Quantifying Urban Expansion in Small Cities: A Case Study of the Al-Qassim Region, Saudi Arabia

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Abstract
Urban expansion in developing countries has proven to be a controversial topic among scholars and researchers. This study aimed to measure spatiotemporal patterns of urban expansion in three cities in Al-Qassim Province: Unaizah, Ar Rass, and Al Mithnab. The research employed various methods used in urban expansion analysis and measurement. Four satellite images from 2013 to 2023 were used to monitor changes in urban expansion using the support vector machine algorithm in geographic information systems, considered an essential and standard technique for understanding and measuring urban land use patterns. Land use classifications (urban land, non-urban land, and agricultural land) were extracted using this method. The study used three methodological approaches to help measure urban expansion: the urban expansion intensity index, the Shannon entropy index, and landscape metrics. The study found that all three measures can contribute to detecting different patterns of urban expansion. Therefore, the results are as follows: First, the three study cities experienced urban expansion based on the increase in the urban expansion intensity index, with their development rate ranging from moderate to high speed. Second, the study revealed that the Shannon entropy index for expansion exhibits a highly compressed development distribution. Third, the results of the landscape metrics measurements using the FRAGSTATS program indicate that urban expansion generally exhibits an irregular distribution. The study emphasizes the necessity of considering environmental, social, economic, and cultural factors, as this significantly improves the understanding of relationships between causes, characteristics, and changes resulting from urban expansion in cities.

Keywords: GIS, FRAGSTATS, Landscape Metrics, Shannon Entropy Index, Urban Expansion, Urban Expansion Intensity Index

1. Introduction

Urban expansion began to spread within developed Western countries during the 1970s. The concept of urban expansion lacks widespread acceptance, and scientific debates on the topic have not reached a consensus. Therefore, the definition of expansion typically depends on the context in which the term is used, and its application is greatly influenced by the availability of relevant data [1] and [2]. Urban expansion, commonly characterized as an unequal urbanization phenomenon, is defined by low-density, inefficient, and fragmented land development patterns on the metropolitan edge [3]. The investigation of growth patterns has recently emerged as a significant area of inquiry worldwide. Urban expansion is a multifaceted phenomenon that encompasses several dimensions, such as economics, population dynamics, and spatial distribution at the regional level. This process of evolution includes the outward expansion of urban construction land [4] and [5]. Furthermore, several studies have been conducted on the distribution of populations and systems of society, particularly the urbanization process. Based on an analysis of previous research, it can infer that the continuous growth in urban land usage has several consequences, including improved residential area quality and security, increased employment opportunities, and economic growth. In addition, the proliferation of informal dwellings and the reduction of arable land are linked to the expansion of urban land use [6][7][8][9][10] and [11]. The phenomenon of urban growth yields both positive and negative consequences. The impacts of socioeconomic factors include reduced social mobility, increased social segregation and inequality, higher infrastructure and public service costs, rising family vehicle expenses, and the decline of metropolitan centers.

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The environmental consequences encompass the encroachment into metropolitan green spaces, permanent damage to ecosystems, increased energy consumption, air pollution, and the development of urban heat islands [12]. On the one hand, it enhances the quality of life for inhabitants; on the other hand, it gives rise to many environmental and ecological challenges within metropolitan areas. The expansion of cities has been shown to significantly affect the surrounding landscape and associated biophysical and biological systems. Regardless of whether population density and economic development increase simultaneously, the rapid expansion of urban areas will continue. Urban expansion may take the form of increased construction density within established regions, occupation of the remaining available space within the developed area, or expansion within previously designated non-urban areas [13][14] and [15].

In any case, fast urban land use change leads to the undesirable expansion of metropolitan areas, also known as urban sprawl. The issue of urban sprawl arises from the management of urban land use change and the growth of metropolitan areas. The lack of a globally acknowledged definition for urban sprawl may be attributed to the divergent features seen in industrialized and developing countries [16]. Earle Draper first proposed the idea of urban sprawl in 1937 during his speech to a national gathering of professional developers, where he discussed the adverse effects it had on society as a whole and the economy [17]. After 1961, the notion of urban sprawl surged in popularity with the publication of Jane Jacobs' renowned article titled "The Death and Life of Great American Cities" [18]. A study by Zhang [19] showed that urbanized areas in the United States expanded significantly throughout the middle of the 20th century. Urban development on former agricultural lands and forests allowed for this expansion. Strategies and policies to effectively mitigate and manage urban growth phenomena must be developed and implemented to prevent the escalation of adverse impacts on the biosphere [13]. These strategies and policies include long-term plans implemented at the local, regional, and national levels as well as worldwide [20]. These plans may involve demographic and economic strategies. Alternatively, these plans and policies might manifest as technological solutions that oversee and regulate urban expansion [21].

