MEASURING LAND USE CHANGES AND QUANTIFYING URBAN EXPANSION USING REMOTE SENSING AND GIS TECHNIQUES - A CASE STUDY OF QOM

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ABSTRACT:

Rapid urban sprawl necessitates solid urban planning tactics, which requires assessing and quantifying the sustainable or unsustainable encroachment of urban settings towards the urban periphery. Like many cities in developing countries, Iranian cities have witnessed tremendous changes in recent decades. The process of urbanization following economic and social developments has caused the intractable and unrestrained growth of cities with a national and regional role. Remote sensing and geospatial information system technology give urban planners the appropriate and pertinent information they need to guarantee the sustainable management of urban environments. This study explored the changes in Qom metropolis, Iran during four time periods, from 1985, 2000, 2010, and 2021, and assessed how the city expanded using Shannon's entropy model and the Urban Expansion Intensity Index. In this study, Landsat satellite images from the selected years were employed, and three land use/land cover classification types, including agricultural, built-up, and others, were derived using the maximum likelihood classification approach. The relative Shannon's entropy result for the study years (1985, 2000, 2010, and 2021) are 0.66, 0.68, 0.69, and 0.86 respectively, which demonstrate a dispersed expansion pattern, with the maximum value in 2021. Also, the Urban Expansion Intensity Index, with the values 0.33, 0.33, and 0.51 for three periods (1985-2000, 2000-2010, 2010-2021), indicates that the city's expansion rate was low-speed throughout the chosen periods, despite having reached its peak between 2010 and 2021.

1. INTRODUCTION

In the last few decades, cities have expanded rapidly due to increasing birth rates, population growth, and mass migration, so that the increase in urbanization and urban population, which is one of the most important aspects of global change, is a reality (Xu et al., 2007). Global economic growth is accelerating urbanization in many regions of the world, which is physically changing the face of the planet. Metropolitan areas have expanded substantially throughout each developing country as a result of population increase and industrial development (Al-Sharif and Pradhan, 2016; Metzger et al., 2016). The degree of suburban growth and urban sprawl is used to assess how quickly cities are expanding (Sajjad, 2014). Undoubtedly, it has contributed to significant changes in land use on a local to global scale and served as a precursor to broadening urban expansion and development (Yu and Ng, 2007). In this regard, various studies show that the world's urban population will grow by more than 2 billion by 2030, of which about 94% of this growth will occur in less developed countries (Millennium, 2005). Consequently, the uncontrolled growth and increase of migration to cities, leads to intractable development of urban areas, creation of new settlements, reduction of human welfare (Ortega-Álvarez and Macgregor-Fors, 2011), unplanned constructions, unmanageable expansion, the tendency to suburbanization, urban sprawl, as well as many problems for various urban managers, especially in developing countries (García-Palomares, 2010).

Today, the aforementioned problems, combined with urban stagnation, have drawn urban planners' attention and formed the foundation for significant research by geographers, urban planners, and decision-makers (Al-Ahmadi et al., 2009). Different approaches were needed to identify the underlying causes of urban sprawl since they varied across developed and developing countries (Sinha, 2018). On the other hand, in order to create urban and regional plans, managers and decision-makers are required to obtain decisive information about the extent of urban sprawl and the variables that affect the sprawling impact (Pradhan, 2017; Rosni and Noor, 2016). Urban sprawl in land use planning is mostly assessed through mapping and measurement. The determination of urban sprawl is challenged by ambiguous definitions and a wide range of attributes (Hoffhine Wilson et al., 2003). Therefore, urban growth policy is a very significant and serious obligation, as it must both address the issues of urban sprawl and avoid the creation of anomalies, particularly in the physical dimensions of space, by carefully regulating the construction process (Rafiee et al., 2009). Therefore, it has become vital in this study to pay attention to urban concerns, particularly its

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physical issues, in the form of a scientific framework (Al-Shalabi et al., 2013; Ramachandra et al., 2013). The metropolis of Qom, one of the most prominent cities in Iran, was chosen to research as a case study.

