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UNRAVELING THE TRANSFORMATION OF URBAN AGRICULTURE IN DAMAVAND: A MIXED-METHODS EXPLORATION OF LAND USE CHANGES

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ABSTRACT

Urban Agriculture (UA) in Iran plays a pivotal role in economic sustainability and food security. Recent years have witnessed significant transformations in UA land use, posing challenges to households and affecting urban planning efficiency. This study employs a mixed-methods approach to comprehensively investigate the 'how' and 'why' behind land changes in UA Damavand, located adjacent to Tehran, Iran. Geospatial and quantitative analyses, coupled with qualitative assessments, aim to uncover the driving factors behind these alterations. Google Earth Engine (GEE) and NDVI mapping from 1995 to 2022 are used to analyze vegetation changes. Geospatial techniques in QGIS are employed to assess changes, complemented by qualitative data gathered through semi-structured interviews with 15 participants from diverse backgrounds. Additionally, the study explores the applicability of Q-methodology in understanding the causes of UA land use changes in Damavand. Findings indicate a substantial increase in built-up land (109 %), alongside declines in barren (14.34 %) and vegetation (22.44 %) classes, including UA lands. Correspondingly, four thematic factors have been identified as primary reasons for UA changes: land value changes and attraction to urban livelihoods, management and planning factors, physical-environmental factors, and the availability of urban infrastructure. The study underscores the urgency of effective planning to mitigate the threats posed by extensive UA transformations in Damavand. It highlights the significant role of analyzing land markets in

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integrating UA into urban planning policies, providing essential insights for informed policymaking.

Keywords: Urban Agriculture; Land Use change; Mixed-Methods; Damavand.

INTRODUCTION

Problem

Rapid urban growth, urban sprawl, and the simultaneous conversion of fertile agricultural land into built-up urban areas are key challenges for urban sustainability. By 2050, approximately two-thirds of the world's population is expected to reside in cities, with most future urban growth (approximately 90 %) projected to occur in the Global South (Follmann *et al.,* 2021; Youssef *et al.,* 2020), including Iran. Agriculture is vital for Iran's economy, supporting income generation, poverty alleviation, and employment development (Mostashari-Rad *et al.*, 2019). It sustains the livelihoods of approximately 23 million Iranians in both rural and urban areas, accounting for about 30 % of the population (Seyf, 2006). Urban agriculture (UA) in Iran not only has economic value but also provides environmental benefits and addresses urban challenges related to food security, as nearly 90 % of the country's food needs are met through domestic production (Khorami & Pierof, 2013). Despite its importance, UA has historically been "undervalued" (Pirasteh, 2003, p. 46) and faces challenges, including limited available land.

Changing UA land use in Iran is the second major challenge in urban planning after water scarcity (Rahmani *et al.*, 2022). Between 1961 and 2018, the proportion of agricultural land, including areas within urban environments, decreased from 0.4 % to 0.28 % (Lahai *et al.*, 2022). Recognizing UA as a legitimate urban land use is a critical first step for effective regulation and development (Simatele *et al.*, 2012). The conversion of UA land to other uses in expanding urban areas poses a threat to the agricultural sector, putting the country's food security and the livelihoods of over four million urban households at risk (Maleksaeidi *et al.*, 2020).

However, the reasons behind the decline in UA land in Iran remain poorly understood. Despite the enactment of several laws, such as the Urban Land Laws[1] (1987) and the Conservation of Agricultural Lands and Gardens [2] (1995), urban planning tools fall short of addressing the challenges posed by these extensive transformations and their consequences. Furthermore, urban planners frequently overlook the crucial role of UA within cities, hindering land access for various sectors. Moreover, there is limited or non-existent planning support to facilitate land access for UA.

Damavand City, situated 70 kilometers east of Tehran, has been chosen as a case study due to its essential role in agriculture and its proximity to the capital. Approximately 70 % of the city's area (Sharmand Consultants, 2004) is designated as farmland, making it a vital supplier of agricultural products to Tehran and contributing to both environmental and economic sustainability. The region's diverse climate and vegetation further enhance its agricultural significance. However, similar to broader national trends in Iran, the reasons for the decline of urban agricultural land in Damavand are not well understood. This makes Damavand

[1] Conversion, separation, and changes in land use, as well as the division of gardens and agricultural or croplands, are permissible when they adhere to the rules and regulations set forth by the Ministry of Housing and Urban Development and the provisions outlined in this law.

[2] Starting from the date of enactment of this law, altering the use of agricultural lands and gardens located outside the legally defined boundaries of cities and towns is prohibited, except in cases deemed necessary.

a relevant and insightful case for examining the transformation of urban agriculture in peri-urban areas across the Global South.

Challenges of Urban Agriculture and Land Use Planning: Common Roots; why is it a challenge in Iran?

Global society recognizes the importance of integrating UA into urban planning (Fox-Kämper *et al.*, 2023). While urban and peri-urban agriculture has a long history worldwide and takes on both formal and informal manifestations (Knoblauch, 2012), defining the "urban" aspect in UA has sparked debate and differing interpretations. During the 18th and 19th centuries, due to industrialization, agriculture increasingly shifted away from urban areas as land, a primary agricultural resource, was redirected to economically more profitable sectors, such as industry and production (Gunapala *et al*., 2025; Dobele & Zvirbule, 2020). In essence, UA is defined as "The production of food and other outputs and related processes, taking place on land and other spaces within cities and surrounding regions" (FAO *et al.*, 2022, p. 11). UA relies on urban resources, competes with other urban functions for land, is influenced by urban policies, and plays a role in both using and providing urban products and services. The term 'urban' in UA primarily signifies its connection to the neighboring city through markets, resources, and services rather than specific features or locations (Jansma & Wertheim-Heck, 2021). Glaeser & Kahn (2004) assert that urban growth and sprawl are related concepts, but they highlight different aspects of how cities evolve. Urban growth broadly refers to the overall increase in urban built-up area, encompassing the densification of existing areas and the gradual outward expansion of urban territory to meet increasing demand. In contrast, urban sprawl is a specific pattern within this broader growth, characterized by low-density, horizontally expanded development where constructions decentralize from a compact core, leading by the end of the 20th century to the prevalence of edge cities and sprawling suburbs that either replace or supplement traditional dense urban centers (Glaeser & Kahn, 2004).