Mapping and quantification are essential evaluation components of spatial planning when studying urban growth. Unspecified definitions and the presence of varied features cause the measurement of urban growth to be a challenging task [22]. The proliferation of urban populations and urbanized areas on a global scale has had many effects on the mechanisms of ecological systems across multiple scales. Identifying and understanding shifting urban development patterns is crucial for addressing these issues [23]. Spatial pattern metrics aim to magnify distinct spatial attributes of patches or the entirety of landscape mosaics [24]. These metrics have been derived from a combination of statistical measures and data theory and can typically be computed using specialized landscape analysis software, such as FRAGSTATS [24][25] and [26]. The quantification of landscape features and their temporal variations is crucial for monitoring and evaluating the ecological impacts of urbanization. Quantifying urban patterns and projecting their spatiotemporal dynamics is the first step in comprehending city ecology. Urban planners and policymakers use contemporary methodologies, such as geographic information systems (GIS), and simple techniques in their discussions to formulate prospective policies. The use of GIS is warranted for several reasons, including its ability to incorporate both temporal and spatial dynamics. These approaches facilitate the monitoring, control, analysis, evaluation, and measurement of patterns of urbanization and urban land use changes [27][28] and [29]. Landscape indices are increasingly used to describe spatial land use heterogeneity and urban morphology, leading to increased interest in analyzing land use and urban development. The urban expansion intensity index (UEII) has been employed in a similar manner to facilitate the efficient control of urban development [30] and [31]. The UEII is often employed in conjunction with GIS to enhance the effectiveness of urban development management strategies. Moreover, entropy indices, such as Shannon entropy, have been integrated with GIS to assess the extent of urban sprawl in the specific geographical region under investigation. The Shannon entropy method has been applied to determine the level of concentration or dispersion of urban growth and the existence or nonexistence of urban sprawl [32]. This method is widely recognized as an effective technique for examining urban expansion, particularly its implications for urban sustainability [18][33] and [34]. Therefore, several different statistical measures and variables have been established to evaluate urban growth by integrating these GIS and remote sensing approaches.

As the literature has shown, urban sprawl's complexity not only makes it difficult to measure and evaluate but also challenging to define. The change from a "sprawl" shape to a "compact" shape is more likely a direction on a continuum than a clear-cut category that can be measured.

Numerous studies, however, have attempted to address this issue by proposing various urban sprawl policies [35][36] and [37]. To follow the urban expansion effects of cities, research has been conducted to simulate and analyze urban expansion and land use/land cover changes using the landscape metrics and the Shannon entropy model, and several studies have been undertaken to map and track urban growth and spatial development trends [38][39] and [40]. Thus, this study aims to measure urban sprawl between 2013 and 2023 in three cities in Al-Qassem Province, Saudi Arabia: Unaizah, Ar Rass, and Al Mithnab. The significance of this study comes from the scarcity of studies on urban sprawl in Saudi Arabia, where most studies related to urban sprawl have been limited to large cities (e.g., Riyadh, Jeddah, and Makkah), and small cities have yet to be noted. Since small cities lack the necessary research and data, this research will benefit city planners and developers by applying evaluation and analytical techniques to examine urban expansion. To measure urban sprawl, this study implemented several strategies to quantify sprawl, including map classification, which depends on support vector machines (SVMs), the UEII, the Shannon entropy index, and landscape metrics.

2. Study Area

The Kingdom of Saudi Arabia has 13 administrative areas, as shown in Figure 1(a); one of these is AI-Qassim. The region of Al-Qassim, which is roughly in the center of Saudi Arabia and the Arabian Peninsula, covers 73,000 km^2 and comprises around 3.2% of the kingdom's total area. The integrated network of roads and airplanes traversing the area enhances Al-Qassim's significance as an essential link connecting various regions of Saudi Arabia. Al-Qassim is renowned as the “food basket” of the nation since it is the most agriculturally productive area (see Figure 1(b)). The region's high groundwater levels boost agricultural output, supporting the production of the primary agricultural products of the area, namely vegetables, wheat, dates, and various fruits [41]. This study focuses on three small cities located in the Al-Qassim region. In 2019, UN-Habitat defined large cities as metropolitan areas boasting a populace exceeding one million, medium cities as those with a population between 300,000 and one million, and small cities as those with a population size of less than 300,000.

