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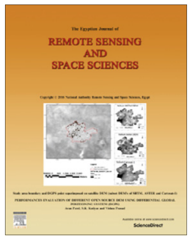

RESEARCH PAPER

Monitoring land use change and measuring urban sprawl based on its spatial forms The case of Qom city

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Qom city

Abstract As a response to the challenge of rapid pace of urbanization and lack of reliable data for environmental and urban planning, especially in the developing countries, this paper evaluates land use/cover change (LCLU) and urban spatial expansion, from 1987 to 2013, in the Qom, Iran, using satellite images, field observations, and socio-economic data. The supervised classification technique by maximum likelihood classifier has been employed to create a classified image and has been assessed based on Kappa index. The urban sprawl was also measured using Shannon's entropy based on its primary spatial forms. To our knowledge, measuring urban sprawl based on its spatial forms would contribute to prioritizing policies and specific regulations in dealing with its dominant form. Finally, LCLU change and urban growth were simulated for 2022, using CA-Markov model. The results revealed that dramatic growth of built-up areas has led to a significant decrease in the area of agriculture, gardens and wasteland, from 1987 to 2013. The obtained relative entropy values have indicated that the Qom city has experienced increasing urban sprawling over the last three decades. The continuous linear and non-continuous linear developments along the major roads and highways are the dominant forms of sprawl in Qom city. The CA-Markov model estimated that this unsustainable trend will continue in the future and built-up areas will be increased by 10% by 2022 resulting in potential loss of 438.03 ha agriculture land, 638.37 ha wasteland, and 17.01 ha gardens. Those results indicated the necessity of appropriate policies and regulations particularly for limiting linear sprawl along the main roads.

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1. Introduction

The rapid pace of world's urban population growth, especially in developing countries, is one of the major challenges for governments and planning agencies. Today, 3.9 billion people—54 percent of the world's population—reside in urban areas and is expected to reach 6.3 billion in 2050, with nearly 90 percent of the future urban population increase being in developing world cities (United Nations, 2015). Without any doubt, this trend has been the considerable spatial manifestation and will continue in future. The inevitable outcomes from this process are the spatial expansion of towns and cities beyond their juridical limits and into their hinterlands and peripheries in order to accommodate the growing urban population. In this condition, we will need to adapt to this process. Therefore, effective governance and planning to achieve a more sustainable urban form are crucial for urban planners and policy makers. In other words, urban areas and their spatial extension are needed to minimize wasteful use of non-renewable resources, to avoid the disruption of the ecosystem equilibrium, to reduce social inequities, and to promote inclusive and sustainable development (Burgess and Jenks, 2002; UN-Habitat, 2008). However, since World War II, urban sprawl has gradually become one of the dominant urban spatial expansion patterns throughout the world, with the differences in dates, causes, and consequences (Ewing et al., 2003a; Gill, 2008; EEA, 2006; Gómez-Antonio et al., 2014). The literature review indicated that there is no clear-cut consensus on the definition of urban sprawl which is strongly dependent on the cultural, geographic and political context' (see Torrens, 2008; Besussi et al., 2010). In general, urban sprawl refers to certain forms of city spatial expansion toward suburbs and peripheral areas with, low density, single-use, extensive road and highway networks, car-dependent, open up vast space of territory, scattered and ribbon development in an mono-centric urban structure. (Ewing, 1997; Galster et al., 2001; Hasse and Lathrop, 2003; Zhang, 2001; Tewolde and Cabral, 2011; Gómez-Antonio et al., 2014). In developed countries, it has been fueled by globalization, market economy and dominance of capitalism ideology, particularly in automobile industry and fuel market, as well as reduced livability of inner-city, (Ewing, 1997; Snyder and Bird, 1998; Galster et al., 2001; Besussi et al., 2010); in developing countries, it is often the result of overtaking of urbanization from urban planning, inappropriate government's land and housing policies, urban–rural migrations and low and middle-income household's efforts to find an affordable housing in the urban fringe (see Deng and Huang, 2004; Menon, 2004a,b). However, a major concern with the urban sprawl and LULC change is associated with negative environmental, social and economic impacts (Buiton, 1994; EEA, 2006; Hasse and Lathrop, 2003). The environmental dimension impacts include the loss of fertile lands, open space and biodiversity (Harris, 1984; Benfield et al., 1999; McKinney, 2002; Atu et al., 2013) spoiling water quality (Allen and Lu, 2003; Wilson et al., 2003; Tu et al., 2007), higher GHG emissions and pollutions levels (Glaeser and Kahn, 2004) and increasing runoff and flood potential, and increase of energy consumption. (EEA, 2006; Sung et al., 2013) In the socio-economic dimension urban sprawl leads to excessive infrastructure and public service costs (Lee et al., 1998; Burchell and Listokin, 1995; Batty, 2008) the decline of downtown and public space, reducing social cohesion, loss of a sense of community, reducing public health, safety and security, loss of cultural values (Freeman, 2001; Nechyba and Walsh, 2004; EEA, 2006; Resnik, 2010; Jaeger et al., 2010; Pereira et al., 2014), increase of income inequality and polarization (Carruthers and Ulfarsson, 2003; Brueckner and Helsley, 2011) traffic congestion (Ewing et al., 2003b; Hathout, 2002) longer travel distance and limited access, especially for non-driver people. (Ewing, 1997; Kain, 1992; Bento et al., 2003).

Over the last few decades, the exacerbation of these issues not only has led to rising new approaches to achieving a more sustainable urban form such as smart growth and compact city (Ewing, 1997; Kushner, 2002; Shaw, 2000; Jenks and Dempsey, 2005), but also new methods and techniques have been developed to monitor and analyze urban sprawl phenomenon and its consequences. In an effort to monitor and analyze urban sprawl, some research organizations and researchers (Peiser, 1989; Sierra Club, 1998; El Nasser and Overberg, 2001; Galster et al., 2001; Ewing et al., 2003a) measure urban sprawl by their indicators, while other scholars emphasize the spatial and temporal technologies such as GIS and remote sensing in combination with statistical techniques (Clarke and Gaydos, 1998; Galster et al., 2001; Yeh and Xia, 2001; Hasse and Lathrop, 2003; Thomas et al., 2003; Ji et al., 2006; Jat et al., 2008a; Dewan and Yamaguchi, 2009; Tewolde and Cabral, 2011; Rawat et al., 2013; Deep and Saklani, 2014; Alexakis et al., 2014; Liu and Yang, 2015). However, the mapping and monitoring of urban sprawl and LULC changes using GIS and remote sensing techniques has attracted more interests and has largely proved to be effective and valuable tools for monitoring and estimating urban sprawl over a time period (Yeh and Li, 1997; Masser, 2001; Jat et al., 2008b; Belal and Moghanm, 2011; Butt et al., 2015; Dadras et al., 2015). Those tools are also effective in cost and time related barriers (Epsteln et al., 2002; Haack and Rafter, 2006).

