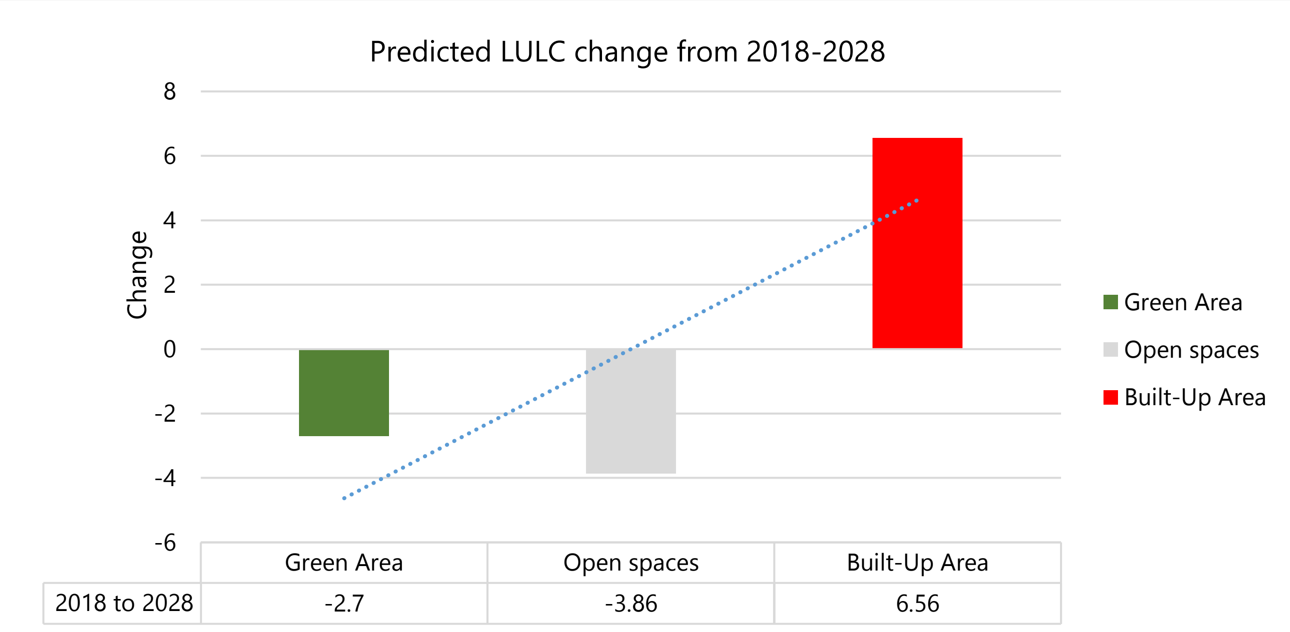

Figure 10 Showing the predicted LULC change

3.5 Land use and land cover transition probabilities of the year 2018 (Predicted)

The transition matrix shows the number of cells expected to change from one land-use class to another over a period. The transition probability shows the green area has 67.48% chances of remaining as a green area and have moderate chances to convert into other classes. Open spaces have a probability of 64.11% as open spaces are mentioned in Table 7, which has a high probability of changing into other classes. However, the built-up class is more stable, showing a 99.13% probability to remain as a built-up area. Table 7 shows the projected transition in 2018 from each class to others in km^2.

Table 7 Transition probabilities matrix for predicted LULC of 2018 using 1998 and 2008 images

LULC Class	Green Area	Open spaces	Built-Up Area
Green area	0.6748	0.0307	0.2945
Open spaces	0.0579	0.6411	0.3011
Built-up area	0.0000	0.0087	0.9913

Source: Authors' calculations

3.6 Land use and land cover transition probabilities of the year 2028 (Predicted)

Statistics in Table 8 shows that the green area is more in danger of changing into other classes because this has only a 38.22% probability of remaining a green area. As compare to a green area, open spaces have a 55.94% probability of remaining as open spaces, whereas the built-up area has no or very little probability of changing into another class because it has a 97% probability to remain as a built-up area.

Table 8 Transition probabilities matrix for predicted LULC of 2018 using 1998 and 2008 images

LULC class	Green area	Open spaces	Built-up area
Green area	0.3822	0.0451	0.5727
Open spaces	0.0122	0.5594	0.4283
Built-up Area	0.0008	0.0202	0.9700