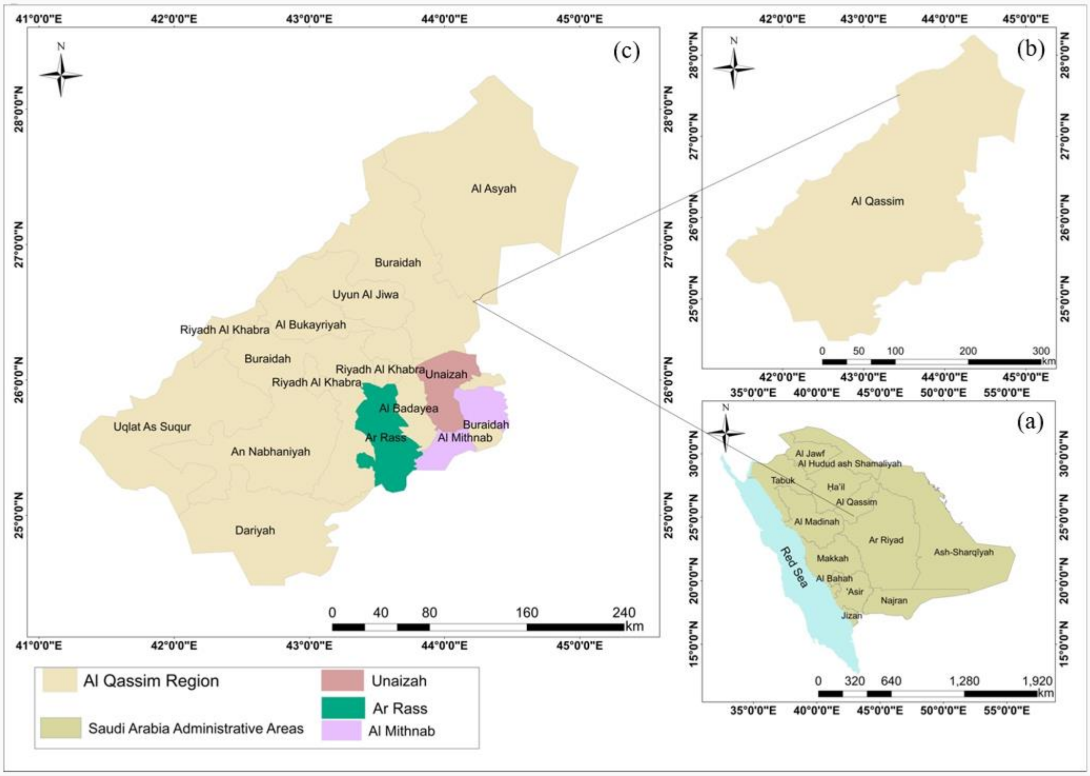

Figure 1: (a) Saudi Arabia (b) Al-Qassim region (c) Study area in Al-Qassim

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The first city in the study area is Unaizah, which is heavily agricultural and blessed with abundant water. The city also serves as a significant resting place for pilgrims journeying from Iraq. Unaizah is located at N 26° 5’ 7.72”, E 43° 58’ 36.52” and covers about 1,290.6 km^2. The second city is Ar Rass, which is situated in a desert environment atop the Arabian Shield. This geological formation, characterized by a rigid layer of bedrock, spans the western portion of the Qassim Region. Ar Rass is located at N 25° 52’ 12.13”, E 43° 30’ 0.7” and covers about 1,600 km^2. The third city is Al Mithnab, which boasts valleys and reefs and is well-known for its lush green spaces, parks, and rich soils. Al Mithnab is located at N 25° 51’ 36.43”, E 44° 13’ 20.21” and covers about 11,800 km^2 (see Figure 1(c)). According to the Saudi General Authority for Statistics, in 2023, Unaziah City had about 183,319 residents, Ar Rass City had about 107,902 residents, and Al Mithnab City had about 33,341 residents.

3. Data Collection and Methods

The present study used four Landsat images from satellites for 2013 and 2023 to obtain land use data for Unaizah, Ar Rass, and Al Mithnab. The researcher downloaded these images from the US Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov). Table 1 lists the Landsat satellite images from the Landsat 8 and 9 Operational Land Imagers (OLIs). The current study employed several different approaches, as shown in Figure 2. For instance, in the context of image classification, we used supervised classification for each year during the research period, implementing a well-known SVM, an algorithmic machine learning technique often employed in regressions and classifications. This methodology establishes correlations between urban land use shifts and various elements, including population growth, proximity to transportation infrastructure and amenities, and nearby patterns of land use [42].

