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RESEARCH

Measuring the extent and impact of urban expansion in an agricultural-urbanized landscape in Central Iran

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Abstract The unplanned urban expansion is a major environmental challenge in Iran resulting in vast degradation of agricultural lands. Focusing on an agricultural-urbanized landscape in Central Iran, the spatial pattern of built-up expansion was assessed from Landsat data processed in 1992 (TM), 2002 (ETM+), 2012 (TM), and 2022 (OLI). Multi-year crop NDVI was also used as a proxy for cropland suitability to assess the intensity of the urban growth impact. Results showed that (1) the area of built-up surfaces increased almost up to double than that of 1992 and passed 36% (413.42 km^2) by 2022, (2) the region experienced a coalescence-diffusion transition phase with decreasing spatial connectivity of newly developed patches with old ones, (3) the most suitable croplands were lost in the middle period (2002–2012) when urban patches started to diffuse, and (4) a significantly positive spatial (Spearman's) relationship (r (22100) = 0.181, p = 0.000) was found between the area and quality of croplands which further highlights the high importance of cropland protection in the region.

Keywords Landsat · Urban transition phase · Crop NDVI · Central Iran

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Introduction

Due to the progressing globalization process, nearly more than 50% of the world's population is now dwelling in urban and the underlying urbanization (also known as urban expansion (Akubia & Bruns, 2019)) is projected to continue increasing in the coming decades (DESA, 2018). This process has triggered a pervasive urban expansion megatrend in the twenty-first century (Nowosad et al., 2019) and caused tremendous adverse impacts on biodiversity (Huang et al., 2018), land resources (Radwan et al., 2019), and ecosystem functioning (Xie et al., 2018). Agricultural land loss is among the most evident consequence of this contemporaneous phenomenon which indicates a paradoxical competition between agriculture and urban development (Martellozzo et al., 2018). In some parts of the world, this competition resulted in the degradation of high-quality farmlands (Huang et al., 2020; Radwan et al., 2019) which is more evident in arid and semi-arid areas

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where residential areas have been historically land resource-dependent and have grown in the center of the most suitable agricultural lands to have access to limited freshwater resources for both municipal and agricultural activities (Al-Quraishi & Negm, 2020). In agrarian economies, particularly, the urbanization-related farmland loss also imposed substantial effects on the livelihood of agriculture-dependent communities (Bonye et al., 2021).

Agricultural activities are the main source of livelihood in Central Iran where it has been experiencing a significant urban expansion and the consequent loss of agricultural lands over the past four decades (Soffianian & Madanian, 2015). The rapid-paced population growth and increasing urbanization in Iran coincided with the post-Islamic Revolution, during which land use planning such as urban growth management, urban site selection, and allocation received minimal practical attention (Makhdoom, 2005). As a consequence, mid-sized towns located within highly productive arid agricultural lands have grown unprecedentedly at the sole expense of agricultural areas (Martellozzo et al., 2018; Rimal et al., 2018). Until today, the extent and impact of such land surface modifications have been unknown due to the scale and dynamicity of the urban growth process.

Thanks to the advancement of satellite remote sensing (RS) and GIS techniques, it is now routinely possible to assess LULC change and urban expansion at various spatial and temporal scales. The majority of studies in this field adopted a post-image classification procedure in which time-series images are classified into a certain number of LULC classes, thus measuring the area converted from a particular LULC class to another one (Hawash et al., 2021; Zubair et al., 2019). In Central Iran, for example, Soffianian and Madanian (2015) performed a post-classification Landsat-based change detection, showing that Isfahan Province underwent an extensive unplanned urban expansion and agricultural land conversion from 1975 to 2010. In Iran, Ahmadi Nadoushan (2022) studied urban planning in arid agricultural-urbanized landscapes of Iran. Two scenarios of business as usual (BAU) and agricultural land protection (ALP) were simulated using the SLEUTH model and compared statistically to provide relevant urban planning insights. In China, Hou et al. (2021) not only showed the threat of farmland-to-urban conversion but also used the post-classification results to quantify the spatiotemporal trajectories of farmland abandonment and recultivation, indicating that the impacts of the process are beyond the simple change detection scope. In this case, a wealth of studies have accentuated the importance of ancillary data to undertake this task. Asgarian et al. (2018) used an agricultural suitability layer to determine the quality of farmlands converted to urban areas in Isfahan, Central Iran. Chen et al. (2021) also showed that spatial connectivity and the quality of farmlands are important criteria to measure the threat of agricultural land loss.

