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Modeling Urban Land use Changes in Peshawar by the integration of Land Change Modeler and Markov model to Promote Sustainable Urbanization

Aqil Tariq (aqiltariq@whu.edu.cn)
LIESMARS: Wuhan University State Key Laboratory of Information Engineering in Surveying Mapping and Remote Sensing
https://orcid.org/0000-0003-1196-1248
Faisal Mumtaz
Chinese Academy of Sciences

Research Article

Keywords: Urbanization, Urban Sprawl, GIS, Remote Sensing, Maximum Likelihood Classification, Land Change Modeler, Markov Chain Model

Posted Date: June 24th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1660906/v1

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Version of Record: A version of this preprint was published at Environmental Science and Pollution Research on February 6th, 2023. See the published version at https://doi.org/10.1007/s11356-023-25722-1.

Abstract

Urbanization is a global phenomenon that caused many regions worldwide to face dramatic land use land cover (LULC) changes associated with urban sprawl and significant consequences. This study uses satellite images from the last two decades to examine Peshawar's geographical and temporal changes in urban expansion. Analysis of urban sprawl was carried by using the Maximum Likelihood Classification (MLC). Land change modeler combined with the Markov chain model was used to explore the patterns of urban sprawl. Later, the Cellular automata (CA) model was combined with the Markov chain model. Finally, the kappa coefficient and confusion matrix were used to validate the models and LULC maps accuracy. Results indicate a substantial expansion in built-up and vegetation class for Peshawar city replacing bare land. Peshawar's vegetation cover has increased by 25.6% throughout the study period, especially 12.7% under the billion-tree project (from 2013 to 2018). The urban area has increased by 16.3% and will continue to grow in the future, costing the bare land and affecting the water land. Classified images had an overall accuracy rate of almost 80%. According to a 2017 study by the Peshawar Development Authority (PDA), the entire urban built-up area was 264 square kilometers. As a result of our research, the total constructed area in 2018 was 272 km^2. Also, the results of 2028 and 2038 indicate that in the future, the vegetation cover will increase from 50.63% in 2018 to 59.23% by 2038. But also the built-up area would be increased from 21.52–25.23% respectively. Education, health, and small-business centers were essential to the development. In addition, the population of the Peshawar District relocated from nearby tribal areas due to military operations.

1. Introduction

Currently, half of the world's population lives in cities and metropolitan regions. According to current estimates, this ratio will rise to 70% by 2050, up from about 33% in 1960 (Mumtaz, Tao, De Leeuw, Bashir, et al., 2020). During the past several years' massive urbanization in and around the global metropolitan cities has significantly reduced the green cover layer (Choudhury et al., 2019; Dhar et al., 2019), which is most important for the equilibrium of several land surfaces and atmospheric parameters (Mumtaz, Tao, De Leeuw, Bashir, et al., 2020; Tariq et al., 2020). The LULC has seen a dramatic shift in recent years, with significant swaths of forest area being transformed into cropland. Urban areas are progressively taking over the countryside (Foley et al., 2005), which has dramatically influenced the eco-environment (Wu & Zhang, 2012), and resulted in local food shortages (Mehmood et al., 2016). The most critical variables that contribute to urban growth include good infrastructure,recreational facilities, banking systems, schools, hospitals, and etc. (Mumtaz, Tao, & Bashir, 2020).

There is a lack of healthy food and unplanned settlements in developing nations, and ecological difficulties and pollution, all of which harm the natural structure of the region (Wu & Zhang, 2012). Pakistan is one of those countries where urbanization has mainly grown in big cities due to a lack of management, planning and policies (Mumtaz, Tao, & Bashir, 2020). At least 5,000 people must be considered urbanized in Pakistan for a location. They must meet specific criteria, such as those related to municipal services, their socio-economic status, and their ability to obtain even the most basic amenities (Raziq et al., 2016b). Large urban areas make about a third of Pakistan's population. Pakistan's urbanization rate has increased steadily over the previous four decades, from 4.9% in 1951 to 6.5% annually. It increased by 236 percent overall, and 49.5 percent in the cities. Megacities like Karachi (population 8–10 million) and Lahore have emerged as a consequence of urbanization (approximately 5 million) (Mehmood et al., 2016). Also, in Peshawar, unplanned urbanization is wreaking havoc. Peshawar's urban areas flourished and expanded significantly due to Afghan refugees and IDPs from the tribal areas (Qadeer, 1996). Hayatabad Township, Regi Model Town, and several regional initiatives are examples of the newly urbanized regions where urban settlements have developed and new urban areas have arisen.

The combination of Remote Sensing (RS) and Geographic Information System (GIS) provides an efficient scientific tool to identify changes in land use and assess their environmental impacts that cannot be supported by monitoring and fieldwork methods by the authorities (Mumtaz, Tao, De Leeuw, Bashir, et al., 2020; Tariq et al., 2021). Since 1972, the launch of the different Landsat satellites has, continuously provided remote sensing data free of charge at a large scale for numerous applications in environmental and socio-economic properties of urban areas (Wulder et al., 2016). It is possible to employ RS and GIS expertise to investigate and classify urban development and Land Use/Land Cover (LULC) changes, and track the progress of any city area (Tariq et al., 2021). Reliable and exact data regarding urban spread trends are required to monitor urban sprawl and decide sustainable urbanization (Wulder et al., 2016).

Recent research has shown that the CA-Markov Model paired with RS and GIS is a valuable and robust modeling tool for the transition and future projections of LULC (Akın et al., 2015; García et al., 2013; Guan et al., 2011; Ke et al., 2016; Kityuttachai et al., 2013; Maithani, 2010; Nouri et al., 2014), which can provide comprehensive information on a large-scale synoptic level (Kamusoko et al., 2009; Riccioli et al., 2013; Roose & Hietala, 2018; Steeb, 2014). It has been largly used for the urban dynamic studies in many cities, including Wuhan, China (Ke et al., 2016), HuaHin, Thailand (Kityuttachai et al., 2013), Setúbal Sesimbra, Portugal (Araya & Cabral, 2010); central Germany (Keshtkar & Voigt, 2016), London, United Kingdom (Lu et al., 2018), Ahmedabad, India (Munshi et al., 2014), Lahore, Pakistan (Mumtaz, Tao, de Leeuw, Zhao, et al., 2020). Simulating urbanization has also been done using different models (Dubovyk et al., 2011; Xia Li & Yeh, 2000; Poelmans & Van Rompaey, 2009; Wu & Zhang, 2012). There are reasons why the CA-Markov model has been employed in this investigation, which are outlined in detail in Section 2.5.1.

Remote sensing technologies have risen to prominence in recent years, thanks mainly to their cheap cost, wide geographical swath, high temporal resolution, and reliable data collecting capabilities. To monitor changes in LULC through time and the expansion of the city area, planners and urban researchers have been recommended to use RS data (Lu et al., 2018). For example, data collection for urban land usage in China has been made more efficient and accurate because of RS and GIS (Zeng et al., 2008).

There's a possibility that the Peshawar Development Authority (PDA) may have to devise a new development management system and a strategy that focuses only on long-term prosperity. The Peshawar district's urban region is rapidly expanding in terms of population and development. As a result of its fast proliferation, several challenges have been overcome. No doubt, several studies have already been conducted to predict land use over the many global regions. However, most of the studies pay less attention to monitoring the land use dynamic in the past and future periods over the urbanized regions of Pakistan, where land has transformed from the past several years. This study concentrates on rapid growth, illegal encroachment, and unplanned development. The primary goals of this study were to investigate the spatio-temporal trends of urban growth in Peshawar, Pakistan, and to determine the causes of urban growth. This study provides a baseline reference to urban planners and policymakers for informed decisions because updated maps of past and current LULC can help understand the dynamics of LULC transition.