Beyond methods, investigation and monitoring of urban growth and LULC change are necessary to examine the impacts and identifying the points of intervention and to direct growth away from sensitive ecological areas, especially in developing countries. Like most of the developing countries, Iran has experienced high urban population growth in the last five decades. The number of cities has increased substantially from 199 in 1956 to 1139 in 2011, and the urban population has grown about nine times in the same period (Statistical Center of Iran, 2011). According to Statistical Center of Iran, more than 71.4 percent of the Iran's population – 53.646.661 people – living in towns and cities in 2011. In Iran, urbanization growth has been fueled by governments' incentives and policies particularly after Islamic Revolution and disparity in regional development which resulted in urban–rural migrations. One of the major consequences of this trend has been the urban sprawl over the last few decades (Shahraki et al., 2011; Roshan et al., 2010; Arsanjani et al., 2013; Dadras et al., 2014; Mohammady, 2014; Ebrahimpour-Masoumi, 2012). Since the big cities and metropolitans in Iran are situated at the heart of fertile agricultural regions, understanding and monitoring the urban growth and LULC change is crucial and would be helpful for the city planners and policy makers to direct future developments and for environmental management (Sudhira et al., 2004; Knox, 1993; Simmons, 2007). Accordingly, this paper aimed to indicate and monitor urban spatial expansion patterns and land use change in the Qom city based on spatial forms of urban sprawl. Also, future directions and growth patterns of the city by 2022 are estimated.

2. Materials and methods

2.1. Setting

The study has focused on the land use changes and sprawl analysis of Qom city. Geographically the city is located in between 34°26′49″ and 34°47′41″ North latitudes and 50°41′10″ and 51°23′4″ East longitude. Qom city situated in the arid region and annual rainfall average is 161 mm (IRIMO, 2006). It's characterized by limited access to arable land and water resources.

Qom city, as a center of Qom province and county and the second holy city of Iran (after Mashad), has been experienced rapid pace of population growth over last six decades, from 96,499 people in 1957 to more than 1.08 million in 2011 (Statistical Center of Iran, 1956, 2011; AMCO Consulting Engineers, 2003). It's also the destination of international migrants largely from Iraq and Afghanistan (Statistical Center of Iran, 2011). The city has been selected as a case study because has been experienced rapid spatial expansion into its peripheries and includes a diversity of LULC classes. In addition, on average, there are 246 sunny days per year in Qom (IRIMO, 2006). Hence this city has been viewed as an ideal test-bed area for the classification. Analyzing these trends and employing an advanced approach to predict changes in LULC may provide valuable information for policy-makers and urban planners.

Like other Iran's cities, Qom has two boundaries namely; legal/official city boundary and authority boundary. The legal/official city boundary is the main urban area being under the control of the Qom municipal where urban services and facilities are provided by the municipality. The authority boundary (or *Harime Shahr*) is identified outside the official city boundary and preserved for future urban growth. Although in this boundary urban development is limited and any residential development considered as illegal, there are many informal settlements and other construction such as small scale manufacturing. In this paper all LULC and spatial forms of urban sprawl statistics were calculated based on authority boundary. However, Shannon's entropy analysis was based on legal city boundary.

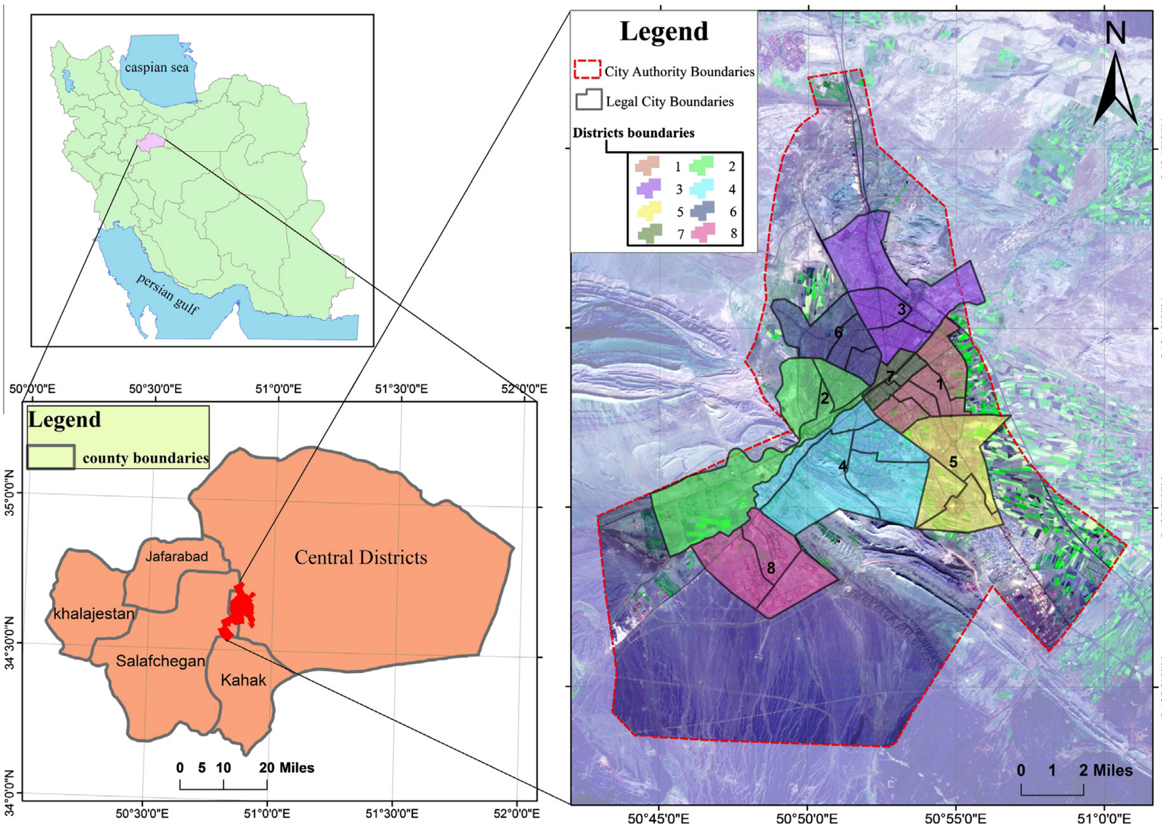

Figure 1 Location map of the study area and Qom city districts.