UA in Iran remains underdeveloped, particularly in large cities, where rapid urbanization and population growth underscore the lack of precise planning and supportive policies (Cinà & Khatami, 2017; Rahimi & Nobar, 2023). Despite a slight decline in malnutrition—from 5.2 % in 2004–2006 to 4.7 % in 2017–2019—Iran has not met the Millennium Development Goal of halving this rate, indicating that efforts to improve food security must be strengthened (Ghalibaf *et al*., 2023). The Global Hunger Index ranks Iran 39th out of 107 countries, with a score of 7.4, reflecting better conditions than neighboring West Asian countries but ongoing food insecurity (Concern Worldwide *et al*., n.d.). Worldwide, approximately 800 million people practice UA, and in Tehran, it is viewed as a complementary tool to reduce poverty, enhance food security, and support urban environmental management (Rezvanfar *et al*., 2016). UA only became part of Iran's formal urban planning framework in 2021, when the Supreme Council of Urban Development and Architecture permitted its development in urban parks and peri-urban spaces (Hedayatifard & Azimi, 2022). External pressures, like the 2018 reimposition of sanctions, have worsened food insecurity by raising prices while incomes stagnate, with about 20 million Iranians living in poverty-stricken slums, highlighting the urgent need for stronger UA and food security policies (Joulaei *et al*., 2023).

In Iran, the terms "agriculture" and "urban planning" often appear incompatible. Agricultural activities are frequently pushed to the city outskirts, far from markets and essential infrastructure, often without a comprehensive analysis of their economic, environmental, and intersectoral connections. UA is often informal, encompassing aspects like land use and labor markets. These informal activities lack official oversight, and urban planners typically overlook agriculture in their mandates. Land use planning in Iran typically begins with estimating land requirements for various purposes, taking into account projected population growth, and establishing per capita land use standards. This information is then documented in a report, complete with proposed regulations. Once approved by provincial authorities and urban planning and architecture councils, the plan is forwarded to the municipality and relevant organizations for implementation (Ramezani *et al.,* 2023). Excluding UA from planning processes creates challenges in cities, mirroring the situation in Damavand. This tension intensifies as the need to balance local agricultural preservation with rapid, uncontrolled urban expansion grows. Urban farmers are increasingly recognized as stakeholders, and local interactions between agricultural and urban stakeholders significantly influence the development patterns. Conflicts often arise between customary and modern land tenure systems, particularly in the transition from communal to freehold land tenure. Such transitions result in fundamental changes in UA and hinder the goal of "putting urban land resources into efficient and sustainable use" (Drescher, 2001). Clarifying the role of Land Boards and traditional authorities in interpreting and managing local land rights is essential (Horst *et al.*, 2017; Aubry *et al.*, 2012).

Agriculture in Iran has been a widely debated topic, with extensive discussions among scholars at both national (e.g., Karimi *et al.*, 2017; Mesgaran *et al.*, 2017; Mirzaei *et al.*, 2019) and urban levels. Different studies have focused on various urban-related themes. These include factors affecting agricultural sustainability (Hosseini *et al.*, 2022; Ataei *et al.*, 2021) and the role of water scarcity (Maghrebi *et al.*, 2020; Farhangi *et al.*, 2021). Further research has explored the impact and reasons behind rapid urban changes and their effects on agricultural land loss (Dekolo *et al.*, 2015; Movahedi *et al.*, 2021; Salami, 2018; Barati *et al.*, 2021). Scholars have also scrutinized the influence of agricultural policies (Shirzad *et al.*, 2022; Asimeh *et al.*, 2020) and explored the reasons for the ineffectiveness of planning regulations in controlling these transformations.

The importance of mixed methods

Employing a mixed-methods approach is increasingly recognized as crucial within urban planning research, as highlighted by a review of the existing literature (Namaganda *et al.*, 2023). This methodological triangulation enriches the theoretical underpinnings of urban studies and enhances their technical rigor. Subsequently, several scholars, including Zare *et al.* (2017), have utilized geospatial methods to analyze UA dynamics. However, the limited integration and understanding of UA within mainstream urban planning practices often hinder planners' ability to effectively leverage these sophisticated methods for monitoring urban transformations. Current research has predominantly focused on technical approaches, relying heavily on mathematical models and inductive reasoning to monitor processes and forecast changes in UA land use.

To address this gap, the article employs a mixed methodological approach to investigate both the patterns and underlying drivers of changes in UA land use. Specifically, it poses the question: How and why is urban agricultural land being transformed over time? To answer this, geospatial assessments are utilized to visualize and analyze the spatial dynamics of UA change, addressing the "how." Meanwhile, qualitative research explores the underlying factors that influence these changes, focusing on the "why." This study examines how individual perspectives contribute to the drivers of UA change, offering a more nuanced understanding of the complexities involved. Such an integrated approach can provide valuable insights for improving urban planning strategies in Iran.