2. Materials

2.1. Study Area

In the eastern part of Khyber Pakhtunkhwa, the city of Peshawar is one of the country's oldest and biggest capitals. A total land area of about 1,264 square miles, Peshawar is located in 33° 41' – 34° 12' N, and from 71° 27' – 71° 47' E (see Fig. 1). From November through March, the winter season is in full swing. From May through September, the summer season is in effect. Agricultural products, manufacturing, and industrial production contribute to the local economy. It is the province's economic and educational hub, and central hub for other public services (Arif et al., 1998). Peshawar's urban population accounted for 33 percent of the city's total, according to the most recent available census data from 1998 (Mumtaz, Tao, De Leeuw, Bashir, et al., 2020). After 1978, the influx of Afghan migrants sparked rapid urbanization in Peshawar, which culminated in the 1998 census. Without the Afghan refugees, the population grew to 2.01 million (Mumtaz, Tao, De Leeuw, Bashir, et al., 2020). The fact that the sex ratio is 106.5 while the yearly growth rate was 4% between 1998 and 2017 seems to be another contributing factor. The growth of the city relies on a number of active commercial activity (GOP, 2017; Mumtaz, Tao, & Bashir, 2020).

Insert Fig. 1. Geographical location of study area.

2.2. Datasets

Both primary and secondary sources were used to get the information. For the Peshawar district, remote-sensed multi-spectral satellite imagery of the 30-by-30-meter spatial resolution Landsat series was retrieved from the USGS website (https://ers.cr.usgs.gov/) (see Table 1).

Table 1
Satellite images used for LULC Classification in this study.

S. No	Row	Path	Year	Date	Sensor
1	151	36/37	1998	08th June	ETM
2	151	36/37	2003	13th May	ETM+
3	151	36/37	2008	19th June	ETM+
4	151	36/37	2013	1st June	OLI/TIRS
5	151	36/37	2018	30th May	OLI/TIRS

Insert Table 1

Satellite images used for LULC Classification in this study.

The Peshawar district's population figures from the 1998 and 2017 censuses were used as secondary data. Figure 2 depicts the study's methodological flow diagram. The detailed methodology flowchart is given below for a better understanding;

Insert Fig. 2

General description of the methodology.

2.3. Satellite data

ENVI classic 5.3 software was used to perform gap filling, radiometric correction, IAR reflectance, and the DOS approach to get the whole image to standard reference spectral characteristics (ENVI Version 2009) (Research Systems, 2003). It was then used to analyze land-use patterns and trends better to understand urban development variances better. It has been determined that satellite photos may be used to identify various land use classifications in the area. Ground uses such as urban/built-up, vegetation, barren land, and water bodies were identified and described (Table 2). Multiple images were classified with the help of supervised classification using the Maximum Likelihood Classification (MLC) method (Eq. 1) (Lillesand et al., 2015; Shawul & Chakma, 2019). It was found that a textural difference between the built-up and barren land classes solved the intrinsic issue of MLC approaches, such as blending of the two. Undeveloped terrain has a smooth surface compared to the built-up area's rough one. Images of the constructed area were also collected on Google Earth and correlated with Landsat MLC-classified satellite images. An expert approach was applied to enhance the quality of primary categorized photos (Foody, 2002;Zeng et al., 2008).

Table 2
Different Land Use Land Cover description.

Class name	Description
Built up areas/Urban area	Commercial and service area, manufacturing, transportation, roads, built-up and etc.
Vegetation/Agriculture	Agricultural farms, croplands,, greenhouses, forests, and etc.
Open spaces/Bare land	Rocks, soils, open land and etc.
Wetland/Water bodies	Lakes, rivers, canals, streams, ponds and etc.

$g_i\left(x\right)=1np\left(w_i\right)-\frac{1}{2}1n\left|\varSigma_i\right|-\frac{1}{2}\left(x-m_i\right)^T=\varSigma_i^{-1}\left(x-m_i\right)\left(1\right)$ where i represent the class, while x is the number of bands - dimensional data, p$\left(w_i\right)$ represent the probability of the occurrence of class w_i In the image. $\left|\varSigma_i\right|$ represent the determinant of the covariance matrix of the data in classw_i, $\varSigma_i^{-1}$ is equal to the inverse matrix and m_i is mean vector.

Insert Table 2

Different Land Use Land Cover descriptions.

2.4 Accuracy Assessment

Confusion matrix were utilized to measure the accuracy of each classified image. During this year's study area survey, 100 points were tallied. There were more than 75 points generated randomly from different years' worth of categorized pictures and verified using Google Earth in 1998, 2003, 2008, 2013, and 2018. The confusion matrix is used for the following accuracy.

$$OverallAccuracy = \frac{Totalnumberofclassifiedpixelsinthecategory\,(diagonal)}{} \times 100\,)(\,2)$$

$$Totalnumberofreferencepixels$$

$$UserAccuracy = \frac{Numberofcorrectlyclassifiedpixelsineachcategory}{Totalnumberofclassifiedpixelsinthecategory\,(rowtotal)} \times 100\,(3)$$

$$ProducerAccuracy = \frac{AccuracyNumberofcorrectlyclassifiedpixelsineachcategory}{TotalEquationNumberofclassifiedpixelsinthecategory} \times 100$$

4

Kappa coefficient (T) was used to compare the simulated and original land use for accuracy comparison. KAPPA Statistic can measure classification accuracy with random classification and absolute Classification 0 to 1 (Lillesand et al., 2015; Shawul & Chakma, 2019). $kappaCoeffiicient\,(T)$ Statistic was calculated by the given formula accuracy.

$$kappaCoeffiicient\,(T) = \frac{Totalsample \times Totalcorrectedsample) - \Sigma(columntotal \times Rowtotal)}{Totalsample^2 - \Sigma\,(columntotal \times Rowtotal)}(9)$$

2.5. LULC Transition Analysis:

After classifying the Landsat imagery and accuracy assessment, the cross-tabulation method was utilized by using the Terreset 2020 (https://clarklabs.org/terrset/land-change-modeler/) to quantify the Net change by category in $km^{2,}$ patterns of aerial exchanges, and Gain and loss of each LULC Class for the period: (a) 1998–2003; (b) 2003–2008; (c) 2008–2013; (d) 2013–2018. At the same time, the Markov Chain model (MCM) was utilized to understand the transition probabilities.

2.5.1 CA Markov chain model:

Cellular Automata (CA) integrated with the Markov Chain model provides a significant opportunity for urban growth (Bhandari, 2014; Fathizad et al., 2015; Han & Jia, 2017; Wang et al., 2014). Halmy et al.(2015) explained the Markov chain model predicts future changes by estimating the state of LULC change across two time periods. The Markov model can also account for the transfer rate among various land use categories. Using it in spatial modeling, one may predict how the land will be utilized in the future (Meerow & Newell, 2017). The basic principle of the Markov chain model is that the current state can explain the land-use changes for any location (cells) and changes in neighboring cells (Santé et al., 2010). The cellular automata (CA) in the CA-Markov model detects changes in spatial position, while the Markov chain predicts future changes (Arsanjani et al., 2013; Mumtaz, Tao, de Leeuw, Zhao, et al., 2020). The model can be mathematically described as follows (Mumtaz, Tao, De Leeuw, Bashir, et al., 2020; Tariq & Shu, 2020):

$$S\,(t+1) = Pij * S\,(t)\,(5)$$

where S represents the land use status at time t, and S (t + 1) is the land-use status at time t + 1, while Pij is the transition probability matrix in a state which is calculated as follows (Kumar et al., 2013; Mumtaz, Tao, De Leeuw, Bashir, et al., 2020).

$$\|Pij\| = \left\| \begin{matrix} P_{1,1} & P_{1,2} & P_{1,N} \\ P_{2,1} & P_{2,2} & P_{2,N} \\ P_{N,1} & P_{N,2} & P_{N,N} \end{matrix} \right\| \; (6)$$

$$(0 \leq Pij \leq 1) \; (7)$$

P is the transition probability; Pij stands for the likelihood of converting from current state I to another state j next time; PN is the state probability of any time. The Low transition will have a chance near 0, and high growth has possibilities near 1 (Kumar et al., 2013; Mumtaz, Tao, De Leeuw, Bashir, et al., 2020).