The total area of Qom's authority boundary is about 34850 ha. The legal/official Qom boundary has been divided into 8 districts (Bavand Consultant Engineers, 2013). Fig. 1 represents an overview of Qom and the city's geographic locations, boundaries as well as administrative districts (Fig. 2).

2.2. Data sets

Landsat TM satellite images for the years 1987, 1999, and 2013 were obtained from United States Geology Survey (USGS) and were utilized in this paper. Detailed information about the remotely sensed images is listed in Table 1.

In image acquisition, we have considered to the impacts of Sun's inclination, season and cloud cover. In supporting the study, secondary data were obtained from the different Qom's organizations. The City boundaries map, districts shape file and land use maps were obtained from Qom municipality and General Bureau of Road & Urban Development of Qom Province. (Bavand Consultant Engineers, 2013; EMCO IRAN Consultant Engineers, 2003). The demographic details were obtained from Iran's Census Center and Qom municipality. In addition, the region's aerial photographs were acquired from National Cartographic Center of Iran (NCC). We also have conducted fields' observations in study area as a basis for accuracy assessment.

2.3. Image pre-processing and classification

The atmospheric correction is a necessary step to accurately extract quantitative information from the Landsat (Liang et al., 2001). To image pre-processing, Landsat 8 OLI image rescaled to the Top of Atmosphere (TOA) reflectance and/or radiance using the standard Landsat equations and scaling factors (United States Geological Survey, 2015). Then, Dark Object Subtraction (DOS) was used for atmospheric correction. The atmospheric correction of Land sat 5 imageries was conducted using QUick Atmospheric Correction (QUAC) in the ENVI 5.1. The supervised classification by IDRISI Selva was employed to process and classify of the images of the case study. The reference data include aerial photographs, land use maps were used to assist in supervised training site selection for LULC features of interest. It also supplemented by field observations. Based on different bands of the Landsat images a composite image was created that helps us to clear distinguish the different LULCs in images. We included at least 100 pixels in each individual training sites that are created by digitizing polygons. Based on identified training sites, the signature file is created for each land cover class using the signature development tool MAKESIG. The maximum likelihood classifier (MLC) was used for spectral classification of the land sat images based on the training sites (signatures), at a 30 m resolution and a projection system (UTM-WGS 1984 Zone 39 N). The five land cover classes were identified in the study area, namely, built up area, agricultural land, wastelands, gardens, and rocky outcrop (Table 2). Afterward, post-classification refinements were used to reduce classification errors created by the similarities in spectral responses of individual classes. Additionally, a normalized spectral mixture analysis (Wu, 2004) was applied to address the problem of mixed pixels (Lu and Weng, 2005) After image classification, mode filter (5×5) was used to each classification to generalize the supervised classified LULC images and remove the isolated pixels (Lillesand and Kiefer, 1999). Finally, the generalized images are reclassified to create the final version of LULC maps for 1987, 1999 and 2013.

2.4. Classification accuracy assessment

Accuracy assessment for individual classification is essential to correct and efficient analysis of LULC change (Butt et al., 2015). It indicates the degree of deference between classified images and reference data. Thus, to determine the quality of information extracted from the data, classification accuracy of 1987, 1999 and 2013 images was analyzed. An independent sample was chosen from the ground or reference data and sample size for each class was 30 (Congalton and Green, 1999). Based on error matrix (Congalton and Green, 1999: 34–64) the accuracy assessment of LULC maps was carried out. The error matrix compares the relationship between known ground

Table 1 Detailed information of utilized satellites imagery (Source: US Geological Survey, 2013).

Satellites	Acquisition date (Dar/Month/Year)	Sensor	Spatial resolution	Projection	True color composite (TCC)
Landsat 8	10/18/2013	OLI_TIRS	30 m	WGS84 UTM Zone 39 N	BAND 7, 5, 3
Landsat 5	8/9/1999	TM	30 m	WGS84 UTM Zone 39 N	BAND 7, 4, 1
Landsat 5	8/24/1987	TM	30 m	WGS84 UTM Zone 39 N	BAND 7, 4, 1

Table 2 Identified classes by supervises classification.

NO.	Land classes	Description
1	Built-up	Residential, Commercial, Industrial, Roads, Railway, mixed urban or build-up land
2	Agriculture land	Crop land, Fallow land
3	Wasteland	Salt affected land, waterlogged land
4	Gardens	Forests, Vineyards, Parks, Orchards, Groves, Nurseries
5	Rocky outcrop	Barren rocky/stony, Mountain, Barren hill

or reference data and the corresponding outcomes of an automated classification. In this paper, some of the accuracy statistics namely; the overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and Kappa Index of Agreement (KIA) as accuracy statistics were derived from the error matrices to assess the classification accuracies (Congalton and Green, 1999).

2.5. Change detection

The post-classification method is one of the most common methods to change detection (Jensen, 2004). In this study, this method was used to determine changes in LULC in three intervals (i.e. 1987–1999, 1999–2013, and 1987–2013). Pixel-by-pixel cross tabulation analysis was applied to determine the quantity of conversions from a particular LULC class to other LULC categories.

2.6. Urban sprawl measurement

It is necessary to prove occurrence of this phenomena in Qom city prior to measuring urban sprawl based on its spatial forms. Thus, urban sprawl over the period of 1987 to 2013 was determined using Shannon's entropy along with GIS tools. Shannon's entropy is one of the commonly used and effective technique for monitoring and measuring of urban sprawl (Yeh and Xia, 2001; Jat et al., 2008a; Sarvestani et al., 2011; Punia and Singh, 2012). It has been used to measure the degree of compactness and dispersion of a geophysical variable (city lands) among 'n' spatial units (Theil, 1967; Thomas, 1981). Shannon's entropy is calculated by the following equation (Yeh and Xia, 2001):

$$H_n = -\sum_{i}^{n} P_i \mathrm{Log}(1/P_i)$$

where: p_i is the probability or proportion of the variable occurring in the ith districts and n is the total number of districts or zones. We have used relative entropy for scale the entropy value from 0 to 1. The relative entropy is calculated by following equation (Thomas, 1981):

$$H_n = -\sum_{i}^{n} P_i \mathrm{Log}(1/P_i)/\log(n)$$

The Shannon's entropy values are different between 0 and Log(n). The value closer to zero means compact urban growth (higher density), while values closer to 'log n' indicates dispersed distribution of city's built environment (Yeh and Xia, 2001). After measuring urban sprawl, we have analyzed spatial forms of sprawl in Qom.