Table 1: Landsat data information

Years	Satellite	Path/Row	UTM zone	Date of acquisition	Resolution
2013	Landsat 8	168/042	38	Oct 10, 2013	30
2013	Landsat 8	167/42	38	July 19, 2013	30
2023	Landsat 9	167/42	38	Aug 09, 2023	30
2023	Landsat 9	167/42	38	Aug 25, 2023	30

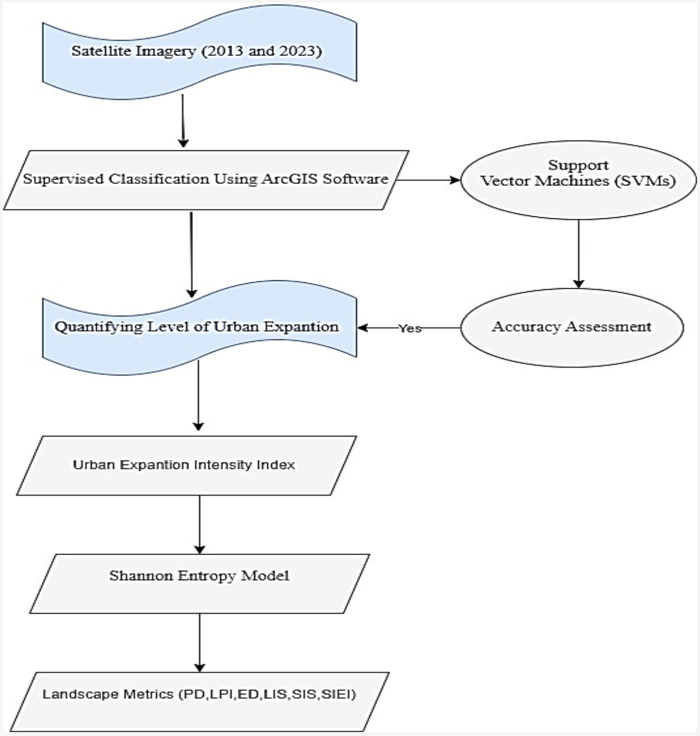

Figure 2: Research methodological flowchart

This study used ArcGIS 10.8 to pre-process all satellite images and categorize land use. The current research employed three different classifications: urban, agricultural, and non-urban land and also carried out an accuracy assessment, an essential final process that utilizes a random stratified sampling approach [43] to establish a reference point for each Landsat image from 2013 and 2023. The researcher generated 300 points by sampling the categorized imagery from satellites in each study area. Additionally, the matrix of confusion was computed to evaluate the accuracy of classifying images into three categories based on their truth after identifying them from a Google Earth image. For the main objective of determining the extent of urban sprawl in the areas of interest, several methods have been used, as outlined below.

3.1 Urban Expansion Intensity Index (UEII)

The UEII is frequently used as a quantitative tool for evaluating and analyzing variations related to urban spatial growth. Furthermore, the UEII can be used to determine the inclination toward urban expansion over a certain period [44]. The UEII is a valuable tool for assessing the expected direction and possibility of urban growth. The interpretation of UEII values presents in Table 2. It computed the UEII for the whole research area as well as for each period and every zone, adopting equation 1 as follows:

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

Equation 1

Where $UEII_{it}$ is the average yearly intensity of urban land expansion in the i-th zone, t is the time period, $ULA_{i,b}$ is the quantity of urban land area at time period b, $ULA_{i,a}$ is the quantity of urban land area at time period a, and TLA_i is the whole area of the i^{th} spatial zone.

3.2 Shannon Entropy Model

Numerous recent studies have focused on understanding and analyzing the equilibrium rate of relative urban phenomena at the regional and global levels using the Shannon entropy model [46]. The concept of entropy is frequently employed in assessing the extent of urban expansion within a particular area. This evaluation is achieved through a combination of GIS and remote sensing methodologies using a spatial database [47]. Shannon entropy is an index that quantifies the level of dispersion or spatial concentration within a given geographic unit. The following formulas are used to calculate the model's structure: absolute entropy (equation 2), relative entropy (equation 3), and changing urban sprawl rate (equation 4).

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

Equation 2

Where P_i indicates the quantity of the variable's value (urban expansion area) inside the zone, n is the overall number of zones, and the range of values for absolute entropy is 0 to $log_e(n)$. Urban growth is distributed relatively compactly when the entropy value is zero, and it is extensively scattered when it is closer to $log_e(n)$.