Landscape ecology plays a significant role in the determination of the processes operating between different LULC types (habitats) by means of landscape metrics (Yu et al., 2019). Landscape metrics are now included in all studies dealing with spatial analysis. Particularly, they have been employed extensively to measure the pattern of urban physical growth and LULC conversion (Akın & Erdoğan, 2020; Das & Angadi, 2021). Together with the measurement of structural changes, pre-classification image techniques are used to measure the impacts of LULC conversion, mostly using spectral-band ratio indices. In vegetation covers, for example, the normalized difference vegetation index (NDVI) represents vegetation abundance, and its temporal variation is used as a proxy for the intensity of changes. In agricultural landscapes, it displayed a high potential for crop growth monitoring, farmland management, and crop production prediction. For example, Wang et al. (2019) found that seasonal and annual crop NDVI is associated with variations in precipitation, temperature, and sunshine such that the crop NDVI increases with the suitability of climatic variables. Mao et al. (2021) showed that the NDVI-based crop growth is positively correlated with soil moisture and air relative humidity. The use of these indices can be considered as a promising solution for calculating the intensity and magnitude of land use changes which, in many cases, cannot be properly estimated by measuring the rate of area conversion between different land use classes. This view is particularly important in areas with high spatial variabilities of land resources where different patterns of land use allocation might result in different impacts on the region's land resources. In the present research, the significant spatial disparity in the quality of agricultural lands formed the basis of spatial analysis to measure the land use change from the perspective of both the quality and quantity of the converted agricultural lands.

Focusing on an urbanized-agricultural arid landscape in western Isfahan City at the beginning of the Zayandeh-rood River mid-stream zone in Central Iran, this study used Landsat images to investigate rapid urban expansion and agricultural conversion over the past three decades. Urban areas were delineated using image classification and analyzed in terms of the area and spatial pattern to assess the extent of urban expansion. The Landsat 10-year NDVI layers were also utilized as a proxy for agricultural land quality due to the absence and negligible content of other vegetation covers. Therefore, urban expansion was analyzed in terms of the extent (area of change) and impact (high-quality cropland loss). Finally, a comparison was made to assess the association between the spatial distribution of the extent and impact of urban expansion in the study region.

Material and methods

Study area

This study was carried out in an agricultural-urbanized landscape located at the beginning of the Zayandeh-rood mid-stream zone in Gavkhooni Basin in Central Iran (between 51.267° to 51.880° Eastern longitude and 32.459° to 32.781° Northern latitude) (Fig. 1). It has a high spatial variability in the quality of soil and water allocation as well as built-up distribution which candidates it for urban growth change detection in terms of its effect on quality and extent of cropland loss. The region covers an area of 1146.63 km^2 and is located at the intersection of four Isfahanian Townships. According to National Census data (Statistical Centre of Iran, 2015), more than 4.5 million people live in more than 22 major cities (area of 300 ha<). Isfahan, the third most populous urban area following Tehran and Mashhad (Karbalaei Saleh et al., 2021), is located on the eastern side of the region. The main north-to-south transport road of Isfahan Province passes through the region. Moreover, the Zayandeh-rood River with an approximate length of 38.6 km flows within the region and south of Isfahan City, providing fresh water for municipal, agricultural, and industrial activities. Due to extensive industrial development and population growth, Isfahan Province (particularly including the study area) experienced one of the fastest and greatest urban expansions in Iran, equaling more than 7 times during a period of 35 years (from 1975 to 2010) (Soffianian & Madanian, 2015). The region is characterized by an arid and semi-arid climate. The long-term precipitation and mean annual temperature of the region are approximately 110 mm and 21° C (Asgarian et al., 2018).