Urban sprawl, which is considered as low-density areas that lack spatial planning and coherence and expand away from the city center as the population of the city grows, has become a defining attribute of the cities in developing countries (Ewing, 2008). Some scholars suggest employing sprawl metrics to track and study urban sprawl, while others highlight the use of geospatial methods like Remote Sensing and Geospatial information systems (GIS) in addition to statistical methods (Yang et al., 2018). When it comes to tracking, mapping, and evaluating urban sprawl as well as creating Land-Use/Land-Cover Change (LULCC) maps, the use of GIS and Remote Sensing (RS) techniques have shown to be effective. GIS and RS technologies are being utilized together in a more efficient approach to bring spatial data to urban expansion investigation. Research on urban sprawl using maps of LULCC frequently uses RS and GIS technologies. The transition from permeable to impervious surfaces with urban growth is one of the variables that LULCC maps illustrate and measure. The technologies that play a significant role in gathering, displaying, and measuring spatial data on urban sprawl in order to evaluate the environmental effects have been made available by RS and GIS (Urbaniak, 2007). These technologies have enabled the development of tracking, analyzing, and modeling for the prediction of urban growth dynamics and land use changes all over the world (Al-Shalabi et al., 2013; Taubenböck et al., 2009; Ramachandra et al., 2013).

Various efforts have been taken to simulate urban expansion and study urban spatial patterns using a variety of techniques, including artificial neural networks (Pijanowski et al., 2005; Maithani, 2009), geographical weighted regression (Mondal et al., 2015), cellular automata (Li et al., 2014; Ke et al., 2016; Mondal et al., 2017), and Markov chain (Mondal et al., 2017), etc. The proper quantification and statistical recapitulation, such as Shannon entropy, patchiness, landscape metrics, regression analysis, etc., are necessary to characterize urban sprawl (Rabbani et al., 2018). It is possible to study any geographic measures using Shannon's entropy, which serves as an index of spatial compactness or dispersion. This metric is used to scientifically quantify the patterns of urban sprawl (Cegielska et al., 2019). It can also determine the extent of urban growth by looking at how densely or sparsely the land has been developed (Biney and Boakye, 2021). The purpose of this study is to demonstrate how RS, GIS, Shannon's entropy, and the Urban Expansion Intensity Index (UEII) could be used in concert to solve fundamental environmental challenges in developing nations at the local level. According to the aforementioned variables, the research goals can be encapsulated as follows:

- Trend analysis on land use and land cover using Shannon's entropy model
- Creating Land-Use/Land-Cover Change maps to monitor where the land cover types are changing and how much these changes are
- Measuring the Urban Expansion Intensity Index to assess the pace or intensity of changes in urban land use over specific periods

1.1 Study area

Qom is the seventh largest metropolis in Iran. The city of Qom serves as the administrative center for the province of Qom and is situated at 34°38′N and 50°52′E, 140 kilometers (87 mi) south of Tehran, the capital of Iran. Qom Province covers a total area of 11238 km^2 and has a population of 1,292,283 as per the 2016 Census which makes a population density of 115 per km^2 93 percent of the population reside in Qom city (Statistical Centre of Iran, 2016). The metropolis of Qom is one of the most important cities in Iran, which is considered one of the most influential cities in the Islamic world due to its proximity to Tehran and its strong religious-historical functions. This city is the largest base for Shi'a education in the whole world and is known as one of the main bases for the development of Islamic, economic and scientific values at the level of the country and the world. It has received a huge flood of immigrants on a national and international scale after the victory of the Islamic Revolution in Iran. Around 20 million visitors go to the city annually, most of whom are Iranians but also other Shi'a Muslims from all across the globe. As a metropolis, it is assumed that Qom city has gone through its stages of growth and expansion much faster than the natural rhythm. In recent years, its size and population have increased rapidly. Figure 1 shows Qom province and the study area.

2. MATERIALS AND METHODS

2.1 Data Collection

The study makes use of a collection of Landsat satellite images (thematic mapper [TM] and enhanced thematic mapper [ETM+]), which were collected in 1985, 2000, 2010, and 2021. To increase transparency, the images from the United States Geological Survey (USGS) website, provided in Table 1, were given a cloud cover threshold of less than 8 percent. Path and row scene 164/36 (images from 1985, 2000, and 2021) and 165/36 (image from 2010) and a resolution of 30m were the specifications for all Landsat images. The data were projected to the Zone 39 North coordinate system of the UTM (Universal Transverse Mercator).