Source: Authors' calculations

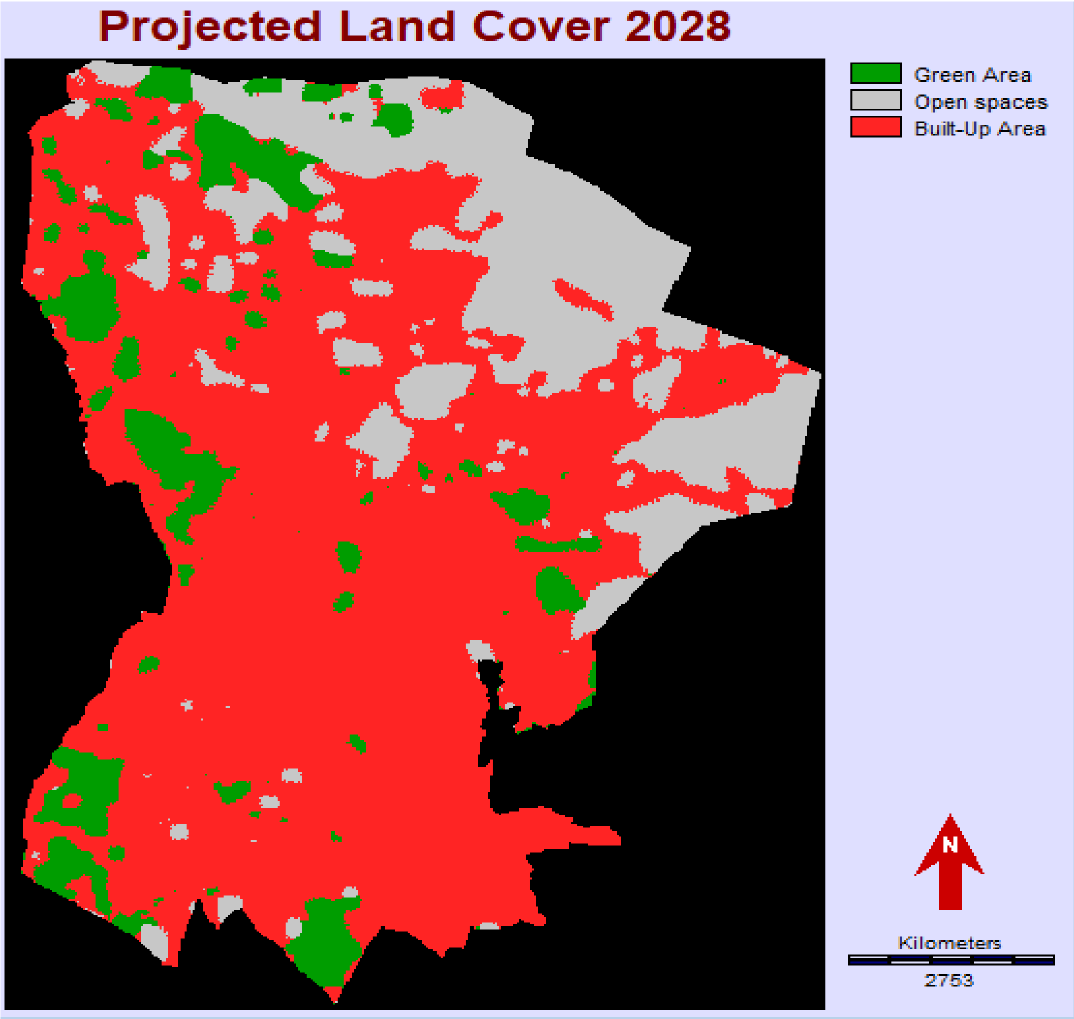

Figure 11 Projected LULC for year 2028
Source: Authors' calculations

3.7 Validation of the CA-Markov Model Results

The present study used the CA-Markov model to predict future land use and land cover. The IDRISI Selva was used for both prediction and validation of predicted LULC. The predicted 2018 LULC compared with the actual 2018 LULC map using the VALIDATE tool. The kappa index values are mentioned in Table 9, Kno is 0.8546, Klocation is 0.9128, Klocation strata is 0.9128, and Kstandard values are 0.8358. All the values are greater than 0.80, which shows a strong agreement between 2018 simulated and actual LULC Maps (Table 9).

Table 9 Result of Kappa index for model validation

Kappa Indices	CA-Markov
Kno	0.8546
Klocation	0.9128
Klocation strata	0.9128
Kstandard values	0.8358

Source: Authors' calculations

Table 10 Statistics of actual and predicted LULC of 2018

Classes	2018 Actual Area km^2	2018 Predicted Area km^2
Green area	10.45	12.35
Open spaces	15.69	16.50
Built-up area	68.86	66.15

Source: Authors' calculations

4. DISCUSSION

LULC change detection and prediction studies are of great significance worldwide due to their major implications for monitoring changes and predicting future trends in a built-up area, vegetation, and open land (Mannan et al., 2019). The development of GIS and RS technologies and the use of spatio-temporal data can help managers and decision-makers in designing a sustainable plan for development (Fathizad et al., 2015). Moreover, for predicting land-use changes in the future, CA-Markov has a high capability (Arsanjani et al., 2013). The satellite data used in the current study have provided enhanced spatial visibility for LULC change (Wang et al., 2014). In the current study, the predicted area of a CA-Markov was rectified with the actual area of land uses for the year 2018. This indicates very near-to-ground differences between actual and predicted areas (table 10). Moreover, a high accuracy of 83.58 % was achieved through a validated tool in IDRISI Selva using the kappa coefficient (Ullah et al., 2019).

