ZIBELINE INTERNATIONAL
PUBLISHING

ISSN: 2521-5035 (Print)

ISSN: 2521-5043 (Online)

CODEN: ESMACU

Earth Sciences Malaysia (ESMY)

DOI: <http://doi.org/10.26480/esmy.02.2020.146.151>

RESEARCH ARTICLE

TRANSITION OF LULC AND FUTURE PREDICTIONS BY USING CA-MARKOV CHAIN MODEL (A CASE STUDY OF METROPOLITAN CITY LAHORE, PAKISTAN)

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ARTICLE DETAILS

Article History:

Received 28 August 2020

Accepted 12 September 2020

Available Online 06 October 2020

ABSTRACT

Land use and land cover transition is continue process due to various anthropogenic activities and altering the landscape pattern of the metropolitan area of Lahore over the last two decade. LULC has been emerging masses of environmental problems including land use issues for the inhabitants, city planners, and managers. This research has been focused on the LULC change from 1998 to 2018 and their impact to forecast the landscape pattern of 2023 and 2028 in metropolitan area of Lahore. Numerous satellite imageries including land sat 5 TM and landsat 8 OLI has been undergone by supervised classification for the preparation of LULC map, land change moderler MCL to calculate the transition in LULC and CA-Markov model for predicting upcoming transitions. Results have validated by transition matrix, Google Earth data and kappa statistics. Derived results has depicted the decreased in water bodies 2.70% to 0.60%, vegetation 24.90% to 22.60% and barren land 42.50% to 35.70% and increased in built up area 29.80 % to 41% between 1998 to 2018. Finding clearly represents the loss of ecological and barren landscape over the last two decade and therefore urban expansion will likely to continue the change in landscape. This study will provide a baseline reference to urban planners and policymakers to make informed decision for management of land resources, urban land planning and for maintain sustainable land development.

KEYWORDS

Land use land cover (LULC), CA-Markov Model, KAPPA statistic.

1. INTRODUCTION

Currently, many regions around the globe under the different environmental conditions are facing the dramatic changes in LULC (Solaimani, 2010). These changes in LULC are the prompt response of anthropogenic activities upon nature followed by significant consequences (De Sherbinin, 2002; Eastman et al., 2005; Rai, 2017; Briassoulis, 2019). The primary and most significant cause of change in LULC is urbanization (Omar, 2014; Kalnay and Cai, 2003; Chen, 2006). Urbanization has become a universal trend under the combined influence of biological factors and anthropogenic activities, which plays a vital role in the LULC changes all over the world (Sun, 2013; Zhao, 2018; Lu, 2018; Bk, 2003; Seto, 2011). Urbanization has not only influences on socioeconomic changes but also cause the loss of farmlands, In recent eras, the LULC has changed at large scale which transforming forest land into farmland and farmland into urban areas, resulting in unsustainable urban development (Seto, 2011; Li and Yeh, 2000; Mumtaz, 2020; Foley, 2005; Dubovyk et al., 2011; Poelmans and Rompaey, 2009). Rapid growing population trends to move the people from rural to urban areas ultimately causing adverse growth in urbanization. Moreover, increase in urban population demands metropolitan luxuries and facilities for their livings, including construction of new residential and commercial areas, public utility and road infrastructures which ultimately leaving footprints on eco-environment (Nasir, 2012).