The entropy value (H_r) in equation 2 can be transformed to a scale ranging between 0 and 1 through the utilization of relative entropy (H_r), as defined in Equation 3.

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

Equation 3

Disparity of relative entropy value between two time periods (ΔH_r) is determined from Equation 4.

$$\Delta H_r = H_r(t_2) - H_r(t_1)$$

Equation 4

3.3 Landscape Metrics

An increasing number of studies have implemented the landscape metric to measure urban patterns. Many scholars have emphasized using spatial measures derived from ecological landscapes to represent spatial urban features [48][49][50] and [51]. The landscape metrics include 41 types of landscapes. The metrics come in a variety of forms, ranging from basic geometric assessments such as "patch area" to complex ones based on ratios of area to perimeter (e.g., fractal dimension, shape index) or statistical measures such as Shannon's diversity and evenness index [52]. This study aims to investigate the urban land-use class of patches based on the spatiotemporal characteristics of urban growth patterns utilizing the FRAGSTATS 4.2.64 software. Table 3 presents the four categories into which landscape metrics can be classified [52].

Table 2: UEII value ranges [45]

UEII values	Interpretation
0–0.28	Gradual development
0.28–0.59	Sluggish development
0.59–1.05	Intermediate-paced development
1.05–1.92	Rapid development
>1.92	Extremely rapid development

Table 3: Landscape metrics categories [53]

Categories	Metrics	Description	Range
Shape irregularity	Edge density (*ED*) $$ED = \frac{E}{A} \times 10,000$$	*ED* represents the calculated value obtained by summing the lengths of all individual edge segments in a landscape, dividing it by the total area, and multiplying the results by 10,000 to convert it to hectares (ha). E = total length (m) of edge in landscape A = total landscape area (m)	$ED \geq 0$, without limit. $ED = 0$ when there is no edge in the landscape.
	Standardized index of shape (SIS) $$SIS = \frac{0.25 p_{ij}}{\sqrt{a_{ij}}}$$	The shape's perimeter (in meters) divided by the square root of its area (in square meters) is adjusted by a constant to account for standardized square shape. p_{ij} = perimeter (m) of patch ij a_{ij} = area (m) of patch ij	$SIS = 1$ when the patch is square and increases without limit as the patch shape becomes more irregular.
	Landscape shape index (LSI) $$LSI = \frac{0.25 p_{ij}}{\sqrt{A}}$$	*LSI* calculated by dividing the whole landscape spot (m) by the square root of the whole landscape spot (m), including any bordering edges.	$LSI = 1$, is infinite if the landscape has a square patch.
Fragmentation	Patch density (*PD*) $$PD = \frac{N_i}{A}$$	*PD* is calculated by dividing the number of patches by the total landscape area (sq.m.). N_i = number of patches in the landscape of patch type (class) i	*PD* is bigger than 0, inhibited by the measurement of cell. The grain size of the raster image restricts the *PD* due to the maximum *PD* being achieved through every cell in each distinct patch.
Diversity	Simpson's evenness index (*SIEI*) $$SIEI = 1 - \frac{\sum_{i=1}^{m} p_i^2}{1 - \frac{1}{m}}$$	To calculate *SIEI*, the proportional abundance of each patch type is divided by the number of patch types, minus one. p_i^2 = proportion of the landscape occupied by patch type (class) i	$0 \leq SIEEI \leq 1$ SIDI = 0 when the landscape has only 1 patch and $SIDI = 1$ when the distribution of area among patch types is equal.
Other	Largest patch index (*LPI*) $$LPI = \frac{P_{iMAX}}{A} \times 100$$	*LPI* is the area of the landscape comprised by the largest patch, calculated by dividing the total landscape area by the area of the largest patch.	$0 < LPI \leqq 100$ *LPI* reaches 0 when the biggest patch of a particular type is smaller, and $LPI = 100$ when the whole landscape is a single patch of the same type.

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4. Results and Discussion

4.1 Supervised Classification and Accuracy Assessment

The researcher generated three land use classes using Landsat imagery for 2013 and 2023 to improve the depiction of the land cover characteristics. These include urban, agricultural, and non-urban land. Figure 3 shows the supervised class categorization for the research based on SVM using ArcGIS. Figure 4 illustrates the continuous rise in urban land use during the 10-year study period, ascribed to consistent population growth within the examined regions from 2013 to 2023. Non-urban land in Unaizah declined steadily from 105 km^2 in 2013 to 97 km^2 in 2023. Similarly, in Ar Rass, non-urban land decreased from 90 km^2 in 2013 to 69 km^2 in 2023. In Al Mithnab, the area of non-urban land decreased from 17 km^2 in 2013 to 14 km^2 in 2023. Additionally, the amount of land used for agriculture shows inconsistencies, leading to irregular rises and decreases in the overall land area over time.