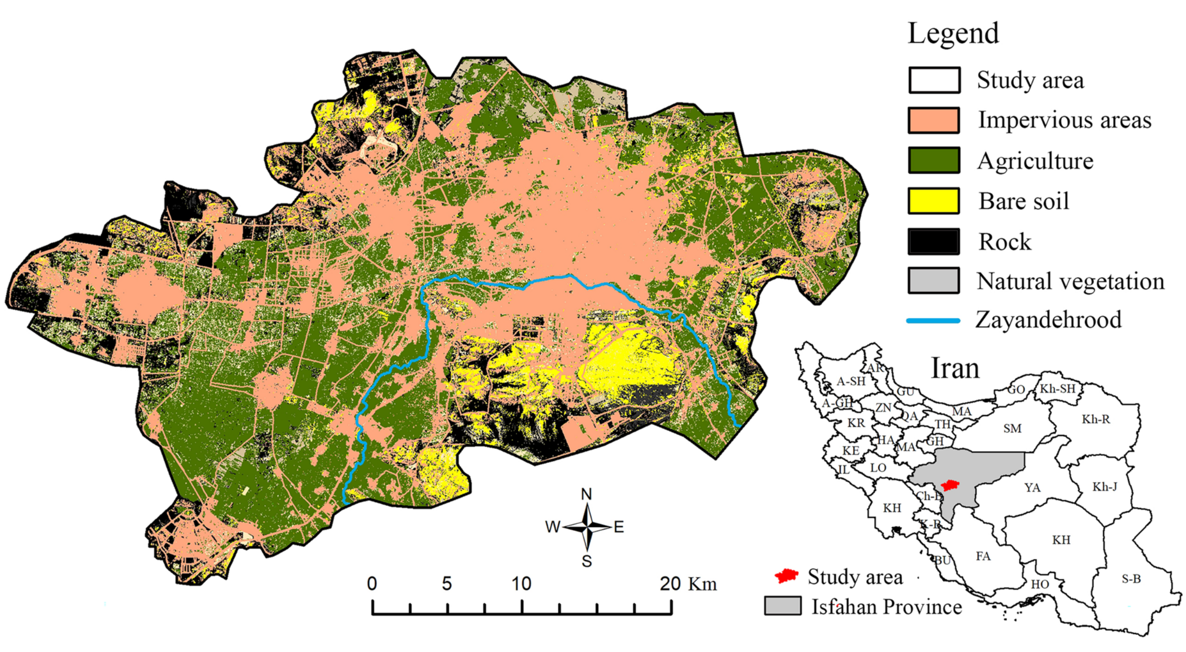


Fig. 1 Location of the study region; Western Isfahan in Gavkhooni Basin, Central Iran

Methods

Image classification

Built-up areas were extracted from different Landsat images in 1992, 2002, 2012, and 2022. The 1992 and 2012 images were obtained from Landsat 5-TM (Thematic Mapper). The 2002 and 2022 built-up areas were extracted from Landsat 7 ETM+(Enhanced Thematic Mapper Plus) and Landsat 8 OLI (Operational Land Imager) images (Table 1). All images were calibrated radiometrically and atmospherically to obtain their top-of-atmosphere (TOA) reflectance.

Given the strong salt and pepper effect that occur during built-up extraction using the pixel-based Landsat classification in central Iran (Sarvestani et al., 2011) and according to the research objectives, the object-oriented image classification was utilized to distinguish between built-up and non-built-up areas. To do so, image segmentation was performed using a multi-resolution segmentation algorithm which controls the level of compactness, shape, scale (size of objects), and the weight of the bands incorporated in the segmentation process (Tonbul & Kavzoglu, 2017). The scale factor, as the most important criterion, indirectly determines the size of the segments. The compactness factor controls the smoothness of the segments' border and the shape factor determines their geometry. The best combination of the values of these factors was achieved through trial and error as adopted in previous studies (Bialas et al., 2019; Modica et al., 2020). Hence, having the best visually pleasing segments, the process of the segment classification into built-up and non-built-up classes was performed using visual interpretation.

Pattern analysis of built-up expansion

Built-up layers were overlaid successively to measure the expansions that occurred between the consecutive years. Landscape metrics as the most popular tools in spatial pattern analysis of LULC change were employed to assess how urban patches expanded horizontally during the study period. Different from the majority of the studies in this field, the selected landscape metrics were applied only to the newly grown patches grown in each period. The number of patch (NP) was utilized to calculate and compare the difference between the number of individual built-up patches produced in each period. Patch density (PD) was also used to measure changes in the distribution of the newly grown built-up patches across the landscape. The mean size of new patches and their mean Euclidean distance to other patches were also computed and compared using the mean patch size (MPS) and Euclidean nearest neighbor distance (ENN) metrics. These metrics were calculated using the landscape structure analysis program FRAGSTATS (McGarigal, 1995). Further information regarding the formula and calculation of these metrics is given in Table 2.

In addition to the landscape metrics (Table 2), the common edge (CE) metric was developed to measure the spatial connectedness of a new built-up patch to previous ones. To do so, all built-up layers were converted to the vector format in a GIS environment. Then, a 1-m buffer was calculated for the newly grown patches and intersected with the old ones. For each patch, the area of the buffer zone was divided by the intersected area. A ratio of 0 indicates that the newly grown patch has no spatial connection to previous ones, while a ratio of 1 shows that the patch is completely grown inside the previous built-up patches which is known as the infilling growth pattern (Rao et al., 2021). In this research, we divided the intersected area of the buffer zones by the total buffer area (the CE metric) to track the trend of the spatial connection between new and old patches over the study period.