2.6 Measurement of the urban expansion rate

An annual growth rate was determined by calculating the total new metropolitan area for each era and determining the total new metropolitan area for each time (Rimal et al., 2018).

$$\mathrm{MUER} = \frac{(U_2 - \mathrm{U}_1)}{(T_2 - \mathrm{T}_1)} \times 100 \; (8)$$

Where MUER is the urban expansion rate (km^2 / Year), U is the urban area in km^2 between T_1 and T_2 years.

3. Results And Discussion

3.1 LULC dynamics

Maps of LULC obtained by the supervised classification are presented in Fig. 3. Table 3 summarizes the LULC classification accuracy, assessed by ground truth data obtained from field survey and Google Earth. The data in Table 3 show that all LULC classes were classified with more than 80% accuracy. Results in Fig. 3 and Table 4 indicate that the bare area declined from 860.14 km^2 (68.10%) in 1998 to 322.03 km^2 (25.50%) to 2018, A total reduction of 538.11 km^2 (42.6%) in the 20 years (1998 to 2018). Most of the bare land was transformed into urban land and vegetation land. In the end, the vegetative areas were also developed into the built-up part of the site. With the construction of new infrastructure, including roads, buildings, and residences, Peshawar has seen its amount of barren land decrease (F. Ahmad & Goparaju, 2016) in response to Afghan refugee migration (Turton & Marsden, 2002) and billion tree projects (Mumtaz, Tao, De Leeuw, Bashir, et al., 2020).

Table 3
Accuracy assessment derived by satellite images from 1998 to 2018.

LULC	1998				2003				2008			
	UA	**PA**	**OA**	**K**	**UA**	**PA**	**OA**	**K**	**UA**	**PA**	**OA**	**K**
Water	77.77	86.67	79.06	76.02	74.19	81.33	82.19	78.79	74.19	78.12	77.72	74.01
Vegetation	80.83	81.33			70.83	77.77			70.83	74.19		
Built-up	71.29	82.66			77.66	86.67			77.66	77.77		
Bare Land	74.19	80.83			73.38	70.90			73.38	80.83		
	2013				**2018**							
	UA	PA	OA	K	UA	PA	OA	K				
Water	77.77	76.08	78.91	77.30	71.23	73.38	77.76	75.10				
Vegetation	70.96	74.19			75.00	74.19						
Built-up	81.74	80.83			76.08	80.83						
Bare Land	78.76	78.12			78.12	82.66						
Note; UA = user's accuracy; PA = producer accuracy; OA = overall accuracy, K = Kappa Coefficient												

Table 4
LULC Change of Peshawar from 1998–2018

LULU	1998	2003	2008	2013	2018
	Km^2 (%)	**Km^2 (%)**	**Km^2 (%)**	**Km^2 (%)**	**Km^2 (%)**
Water	22.38 (1.80)	29.64 (2.30)	37.65 (3.00)	53.25 (4.20)	29.90 (2.40)
Vegetation	316.30 (25.00)	457.43 (36.20)	475.64 (37.60)	479.39 (37.90)	640.02 (50.60)
Built-up	65.13 (5.20)	135.38 (10.70)	173.39 (13.70)	227.19 (18.00)	272.07 (21.50)
Bare	860.14 (68.10)	641.55 (50.80)	577.32 (45.70)	504.17 (39.90)	322.03 (25.50)
Total	1264 (100)	1264 (100)	1264 (100)	1264 (100)	1264 (100)

Insert Fig. 3

Spatial patterns of LULC in Peshawar (a) 1998, (b) 2003, (c) 2008, (d) 2013, (e) 2018.

Insert Table 3

Accuracy assessment derived by satellite images from 1998 to 2018.

The area of vegetation land was 316.30 km^2 (25%) in 1998, 457.43 km^2 (36.50%) in 2003, 475.64 km^2 (37.60%) in 2008 while 479.39 km^2 (37.90%) in 2013, but its further increase abruptly in response to Billion tree of Project of the KPK government from 479.39 km^2 (37.90%) to 640.02 km^2 (50.62%) in 2018. That significant increase within five years was because, in 2013, the provisional government of KPK implemented a billion tree project in the whole region (N. Khan et al., 2019) to cover the bare land and control deforestation. Such changes of LULC also cause the manipulation in temperature and topography of the neighborhood (Goksel et al., 2004). However, there was a sharp drop (see Table 4).

The urban land of Peshawar was approximately 65.13 km^2 (5.20%) in 1998, 135.38 km^2 (10.70%) in 2003, 173.39 km^2 (13.70%) in 2008 (that increase was mainly because of the migration of Afghan people towards Pakistan. In response to the war in Afghanistan), 227.19 km^2 (18.00%) in 2013 and then an increase to 272.07 km^2 (21.50%) in 2018 (see Fig. 3, Table 4 below). The floods of 2010 or the 2.5 million Afghani Refugees are to blame for this surge. A large-scale exodus of Afghans to the Kurram tribal region. Province in 1998 to 2003, because of a sharing border with Afghanistan and under the unfriendly atmosphere in Afghanistan because of war. People who moved to Pakistan during the Soviet invasion of Afghanistan from 1979 to 1989 (Goksel et al., 2004). Between 2009 and 2012, Khyber Pakhtunkhawa (KP) was home to around 3 million internally displaced people, the majority of whom came from the districts of Federally Administered Tribal Areas (FATA). The floods forced an additional 1 million people inside, while the military operations in FATA against extremists or the Taliban forced an additional 5 million inside. More than 3 million IDPs were reported in KP between 2009 and 2010, and by the end of 2012, the number had risen from 300,000 to 700,000 in the province. Peshawar was home to over 43% of all officially registered IDPs. Researchers looked at how much space has been converted from agricultural and barren land to residential areas (Turton & Marsden, 2002).

Insert Table 4

LULC Change of Peshawar from 1998–2018.

As expansion accelerated away from the city center, it spread out in all directions (supplementary Fig. 1). Built-up areas expanded in tandem with Peshawar's premier road network. Most of the Peshawar district's expansion was unplanned, as seen in Supplementary Fig. 1. In the last two decades, barren land has been reduced by 42.60 percent (1998–2018). Peshawar's unanticipated and quick urbanization was to blame for this setback. Supplementary Fig. 1 shows how land usage and cover types have changed over 20 years. There are only a few water resources, biodiversity and farmed lands in the research region. Peshawar Cantonment, Hayatabad Sector, and Peshawar University make up the district Peshawar's entire planned area of 30.99 kilometers. According to statistical bearue of Pakistan, Peshawar's built-up area has grown at yearly rates of 1.1%, 0.47%, 0.86%, and 0.7% between 1998 and 2003, 2003–2018, 2008–2013, and 2013–2018, respectively on changes in LULC throughout time.