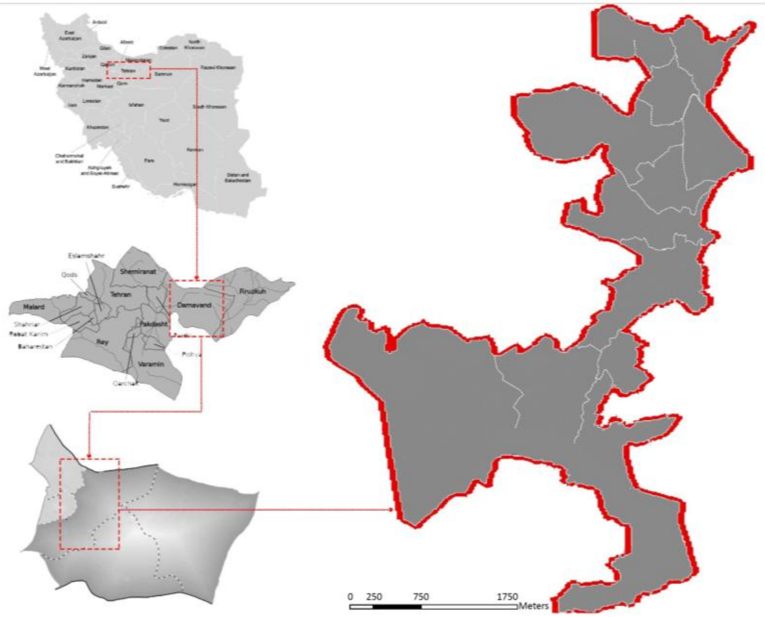
DATA AND METHODS

Study context

Damavand, located approximately 70 kilometers east of Tehran Province, lies within the geographical coordinates of 52° 07'E ~ 35° 72'E (see Fig.1). It encompasses an expansive area of 2,242 ha, extending roughly 10 kilometers in length with an average width of around 1.5 kilometers. The local climate is characterized as a cold, semi-arid variant featuring an average annual temperature of 11.1 °C (Sharmand Consultants, 2004). The region features three distinct zones: northern mountainous terrain, gently rolling foothills, and expansive plains to the south and southeast. This diversity provides a favorable environment for cultivating a wide range of agricultural products. Among the cities in Tehran Province, Damavand plays a significant role in supplying agricultural products to the capital, contributing to environmental conservation, economic vitality, and the city's unique identity According to the 2016 census, Damavand's permanent population was 48,380 residents (Statistical Center of Iran, 2016), accounting for 0.4 % of the province's total population.

In recent years, rapid industrialization and urbanization have led to an increased demand for land for construction in Damavand and an emerging threat to the city's farms. If this trend continues without considering its economic, social, and environmental consequences—including impacts on investments, sustainable economic growth, social development, and environmental degradation—it could deplete the city's critical resources. Controlling urban growth to optimize land use is as old as the concept of spatial planning (Fertner *et al.*, 2016). However, there is still a need for effective monitoring of UA land use changes, and a deeper understanding of the underlying causes is essential to address these issues.

Fig. 1: Study Area

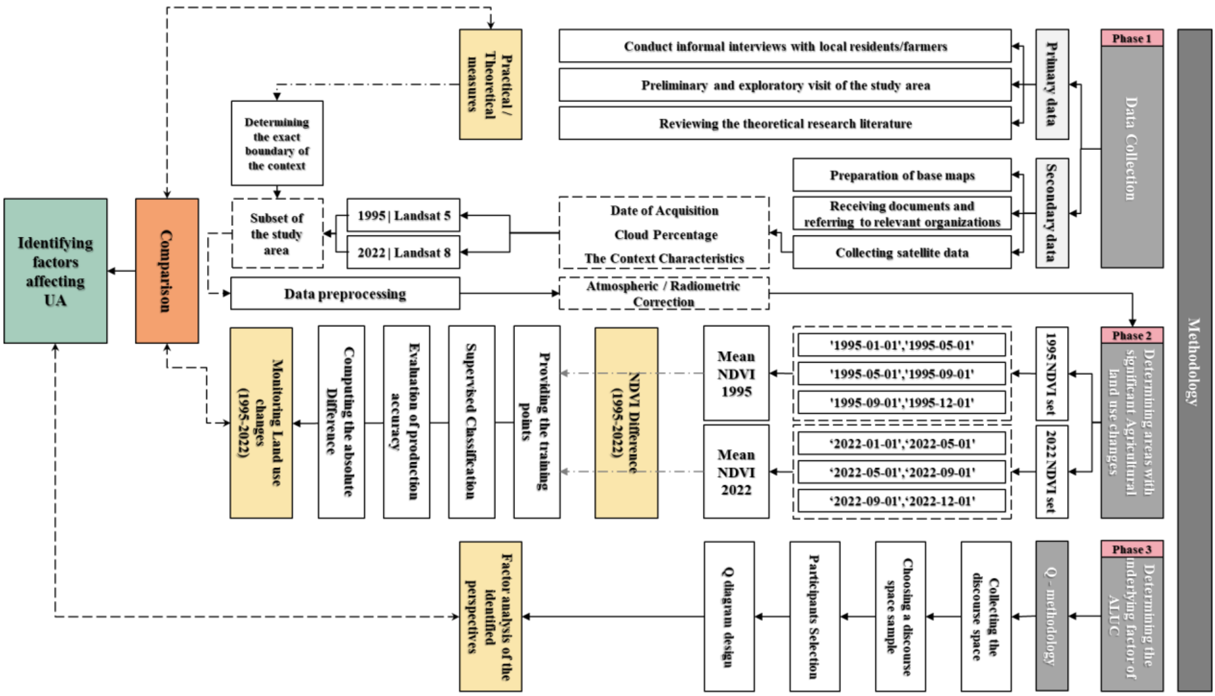


Study design

This study employs a mixed-methods approach, utilizing open-access global satellite data and geospatial analysis tools to explore the social, environmental, and economic dimensions. Figure 2 presents an overview of the research design.

- **Phase 1:** Initial and Secondary data collection involves utilizing the theoretical literature, field studies, semi-structured interviews, and satellite databases.
- **Phase 2:** This phase involves an innovative change detection methodology for Damavand from 1995 to 2022, utilizing the NDVI (Normalized Difference Vegetation Index) and supervised classification methods, which enable the tracking of UA change and the identification of their current use.
- **Phase 3:** This phase involves defining the steps of Q-methodology, complemented by in-depth and semi-structured interviews.