Mission	Sensor	Date Acquired	Path/Row	Resolution
Landsat 5	TM	1985-04-12	164/36	30 m
Landsat 7	ETM +	2000-05-15	164/36	30 m
Landsat 5	TM	2010-05-26	165/36	30 m
Landsat 8	OLI TIRS	2021-04-15	164/36	30 m

Table 1. Details of satellite data used in the study

2.2 Pre-processing

To accurately obtain quantitative data from Landsat, atmospheric correction is a crucial step (Liang et al., 2001). Using Radiometric Calibration and Flaash Atmospheric Correction tools in ENVI 5.3 software, the atmospheric correction was applied to Landsat images.

2.3 Land Use Classification and Accuracy Assessment

Pixels of input images were categorized into types of land use/land cover using supervised classification. The writings of

Belal and Moghanm (2011), and Hegazy and Kaloop (2015) provided insight into the utilization of these land cover types (Belal and Moghanm, 2011; Hegazy and Kaloop, 2015). Belal and Moghanm employed three types of land cover—urban, agricultural, and water—to identify urban expansion in Al Gharbiya, Egypt (Belal and Moghanm, 2011). Hegazy and Kaloop, on the other hand, hired agricultural, built-up barren land, and water to track urban expansion and discover land-use changes in Egypt's Daqahlia Governorate (Hegazy and Kaloop, 2015). Respectively, because Qom is an arid and dry region, it appeared appropriate to adopt land cover classifications such as urban (built-up), agricultural, and others (barren land, rocky outcrop) to identify urban expansion. ArcMap was used to accomplish the image classification method.

The ArcMap spatial analyst extension includes capabilities for both supervised and unsupervised classification. The Maximum Likelihood classification method was performed for classification purposes. Maximum likelihood classification determines the prospect that a particular pixel fits a certain class by assuming that the statistics for each class in each band are evently dispersed.

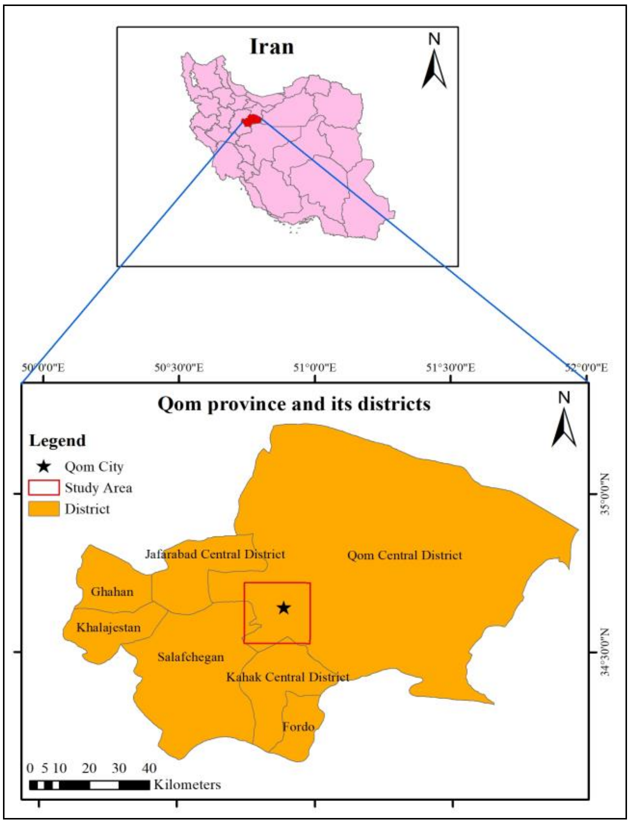

Figure 1. Map of the study area

The categorization of unidentified pixels in supervised classification is done by leveraging examples of known land use/land cover classes. Training the classification algorithm is employed by supervised image classification to spot related patterns in the image during the classification procedure. A supervised classification was conducted in this research in 1985, 2000, 2010, and 2021. These epochs were used because the research region saw significant LULCC over the years of evaluation. To better understand changes over time, it was crucial to classify the data that were discovered in the Qom metropolitan. The decision to employ supervised classification was made so that the researcher could independently assign the proper classifications to each of the pixels in the investigation. Maximum likelihood classifications were performed on the images once the sites had been trained. The supervised image classification yielded three classes for this experiment (built-up area, agricultural land, and others).