3.2 Land use land cover transitions from 1998–2018

Further LULC transition matrixes were prepared to understand the spatial extent of land encroachment over the study period from 1998–2018. For a better understanding, we divided our study years into groups of 5 years intervals, including (a) 1998–2003; (b) 2003–2008; (c) 2008–2013; (d) 2013–2018. Figure 4 and Table 5 illustrate the detailed change matrix, i.e., the nature of change from one class to another during 1998–2018.

Table 5
Peshawar city's transition between LULC classes (1998–2018).

Year	LULC	Water	Vegetation	Built-up	Bare land
		km^2 (%)	km^2 (%)	km^2 (%)	km^2 (%)
1998–2003	Water	15.92 (1.26)	3.37 (0.27)	0.13 (0.01)	2.93 (0.23)
	Vegetation	3.22 (0.25)	178.09 (14.09)	5.11 (0.40)	129.92 (10.28)
	Built-up	0.66 (0.05)	6.86 (0.54)	42.45 (3.36)	15.1 (1.19)
	Bare land	9.62 (0.76)	269.08 (21.29)	87.67 (6.94)	493.58 (39.05)
2003–2008	Water	29.12 (2.30)	0.29 (0.02)	0.11 (0.01)	0.01 (0.00)
	Vegetation	2.12 (0.17)	371.63 (29.40)	3.23 (0.26)	80.44 (6.36)
	Built-up	1.23 (0.10)	2.44 (0.19)	122.82 (9.72)	8.87 (0.70)
	Bare land	4.96 (0.39)	101.22 (8.01)	47.23 (3.74)	487.99 (38.61)
2008–2013	Water	37.44 (2.96)	0 (0.00)	0 (0.00)	0 (0.00)
	Vegetation	3.83 (0.30)	469.31 (37.13)	1.99 (0.16)	0.5 (0.04)
	Built-up	2.64 (0.21)	0 (0.00)	170.74 (13.51)	0 (0.00)
	Bare land	9.11 (0.72)	10.07 (0.80)	54.46 (4.31)	503.67 (39.85)
2013–2018	Water	43.28 (3.42)	1.4 (0.11)	0 (0.00)	0 (0.00)
	Vegetation	7.86 (0.62)	462.21 (36.57)	5.48 (0.43)	5.57 (0.44)
	Built-up	4.18 (0.33)	0.01 (0.00)	199.81 (15.81)	0.01 (0.00)
	Bare land	12.97 (1.03)	18.27 (1.45)	68.15 (5.39)	434.69 (34.39)

Insert Table 5

Peshawar city's transition between LULC classes (1998–2018).

Insert Fig. 4: LULC change matrix showing land encroachment in Peshawar: (a) 1998–2003; (b) 2003–2008; (c) 2008–2013; (d) 2013–2018.

The results indicate that from 1998–2003 the LULC transition in Peshawar city was mainly from bare land to built-up area, with an average of 6.94, While 21.29% of bare land was transformed to Vegetation. However, at the same time, 10.28% of vegetation land was converted to bare land, associated with deforestation. In the next, all periods, e.g., 2003–2008, 2008–2013, that phenomenon was happening at the same way, but from 2013–2018, the scenarios changed suddenly where 18.27% of bare land was shifted to vegetation land in response to Billion tree project, and 5.39% of bare land was shifted to Built-up land. These all LULC transitions were mainly associated with the Billion tree project (BTP) (Khan et al., 2019) and the migration of people from Afghanistan toward the KPK (Raziq et al., 2016a).

3.3 Net change by category / Gain and Loss of Each LULC Class during 1998–2018

Gain and loss analyses (Fig. 5) were combined with the net change rate (Supplementary Fig. 2) using a land change modeler to better understand the Land encroachment. Figure 5 illustrates the spatial location of Gain and loss of each LULC Class, including (i) Water, (ii) Vegetation, (iii) Build-up and (iv) Bare Land for Peshawar city throughout the study period. Where the Red color represents the "Loss," Green for "gain," and "Yellow" for Persistence (Hevia & Neumeyer), while the Black color represents No data value, which means that area belongs to another LULC type instead of the selected class.

Results indicate that during the study period (1998–2018), the water gained 13.87 km^2 area while losing 9.27 km^2. A total of 13.03 km^2 areas remain persistent during the study period. Vegetation and Built-up experience a considerable gain under the study period 403.45 km^2 and 227.68 km^2. Which mainly results from loss of barre land with a 600.23 km^2. Graphs of LULC transition also indicate a continuous decrease of bare land and a significant increase in Vegetation and build-up land.

Insert Fig. 5

Gain and Loss of Each LULC Class from1998-2018 in Peshawar.

Supplementary Figs. 2 and Fig. 5 indicated that between 1998 and 2008, the urbanized area grew from 65.13 square kilometers to 173.09 square kilometers. In the five years from 2008 to 2013, the built-up area rose by over 227 square kilometers. Bare land decreased by 538.11 square kilometers between 1998 and 2018, a significant decline. As the indigenous population has grown and people have moved from rural to urban centers, the built-up area has developed dramatically. As a result of the Taliban conflict, many Afghans and people from the tribal regions moved to Peshawar, causing the city to grow and urban sprawl (Roehrs, 2015). Studies carried out by Sajjad et al., (2009) can be observed that the transition of land cover types influences the environment worldwide. The human-made transition of LULC, especially the conversion of natural land, Urbanization, and deforestation, affect the annual temperature because different LULC types have unique qualities in terms of absorption and energy radiation.

Figure 6, Table 6 represent the results of the future simulation, which indicate that in the future years 2028 and 2038, The LULC changes at a large scale in which the vegetation cover will increase from 50.63% in 2018 to 59.23% till 2038. But also the built-up area would be increased from 21.52–25.23% respectively. Which will not only cost the bare land but will also affect the water land.

Table 6
Predicted LULC for different classes in 2028 and 2038 for Peshawar City

Study region	LU Class	2018		2028		2038	
		km^2	%	km^2	%	km^2	%
Peshawar	Water	29.90	2.36	19.87	1.57	14.43	1.14
	Vegetation	640.02	50.63	701.38	55.48	748.69	59.23
	Built-up	272.07	21.52	299.75	23.71	318.92	25.23
	Barren	322.03	25.47	243.02	19.22	181.98	14.39

Insert Fig. 6

LULC predictions for 2028 and 2038 for Peshawar city.

Insert Table 6

Predicted LULC for different classes in 2028 and 2038 for Peshawar city.

Supplementary Fig. 3a,b, and c shows the generalized spatial trends of (a) change from bare land all other classes, (b) trend of change from bare land all urban area, and (c) trend of change from bare land all Vegetation between 1998–2018. According to the LULC map of 1998 and 2018, a Cubic Analysis was performed. The deeper red patches show the places that have seen the most alteration, decreasing as one moves out of the city. Compared to the eastern and northern regions, the central and southern areas have a higher density of urban areas. It's common to think of the city's core as its social and economic hub (Xiaoma Li et al., 2013). The study area's socio-economic process has had a more significant impact on urban growth than its geographical environment.

3.4 Urban growth in Peshawar city

Map density values are determined by dividing the number of built-in pixels by the kernel's actual number of pixels. When applied to a categorized satellite picture, it transforms the land cover classification into a density classification. The density scale may be divided into low, medium, and high-density groupings. On this basis, the percentages of each class were computed. Peshawar's built-up density might be divided into four categories: high, medium-high, medium, low medium, and low, as a result of the density calculation results. Built-up regions with a high density may indicate a more compact and clustered form of the built-up pattern, followed by medium to high-density areas.