Extent and impact analysis of urban expansion

Given that the region is primarily an agricultural landscape, the intensity of urban expansion was considered

Table 1 Details of Landsat images used to extract built-up areas

Satellite	Sensor	Acquisition date	Path/ Row	Spatial resolution	Cloud cover (%)
Landsat 5	TM	1992–06-26	164/ 37	≈ 30m	0
Landsat 7	ETM+	2002–05-05	164/ 37	≈ 30m	0
Landsat 5	TM	2012–06-17	164/ 37	≈ 30m	0
Landsat 8	OLI	2022–06-05	164/ 37	≈ 30m	0

Table 2 Equation and range of the landscape metrics used to assess the spatial patterns of newly-developed built-up patches

Metric	Formula	Remarks	Range
NP	n_i	n is total number of patches	NP ≥ 1
MPS	$\frac{1}{n_i}\sum_{j=1}^{n_i} a_{ij}$	n is total number of patches a_{ij} is area (m^2) of patch ij	PD ≥ 0
PD	$\sum_{j=1}^{n_i} P_{ij}/A(10000)$	P is patch perimeter (m) A is patch area (m^2)	MPS ≥ 0
ENN	$\sum_{j=1}^{n_i} h_{ij}/n_i$	Distance (m) from patch ij to nearest neighboring patch	MNN > 0

as the conversion of croplands with different levels of suitability (quality) to built-up areas. In other words, the conversion of high-quality croplands to urban areas was assumed to have a higher conversion impact. Among the different methods used to assess the cropland quality such as the utilization of cropland suitability layers (Asgarian et al., 2018; Sakieh et al., 2015) and spatial structure characteristics (Chen et al., 2021), we used the crop NDVI index to show cropland quality. In the region, croplands with low suitabilities (especially with significant irrigation water deficit) are used for the cultivation of low-density and low-vegetation crops such as wheat while rice and potato which have relatively high vegetation abundance are cultivated in high-quality units (Asgarian et al., 2016). Moreover, croplands with lower qualities usually experience more fallow periods and exhibit near-to-zero NDVI values. Hence, we calculate the NDVI of all cloud-free Landsat images from 1992 to 2022 in the Google Earth Engine platform (Mutanga & Kumar, 2019), averaged them by year to have mean annual NDVI layers and masked by the agricultural class to eliminate the effect of other green regions on the results. For 2002, 2012, and 2022, the last 10-year mean annual NDVI layers were averaged and the resulting layers were considered as the cropland quality layer.

We calculated the area and mean 10-year NDVI (hereafter mean NDVI) for each newly grown built-up patch. The normalization equation (Eq. 1) was used to convert area and mean NDVI values into normalized values where N is normalized values, X in the variable, and X_{max} and X_{min} are the maximum and minimum values of the variable. Finally, the correlation analysis was employed to determine the spatial dependency between different levels of the extent and impact of built-up expansion from 1990 to 2002. Figure 2 shows the key step employed in the present research.