The findings of this study show a 64% increase in the built-up area while 53% decrease in open spaces and 49% in green areas. On the other hand, the predicted result for the year 2028 indicates an increase of 9.53% in a built-up area. The decrease that occurred in green areas was higher during the second decade (2008-2018) than the first decade (1998-2008) these results are accordance with different earlier studies (Aziz & Ghaffar, 2017; Bazai & Panezai, 2020; Bhalli et al., 2012; Mahboob et al., 2015). The projected results showing similar decreasing trends in green areas. While the increase in built-up areas and a decrease in open spaces were higher during the first decade (1998-2008) than the second decade (2008-2018). This significant increase in built-up areas and a decrease in open spaces during the first decade can be attributed to rapid population growth in the city. This population can be attributed to the influx of Afghani migrants and migration of rural people to Quetta city for livelihood sources.

From the above results, it can be inferred that the state of affairs in the study area is much precarious. These changes that occurred in land use and land cover of Quetta city are mainly due to haphazard development and uncontrolled urbanization in the city (Bazai & Panezai, 2020). These drastic changes occur due to non-existence of urban development plans including a master plan for residential, commercial areas, the cheaper land available in the outskirts of the city can attract the people towards the city, the leapfrogging development and availability of cheaper land in the outskirts of a city is also a cause for these changes. Several other factors could be responsible for the LULC changes and uncontrolled urbanization, such as; population growth in the city, business and other economic activities, On the other hand, hundreds of unapproved private housing schemes, private schools and hospitals with no compliance to the Quetta development authority (QDA)'s laws and regulations in the jurisdiction of city area could also be equally responsible for this rapid change in land use and land cover of the city

The analysis of the above result shows a clear and great change in LULC of Quetta city. To regulate these changes, the responsible department should take serious development steps and generate a master plan for a city to control these changes. The current study can help the planners and policymakers to see the past and future growth of the city. The study results show that most of the development is taking/flowing towards the North of Quetta the planner need to introduce different approved housing schemes towards the south of Quetta to change the flow of development towards the south.

4.1 Limitations of the study

This study used 30-meter resolution satellite imagery because of non-availability of high-resolution satellite imageries free of cost in Pakistan. The high-resolution images can reduce the chances of errors in prediction models which is associated with low-resolution imageries.

5. CONCLUSION

The Pakistani cities have experienced great changes in LULC during the last few decades due to the rapid increase in population and anthropogenic activities. The study used three temporal imageries for detecting and predicting changes in LULC. The results show a significant increase (27.1 Km^2) in the built-up area while there is a massive loss of 15.4 km^2 and 11.7 km^2 in open spaces and green areas, respectively from 1998 to 2018. The prediction model result shows that there would be an increase of 6.65 Km^2 in a built-up area, there would be a decrease of 3.86 km^2 in open spaces, and a 2.7 km2 decrease would occur in the green area till 2028. The current study concluded based on the current and future prediction statistics, which revealed that the condition of green areas and open spaces are much precarious due to the rapid urbanization in the city

Additionally, the study revealed from the results that the unplanned and unregulated development in the city shows the absence of any policy, planning and management processes due to which city is facing serious challenges in various sectors, such; traffic congestion, solid and liquid waste management, sewerage and sanitation, water shortage, poor hygiene and many more. To control the increase in a built-up area (residential, commercial, and industrial) and to control and manage rapid urbanization in the city, the concerned departments and policymakers should develop a reasonable land-use plan including a master plan for the city. Furthermore, the regulations for land use should be enforced and the private unapproved scheme should be stopped to manage the rapid growth in Quetta city. The use of GIS and RS can be effective for making a master plan for the city, providing real-time data and detecting and predicting LULC changes. This study may give direction to an urban planner and policymaker while making different policies and introducing housing scheme and may assets the students as literature and guidance for their research work. Further research can be conducted while comparing different prediction models and using detailed socio-environmental variables for better understanding of land LULC changes. The present study can be used as a direction for other studies, projects and making master plan using these models.

DECLARATIONS

Acknowledgement: The authors would like to acknowledge the anonymous reviewers and the editor for their invaluable comments for improving the quality of manuscript. We are grateful to USGS for providing free-of-cost satellite imageries, Pakistan Bureau of Statistics (PBS), Regional Office Quetta for providing shapefile of the city boundary of Quetta city.

Author contributions: Zubair Khan designed the study, collected the data, and wrote the article. Dr. Ahmed Saeed supervised the complete research. Mohammad Haroon Bazai wrote the introduction and discussion sections.

Funding: This research received no external funding.

Conflicts of interest: The authors declare no conflict of interest.

Ethical considerations: This study was based on secondary data, mainly satellite imageries. Hence, no ethical approval was required.

Cite this article as;

Khan, Z., Saeed, A., & Bazai, M. H. (2020). Land use/land cover change detection and prediction using the CA-Markov model: A case study of Quetta city, Pakistan. *Journal of Geography and Social sciences, 2*(2), 164-182.

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Appendix

List of Abbreviation

LULC	Land use land cover
LULCC	Land use Land Cover Change
RS	Remote sensing
GIS	Geographic Information System
GPS	Global Positioning System
DEM	Digital Elevation Model
OLI	Operational Land Imager
TM	Thematic Mapper
ETM+	Enhanced Thematic Mapper Plus
MCE	Multi-Criteria Evaluation
CA	Cellular Automata
MLP	Multilayer Perceptron
WLP	Weighted Linear Combination