In comparison, less densely populated places are considered medium-density. There are low, medium, and low-density built-up zones that are widely and sparsely distributed. Figure 6 depicts the fast-expanding built-up area between 2018 and 2038, notably in the southwest, shown by the red hues. These changes may have been brought about by improvements in the city's transportation infrastructure and modest industrial sector.

3.5 Transition probability matrix

The transition probability matrix was computed based on LULC conditions during 1998–2003, 2003–2008, 2008–2013, 2013–2018 (Table 7) to show how each land type was projected to change. Transition Matrix Probability summarized the possibility of one class converting to another class in a specified time. Here the row and column indicate the categories of LULC over different time intervals, including 1998–2003, 2003–2008, 2008–2013, 2013–2018.

Table 7
Peshawar's land use transition probability matrix, from 1998 to 2018.

LULC	**Transition Probabilities 1998–2003**				**Transition Probabilities 2003–2008**			
	Water	**Vegetation**	**Built-up**	**Bare land**	**Water**	**Vegetation**	**Built-up**	**Bare land**
Water	0.7117	0.151	0.0062	0.131	0.9894	0.01	0	0.0006
Vegetation	0.0102	0.5632	0.0162	0.4104	0.0046	0.8126	0.0071	0.1757
Built-up	0.0103	0.1055	0.6523	0.2319	0.0092	0.0181	0.9072	0.0655
Bare land	0.0112	0.3131	0.1019	0.5737	0.0078	0.1581	0.0738	0.7604
LULC	Transition Probabilities 2008–2013				Transition Probabilities 2013–2018			
	Water	Vegetation	Built-up	Bare land	Water	Vegetation	Built-up	Bare land
Water	1	0	0	0	0.9685	0.0315	0	0
Vegetation	0.0081	0.9867	0.0042	0.0011	0.0164	0.9607	0.0114	0.0116
Built-up	0.0153	0	0.9847	0	0.0205	0.0001	0.9793	0.0001
Bare land	0.0158	0.0175	0.0944	0.8723	0.0244	0.0343	0.1277	0.8137

Insert Table 7

Peshawar's land use transition probability matrix, from 1998 to 2018.

Off-diagonal data suggests that various phenomena will likely be transformed into other phenomena. At the same time, data pieces located on the matrix's diameter imply that a phenomenon will remain constant over time (Guan et al., 2011). The transition probability matrix demonstrates that between 1998 and 2013, there was less than a 1% chance of the loss of bare land to the built-up region, but that chance increased to 1.2 percent between 2013 and 2018.

3.5.1 Factors that contribute to Peshawar’s urban growth

The district had 2,019,000 people in the 1998 census, while Peshawar had 4,269,079 people in the 2017 census (GOP, 2017). In addition to construction, transportation, sewage systems, deforestation, water supply, and industrial operations. Such elements are directly or indirectly linked to urban expansion. There are 2018 public and private schools and 616 public and private universities (Peshawar Development Authority https://pda.gkp.pk/). Eighteen (18) major public and private hospitals and fifty-two (52) dispensaries (Peshawar Development Authority https://pda.gkp.pk/). War and terror in Afghanistan forced three million Afghans to flee to Peshawar in 1979 (Roehrs, 2015). In Peshawar, there were still 31,284 registered families. About 3 million IDPs moved to Peshawar and certain parts of FATA between 2009 and 2012. Flooding and earthquakes have displaced an extra 19 million people. Armed conflict in FATA and a few KPK areas forced approximately 5 million people to flee their homes (Turton & Marsden, 2002).

4. Conclusions

This research was carried out to understand the monitoring of the urban sprawl based on the LCM -Markov chain model and CA Markov chain model to promote sustainable urbanization and future predictions in Peshawar city. It has been found that the urban area has increased by 16.3%. With an average rate of 5.50%, 3.00%, 4.30%, and 3.50% from (a) 1998 to 2003, (b) 2003 to 2008, (c) 2008–2013, and (d) 2013 to 2018, respectively. Mainly along the roadside in the western and southern areas of Peshawar city, urban sprawl can be found. The westward expansion was mainly owing to Afghan refugees, IDPs from tribal territories, and dangerous floods in the north of Peshawar. As a result of the conversion of forest land into urban land, many buildings and built-up sites were constructed on the bare land and valuable farmlands. Sustainable expansion relies heavily on food availability.

Hence preventing unneeded urban growth on agricultural land is critical to its success. A significant increase in vegetation land, almost 12.07% within five years (2013–2018), was seen in response to the Billion tree project. However, that overall increase of Built-up land and vegetation cover was bearing the cost of a decline in bare land. In addition, the results of 2028 and 2038 indicate that in the future, the vegetation cover will increase from 50.63% in 2018 to 59.23% by 2038. But also the built-up area would be increased from 21.52–25.23% respectively. Which will not only cost the bare land but will also affect the water land. The provisional government should make policies to save and utilize their bare land in a planned manner. No doubt urban expansion has some advantages, including (i) providing employment opportunities, (ii) superior lifestyle, (iii) better production of goods & Services, etc. However, some negative aspects also have a rise in surface temperature of urban areas because of loss of agricultural land an increase of artificial material, including asphalt, concrete. It is hoped that this research will assist in constructing a long-term strategy to protect valuable agricultural and barren land from urbanization, as well as to organize urban growth in terms of time and location.

Declarations

Ethics approval and consent to participate

The facts and views in the manuscript are solely ours, and we are responsible for authenticity, validity, and originality. We also declare that this manuscript is our original work, and we have not copied it from anywhere else. No plagiarism is detected in this manuscript.

Consent for publication

We undertake and agree that the manuscript submitted to your journal has not been published elsewhere and has not been simultaneously submitted to other journals.

Acknowledgments

We are highly thankful to the unspecified reviewers and editor of journal for their enthusiastic support and valuable suggestions during the review of the manuscript. All the authors would like to say thanks to Miss Merry and Stephen C. McClure for their enthusiastic support and valuable suggestions during the review of the manuscript.

Author Contributions

Aqil Tariq conducted the overall analysis and led the writing of the manuscript, design and data analysis. Faisal Mumtaz, lend their support to authors for writing analysis of Landsat data.

Funding

This study was supported by National Natural Science Foundation of China (grant 41907192) and civil aerospace pre-research project (D040102).

Competing interests

The author declares no conflict of interest in this manuscript's publication. Moreover, the writers have thoroughly addressed ethical issues, including plagiarism, informed consent, fraud, data manufacturing and/or falsification, dual publication and/or submission and redundancy.