$$N = \frac{(X - X_{\mathrm{min}})}{(X_{max} - X_{min})} \tag{1}$$

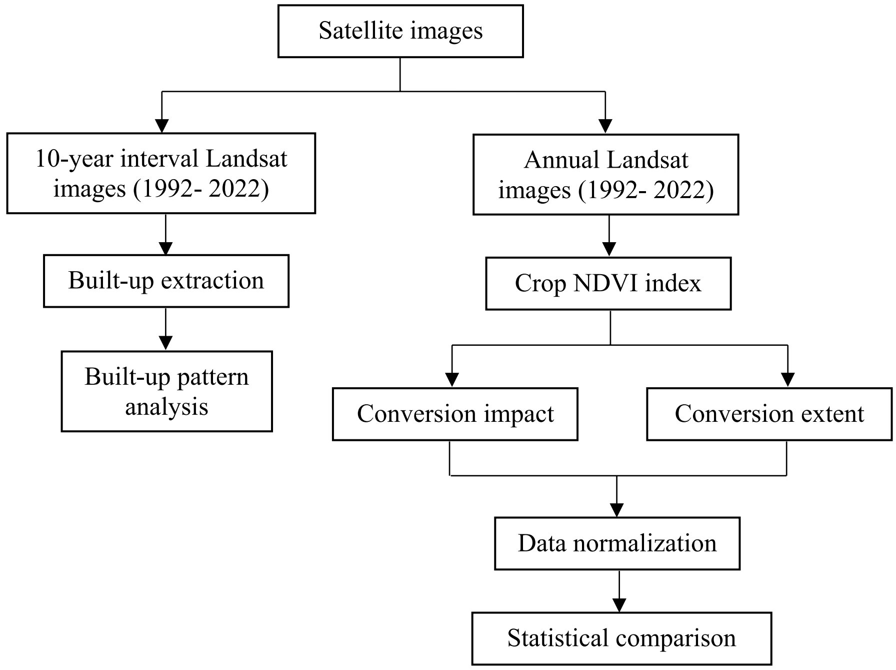
Results

Built-up areas were visually extracted from the spectral segments. Both shape and compactness factors were set to 0.5. The optimum Scale factor was 25 and all bands received equal weights. In 1992, 17.6% (201.42 km^2) of the region was occupied by built-up area which increased to 24.1% (276.96 km^2) and 30.6 (351.09 km^2) of the study area in 2002 and 2012, respectively (Table 3). In 2022, the area of built-up surfaces increased by almost double that of 1992 and passed 36% (413.42 km^2). The distribution of built-up growth is shown in Fig. 3. In 1992, the region was composed of a large urban center is the east with numerous small and mid-sized (between 100 and 300 ha) urban patches distributed unevenly across the landscape. Built-up expansions mostly occurred on the edge of old urban patches while detached growth was occasional in some parts of the west and south of the region.

Results of landscape metrics measured from newly grown urban patches are shown in Table 4. Accordingly, the number of new built-up patches decreased from 8608 to 5856 from 1992–2002 to 2012–2022. Contrarily, their density exhibited an increasing trend from 0.13 to 0.43, indicating that new urban patches tended to create spatial clusters with further expansion of built-up areas. The lowest ENN values were observed in 2012–2022 in which newly grown urban patches were located closer to each other than the two previous intervals. The mean size of built-up patches ranged from 0.74 (during 2012–2022) to 0.88 (2002–2012).

The average CE ratio measured for all new urban patches detected in 2002, 2012, and 2022 was 0.53 ± 0.64, 0.46 ± 0.49, and 0.31 ± 0.41, respectively (Table 4). The decreasing trend of the CE index indicates that the spatial connection of new patches

Fig. 2 Research flowchart



with old ones decreased over the past three decades and resulted in a fragmented landscape. The mean 10-year NDVI value of pixels occupied by built-up areas was lowest during 1992–2002 (0.14 ± 0.09) and highest during 2002–2012 (0.23 ± 0.11) (Table 4). Assuming that higher mean 10-year NDVI values show more suitable agricultural areas, the quality of agricultural lands converted to built-up areas during 2002–2012 was higher than the other time intervals.

Using Eq. 1, the area and mean NDVI values of all newly grown built-up patches from 1992 to 2022 were normalized and joined to their corresponding patches to visually observe the areas that experienced the highest increasing area and occupation of high-quality croplands. As shown in Fig. 4, the normalized area of new patches was low near the Isfahan City in the west and increased toward the southwest. The highest normalized area belonged to a new urban center (Foolad-Shar City) in the southwest of the region. The highest normalized mean NDVI values were distributed along the Zayandeh-rood River where the quality of croplands is relatively higher than other parts of the study region. According to the Kolmogorov–Smirnov test (Table 5), the normalized area and mean NDVI values had a non-normal distribution (Table 5). Using the Spearman's non-parametric correlation test, there is a highly significant spatial dependence between the areas that experienced large built-up expansion and conversion of highly suitable agricultural lands (r (22100) = 0.181, p = 0.000).

Table 3 Built-up area and the segment attributes measured in 1992, 2002, 2012, and 2022

Image year	Built-up class	
	Area (km^2)	% Area
1992	201.42	17.6
2002	276.96	24.1
2012	351.09	30.6
2022	413.42	36.1

Discussion

General remarks

Unplanned urban expansion has been a serious problem in Iran (Soffianian et al., 2013). The post-revolution (1975–onwards) national population strategies and the global urbanization trend resulted in unprecedented Iranian population growth and a vested interest in urban expansion. Accompanied by the poor implementation