It is critical for the analysis of change detection to evaluate the reliability of the outcomes obtained after categorization using satellite images (Othow et al., 2017). The degree of confidence between the classified images and the reference data is reflected in the accuracy evaluation, which indicates how precisely the classified image corresponds with the reference data (Mosammam et al., 2017). To establish the quality of classification results, an accuracy assessment was conducted on classified images from 1985, 2000, 2010, and 2021. For this work, the classification accuracy was assessed using independent sample points taken from reference data. The accuracy assessment was conducted by using random points that were taken from the Google Earth images. As a first step in boosting the study's validity, an overall accuracy and kappa coefficient were calculated. The Kappa coefficient is used to determine how well the categorised image matches the real-world context. Table 2 depicts the accuracy assessment on the classified images. The outcomes showed that the categorized image's overall accuracy in 2021 is 89.1 percent. Additionally, it was discovered that the Kappa coefficient for 2021 was 83.7 percent. The classified images from 1985, 2000, and 2010 also underwent similar calculations.

2.4 Shannon Entropy

Entropy is a term that Shannon introduced in 1948 as a means to quantify randomness and disarray. Shannon's entropy is widely adopted by scholars in measuring urban sprawl statistics for describing the degree of dispersion or geographic compactness of a certain characteristic in a given region (Cabral et al., 2013). Incorporating ArcGIS software allows the entropy model to analyze the dispersion of geographical phenomena by featuring the configuration and direction of spatial patterns and indicators (Yeh and Li, 2001). The combination of GIS and remote sensing technology enables the entropy concept to be efficiently applied in the computation of urban sprawl. In order to compute the concentration and dispersion of urban sprawl, the area must be divided into 'n' geographical zones. The Shannon's entropy value ranges between 0 and Log(n). A number near zero suggests concentrated urban expansion (higher concentration), whereas a value near Log(n) implies that the urban sprawl is highly dispersed. Hence, Shannon's entropy and GIS technologies were used to calculate urban sprawl from 1985 to 2021. Equation (1) is used to determine Shannon's entropy (Yeh and Li, 2001):

$$H_n = \sum_{i}^{n} P_i \log\left(\frac{1}{P_i}\right) \qquad (1)$$

Where n is the total number of zones, and P_i is the prospect or portion of the variable happening in the i^{th} zone. We have applied relative entropy to make the entropy value range

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between 0 and 1. Equation (2) is used to compute the relative entropy (Thomas, 1981):

$$H_n = \frac{\sum_i^n P_i \log\left(\frac{1}{P_i}\right)}{\log_e(n)} \tag{2}$$

In order to apply the entropy model, the land use/land cover maps were reclassified into two classes. Afterward, with the help of the municipality's center, 8 concentric buffer zones of 2000 m were generated to determine the concentration of built-up areas in each zone.

Year	User's accuracy (%)			Producer's accuracy (%)			Overall accuracy (%)	Kappa coefficient (%)
	Built-up	Agricultural	Others	Built-up	Agricultural	Others		
1985	98.4	93..4	87.2	83.3	94	100	92.4	88.7
2000	100	100	78.1	81.3	90.7	100	90.7	86
2010	88.7	94.2	80	84	86.7	90.7	87.1	80.7
2021	87.7	95.1	85.2	85.3	90	92	89.1	83.7

Table 2. Accuracy assessment on the classified images

2.5 Urban Expansion Intensity Index

The urban spatial expansion difference is evaluated quantitatively using the Urban Expansion Intensity Index (UEII). Moreover, UEII can also be used to assess the pace or intensity of changes in urban land use over a specific period and identify the inclinations of urban expansion. The calculation for UEII is shown in equation (3) (He et al., 2000; Hu et al., 2007).