Availability of data and material

The datasets generated and analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

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Supplementary Figures

Supplementary Figures are not available with this version

Figures

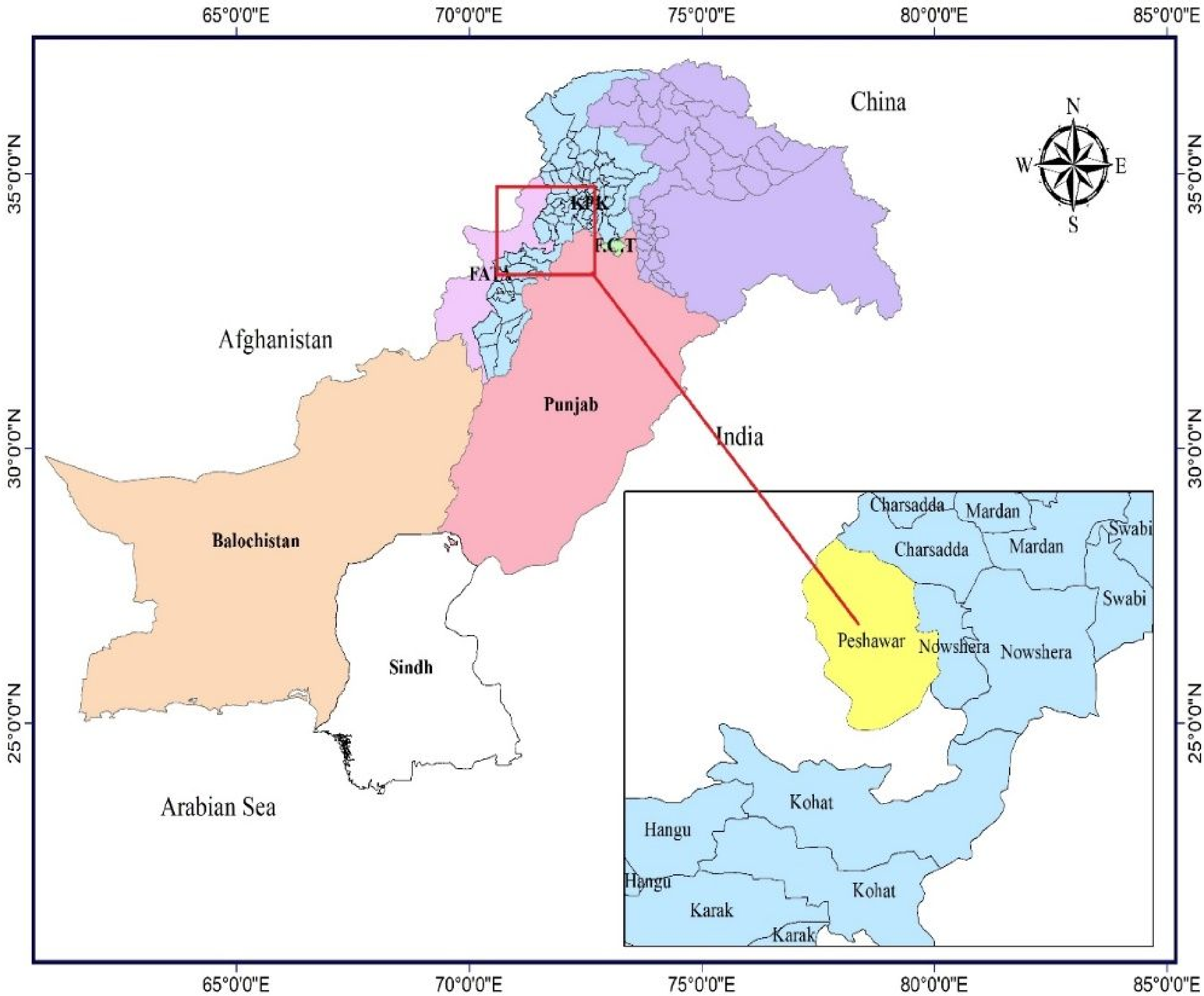

Figure 1

Geographical location of study area.

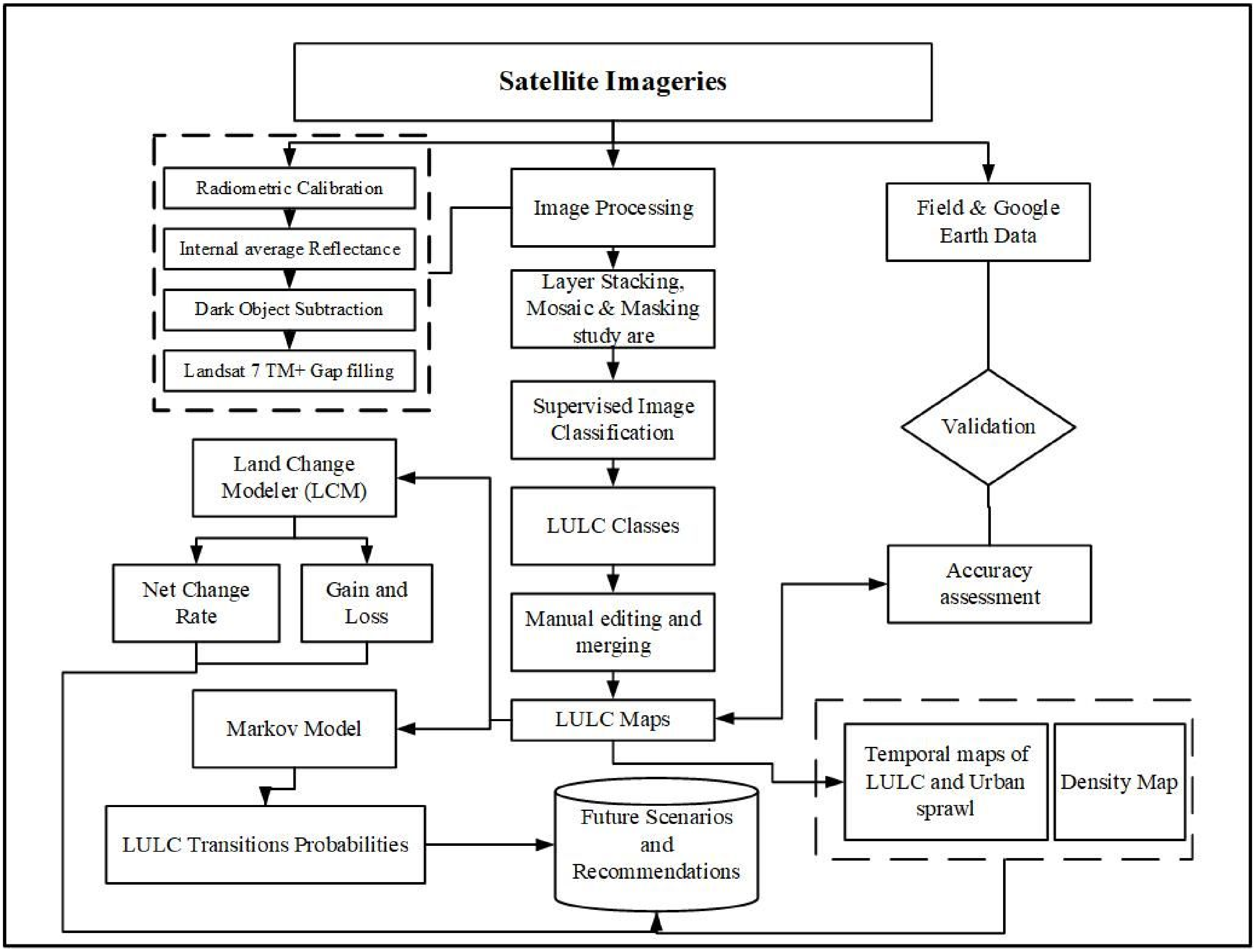

Figure 2

General description of the methodology.