2.7. Urban land use change modeling using CA-Markov

2.7.1. CA-Markov model and validation

LULC simulation involves measuring LULC changes between t_1 and t_2 and extrapolating these changes intofuture (Eastman, 2009). CA-Markov Model is one of the most common modeling methods that many researchers have proven the efficiency of the model for simulating urban growth (White and Engelen, 1997; de Noronha et al., 2012). The Markov Chain Model is a stochastic progression that analyzes the probability of LULC change over the times period by developing a transition probability matrix (Eastman, 2006; Sun et al., 2007; Muller and Middleton, 1994; López et al., 2001). The output of Markov Chain analysis is a transition probability matrix between t_1 and t_2 that indicates the probability of LULC change from one period to another. However, lack of the spatial dimension is one of the major limitation of Markov and it cannot identify spatial distribution of occurrences within each LULC category (Eastman, 2003; Ye and Bai, 2008). The Cellular Automata (CA) methods are very efficient tools for imitating complex spatial processes based on simple decision rules (Wolfram, 1984). Each cell has a certain condition or function that is influenced by its neighboring cells as well as features of the cell itself (Eric et al., 2007). CA- Markov chain is a combination of Markov Chains and Cellular Automata that was developed to solve Markov chain limitation through adding a spatial dimension to the model by Cellular Automata. CA-Markov model in IDRISI Selva was used for LULC modeling and simulation in Qom city. In this study, simulating future LULC change and urban growth using a CA-Markov model occurred in several steps. In the first step, LULC maps for the years 1987, 1999, and 2013 resulting from the supervised classification were applied to measure transition probability matrices of LULC classes between 1987 and 1999, and 1999 and 2013 using Markov model. In the second step, transition matrix probabilities were employed in simulation of future LULC changes. Step 2 was to create suitability maps and some indicators including elevation, barren areas, population density, and distance to the road are selected to create transition potential maps of LULC. Transition suitability maps were generated based on certain weights for those factors (Saaty, 2003). The suitability map values was standardized from 0 to 255 as the CA transition parameters, with higher values indicating more suitability (Poska et al., 2008). In the third stage, a standard 5×5 contiguity filter was employed to determine the CA filter to define the neighborhood in this study (Sang et al., 2011).

For model validation, the predicted map of 2013 was used as the comparison input in the validation module, and the classified image of 2013 was the reference input. The accuracy of the predicted 2013 LULC map was assessed using the VALIDATE module in IDRISI to estimate the level of agreement with the LULC map of 2013 based on three Kappa indices of agreement namely: Kno, Kstandard, and Klocality (Pontius, 2000; Mitsova et al., 2011). Using the all Kappa indexes for the assessment not only determine the overall success rate but also provide an understanding of the effective factors in the strength or weakness of the results (Geri et al., 2011). For perfect agreement, Kappa equals 1, while a value of 0 indicates the agreement is exactly by chance (Pontius, 2000). Finally, the number of iterations was determined. We took the 2013 LULC map as the base point and selected 18 CA iterations to model the predicted LULC in Qom in 2022. Figure 2 represents the research process.

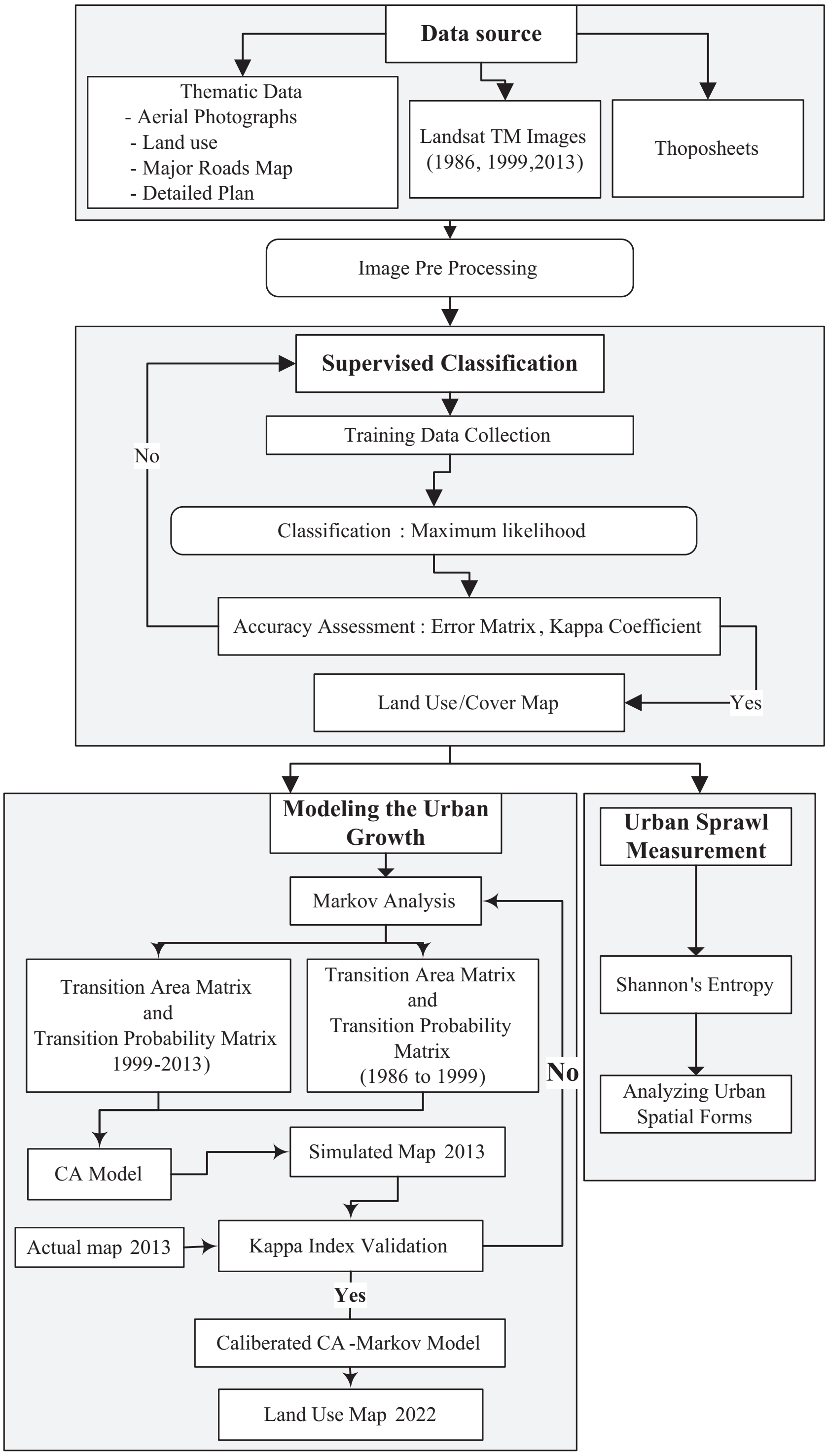

Figure 2 Research flowchart.