Fig. 2: Study Design



Exploring the "How" through the process of agricultural land change: ***Phase 2***

Producing average NDVI maps for 1995 and 2022

Remote sensing data plays a vital role in monitoring terrestrial vegetation dynamics for various purposes, including environmental monitoring, agriculture, forestry, and urban green infrastructure analysis (Kumar *et al.*, 2022; Rajani & Varadarajan, 2020, p. 216). To assess vegetation changes, we have selected a time frame from 1995 to 2022, aligning with intensified population growth and extensive construction activities, which makes this period relevant for analysis.

First, we produce average annual NDVI maps for 1995 and 2022. NDVI measures the health and greenness of vegetation within each pixel of a satellite image. It is widely used due to its simplicity, interpretability, availability from multiple sources, and prevalence in the literature (Tenreiro *et al.*, 2021).

These average NVDI maps serve essential purposes:

- Visibility: Average maps enhance the visibility of UA changes compared to single NDVI maps.
- Vegetation Health Monitoring: By comparing average NDVI maps from different years, we can track changes in vegetation health and density, aiding in the monitoring of UA changes and informed land management decisions.
- Land Use Classification: These average maps can be valuable for more accurate land use classification and predicting future changes in primary vegetation associated with agriculture.

The analysis commenced by obtaining Landsat imagery for Damavand City in 1995 and 2022 through GEE[3]. In addition to accessing imagery via the GEE platform, we also obtained relevant aerial imagery from the USGS[4] database. Given the limitations in data availability for the selected study years, we utilized Collection 2 Landsat data, known for its enhanced sensor calibration and radiometric accuracy, which results in higher-quality data for various remote sensing applications.

These images are filtered for acquisition date and cloud cover percentage to ensure high-quality data at a 30-meter resolution (Table 1). To mitigate the inherent limitations in spatial resolution of the acquired imagery, we employed a strategy of randomly sampling high-resolution aerial imagery from Google Earth and integrating in situ field observations.

Table 1: Satellite imagery information

Data Source	Sensor	Date	Periods	Bands	Wavelength	Dataset Propertise	
						Path	Row
Lansat 5	ETM+	1995	'1995-01-01','1995-05-01'	Band 3 - R	0.63 - 0.69 µm	164	35
			'1995-05-01','1995-09-01'	Band 4 - NIR	0.76 - 0.90 µm		
			'1995-09-01','1995-12-01'				
Landsat 8	OLI	2022	'2022-01-01','2022-05-01'	Band 4 - R	0.64 - 0.67 µm	164	35
			'2022-05-01','2022-09-01'	Band 5 - NIR	0.85 - 0.88 µm		
			'2022-09-01','2022-12-01'				

Data preprocessing includes clipping the images to the Damavand boundary and calculating NDVI using the near-infrared (NIR) and red (RED) bands separately for both years. NDVI is calculated for each Landsat image using the normalized difference formula: (NIR - RED) / (NIR + RED) (Gao *et al.*, 2022). This results in three NDVI images for each year, representing "January to May," "May to August," and "August to December." Overlaying these maps produces the average NDVI map.

Next, we reclassify the Average NDVI maps into categories: "Barren or Non-vegetated," "Sparse Vegetation," "Moderate Vegetation," "Dense Vegetation," and "Very Dense Vegetation" (Table 10) using QGIS. We then calculate the respective areas for each class. Additionally, we utilize the raster calculator to generate an "Absolute Difference" map, highlighting areas with the most significant vegetation changes between the average NDVI values for 1995 and 2022.

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[3] Coding details are in the supplementary data (*Appendix A*).

[4] United States Geological Survey; https://www.usgs.gov/

Producing classified land use maps for 1995 and 2022

Image classification is performed using the maximum likelihood method, validated with training points[5] and utilizing "Average NDVI," "Aerial Images," and "Field Observations." The classification process utilizes training points that represent diverse land uses and coverages within Damavand City, as outlined in Table 2. These classes form the basis for land use mapping on the average NDVI maps.

Table 2: Land use/Land cover Class

Class	Land use/Land cover
Vegetation	High land agriculture, trees, shrub lands
Built-up	Temporary and permanent houses, villages, artificial infrastructure
Barren	Non-arable, mountainous, rocky

Accuracy assessment

A rigorous validation process was undertaken to ensure the accuracy and reliability of the classification. This validation utilized independent reference data, distinct from the training points. It involved calculating an error matrix obtained through a pixel-by-pixel comparison between the known pixels and their counterparts in the classified map. From this matrix, we computed various metrics, including User Accuracy[6], Producer Accuracy[7], Overall accuracy[8], Kappa Coefficient, Errors of Commission[9], and Errors of Omission[10]. These metrics provided valuable insights into the accuracy of the classification process.

The Kappa coefficient includes pixels that are not classified correctly in its calculation, making it a suitable criterion for comparing the results of different classifications. It is calculated using the formula:

Kappa coefficient:

$$\text{Kappa coefficient} = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} \times X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+} \times X_{+i})} \quad \ldots\ldots\ldots\ldots\ldots \quad \text{Eq. (1)}$$

[5] In supervised classification, the users select representative samples for each land cover class within the digital image known. These selected land cover classes are referred to as "training points" or "training sites."

[6] **User Accuracy:** User accuracy is the probability that a value predicted to belong to a particular class does belong to that class. The probability is determined by the ratio of correctly predicted values to the total number of predicted values within a given class.

[7] **Producer accuracy:** Producer accuracy is the probability that a value is correctly classified into a specific class.

[8] **Overall accuracy:** Overall accuracy is calculated by dividing the total number of correctly classified values by the total number of values. This includes both the correctly classified values and predicted values. The correct values are typically found along the diagonal in the error matrix.

[9] **Errors of Commission:** These errors represent the fraction of predicted values in a class that does not belong to that class. They are false positives. In the error matrix, errors of commission in the rows equal the sum of values except those located along the diagonal.

[10] **Errors of omission:** Errors of omission represent the fraction of values that belong to one class but are expected to be different in a class. They are a type of false negative. In the error matrix, errors of omission in the columns equal the sum of values except those located along the diagonal.