No doubt, urbanization is more rapid in the 21th century as compared to past centuries (Montgomery, 2008). According to an estimate, it is considered that the number of people living in the global metropolitan regions are expected to increase ~ 80% from 2010-2050 (Mitchell and Moss, 2012). In South Asia, Pakistan is also expected to be more urbanized in 2050 (Mumtaz, 2020; Mustafa and Sawas, 2013). Pakistan is one of those countries where urbanization has grown largely in major cities due to lack of planning and policies. In recent years, as like many other metropolitan cities of the world, Lahore (a metropolitan city of Pakistan) have also been experienced massive growth in population as well as landscape (Faisal, 2020). Lahore is a commercial hub, for the population living surround and other different cities of the Pakistan in purpose for better life style (Faisal, 2020). Demand of better living style and tremendously acceleration in population has lead to urban sprawl and changes in existing pattern of LULC (Maktav et al., 2005). In result of urban expansion and Over Cutting, the vegetation cover of Lahore has been decreased. Moreover, natural land has been replaced mainly by built-up areas (Mumtaz, 2020; Nespak, 2004). More and more demands of urban area for better lifestyle has turned the agriculture and barren land into different housing societies and other projects by local developers and Lahore Development Authority (LDA) (Faisal, 2020; Nespak, 2004; Shah and Ghauri, 2015). The vegetation cover of Lahore has tremendously decreased due to urban expansion and over cutting resulting in replacement of natural land into built up area (Mumtaz, 2020; Nespak,

Quick Response Code

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Website:

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DOI:

10.26480/esmy.01.2020.146.151

2004). And the city is growing like a concrete jungle without any proper planning (Masood, 2015). Therefore, it is necessary to thoroughly investigate trend of LULC transition by using transition matrix and future prediction to derive the attention of policymakers and planners towards Lahore.

Updated maps of past and current LULC can help to understand the dynamics of LULC transition which will be helpful for future policies (Eastman et al., 2005). Recent advancement in remote sensing technology provides unique opportunity to monitor the changes in LULC (Ullah, 2019; Tao, 2011; Shi, 2013). Since 1972, the launch of the different landsat satellites till present, continuously providing the remote sensing data which is available free of charges at large scale for numerous applications in social, economic, and environmental characteristics of urban areas (Wulder, 2016). Remotely based data available from past several years can provide better understanding to investigate the past and recent dynamics in LULC transitions as well as it's drivers, which can be helpful for future urban sustainable policies (Eastman, 2005). Recently, Cellular Automata (CA) Markov chain model, and advanced tools of GIS & Remote sensing are recognized as a more effective and powerful modeling techniques for transition and future prediction of LULC (Kityuttachai, 2013; Garcia, 2013; Maithani, 2010; Nouri, 2014; Ke et al., 2016; Akin et al., 2015; Guan, 2011). The Markov chain model helps in calculating the future changes based on the past and Cellular Automata (CA) forecast the change in spatial location (Mumtaz, 2020; Arsanjani, 2013; Keshtkar and Voigt, 2016; Rimal, 2017). It has been widely utilized for investigating and planning of the urban areas including Wuhan (China); Hua Hin (Thailand); Saga (Japan); Setúbal/ Sesimbra (Portugal); central part of Germany; London (UK); Ahmedabad (India); Tehran (Iran); Santiago (Chile) and Foshan (China) (Ke et al., 2016; Kityuttachai, 2013; Guan, 2011; Araya and Cabral, 2010; Munshi, 2014; Puertas et al., 2014; Krotkov, 2017).

No doubt, several studies have already been conducted to predict land use over many global regions. Still, very few studies has monitored the land use dynamic for the past and future predictions in the urbanized regions of Pakistan as well as in Lahore. This research attempted to monitor the changes of LULC from 1998-2018 and predicted LULC for 2023 and 2028 by using the CA-Markov chain model for developing an understanding toward the history and current scenarios in transition of LULC. So that this study will provide a direction to urban planners and policymakers to make informed decisions.

2. MATERIAL AND METHODS

2.1 Study Area

2.1.1 Lahore

Lahore is the second largest metropolitan city in Pakistan and capital of the Punjab Province. It lies between 31°15'—31°43' N and 74°10'—74°39' E, comprised of 1,842 km² area (Faisal, 2020). The study area has slopes from north-east to the south-west and located on the alluvial soil of River Ravi (Faisal, 2020; Nespak, 2004).