$$UEII_{it} = \frac{\left[\frac{ULA_{i,b} - ULA_{i,a}}{t}\right]}{TLA_i \times 100} \tag{3}$$

Where: $UEII_{it}$ is the annual average urban expansion intensity index of the (i^{th}) zone in period (t) $ULA_{i,a}$ and $ULA_{i,b}$ are the amount of built-up area during time spans a and b in the (i^{th}) spatial zone, respectively. TLA_i is the total area of the (i^{th}) spatial zone (Pradhan, 2017). The UEII has been classified into several classes, as shown in Table 3 (Ren et al., 2013):

UEII	Speed
>1.92	high-speed development
1.05–1.92	fast development
0.59–1.05	medium-speed development
0.28–0.59	low-speed development
0–0.28	slow development

Table 3. The division standard of UEII

3. RESULT

To investigate the type and trend of urban sprawl, land use/land cover maps from 1985, 2000, 2010, and 2021 were classified as built-up, agricultural, and others as shown in Figure 2. It has been noted that between 1985 and 2021, there was a rise in built-up areas, which are mostly found in the study area's southwestern and south-eastern regions (due to the government's Affordable Housing Plan in these areas). The analysis revealed significant changes in land uses, with an average yearly increase in built-up areas over 36 years (over 1985 to 2021). However, the amount of agricultural land consistently decreased from 1985 to 2021. The main driver of the growth in settlement and built-up was recognized as an increase in urban population and the demand for housing, industry, and commerce that accompanied it. This supports the assumption that human activities have a significant impact on the surface of the planet.

Measuring urban sprawl helps in the development of laws and policies to address the prevailing form. The results of relative and Shannon's entropy are shown in Table 4. Shannon's Entropy spatial-based algorithm yields 0.66, 0.68, 0.69, and 0.86, respectively, for the LULC maps from 1985, 2000, 2010, and 2021. Relative entropy values over the study period revealed a faintly increasing rate in the first three years of the study period, indicating that the study area developed gently toward dispersion. The findings indicate that the built-up area in the district was rather dispersed in the first three years of the study period and this dispersion has evolved to greater degrees in 2021.

Year	Built-up area (km^2)	Value of Shannon's entropy	Value of relative Shannon's entropy
1985	50.84	1.38	0.66
2000	73.94	1.41	0.68
2010	89.45	1.44	0.69
2021	115.93	1.79	0.86
Log(8)		2.08	1

Table 4. Values of relative and Shannon's entropy

The capability for urban expansion is shown by the UEII, which is defined as the average annual growth area normalized by the total area of a geographical unit (Hu et al., 2007). Table 5 shows the result of UEII metric. The findings indicate that Qom city has experienced low-speed development in the study period, though the UEII value in the third term (2010-2021) has undergone a distinct increase which conforms to the highest value of Shannon's entropy in the final year.

Period	UEII	Agreement
1985–2000	0.33	low-speed development
2000–2010	0.33	low-speed development
2010–2021	0.51	low-speed development