3. Results and discussion

3.1. Classification accuracy assessment

Error matrices were employed to assess classification accuracies and are detailed for all three years in Tables 3–5 using maximum likelihood classifier as the classification method. The overall accuracy indicates the percentage of correctly classified pixels. The overall accuracies of the classification methods for 1986, 1999, and 2013 ranged from 91.39% to 98.30%, with Kappa coefficients from 76% to 96%. According to Anderson (1976), 85%, as a minimum accuracy value is

Table 3 Error Matrix (%) comparing the image classification of 1987 to the reference data.

Classes	1	2	3	4	5	Row total	User's accuracy (%)
1	**2184**	8	30	8	92	2322	**93.68**
2	1	**5148**	18	0	30	5197	**98.9**
3	0	0	**323**	0	28	351	**91.89**
4	0	0	0	**101**	0	101	**100**
5	54	57	267	36	**28,717**	29,131	**93.58**
Column total	**2239**	**5213**	**638**	**145**	**28,867**	**37,102**	
Producer's Accuracy (%)	**97.38**	**98.55**	**50.16**	**69.57**	**97.58**		
Overall accuracy	**98.30**	Overall Kappa			**95%**		

Class legend: (1) Built-up, (2) Agriculture land, (3) Wasteland, (4) Gardens, (5) Rocky outcrop.

Table 4 Error Matrix (%) comparing the image classification of 1999 to the reference data.

Classes	1	2	3	4	5	Row total	User's accuracy (%)
1	**2239**	8	36	8	133	**2424**	**91.88**
2	0	**5106**	16	1	31	**5154**	**98.92**
3	0	1	**358**	0	7	**366**	**97.78**
4	0	0	0	**136**	0	**136**	**100**
5	0	98	228	0	**28,696**	**29,022**	**94.94**
Column total	**2239**	**5213**	**638**	**145**	**28,867**	**37,102**	
Producer's Accuracy(%)	**100**	**97.62**	**55.68**	**93.77**	**97.28**		
Overall accuracy	**98.47**	Overall Kappa			**96%**		

Class legend: (1) Built-up, (2) Agriculture land, (3) Wasteland, (4) Gardens, (5) Rocky outcrop.

Table 5 Error Matrix (%) comparing the image classification of 2013 to the reference data.

Classes	1	2	3	4	5	Row total	User's accuracy (%)
1	**2239**	385	37	8	636	**3305**	**65.67**
2	0	**3624**	13	0	417	**4054**	**87.66**
3	0	0	**96**	0	0	**96**	**100**
4	0	0	0	**135**	0	**135**	**100**
5	0	1204	492	2	**27,814**	**29,512**	**74.08**
Column total	**2239**	**5213**	**638**	**145**	**28,867**	**37,102**	
Producer's Accuracy (%)	**100**	**65.78**	**14.83**	**93.08**	**82.17**		
Overall accuracy	**91.39**	**Overall Kappa**			**76%**		

Class legend: (1) Built-up, (2) Agriculture land, (3) Wasteland, (4) Gardens, (5) Rocky outcrop.

acceptable. Hence, the accuracy assessment is reliable. The producer's and user's accuracy for three years are found ranging from 50.16% to 100% (Tables 3–5).

3.2. Land use/cover change

The analysis of LULC changes based on post-classification change detection and landscape metrics has revealed that in the first period, from 1987 to 1999, the built-up area has increased by greater than 1997 ha that is more than 36 percent (Table 6). In other words, it can be observed from Table 6 that in 1987 the built-up area was 5453.73 ha, 15.6% of the study area while the agriculture land covered 8333.91 ha, 23.91% of the study area. The land cover map of 1999, however, shows that the built-up area was 7450.74 ha, about 21.37% of the study area, an increase of 36.47% compared to 1987 (Table 6). The agriculture land had reduced to 8186.04 ha, a reduction about 2% (Table 6). In contrary to agriculture land, the wasteland area and gardens have increased tremendously, from 315.54 ha, and 60.03 ha in 1987 to 484.74 ha, 119.52 ha in 1999, respectively (Table 6).

During the second decade, 1999 to 2013, the built up area kept the pace of growth and gained 2713 ha (Table 6). Unpredictably, agriculture land and gardens decreased by about 39%, 9.2%, respectively (Table 6). The greatest reduction in this period is related to wastelands that have been shrunk about eleven times. Table 7 indicates that more than 1461 ha of agriculture land and 23 ha gardens have converted to the built-up area, from 1987 to 2013. Urban sprawl has occurred mainly in the rocky outcrop and 3187 ha of this land cover converted to built up area.

The built up area not only has led to fragmentation of agriculture land (Fig. 3) and results in the decrease of productivity, but also threatens urban food security, local food and econ-

Table 6 Land use/cover statistics of the Qom City; in 1986, in 1999, in 2013.

Land Class	1987		1999		2013	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Built-up	5453.73	15.64	7450.74	21.37	10163.79	29.16
Agriculture land	8333.91	23.91	8186.04	23.48	5032.62	14.44
Wasteland	315.54	0.901	484.74	1.39	45.72	0.13
Gardens	60.03	0.17	119.52	0.34	108.45	0.31
Rocky outcrop	20686.5	59.35	18608.67	53.39	19,499	55.95
Total	34849.71	100	34849.71	100	34849.71	100

Table 7 Land use/cover change conversation statistics by classes from 1987 to 2013.