In this formula, r represents the number of rows in the matrix X_{ii}, the number of observations in row i and column i, while X_{i+} and X_{+i}, respectively represent the sum of the i-th row and the sum of the i-th column of the error matrix. N is the number of elements of the error matrix. Here, the 1995 and 2022 land use maps were produced with overall accuracies of 97.5 % and 98.004 %, respectively, along with kappa coefficients of 0.95 and 0.965. This classification was achieved by using training points and supervised classification. Table 3 shows the error matrix for both years, where the 1^{st} class represents vegetation, the 2nd class built-up land, and the 3rd class represents barren land.

Table 3: Error Matrix

Class	1995				2022			
	Class 1	Class 2	Class 3	Overall	Class 1	Class 2	Class 3	Overall
Built-up Land	0	0	94.44	**30.69**	0	0	99.69	**32.24**
Barren Land	0	94.38	5.56	**13.47**	3.17	99.1	0.31	**12.87**
Vegetation	100	5.62	0	**55.83**	96.83	0.9	0	**54.89**

Additionally, Table 4 presents the Errors of Commission, Errors of Omission, Producer Accuracy, and user accuracy, which have been calculated and analyzed separately for each class.

Table 4: The number of Errors of Commission, Errors of Omission, Producer Accuracy, and User Accuracy

Class	Errors of Commission		Errors of Omission		Producer Accuracy		User Accuracy	
	1995	2022	1995	2022	1995	2022	1995	2022
Built-up Land	0	0	5.56	0.31	94.44	99.69	100	100
Barren Land	13.4	14.73	5.62	0.9	94.38	99.1	86.6	85.27
Vegetation	1.24	0.18	0	3.17	100	96.83	98.76	99.82

Exploring the “Why” through the causes of the land change; *Phase 3*

Compared to other relevant methodologies, such as the Delphi method and Social Network Analysis (SNA), Q[11] methodology appears promising for our research in understanding the reasons behind UA changes from the respondents' perspectives. While each method has its strengths—Delphi for expert-driven consensus (Masser & Foley, 1987) and SNA for mapping relationships (Zheng *et al.*, 2016) —Q methodology stands out when the goal is to capture and analyze the intricate landscape of individual subjectivities. Its ability to merge qualitative insights with quantitative precision, its suitability for smaller and varied samples, and its compelling visual outputs make it an appealing choice for this study, which aims to explore nuanced perspectives. It also enables us to extract useful information from semi-structured interviews and existing literature. The process involves several steps outlined in the following sections.

Selecting the statements

We begin by selecting statements that represent different viewpoints on the drivers of UA land use changes. These statements are drawn from valid scientific research articles representing various aspects of the subject. In total, after eliminating the redundancy, 50 influential statements related to UA changes are identified (Table 5). To enhance the validity

[11] "Q" represents this quantitative and qualitative research technique.

of the selected statements, we solicited input from *eleven* academic experts in land use. These experts were requested to conduct a thorough review and provide suggestions for improving the comprehensiveness of the statements, preparing them for subsequent stages of the research.

Table 5: Discussion summary: factors affecting UA changes

Aspect	Code	Factor	Aspect	Code	Factor
Population	1	Natural growth	Environment	25	Tourism area
	2	Migration		26	Favorable weather conditions
Lifestyle	3	Disinterest among young people in agricultural activities		27	Historical and cultural value and indicators
	4	Disintegration of traditional/ organic social order		28	Built to barren land ratio
				44	Distance from the city
	5	Changing living standards	Transportation	29	Rising ownership of personal cars
	6	Second house		30	Access routes
Efficiency of agriculture	7	Inefficient agricultural sector support	Urban growth	31	Construction within the city limits
	8	High cost of living and insufficient agricultural income		32	Villages near city limits
	9	Greater land value compared to agriculture		33	Low-density or poorly designed development
	10	Low prices of agricultural products	Urban planning & management	34	Municipal urban development policies
Local economy	11	Employment status		35	Comprehensive and detailed plans
	12	Local economy condition		36	Proposals in approved urban plans
	13	Human activities		37	Land uses approved by urban plans
Residence	14	Increasing construction demand		38	Urban land rules and regulations
	15	Unplanned residential areas		39	Undocumented and temporary urban policies
	16	Settlement construction and infrastructure development		40	Granting unauthorized licenses
	17	Housing cooperatives		41	Institutional monitoring methods
	18	New residential area construction		42	Inadequate natural resource management
Land Value	19	High land prices with non-garden uses, mainly residential use		43	Land exchange and rent-seeking
				46	Municipal financial challenges
	20	Added value from agricultural use change	Facilities	47	Social service land
	21	Urban land price		48	Urban services land
	22	Lower land prices compared to Tehran		49	Access to urban centers
Macroeconomics	23	High inflation			
	24	Exogenous factors and consumption economy		50	Commercial center proximity
	45	Political economy			

The critical statements (Table 5) are narrated as follows with the participants while asking about their perspective on UA changes in Damavand:

- *Population:* Natural population growth and migration can significantly affect UA by increasing land demand.
- *Lifestyle:* Individual satisfaction, desirability, and lifestyles impact agricultural lands in Damavand.
- *Agricultural efficiency:* The agricultural sector's capacity to meet economic needs influences UA patterns.
- *Local economy:* Employment and human activities have a significant effect on UA.
- *Residence:* Quantity, quality, and planning of residential sectors play a role in shaping UA patterns.
- *Land Value:* Land price compared to competing areas determines UA patterns.
- *Macroeconomics:* Exogenous factors like inflation and politics affect UA.
- *Environment:* Environmental potentials in Damavand impact the UA scheme.
- *Transportation*: Changes in transport infrastructure, such as new route construction, influence the UA landscape.
- *Urban Growth:* Planned or unplanned urban growth alters the quality and quantity of UA.
- *Urban planning and management:* Tools and practices struggle to oversee UA changes and their resulting consequences. This highlights the need to identify the governing forces involved in UA.
- *Facilities:* The Spatial distribution of facilities can alter UA patterns.