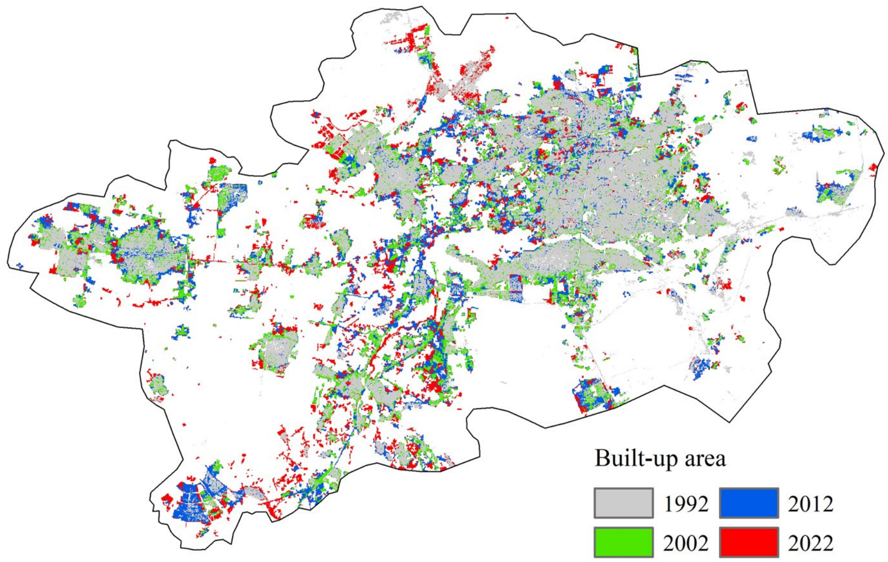


Fig. 3 Urban areas extracted from Landsat images in 1992, 2002, 2012, and 2022

of urban expansion plans and regulations, it created compact urban centers with highly dispersed peri-urban landscapes. This growth pattern was more evident in agricultural-urbanized landscapes which facilitated the low-density and patchy formation of urban areas (Asgarian et al., 2018; Dadashpoor et al., 2019). The availability of freshwater in the study area has allowed the growth of new urban patches independent from core built-up areas and created the most fragmented agricultural landscape all across the country (Asgarian et al., 2018). Over a period of 30 years (1992 to 2022), the region observed a two-time increase in built-up areas. Over a larger provincial scale, Soffianian and Madanian (2015) also found a seven-time increase in the area of impervious surfaces in Isfahan Province from 1975 to 2010. According to the results of this research and similar studies in Iran (Asgarian et al., 2018; Sakieh et al., 2015), the current process of built-up expansion continues to be pervasive and high-rated in the future which requires strict persuasion of urban allocation plans to protect the high-quality croplands and ensure the sustainable development of socio-economic parameters.

Spatial pattern, structural transition, and drivers of built-up expansion

According to the results, new urban patches grown between 1992 and 2022 experienced a coalescence-to-diffusion transition phase in which they gradually lost their dependency on previously grown large patches due mainly to decreasing CE ratio and increasing landscape patchiness. As discussed by Dadashpoor et al. (2019) in the Iranian contemporary urban condition and Li et al. (2021) and Sharma and Kumar (2022) in different social-economic but rapidly urbanizing landscapes, the most likely driver of these changes might be the increasing interest in urbanization and population changes which is in line with the Iranian population growth surge associated with the poor implementation of landscape and urban plans over the last 5 decades (Asgarian et al., 2018).

Table 4 Spatial metrics and mean 10-year NDVI measured from newly grown urban patches

Image year	Landscape metrics					Mean 10-year NDVI (Stdev.)
	MPS	ENN	PD	NP	Mean CE ratio (Stdev.)	
1992–2002	0.80	414	0.13	8608	0.53 (0.64)	0.14 (0.09)
2002–2012	0.88	581	0.22	7636	0.46 (0.49)	0.23 (0.11)
2012–2022	0.74	386	0.43	5856	0.31 (0.41)	0.20 (0.15)