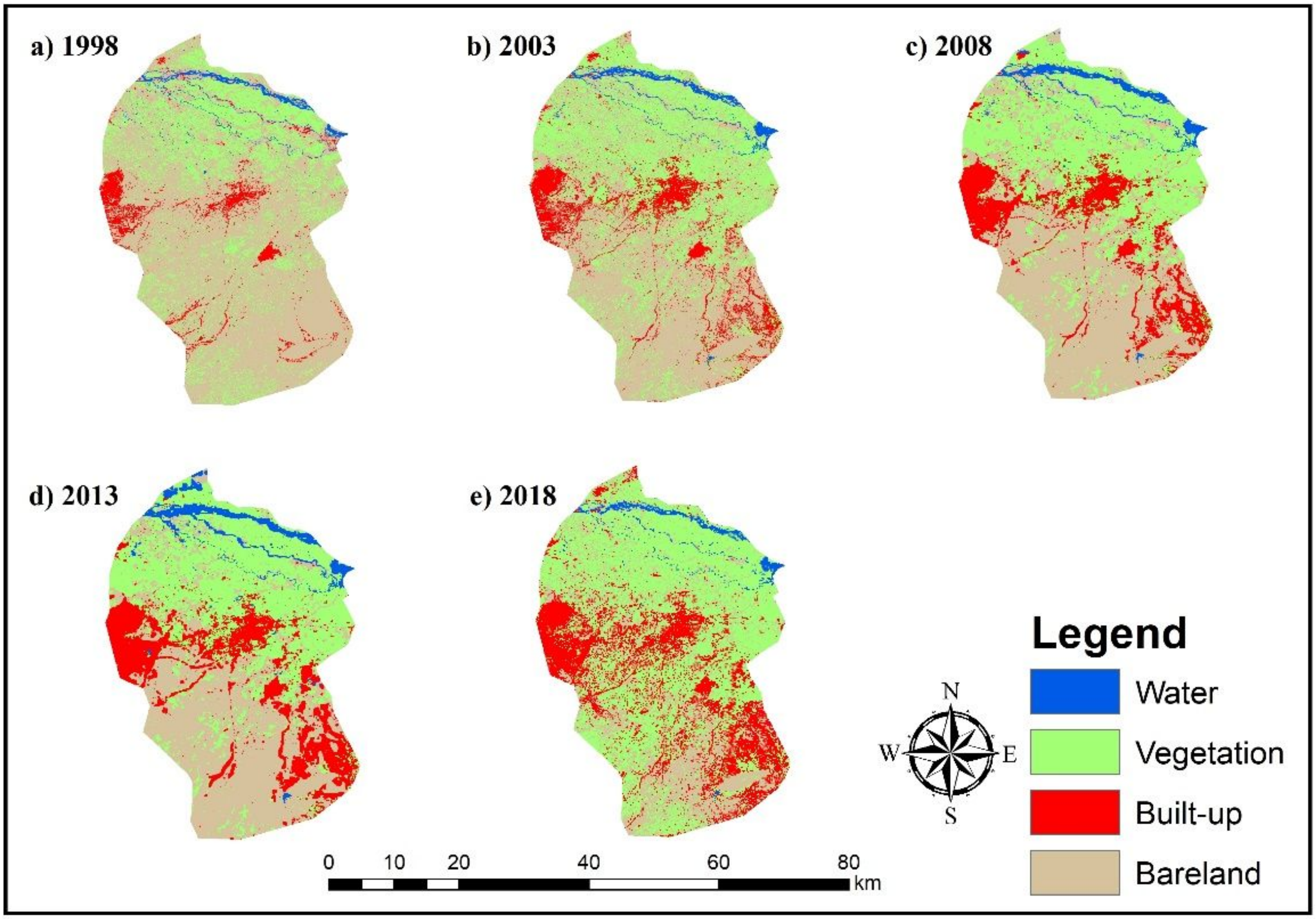

Figure 3

Spatial patterns of LULC in Peshawar (a) 1998, (b) 2003, (c) 2008, (d) 2013, (e) 2018.

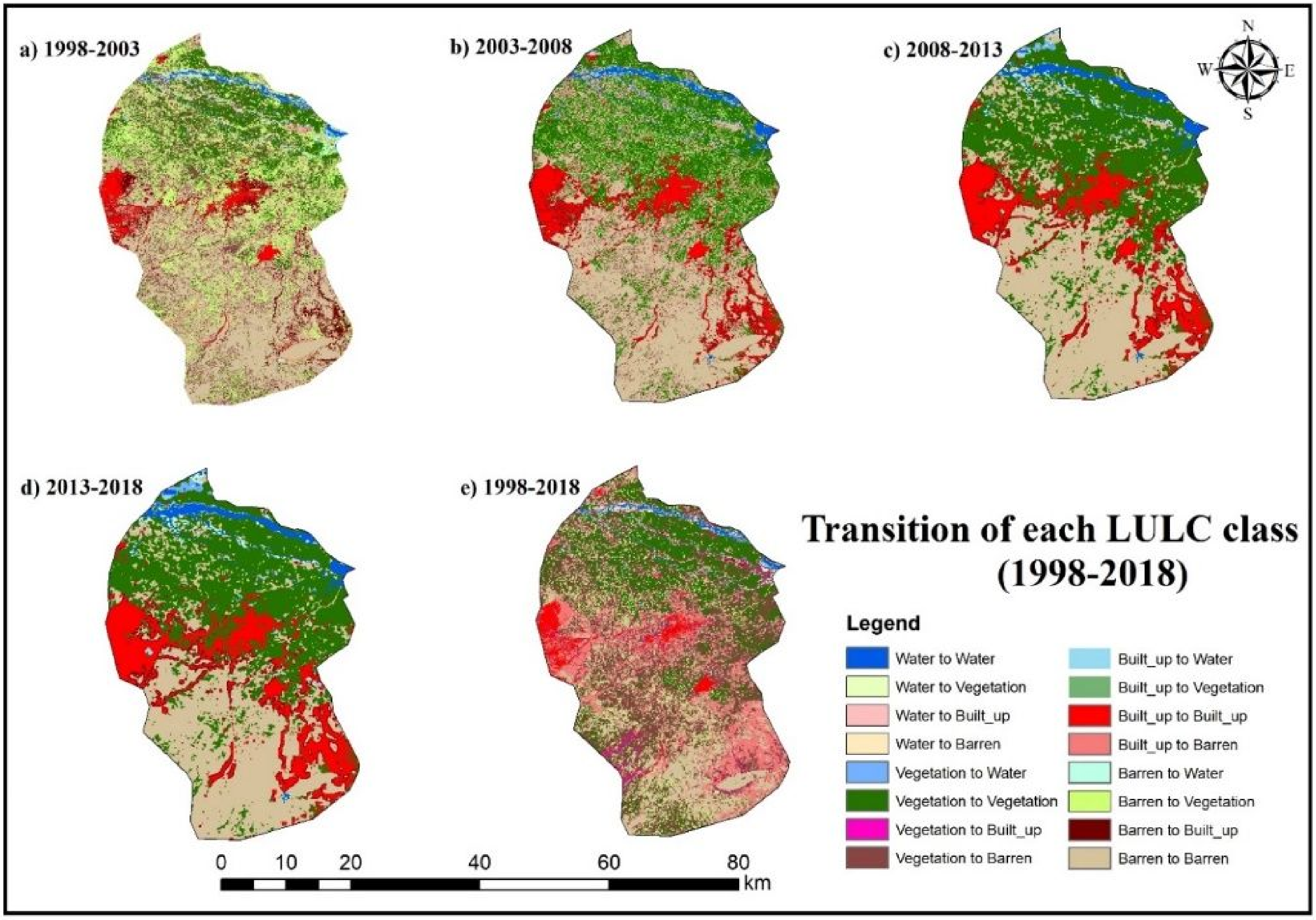

Figure 4

LULC change matrix showing land encroachment in Peshawar: (a) 1998-2003; (b) 2003-2008; (c) 2008-2013; (d) 2013-2018.