Participant selection

Participant selection was strategically designed to capture diverse viewpoints relevant to the study's focus on the change in UA. Fifteen participants engaged in the Q methodology process and subsequent semi-structured interviews, providing rich and multifaceted insights that contributed to the findings. These participants were purposefully selected to represent key stakeholder groups[12] residents (3 participants), agricultural experts (7 participants), and urban planners and academic researchers with specific expertise in UA change studies (5 participants). Participants were purposefully selected to capture informed perspectives on the change processes associated with UA. Residents were chosen based on their direct experience with local UA practices and land-use changes in their neighborhoods. The group of agricultural experts primarily consisted of practicing urban farmers with extensive field experience. Although we recognize the value of broader stakeholder input (e.g., local administrations, NGOs), time and access constraints limited our ability to include these groups in this study.

The sampling logic underpinning this selection was primarily driven by stakeholder representation, ensuring that perspectives from individuals directly impacted by or possessing significant knowledge regarding land use dynamics and urban development were included. While theoretical saturation is a common principle in qualitative research, the specific and defined nature of the stakeholder groups relevant to UA change in this context necessitated a targeted approach to ensure comprehensive coverage of pertinent viewpoints. This deliberate selection strategy aimed to minimize potential bias by incorporating the perspectives of those with direct experience, professional expertise, and academic understanding of the phenomenon under investigation. Representing these distinct groups

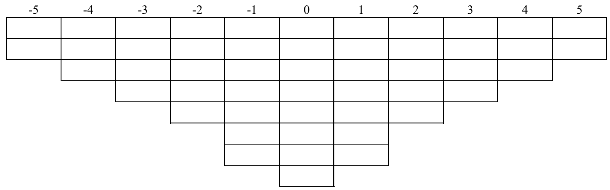
[12] The supplementary data includes participant information (*Appendix B*).

allows for a more nuanced and holistic understanding of the complexities associated with UA change.

Sorting the statements

An 11-point Likert-like chart is designed to align with the statements' numbers (Fig. 3). Participants have sorted the selected statements (Table 5) based on their perspectives, preferences, and judgments using this designed chart and a pseudo-normal distribution.

Fig. 1: Designed Q chart



Data significance

The KMO[13] index is used to determine data efficiency for factor analysis (Significance > 0.5). This index compares simple and partial correlation coefficients on all variables. Bartlett's test is also used to assess the assumption of the unity of the matrix of correlation coefficients. Suppose Bartlett's test is insignificant (Significance > 0.5). In this case, it suggests that the correlation matrix may be a unity matrix, rendering it unsuitable for further analysis (Zare, 2017: 7). Here, a satisfactory KMO index and a suitable significance level confirm the data's reliability (Table 6).

Table 6: KMO assessment

KMO Sample size adequacy test		0.783
Bartlett's Test of Sphericity	Approx. Chi-Square	533.110
	Degree of Freedom	105
	Significance level	0.000

Data analysis

Exploratory factor analysis is calculated using SPSS[14] software, based on the correlation matrix, to identify patterns in participants' perspectives. Also, the principal component analysis method identifies factors, and varimax rotation enhances interpretability. The highest factor scores are calculated and interpreted comparatively, resulting in four perspectives explaining 75.074 % of the total variance. UA change arrays are ranked to categorize these factors (Table 7).

Table 7: Total variance

Factors	Rotation Sums of Squared Loadings		
	Total	Variance Percentage	Cumulative Percentage
1	5.791	38.608	38.608
2	2.470	16.469	55.077
3	1.785	11.897	66.974
4	1.215	8.100	75.074

[13] Kaiser-Meyer-Olkin Measure of Sampling Adequacy

[14] Statistical Package for Social Sciences

The rotated factor matrix (Table 8) identifies four leading groups (characterized by scores above 0.7 on the corresponding factors) in UA changes: Group 1 (seven participants), Group 2 (four participants), Group 3 (three participants), and Group 4 (one participant).

Table 8: Rotated factor matrix

Participants' ID	Factors			
	1	2	3	4
P11	0.925	0.071	-0.022	-0.075
P8	0.914	0.126	0.033	-0.041
P6	0.885	0.062	0.137	0.008
P12	0.878	0.191	0.128	0.193
P13	0.817	0.260	0.193	0.310
P10	0.769	0.261	0.085	0.043
P5	0.732	-0.014	0.413	-0.251
P2	0.573	0.858	0.209	0.079
P9	0.135	0.804	-0.079	0.299
P15	0.328	0.784	0.099	0.027
P1	0.267	0.710	-0.146	-0.003
P14	-0.319	0.628	0.817	-0.160
P7	0.300	-0.266	0.808	-0.004
P4	0.183	0.168	0.791	0.048
P3	0.041	0.106	0.013	0.941