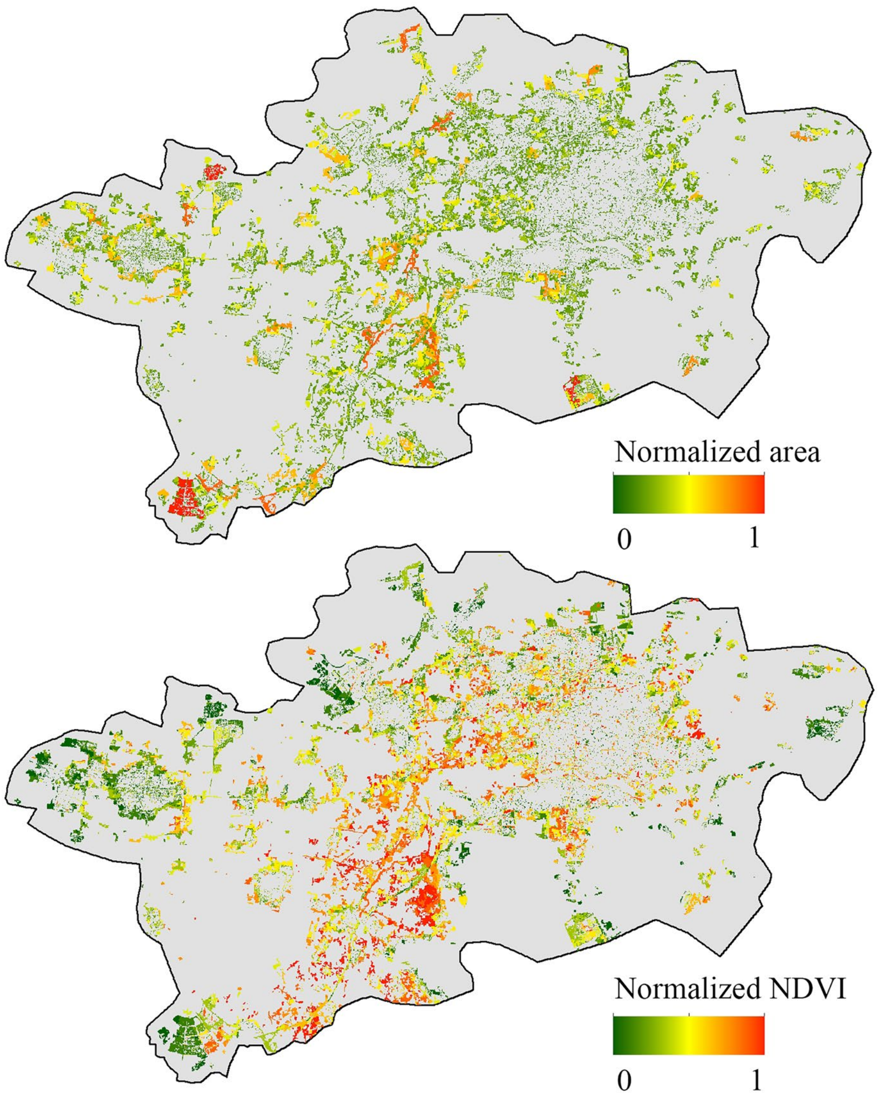


Fig. 4 Normalized area and mean 10-year NDVI measured for all newly grown built-up patches from 1992 to 2022

Coalescence growth

The high diversity of landscape metrics was found to help urban growth scholars to better understand the spatial effects of urban expansion on land use (Magidi & Ahmed, 2019) and land resource characteristics (Sakieh et al., 2015). In this research, landscape metrics were exclusively applied to newly grown urban patches to determine their spatial distribution across the landscape. During the initial period of urban expansion, the highest number of urban patches was produced with a relatively moderate mean size. The high CE ratio in this period indicates that urban patches tended to create a more compact

Table 5 Normality and statistical correlation between normalized area and NDVI

Variable	Df	Kolmogorov–Smirnov		Spearman test	
		Statistic	Sig.	Correlation	Sig. (2-tailed)
Normalized area	22100	0.39	0.00	0.181**	0.000
Normalized NDVI	22100	0.12	0.00		

**Correlation is significant at the 0.01 level and aggregated landscape. In other words, the initial period experienced a significant patchy urban expansion to fill vacant areas inside old urban patches such that more than 50% of the edge of newly developed patches in 2002 was common with the 1992 patches. According to Dietzel et al. (2005), the region experienced a coalescence phase in this period in which the growth enlarged previous urban patches through infilling and edge-expansion patterns. As discussed by Li et al. (2021), the infilling pattern of urban expansion would not be a major concern when they occupy vacant areas in large urban patches. The urban-inside croplands, which are prioritized for the infilling growth, are mostly managed traditionally, highly fragmented and suffer severely from water unavailability. However, with the disappearance of vacant areas, the urban tendency to grow further might result in a phase-shift to other (mostly degrading) growth patterns which was observed in this study area and other parts of the world (Dadashpoor et al., 2019; Nong et al., 2018). As shown in Fig. 2, this shift resulted in the growth of new outlying urban patches along the Zayandeh-rood River before entering Isfahan City where the most suitable agricultural lands are located (Asgarian et al., 2016).

Diffusive growth

During the last period, the number and mean size of urban patches decreased significantly in comparison to the two previous periods which shows decreasing speed of urban expansion and a visible shift to diffusion. The density of newly grown patches increased sharply to more than 0.43, indicating that they are forming new urban clusters in some parts of the study region. The results of the CE index also indicate the increased fragmentation and dispersion of built-up patches in the last period such that the CE ratio dropped by more than 41%. This type of urban expansion is referred to as the outlying pattern and is indicative of the diffusion phase which might be attributed to the decreasing rate of population growth and migration to the region to below 1.3 commenced from the beginning of the twenty-first century (Statistical Centre of Iran, 2015). The most important drivers of the infilling pattern are the unavailability of vacant areas outside the city (Wei et al., 2022) and the dominance of the urbanization trend due to socioeconomic attributes (Omurakunova et al., 2020). In most cases, the latter set of causes usually leads to a shift phase from coalescence to diffusion. It seems that accidental demographic and urbanization changes are responsible for a clear shift in the growth phase. Similar to our findings, Dadashpoor et al. (2019) also found a simultaneous pattern of urban growth in northern Iran due to the prevailing impacts of population growth across the entire Iran. Sharma and Kumar (2022) also attributed the urban growth pattern shift to rapid changes in the interest in urbanization and population changes. Hence, changes in the demographic and socio-economic characteristics should be viewed as an indicator of transition phases which are extremely difficult to be measured in data deficiet developing countries such as Iran. Therefore, continous monitoring of urban exapnsion and categorization of different growth types might play a leading role in its determination. Any changes in the growth rate of each pattern require an explicit consideration to prevent flawed growth of urban areas. Overall, the region observed a coalescence-diffusion transition phase during 1992–2022 in which new urban patches firstly started to fill vacant urban interior patches and enlarge the existing patches but shifted to a low-density and detached growth at the end of the study period.