Figure 1: Study area Map (Lahore)

2.2 Data Processing and LULC map Preparation

This study examines the (a) trend and transition of LULC in Lahore from 1998-2018, (b) predict the LULC in future periods 2023 and 2028 by using different satellite imageries including Landsat 5 (TM) and Landsat 8 (OLI). Cloud free satellite imageries of May and June were collected (table 1) on

the spatial resolution of 30m for the period of 1998-2018. All satellite images were downloaded free of cost from the USGS Earth Explorer website (<http://earthexplorer.usgs.gov>). A vector layer of the Lahore administrative boundary was utilized as mask to subset the image and to clip the area of interest (AOI) in the Tagged Image File Format (TIFF). No atmospheric corrections were executed because of cloud free Landsat imageries (Bhatti and Tripathi, 2014; Deng and Wu, 2013). Then false-colored images were produced by layer-stacking on all spectral bands except thermal bands (Karakus et al., 2014). Maximum Likelihood Classifier (MLC) supervised classification technique was used to classify the pixels into different land-use classes (Asmala, 2012). Then spectral characteristics of Landsat imageries were analyzed by spectral signatures for different land cover classes. The LULC maps of the study area were categorized into four classes: vegetation, water bodies, built-up, and barren land. The error matrix was constructed to evaluate the accuracy of LULC classes after the preparation of LULC maps of all years. Ground truth samples for each land-use class were taken on random locations by using Google Earth (Zhang, 2013). The pixel value at the image was compared with ground truth samples and predicted for each land-use class. Percentage accuracy of each class was evaluated in ArcGIS by using frequency analysis and error matrix (Table 2).

2.2.1 Satellite images Description

Table 1: Satellite Images Description							
Study Region	Year	Row/Path	1998	2003	2008	2013	2018
Lahore	Month	149/036	25 May	31 May	05 June	19 June	01 June
	Sensor		TM	TM	TM	OLI	OLI

2.3 Simulation of LULC Change Using the CA Markov Model

Cellular Automata (CA) integrated with the Markov Chain model offer a significant opportunity for urban growth trend and future predictions (Subedi et al., 2013; Fathizad et al., 2015; Wang et al., 2014; Roose and Hietala, 2018). For the very first time Markov Chain Model were used for land-use simulations (Burnham, 1973). Markov Chain Model computes the comparison between two LULC images to predict the upcoming trend. The Markov model can also forecast the transfer rate among different land use categories. It can be used in spatial modeling for land use future forecasting (Halmy, 2015). The basic principle of CA is to explain the current state of land use changes for any location (cells), and even in neighboring cells (Sang, 2011). Simply, the homogeneous CA Markov model for prediction of land-use changes can be mathematically described as follows:

$$S(t+1) = P_{ij} * S(t) \quad (1)$$

where S represents the land use status at time t, and S(t+1) land-use status at time t+1. Whereas P_{ij} is the transition probability matrix in a state which can be calculated as follows (Mumtaz, 2020).

$$P_{ij} = \begin{bmatrix} P_{1,1} & P_{1,2} & P_{1,N} \\ P_{2,1} & P_{2,2} & P_{2,N} \\ P_{N,1} & P_{N,2} & P_{N,N} \end{bmatrix} \quad (2)$$

$$(0 \leq P_{ij} \leq 1) \quad (3)$$

P is the transition probability; P_{ij} stands for the probability of converting from current state i to another state j in next time; P_N is the state probability of any time. The Low transition will have a probability near (0) and high transition have probabilities near (1) (Mumtaz, 2020).

2.4 Validating LULC Prediction Model

Predicted land use maps simulated by the CA-Markov model were compared with original land use to investigate the uncertainty in Simulation. Kappa Index of Agreement (KIA) approach was used to compare the simulated and original land use for accuracy comparison. The Kappa statistic measures the accuracy of a classification relative to a completely random classification on the scale of 0 (utterly random assignment of class labels) to 1 (100% accuracy of class label assignment) (Lillesand, 2015; Shawul and Chakma, 2019). The given formula calculated KIA Statistic.

$$KIA = \frac{Pr(a) - Pr(e)}{1 - Pr(e)} \quad (4)$$

Where Pr (a) represents the observed agreement, and Pr (e) represents chance agreement.