Table 9: Factor scores of selected statements in UA change

Factor 4	Factor 3	Factor 2	Factor 1	C	Factor 4	Factor 3	Factor 2	Factor 1	C
0.275	2.181	-0.080	-0.453	26	-0.942	-0.401	0.570	0.662	1
0.360	0.935	-1.165	0.428	27	-1.454	0.512	-1.396	1.094	2
-1.225	-0.298	-0.850	-1.268	28	-0.747	0.165	0.828	-0.352	3
-1.509	-0.207	-0.662	-1.379	29	0.962	0.054	0.075	-0.358	4
-1.323	1.143	-0.746	-0.833	30	1.477	0.507	0.628	1.317	5
-1.638	0.934	-0.693	-0.665	31	0.187	0.300	0.444	0.098	6
-0.559	0.985	-1.090	-0.605	32	0.247	0.209	1.534	0.729	7
-0.464	1.026	-1.205	-0.272	33	-0.264	0.408	0.336	-0.432	8
-0.270	-0.548	-0.649	-1.072	34	0.030	0.183	1.525	0.394	9
-1.093	-0.325	-0.687	-1.340	35	1.277	-1.448	-1.091	1.607	10
-2.288	-0.199	-0.264	-0.382	36	1.283	-2.882	-1.105	1.262	11
-0.733	-0.654	1.051	1.007	37	0.998	-1.037	-1.119	1.166	12
-2.716	-2.276	-0.282	-0.512	38	0.455	0.922	0.145	0.756	13
0.620	0.669	2.017	0.797	39	0.731	0.449	0.469	0.833	14
1.073	0.204	1.629	-0.330	40	1.191	-0.277	-0.099	0.806	15
0.787	-2.585	0.889	-1.440	41	-0.389	-0.018	0.459	0.725	16
-0.009	-2.291	2.582	-1.784	42	-0.458	0.147	0.758	0.194	17
0.897	-0.594	1.144	-0.246	43	-0.116	0.365	0.011	-0.002	18
-0.089	0.490	0.309	-0.062	44	0.066	-0.068	0.511	0.790	19
1.088	0.686	-0.530	0.529	45	0.504	0.574	0.074	1.419	20
1.706	-1.228	-0.467	-1.959	46	-0.549	0.870	0.045	0.248	21
1.679	0.869	-1.518	-1.965	47	-0.478	0.761	0.300	1.000	22
-0.357	0.197	-1.332	1.261	48	0.021	0.452	-0.277	0.401	23
0.579	-1.019	-2.003	-2.360	49	-0.012	0.497	-0.068	1.143	24
0.879	0.410	1.626	-0.073	50	0.308	0.247	-0.584	-0.522	25

Weighted averages of participant scores are computed using the formula ($w = \frac{f}{1-f^2}$), where f represents the factor load, and w is the weight (Khoshgovian Fard, 2016, p. 75). Q statements are then reconstructed for each factor based on scores, illustrating the statement priorities (scores) within each leading factor (Table 9) and reflecting the participant's perspectives.

Factor arrays are reconstructed Q-sorts representing respondents' priorities for each statement in the sorting diagram. By examining the position of each phrase within these arrays, a more precise interpretation of each factor (or perspective) can be attained. Statements are ranked based on Table 9, using the primary sorting chart designed in this research (Figs. 4–7). Participants put a code number of 5 to the statement they deemed essential and -5 to the least important, with other statements placed in different chart cells.

Fig. 4: Ranking chart for primary perspective

Highest priority ← → Lowest priority

5	4	3	2	1	0	-1	-2	-3	-4	-5
10	5	12	22	13	9	33	38	34	41	48
20	11	24	14	7	21	40	25	28	43	42
	49	2	15	16	17	3	32	35	47	
		37	39	1	6	4	31	29		
			19	46	18	36	30			
				27	45	8				
				23	50	26				
					44					

Fig. 5: Ranking chart for secondary perspective

Highest priority ← → Lowest priority

5	4	3	2	1	0	-1	-2	-3	-4	-5
42	40	9	3	14	4	23	35	10	33	47
39	50	43	17	16	20	38	31	11	48	49
	7	37	5	6	21	46	30	12	2	
		41	1	8	18	45	28	27		
			19	44	24	25	32			
				22	26	34				
				13	15	29				
					36					

Fig. 6: Ranking chart for third perspective

Highest priority ← → Lowest priority

5	4	3	2	1	0	-1	-2	-3	-4	-5
26	33	31	22	5	18	17	28	37	10	41
30	32	13	45	24	6	4	35	49	38	11
	27	21	39	44	25	16	1	12	42	
		47	20	23	7	19	34	46		
			2	14	40	36	43			
				50	48	29				
				8	9	15				
					3					

Fig. 7: Ranking chart for fourth perspective

Highest priority ← → Lowest priority

5	4	3	2	1	0	-1	-2	-3	-4	-5
47	5	15	4	39	7	18	22	1	2	36
48	11	45	43	50	6	8	21	35	29	38
	10	40	56	20	19	34	32	28	31	
		12	41	13	9	49	37	30		
			14	27	23	16	3			
				25	42	17				
				26	24	33				
					44					

Interpreting the results

Factor scores, factor arrays, and distinguishing propositions facilitate the interpretation of subjectivities. Factor arrays should consider expressions on both ends of the spectrum, indicating solid opinions. Distinguishing propositions contribute to specific interpretations for each factor. It is crucial to recognize statements at the zero degree of the spectrum as they may reveal unique aspects of the perspectives.

RESULTS AND ANALYSIS

Spatial and vegetation changes in Damavand City: Phase 2 results

Creating annual average NDVI maps provides a more comprehensive view of vegetation conditions in both years. For each year, we calculated the average NDVI map (explained in section - Producing average NDVI maps for 1995 and 2022). The triple NDVI maps[15] for 1995 and 2022 reveal significant vegetation variations during low and high rainfall seasons *(Appendix D)*. These thresholds and their corresponding area statistics for 1995 and 2022 are presented in Table 10.

Table 10: NDVI Categories

Category	Description	Range		Area **(ha)**		Differen ce **(ha)**
		Min	Max	1995	2022	
Barren or Non-vegetated	Areas with little or no vegetation, such as deserts, rocky terrain, and urban areas.	-1	0	5.27	109.4	104.13
Sparse Vegetation	Areas with sparse or low-density vegetation, such as grasslands or sparsely vegetated croplands.	0	0.2	132.1	61.1	-71
Moderate Vegetation	Areas with moderate vegetation, such as deciduous forests, croplands, or shrublands.	0.2	0.5	55.2	54.3	-0.9
Dense Vegetation	Areas with lush and healthy vegetation, such as evergreen forests or well-irrigated croplands.	0.5	0.7	55.33	45.4	-9.93
Very Dense Vegetation	Areas with extremely dense and vigorous vegetation, such as rainforests or highly productive agricultural areas.	0.7	1	22.26	0.06	-22.2