Effect of urban expansion on agricultural lands

Magnitude and intensity of built-up expansion

Despite the magnitude of urban expansion and its fragmenting spatial pattern which might disturb the landscape connectivity and functionality, it is of utmost importance to know how land resources are affected by the development of each built-up patch irrespective of its size and spatial structure and configuration. In this research, the crop NDVI was used as a proxy for cropland quality. Using this assumption, results showed that built-up expansion in the first period took place on relatively low-quality croplands. The converted surfaces in this period were mostly urban interior vacant areas such as isolated open spaces or inactive croplands which exhibit low NDVI values. The most suitable croplands were lost in the middle period when the region started to diffuse during the coalescence-to-diffusion transition phase, occupying highly suitable lands along the river. The same trend of land resource loss (ecosystem degradation and fragmentation) through the coalescence-to-diffusion transition phase was also observed in rapidly growing metropolitan regions (Duvernoy et al., 2018; Pili et al., 2019), indicating that diffusive growth of independent urban patches has a non-negligible role in degradation and loss of natural and agricultural lands. Outlying urban patches are more willing to occupy the most environmentally suitable lands as they are inherently independent of other (large) patches. Moreover, the correlation analysis showed a significantly positive spatial dependency between the area and the quality of croplands. Accordingly, the suitability of land resources seems to fuel the physical growth of independent patches and further fragmentation and deterioration of the agricultural landscape. In future studies, the behavior of the outlying growth pattern should be further investigated to understand the tendency of detached urban patches to high-quality agricultural lands. If there is a tendency, further loss of highly suitable agricultural lands is likely in the future unless strong restrictions are put in place to prevent it. Accordingly, the outlying growth of urban patches on the most suitable agricultural lands along the river and during coalescence phases needs more urban planning and management attention. Our results highlight the high importance of cropland protection in the region, strict prevention of patchy and low-density built-up expansion, and identification of new urban centers on low-quality croplands to attract urbanization and slow down the process of edge-expansion in urban areas located within high-quality croplands. However, any conclusion and policy implication of these findings should be aware of the fact that built-up layers were selected over relatively long (decadal) horizons and each year was selected based on the availability of Landsat data. The conclusions made in this study can only be also possible under the uniform distribution of terrain factors which was confirmed by National Land Use Plans (Soffianian et al., 2013), which not only govern the expansion of built-up areas but also determine the suitability of agricultural lands such as the water allocation system.

Conclusion

This study showed that (1) a coalescence-to-diffusion transition phase occurred in urban expansion from 1992 to 2022, (2) during the coalescence phase, urban areas grew on relatively low-quality croplands near the existing urban centers, and (3) the diffusion pattern had a higher impact on agricultural fragmentation and degradation. Hence, to better protect the region's agricultural landscape, the dispersed growth of urban patches during the diffusion phase and over the most suitable agricultural lands should be strictly prevented. Changes in the CE ratio and conversion of high-NDVI agricultural areas were proposed as evaluation indicators of this process. Despite the effectivity of crop NDVI as a proxy for cropland quality, it is suggested to utilize more accurate data and methodologies to explore the suitability of agricultural lands such as multi-criteria evaluation techniques. Land use change models can also portray a probable picture of the landscape's future condition under different urban expansion scenarios to better inform policymakers regarding the outcome of their land allocation decision in the future.

Author contribution Mozhgan Ahmadi Nadoushan wrote the manuscript. Mozhgan Ahmadi Nadoushan, Alireza Soffianian, Sima Fakheran, and Mir Masood Kheirkhah Zarkesh performed the analysis and reviewed the manuscript.

Availability of data and materials There is no data availability statement provided in the manuscript.

Declarations

Ethical responsibilities of authors All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors, and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

Competing interests The authors declare no competing interests.

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