3. RESULTS

3.1 Land use land cover (LULC) dynamics from 1998-2018

The classified images obtained after preprocessing and supervised classification is showing the land use dynamics of Lahore from 1998 to 2018. Ground truth data obtained from Google Earth was used to verify the classification accuracy. Tables 2 present the % of the accuracy assessment of land use land cover (LULC) maps for Lahore from the year 1998 to 2018. Moreover, results indicate that all the classes of Land cover maps have above the 70% accuracy. Figure 2 illustrates the classified images of Lahore city for the years 1998, 2003, 2008, 2013, and 2018. These images capture the spatial and temporal characteristics of land-use dynamics. Table. 3 summarized the variations in trend of different land use classes.

Figure 2: Land use land cover variation for Lahore 1998-2018

Table 2: Accuracy assessment of land use classes from 1998-2018 (Lahore)					
	1998	2003	2008	2013	2018
Water	0.809%	0.782%	0.824	0.806	0.777
Vegetation	0.725%	0.764%	0.739	0.794	0.808
Built-up	0.833%	0.794%	0.801	0.788	0.771
Barren Land	0.79%	0.708%	0.780	0.777	0.708
Overall Accuracy (%)	0.78925%	0.762%	0.786	0.7912	0.766

The vegetation cover of Lahore was almost diminished due to unplanned overcutting and deforestation. Spatial land transition analysis and change detection matrix were prepared to understand the land encroachment for different land categories during the last two decades (Figure 3 and Table 4).

3.2 Future Land Use Dynamics 2023-2028

Land Use land cover (LULC) maps of satellite images 2003 and 2008 were used for prediction of 2013 LULC by using the Probability Transition matrix of the period 2003-2008 (displayed in table 5) for Lahore. Transition Matrix Probability summarized the possibility in which one class in converting to another class in a specified time. Here the Row and column indicate the categories of LULC over 2003 and 2008.

Land use maps of Lahore city predicted by the CA-Markov model were compared with the original LULC map of 2013 to investigate the accuracy of the model prediction. Spatial pattern of all land use categories in the predicted LULC map were noticed similar to the original LULC (Figure 4). KAPPA Statistics were used to perform the accuracy assessment of each land use category predicted by the model with reference land-use classes (Table 6). It was seen that the KAPPA values were found greater than 0.78 for each land use category, but all KAPPA values were 0.96 for Lahore city. A higher value of KAPPA indicated that the CA Markov model suitable for future predictions of LULC maps for the study region.

Table 3: variations and trends of different land use classes in Lahore 1998-2018.

		1998		2003		2008		2013		2018	
Study Region	LULC	Km ²	%	Km ²	%	Km ²	%	Km ²	%	Km ²	%
Lahore City	Water	50.41	2.70	27.21	1.50	23.48	1.30	18.51	1.00	11.41	0.60
	Vegetation	458.73	24.90	432.77	23.50	431.65	23.40	426.98	23.20	416.55	22.60
	Built-up	549.77	29.80	665.77	36.10	685.78	37.20	709.71	38.50	755.91	41.00
	Barren	783.44	42.50	716.61	38.90	701.44	38.10	687.20	37.30	658.59	35.70
Total		1842.4	100	1842.4	100	1842.4	100	1842.4	100	1842.4	100

Table 4: variations and trends of different land use classes in Lahore 1998-2018.

Study regions	LU LC classes	Water	Vegetation	Built-Up	Barren
Lahore city	Water	4.93	10.31	23.33	11.84
	Vegetation	1.26	134.31	150.13	173.04
	Built-Up	4.42	19.13	283.11	143.11
	Barren	0.81	152.75	299.30	330.58

Table 5: Transition probability Metrix for different land use classes from 2003-2008 in Lahore

Study regions	LU classes	Water	Vegetation	Built-Up	Barren
Lahore city	Water	0.7699	0.0672	0.0995	0.0634
	Vegetation	0.0006	0.6112	0.089	0.2991
	Built-Up	0.0033	0.0602	0.8249	0.1115
	Barren	0.0001	0.1747	0.1331	0.6922

Figure 3: Transition of each LULC Class from 1998-2018

Table 6: Overall, the Kappa Statistic between each Class of Original Image and IDRISI Image (Lahore city).