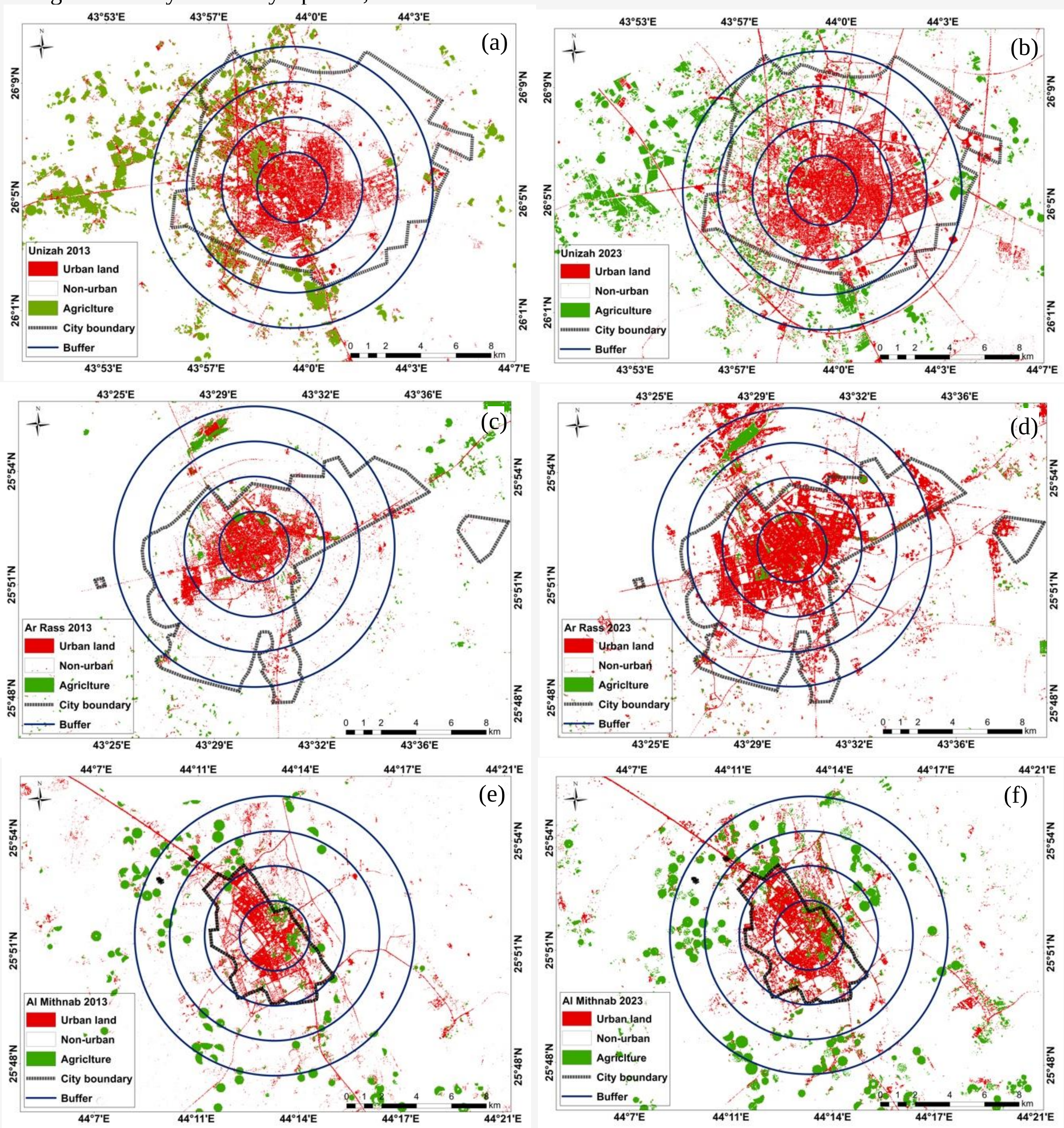

Figure 3: Land use of the study area
(a) Unaizah in 2013, (b) Unaizah in 2023, (c) Ar Rass in 2013, (d) Ar Rass in 2023,
(e) Al Mithnab in 2013, (f) Al Mithnab in 2023