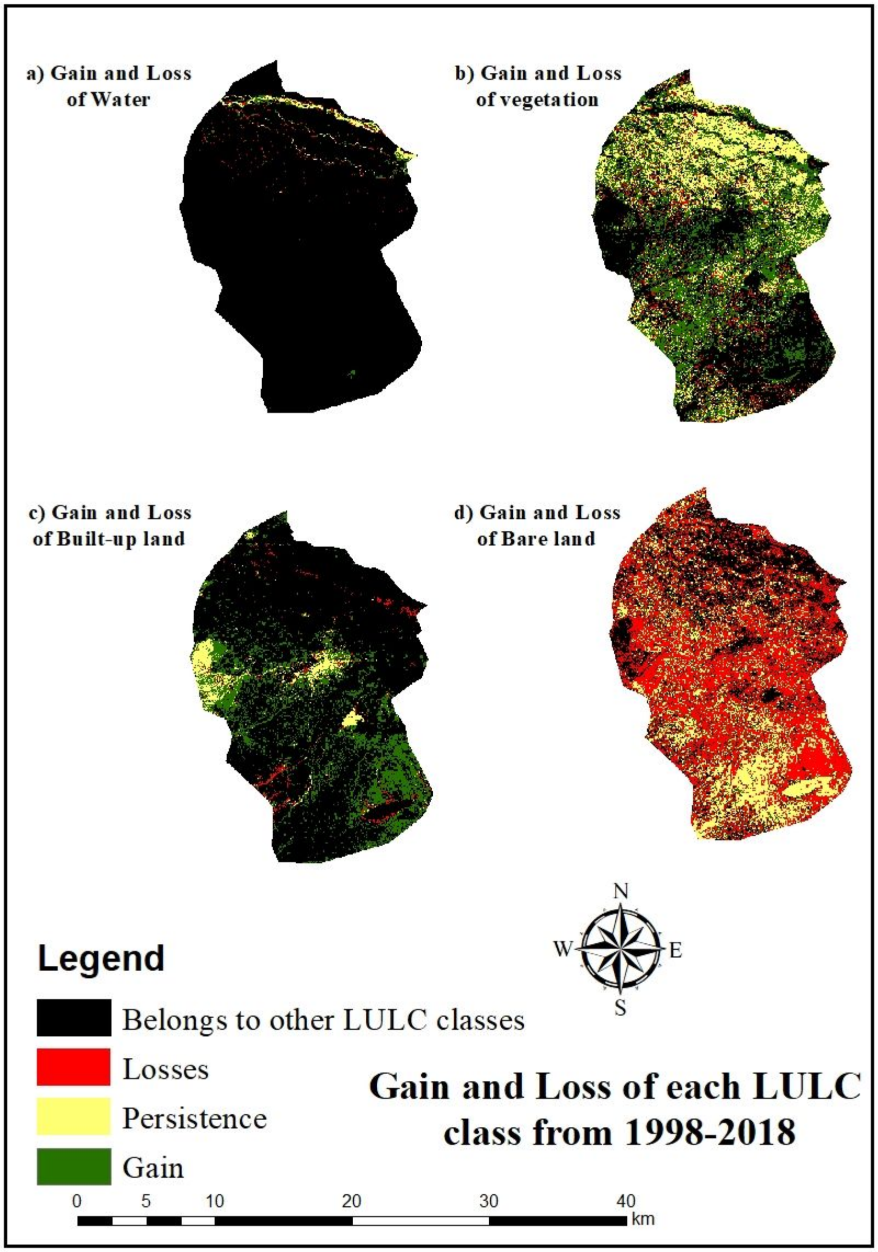

Figure 5

Gain and Loss of Each LULC Class from1998-2018 in Peshawar.

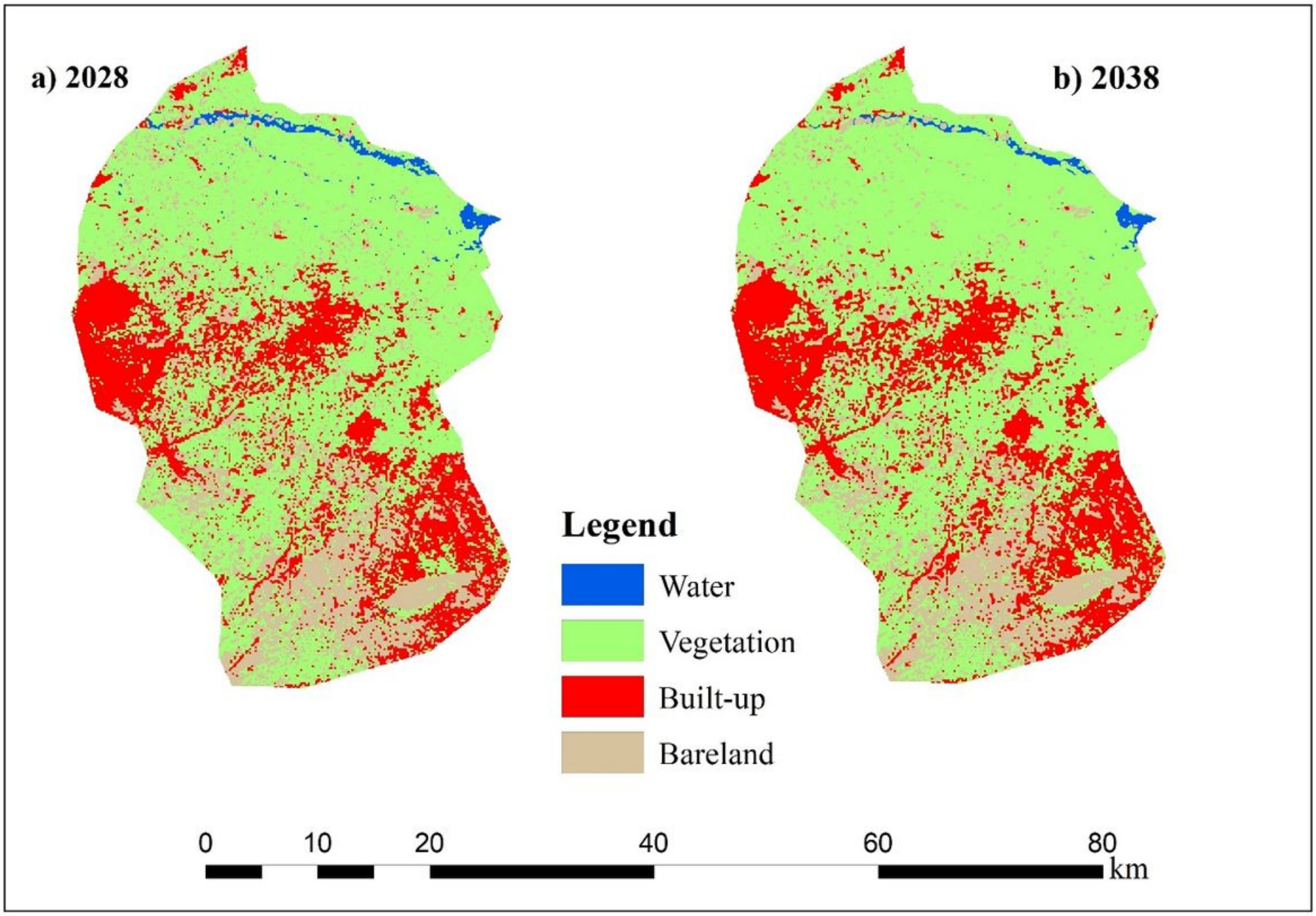

Figure 6

LULC predictions for 2028 and 2038 for Peshawar city.