LULC changes	1987–1999		1999–2013	
	Area (ha)	Area (%)	Area (ha)	Area (%)
Agricultural land to Built up area	595.62	29.83	865.71	31.91
Waste Lands to Built up area	13.68	0.69	55.44	2.04
Gardens to Built up area	11.7	0.59	11.34	0.42
Rocky outcrop to Built up area	1376.01	68.90	1780.56	65.63
Total	1997.01	100	2713.05	100

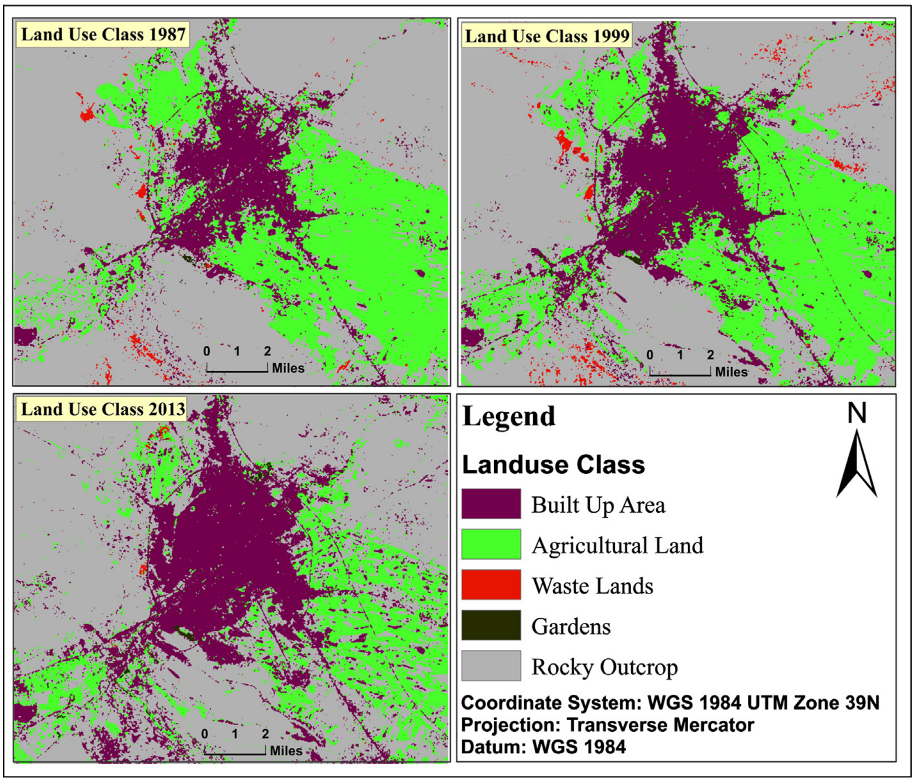

Figure 3 Urban land cover changes between 1986 and 2013.

omy (De Zeeuw et al., 2007; FAO IFAD and WFP, 2005). However, Iran is faced with many climate change impacts (IRIMO, 2006; Mosammam et al., 2016) and increased agriculture imports have led to one of the world's largest markets for crops imports (Ministry of Agriculture Jihad, 2015). It is worth mentioning that, from 1987 to 2013, new technology has greatly increased the use of underground water and has led to the development of irrigated agricultural land in Iran (Ministry of Agriculture Jihad, 2015). Qom is no exception and 3800 ha rocky outcrop and wasteland has been converted to agriculture land by using groundwater over the last three decades. However, like other regions of Iran climate change

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impacts, excessive use of groundwater and significant reduction of precipitation and groundwater aquifers in Qom has led to loss of 5029 ha of irrigated agricultural land over the last three decades (AMCO Consulting Engineers, 2003).

3.3. Urban sprawl in Qom

The Shannon's entropy (H_n) was computed for Qom city built-up area to analyze the level of dispersion or compactness of the spatial expansion of the city. The buffer function of a GIS has been used to define zones from the center of downtown along with density data. In this paper, 17 spatial units (zones) with a radius of a ø mile covered all of the legal city boundaries of Qom. The highest value of Shannon's entropy [Log_e (17)] is 2.833. Total Shannon's entropy results for 3 years (1986, 1999, and 2013) have been presented in Table 8. The entropy results obtained for the three study periods are 2.281, 2.366, and 2.511 respectively. Similarly, lower value of relative Shannon's entropy (0.805) is in the year 1986 and largest value (0.886) is in the year 2013 (the maximum is 1). Those values are larger than half of the Log_e (17), it can be argued that this city is sprawled (Bhatta et al., 2009). In other words, the entropy values reveal that there was less urban sprawl in the year 1986 and it started to increase in 1999 and 2013. It indicates that at the time of 1986 Qom city was more compact compared to 1999 and 2013.

City density patterns in Qom districts were also examined to clearer ascertain whether the different zones have represented different densities (Fig. 4). As you can see, new development area has lower density and result in negative ecological, economic and social impacts on the city (Mumford and Copeland, 1961; Munda, 2006).

3.4. The spatial forms of urban sprawl

By inspiration from the major spatial form of urban sprawl (Galster et al., 2001; Besussi et al., 2010) and using ø mile buffer zone from main roads and highways, the forms of urban sprawl were analyzed in the authority boundaries of Qom city. The built area of Qom city for the year 1956 was based on reference data and built area for 1987, 1999, and 2013 was obtained from spatiotemporal analysis of Landsat images. We also considered the date of new road constrictions to distinguish sprawl form (Bavand Consultant Engineers, 2013; EMCO IRAN Consultant Engineers, 2003). The results revealed that Qom city has four major spatial forms of sprawl namely low density continuous, continuous linear, non-continuous linear, and leapfrog (Fig. 5). There is more spread

Table 8 Shannon's entropy values for three years in the study area.

Year	Built up area	Value of Shannon's entropy	Value of relative Shannon's entropy
1987	5457.87	2.281	0.805
1999	7455.42	2.366	0.835
2013	10175.13	2.511	0.886
Log (17)	2.833	–	–

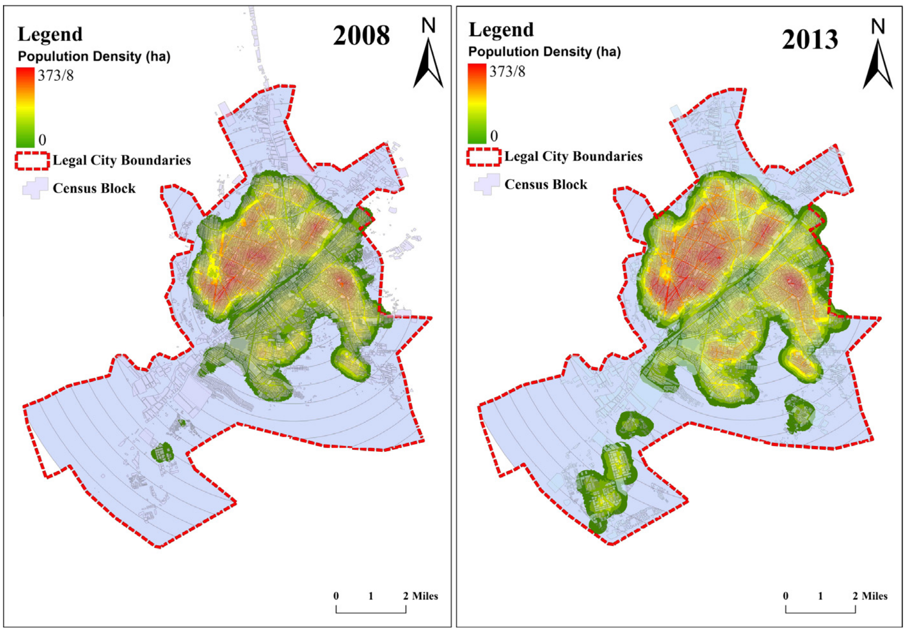

Figure 4 Density of Qom in 2008, 2013.