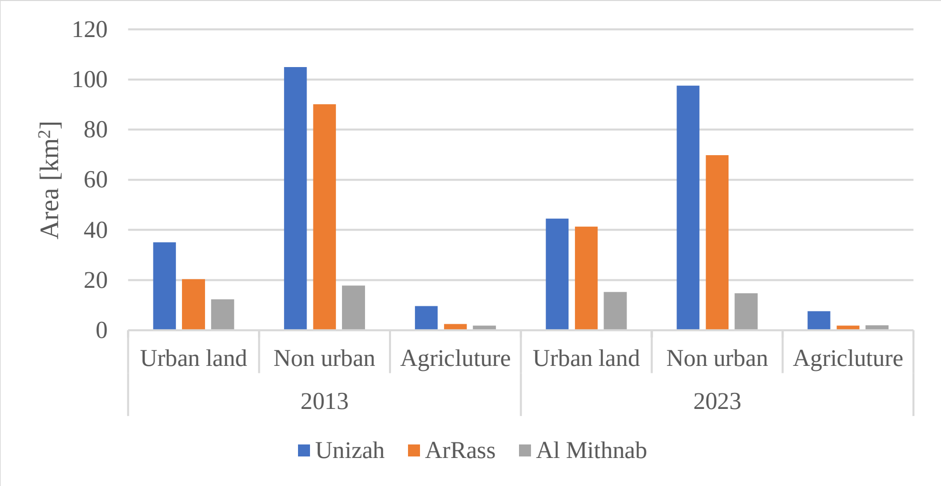

Figure 4: Area of land use classes in 2013 and 2023

Table 4: Accuracy assessment of land use classification

	2013		2023	
	Overall accuracy	**Kappa**	**Overall accuracy**	**Kappa**
Unaizah	97%	0.95	97%	0.96
Ar Rass	91%	0.87	92%	0.88
Al Mithnab	91%	0.87	95%	0.92

Table 5: UEII for the study period

City	2013 to 2023	
	UEII	**Agreement**
Unaizah	0.636	Medium speed
Ar Rass	1.861	High speed
Al Mithnab	0.922	Medium speed

Table 4 indicates the overall accuracy assessment and the Kappa index, and the results show that the ground-referenced information and the classified map are in almost perfect agreement in 2013 and 2023 for all study areas. This is based on the interpretation of the Kappa coefficient, which shows that the result is generally accurate.

4.2 Urban expansion intensity index (UEII)

Table 5 show the quantitative evaluation of the intensity of urban expansion for the three study areas from 2013 to 2023. According to the findings, the *UEII* during this period was 0.63 for Unaizah, indicating medium-speed development. Similarly, Al Mithnab had a *UEII* of 0.92, also considered medium speed. By contrast, Ar Rass city had a *UEII* value of 1.86, indicating high-speed growth from 2013 to 2023. This rapid rise in urban expansion sounds the alarm regarding urban sprawl in Ar Rass.

4.3 Shannon Entropy

Shannon entropy is widely employed to determine the dispersion or compactness of urban expansion patterns. In this research, four buffer rings were introduced at 2 km intervals around the city center. Table 6 shows the overall entropy value and the zonal distribution of urban expansion for 2013 and 2023. The range of the Shannon entropy value is 0 to $log_e(n)$, where n represents the buffer ring numbers. For urban expansion, a determined entropy value near 0 indicates a concentrated and compact urban expansion pattern [54]. In contrast, a more scattered or fragmented pattern of urban expansion is indicated when the entropy value reaches the top limit of $log_e(n)$. Table 6 shows the changes in the Shannon entropy values between 2013 and 2023, which are 0.614, 0.712 in Unaizah, 0.585, 0.748 in Ar Rass, and 0.674 0.689 in Al Mithnab, respectively. In addition, it shows that the level of urban expansion in these cities is a highly compact distribution**.**

Table 6: Shannon's entropy values for 2013 and 2023

City	2013		2023		Spawning change magnitude
	Absolute	Relative	Absolute	Relative	
Unaizah	0.771	0.614	0.987	0.712	0.098
Ar Rass	0.811	0.585	1.038	0.748	0.163
Al Mithnab	0.934	0.674	0.956	0.689	0.015

Table 7: Landscape metrics in 2013 and 2023

City	2013						2023					
	ED	SIS	LSI	PD	SIEI	LPI	ED	SIS	LSI	PD	SIEI	LPI
Unaizah	0	0.989	78.528	99.388	0	77.462	0	1.105	84.259	80.985	0	77.769
Ar Rass	0	0.883	56.865	98.202	0	73.477	0	0.973	45.623	33.962	0	85.448
Al Mithnab	0	0.972	47.123	107.597	0	80.430	0	1.732	29.834	14.202	0	91.519