	Water	Vegetation	Built-Up	Barren	Kappa
Water	20217	856	721	1173	0.9825
Vegetation	27	441709	8986	26310	0.9209
Built-Up	313	6517	760143	10598	0.9544
Barren	18	25341	18726	725483	0.9371
Total	20575	474423	788576	763564	0.9487%

The transition probability matrix were calculated from 2013-2018 to predict the LULC of 2023, and the probability matrix of 2018-2023 used to simulate the LULC map of 2028. Figure 5 illustrates the LULC maps of Lahore, simulated for the future period.

Figure 5: Predicted LULC of Lahore for 2023 and 2028

4. DISCUSSION

That study was carried out monitor the changes of LULC from 1998-2018 and predicted LULC for 2023 and 2028 by using the CA-Markov chain model for developing an understanding toward the history and current scenarios in transition of LULC. Results indicate that in the Lahore city area covered by water bodies, vegetation, and barren area decreasing gradually from 1998-2018, while built-up is increasing. In Lahore city, the area covered by water bodies, vegetation, and barren land was about 50.41 km² (2.7%), 458.73 km² (24.9%), and 783.44 km² (42.5%) in 1998, has decreased to 11.41 km² (0.6%), 416.55 km² (22.6%) and 658.59 km² (35.7%) in 2018. While built-up land has gradually increased from 549.77 km² (29.8%) in 1998 to 755.91 km² (41%) in 2018 due to the transformation of different land use categories into built-up. Barren land was found to be decreased gradually with a higher rate, due to transform into other land use classes. Most of the agriculture and barren land was bought by Local developers or LDS (Lahore Development Authority) have been turned to different housing societies and other projects from the city government (Mumtaz, 2020; Shah and Gauri, 2015).

Further results of Transition matrix from 1998-2018 show that in Lahore city, 23.33 km² area of water has been changed into built-up land, and 11.84 km² area into barren land. Moreover, 150 km² area of vegetation has been changed into built-up land. From 1998-2018 Lahore city has experienced a notable transition of the built-up area from vegetation land and barren land into housing societies, different construction projects under the Lahore Development Authority (LDA) and local developers (Nespaq, 2004; Shah and Ghauri, 2015). Most of the urban expansion has expand due to mega developmental projects like Metro Bus, Orange Train and many other projects under China Pakistan Economic Corridor (CPEC) (Nespaq, 2004; Shah and Ghauri, 2015). No doubt, urban expansion has some advantages, including (i) provide employment opportunities, (ii) superior life style (iii) better production of goods & Services, etc. But also have some negative aspects, including rise in surface temperature of urban areas, because of (i) loss of agriculture land, (ii) increase of artificial material, including asphalt, concrete (Hallegatte and Corfee-Morlot, 2011; Kant, 2009). Future predicted results for 2023 and 2028 indicate that Future urban sprawl is likely to continue, outweighed by the loss of barren land and cultivated land.

5. CONCLUSION

This study was thoroughly continued with the main objectives to examine the (a) Trend and transition of LULC in Lahore from 1998-2018, (b) predict the LULC in future periods 2023 and 2028. Results quantified that from 1998-2018 the LULC of the city has changed at a large scale, especially the growing buildup area. In Lahore city, the area covered by water bodies, vegetation, and barren land gradually have been gradually decreased while built-up land has gradually increased from 1998 to 2018, due to the transformation of different land-use categories into built-up.

Future urban sprawl is likely to continue, which will be outweighed by the loss of barren land and cultivated land as in the previous two decades. Local government should notice trends of LULC transition to plan some policies by keeping in viewing the predicted results of 2023 and 2028 because transitional changes in LULC and development of buildup land can affect the local climate, sustainability, and LST.

ACKNOWLEDGMENTS

Authors, Faisal Mumtaz, Wang Gengke, Lingling Li and Barjeece Bashir acknowledge to Aerospace Information Research Institute, Chinese Academy of Sciences (AIRCAS) and University of Chinese Academy of Sciences (UCAS).

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