Table 5. Values of the Urban Expansion Intensity Index

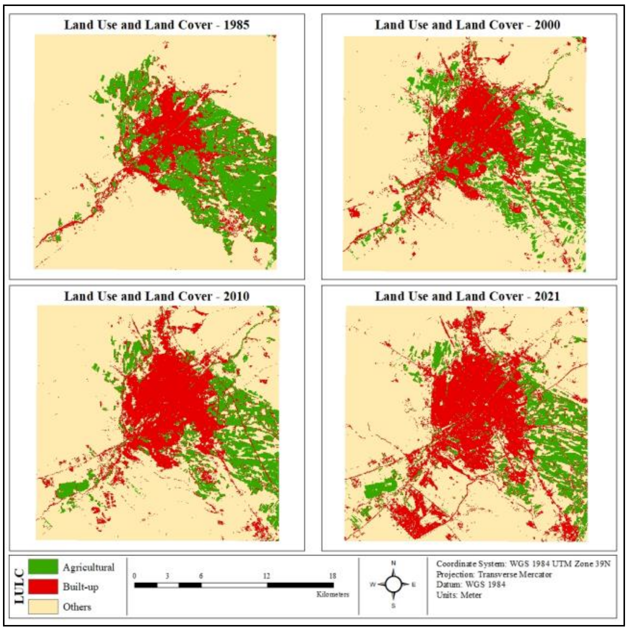

Figure 2. Land use land cover in Qom, Iran from 1985 to 2021

Moreover, land use change can be measured and shown using Land Change Modeler tool in IDRISI software. Figure 3 shows the land use change in Qom city from 1985 to 2021. As such, Table 6 depicts the result of land use change in Qom. The result indicates that 26.7 km^2 of agricultural lands and 49.8 km^2 of other lands have changed to built-up lands from 1985 to 2021. Also, in the same period, 26.1 km^2 of agricultural land has changed to other lands.

Land Use Change	Area (km^2)
Agricultural to Built-up	26.7113
Agricultural to Others	26.1
No Change	354.224
Others to Agricultural	14.7628
Others to Built-up	49.8517

Table 6. Land use Change in Qom, Iran from 1985 to 2021

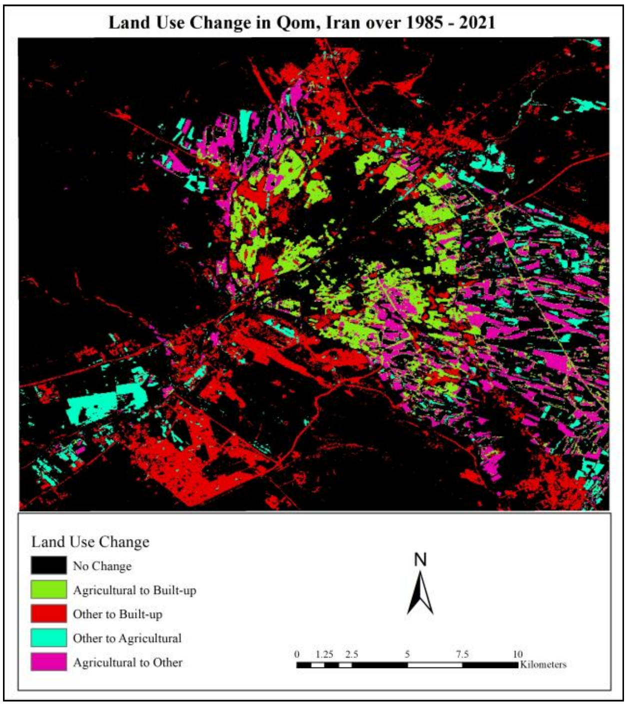

Figure 3. Land Use Change in Qom, Iran from 1985 to 2021

4. CONCLUSION

This study quantified and examined urban development and urban expansion concentrations in Qom metropolis, Iran through the exploitation of Landsat image collections from 1985, 2000, 2010, and 2021. In order to determine if urban expansion in the city is sustainable, statistical models were also used to assess the quality of the expansion. This research primarily uses remote sensing and GIS tools to evaluate urban growth and land-use changes in Qom city. Two different types of metrics—Shannon's entropy model and the Urban Expansion Intensity Index—are used to monitor urban growth and the developing patterns in the city. The use of landscape metrics as a framework to characterize urban structures has shown to be effective. As a result, decision-makers could receive quantitative spatiotemporal information from spatial indicators to assist them in pacing the impact of human alteration on the environment. According to the analysis of land use change, the built-up area has increased steadily, and eventually, it has expanded by more than 128 percent throughout the study period (over 1985 to 2021). Likewise, the amount of agricultural land has constantly diminished. The results of Shannon's entropy analysis revealed that the Qom metropolis is dispersing spatially and the magnitude of dispersion has also increased over the study period (1985–

2021), as the relative entropy value has reached 0.861 in 2021. Moreover, The UEII's findings show that Qom city has experienced low-speed development in the study period, though the UEII value in the third term (2010-2021) has undergone a distinct increase which conforms to the highest value of Shannon's entropy in the final year.

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