4.4 Landscape Metrics

Table 7 provide further details regarding urban expansion in Saudi Arabia's small cities from 2013 to 2023. The patch density (PD) increased significantly in 2013 throughout the study area, with Unaizah at 99.388, Ar Rass at 98.202, and Al Mithnab at 107.597, indicating that the irregular formation and dispersion of urban areas may explain the substantial growth. Nevertheless, by 2023, the PD values in Unaizah 80.985, Ar Rass 33.962 ,and Al Mithnab 14.202 had declined, suggesting that urban aggregation had occurred. The study areas' largest patch indexes (LPIs) were higher in 2023 than in 2013, showing the expansion of the land use. Furthermore, from 2013 to 2023, the landscape shape index (LSI) rose for Unaizah and fell for the other two areas. The decline in the LSI in Ar Rass and Al Mithnab signifies a gradual shift in the landscape's shape toward a more regular shape. The LSI and SIS indicate the irregularity of the study area as a whole. However, the study areas' edge density (ED) metrics show that no boundaries in the landscape or background were considered edges, as ED = 0. In general, the landscape metrics from 2013 to 2023 documented unregulated urban expansion.

This research has explored the contemporary spatial context to understand the urban expansion of small cities in the Al-Qassim region between 2013 and 2023. The amount of urban land was noted in the study area increased during the study period due to rapid population growth, whether natural (due to births) or unnatural (due to the large-scale migration of residents from villages and centers adjacent to the study area), as well as the many government initiatives and programs supporting the residential sector introduced by the Ministry of Housing of the Kingdom of Saudi Arabia in recent years. The use of various methods to measure urban expansion (UEII, Shannon entropy, and landscape metrics) reinforces the research findings, which provide evidence of rapid urban growth in the study areas. This growth could lead to uncontrolled urban sprawl in the city, which may impact the urban environment in the future. It is important to note that the current research includes certain limitations. Initially, the study spanned a long duration (10 years), although more precise data is required to delve deeper into the development of urban areas throughout this period. Additionally, the Al-Qassim region encompasses a vast expanse of undeveloped land, making it challenging to measure using aerial and satellite images. Factors such as rough terrain and agricultural lands can impede urban development.

However, the ecological, social, cultural, and economic factors are crucial elements which affect urban expansion in large and small cities. The results presented in this research will be helpful to academics, researchers, policymakers, and urban and regional planners. The research implications are immediately applicable to policies and regulations pertaining to development and urban planning. The research offers substantiated insights into the phenomenon of urban sprawl in Saudi Arabia. Urban planners should ascertain the cities' needs and create suitable policies for each municipality to guide sustainable development and avoid unsustainable expansion, as urban growth will surely increase in the coming years.

5. Conclusion

This study examined the phenomenon of urban expansion in three small cities in Al-Qassim Province in Saudi Arabia over a 10-year period. The study yielded several findings. First, spatial information sources such as satellite images captured for the three cities in 2013 and 2023 provided an accurate assessment of urban expansion within the study cities, including three land use classifications: urban, non-urban, and agriculture. The results indicated that urban land significantly increased in size in Unaizah, Ar Rass, and Al Mithnab between 2013 and 2023. This can be attributed to the availability of diverse services, which attracted people to live there.

In contrast, non-urban land decreased in size in all three study cities from 2013 to 2023. Additionally, all three study areas are farming areas that occupy large tracts of agricultural land, reflecting the government's focus on agricultural development. Second, the UEII values for the three areas reached 1.86, 0.63, and 0.92, indicating moderate to high-speed urban expansion from 2013 to 2023. Third, the Shannon entropy index values changed by 0.098, 0.1633, and 0.0156 between 2013 and 2023, indicating that the level of urbanization in the study cities exhibited a highly compressed distribution. Fourthly, using landscape metrics helped identify patterns and changes in urban expansion in the study cities. These research findings provide valuable data for the geographical and governmental planners to recognize the nature of urban growth and develop strategies to manage uncontrolled and unplanned urban sprawl.

6. Recommendation

The current study focused on examining three small cities in one of the Kingdom's administrative regions by studying two periods for spatiotemporal analysis. The findings suggest that future research should expand the scope by utilizing multiple-source remote sensing data with better resolution to achieve a more detailed land use categorization over a shorter period. Additionally, incorporating policy, economic, social, and ecological aspects, as well as topographical and geographical elements, will enhance the analysis. Other analytic techniques and indicators should also be used to fully measure the landscape index.

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