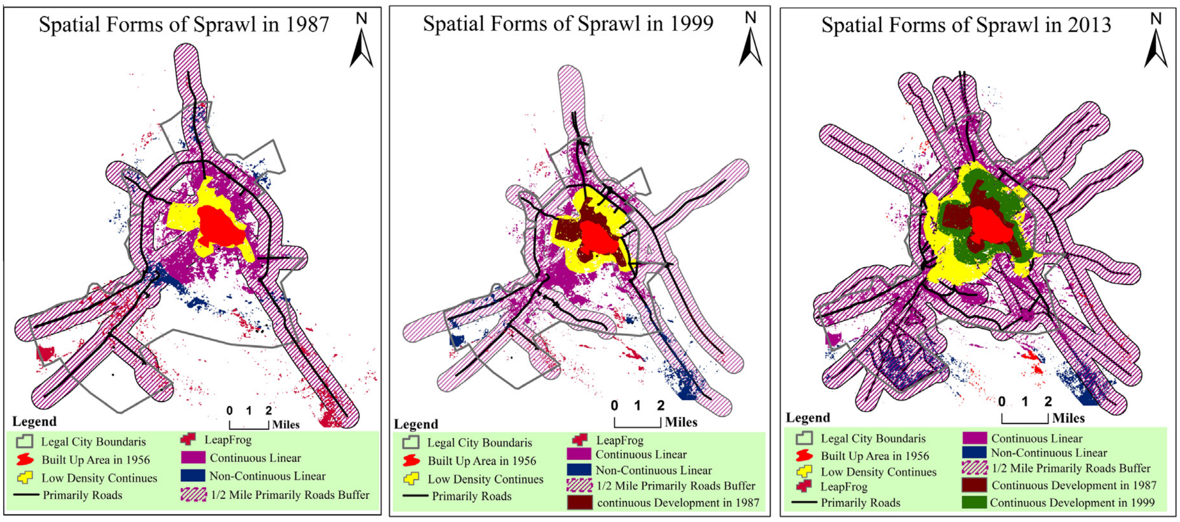

Figure 5 Spatial form of sprawl in Qom, 1987, 1999, 2013.

of land development in the continuous linear, and non-continuous forms.

The continuous linear form is the dominant form of sprawl in Qom city and accounts for more than 2470 ha land development spread over the urban fringe. This form has led to loss of more than 921 ha agriculture land, 8 h gardens from 1987 to 2013 (Table 9). The second form is non-continuous linear form. This form is similar to continuous linear and developed along the primary roads but is separated from the continuous city growth. The form is responsible for 1027 ha land development and has led to the conversion of 52 ha agriculture land to a built up area from 1987 to 2013 (Table 9). It's also the primary form in terms of conversion of gardens to built up area.

During the first period, from 1987 to 1999, leapfrog development was higher compared to the second period, from 1999 to 2013 (Table 9. Fig. 6). In contrast, in the first period, the continuous and non-continuous linear and low density continuous forms were lower than the second period. The major roads which stimulate the linear development are the Persian Gulf and Imam Ali highways, Amir Kabir and Qom-Gasgmar freeways, Al Ghadir boulevard and, Qom-Kashan roads (Fig. 5).

The third form of sprawl is low-density continuous that accounts for 933 ha land development during 1987 to 2013. This form has led to the destruction of more than 3706 ha agri-

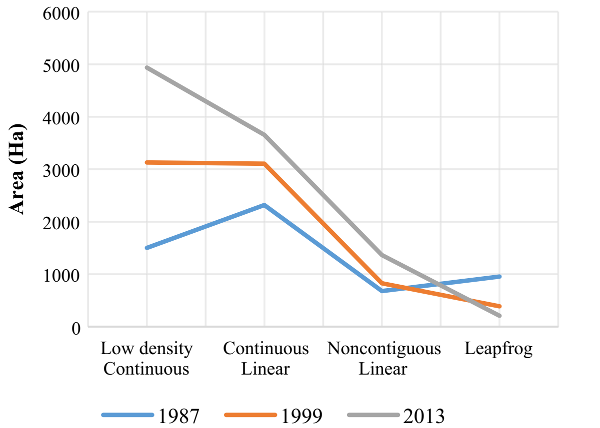

Figure 6 Area of spatial form of urban sprawl in 1987, 1999, and 2013.

cultural land in the same period (Table 9). The leapfrog development has a very small share in the land use change.

The situation of the Qom in the connection path of the two main cities of Iran (Tehran in north and Isfahan in south) and lacking fertile land and water resources in urban fringes and hinterland are major factors in the dominance of linear forms. Unlike American cities in which favorable climate and favorable lands in the urban fringes are the main factors in subur-

Table 9 Spatial forms of urban sprawl Area (ha).

Transition of land classes to built-up	Leapfrog Development		Noncontiguous Linear		Continuous Linear		Low density Continuous	
	1987–1999 Area (ha)	1999–2013 Area (ha)	1987–1999 Area (ha)	1999–2013 Area (ha)	1987–1999 Area (ha)	1999–2013 Area (ha)	1987–1999 Area (ha)	1999–2013 Area (ha)
Agricultural land to Built up area	19.98	39.42	59.76	51.39	331.2	589.95	185.4	185.31
Gardens to Built up area	2.97	1.17	3.96	48.6	5.76	3.78	0.99	2.07
Wastelands to Built up area	0	0	0	0	11.07	3.15	0.63	8.28
Rocky outcrop to Built up area	169.56	47.88	208.53	654.75	769.23	756.63	229.59	321.03
Total	192.51	88.47	272.25	754.74	1117.26	1353.51	416.61	516.69

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Table 10 Actual and simulated LCLU area for the year 2013 (ha).

LULC Classes	Land use/cover area 2013 (Ha)	
	Actual	Simulated
Built up	10175.13	9551.25
Agriculture land	5043.87	8192.43
Wasteland	45.81	476.46
Gardens	108.45	92.16
Rocky outcrop	19559.52	16537.41

Table 11 Kappa statistics for validation results.

K indexes	Value
K_{no}	0.8135
$K_{location}$	0.8599
$K_{locationStrata}$	0.8599
$K_{standard}$	0.7817

banization and scattered development, in Iran often water scarcity in desert regions has limited suburbanization and leapfrog development of cities.

3.5. Land cover modeling and validation

LULC maps in 1986 and 1999 were defined as input data to simulate 2013 land-use. However, model validation is an essential stage of any simulation of LULC change to compare the simulated and reference map. The comparisons between the actual reference map 2013 and the simulated maps of the year 2013 have been performed (Table 10). Table 10 indicates that the simulated LULC for the year 2013 is reasonably similar to the actual map for that year. It's accomplished using the Kappa spatial correlation statistic. Results from analyzing the level of agreement between the reference map 2013 and simulated 2013 LULC datasets using the Kappa spatial correlation statistic revealed that Kno as overall accuracy of simulation is calculated to be more than 81% (Table 11). In addition, other K indexes ($K_{location}$ = 0.8599, $K_{standard}$ = 0.7817) were well above or near 0.80 (Viera and Garrett, 2005; Pontius, 2000). These findings indicated that the two datasets had a high level of agreement (Zhang et al., 2011). Therefore, the transition probability matrices can be applied to predict the distribution pattern of LCLU datasets in Qom city. After assessing the validity, land cover projection for the year 2022 was calculated in the same way (Fig. 7). The Tables 12 and 13 show that by 2022, more than 1102.23 ha will

Table 12 Estimation of urban growth and LULC changes for 2022.

LULC changes	2013		2022	
	Area (ha)	Area (%)	Area (ha)	Area (%)
Built-up	10163.79	29.16	11277.36	32.35998
Agriculture land	5032.62	14.44	4372.83	12.54768
Wasteland	45.72	0.13	28.89	0.082899
Gardens	108.45	0.31	99.9	0.286659
Rocky outcrop	19,499	55.95	19070.73	54.72278
Total	**34849.71**	**100**	34849.71	100

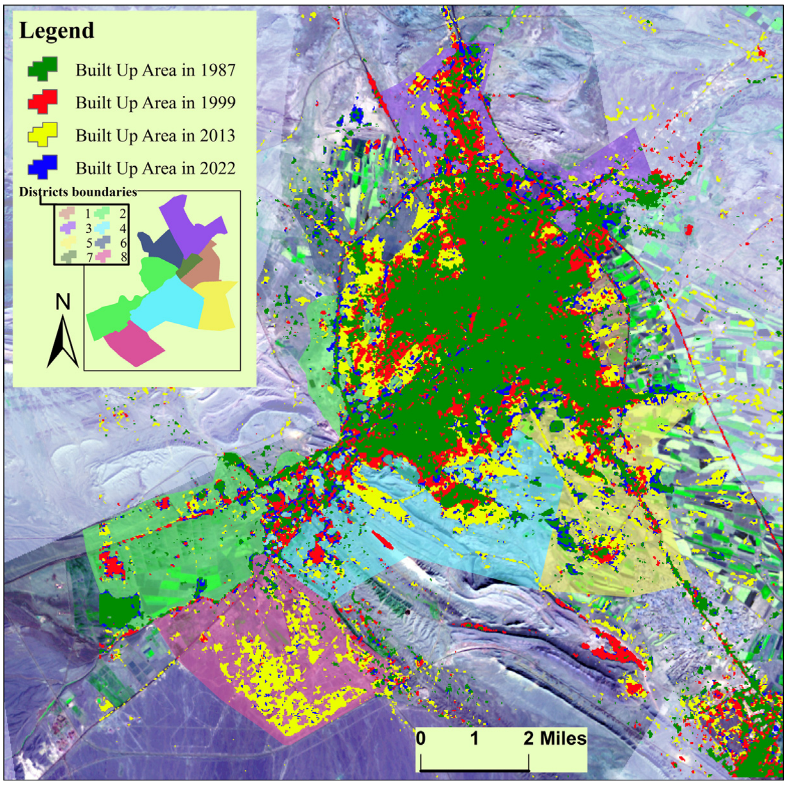

Figure 7 Spatial expansion of Qom in 1986, 1999, 2013 and prediction by 2022.

Table 13 Estimation of LULC conversion by class for 2022.

LULC changes	2013–2022	
	Area (ha)	Area (%)
Agricultural land to Built up area	438.03	39.34
Gardens to Built up area	17.01	1.53
Rocky outcrop to Built up area	20.16	1.81
Wastelands to Built up area	638.37	57.33
Total	1113.57	100

be added to the built up area and 638.37 ha wasteland, 438.03 ha of agriculture land, and 17 ha of gardens are expected to be converted to built up area (Fig. 7).

4. Conclusion

One of the inevitable outcomes from the rapid pace of urbanization, particularly in the developing countries, is the growth of size and number of cities and results in LULC change. Mapping and monitoring of this outcome, note only produced crucial information for policymakers and planners but also help identify areas where ecological systems are threatened and result in eco-friendly urban policies and forms. Accordingly, this paper was analyzed LULC change and was predicted the urban spatial expansion using CA-Markov Model in Qom city over the time period of 26 years. It also measures the urban sprawl using Shannon's entropy and is based on primary spatial forms of urban sprawl. To our knowledge, measuring urban sprawl based on its spatial forms would contribute to prioritizing policies and specific regulations in dealing with this dominant form. The land cover change analysis revealed that the built up area has shown a constant increase and finally it doubled over the last three decades (from 1987 to 2013). Wasteland and gardens have increased in the first decade whereas decreased in the second decade. Agriculture land and rocky outcrop have decreased constantly. The obtained Shannon's entropy values indicated that spatial expansion of Qom city is sprawling and at the time of 1987 the city was more compact compared to 1999 and 2013. Analyzing the sprawl forms indicated that the continuous linear development is the dominant form of sprawl in Qom city and accounts for more than 1790 ha land development spread over the urban fringes. This form has led to the loss of more than 795 ha agriculture land, 7.65 ha gardens, and 69 ha wastelands, from 1986 to 2013. The CA-Markov model estimated that this unsustainable trend will continue in the future and built-up areas will increase by 10% by 2022. It is expected that 638.37 ha wasteland, 438.03 ha of agriculture land, and 17 ha of gardens will be converted to built up area. Those results represent greater importance of appropriate policies and regulations for limiting linear sprawl along the main roads in Qom city.

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