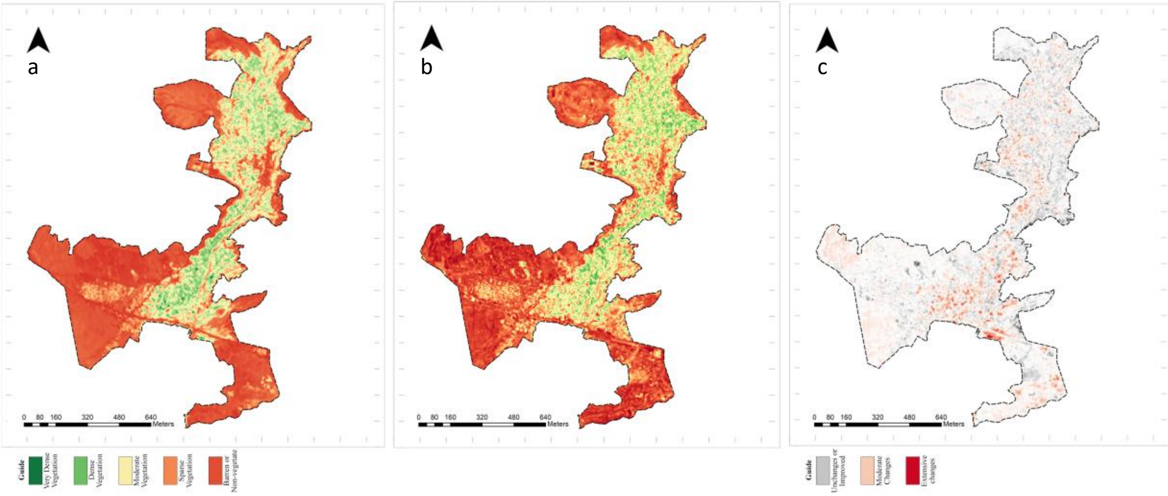
The spatial distribution of average NDVI, categorized in the five categories outlined in Table 10, is illustrated in Fig. 8 (a and b). For further analysis, Fig. 8(c) shows the absolute difference in average NDVI of 1995 and 2022, classified into three types: Extensive changes ($-1<P< -0.5$), Moderate changes ($-0.5<P<0$), and Unchanged ($P= 0$) or Improved ($P> 0$), where P is (Average NDVI 2022 - Average NDVI 1995) (Table 11). The absolute difference map shows extensive changes in the city's center and south.

Table 11: Absolute Difference

Changes	Value Range	Area (ha)
Extensive	-1<P < -0.5	88.178
Moderate	-0.5<P<0	6.649
Unchanged or improved	P>= 0	178.825

[15] Supplementary data includes all maps *(Appendix C)*.

Fig. 8: Average annual NDVI changes in 1995 (a); Average annual NDVI changes in 2022 (b); NDVI Difference between 1995 and 2022 (c)

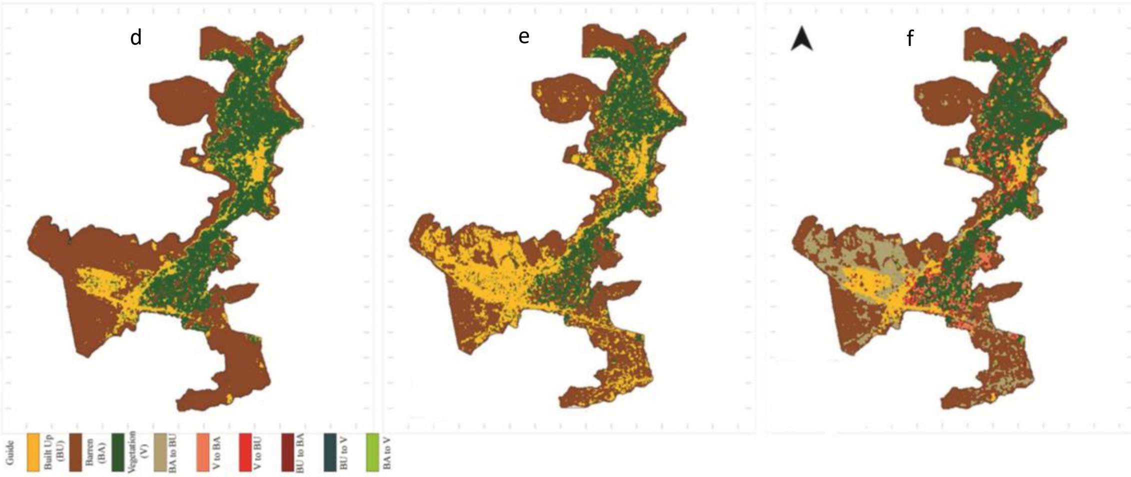


Analyzing land cover changes reveals a 109 % increase in Built-up Land, a 14.34 % decrease in barren land, and a 22.44% decrease in vegetation classes. While the reduction in vegetation cover may not indicate a decrease in agricultural land, a more detailed classification is performed to determine the specific areas where these changes occurred and whether they have transformed into built or barren land. This helps to clarify *thematic changes in UA,* with 1.31 % transitioning to Built-up Land (Table 12). Notably, changes from Vegetation to Built-up land have occurred near agricultural lands and gardens, showing a growing trend of clearing vegetation for construction (Fig. 9). This poses a significant threat to our urban capital, the farmlands. Further exploration is undertaken in Section 3.2 to understand the underlying reasons for this substantial decrease in vegetation. Additionally, a comparison of the results is provided in the discussion (Section - *Rapid conversion of UA lands to other uses*).

Table 12: Land use comparison: 1995 and 2022

	Land use 1995							
	Land class	**Built-up**		**Barren**		**Vegetation cover**		**Overall**
		Area (ha)	Percent	Area (ha)	Percent	Area (ha)	Percent	Area (ha)
Land use 2022	Built-up	276.79	71.167	409.815	25.422	127.035	14.725	813.667
	Barren	70.04	18.009	1169.775	72.564	140.940	16.336	1380.892
	Vegetation	42.097	10.824	32.220	1.999	594.765	68.939	669.105
	Thematic change in UA	108.967	1.31	123.660	1.48	644.917	7.736	
	Overall	388.935	100	1612.057	100	862.740	100	
	Class Change	112.140	28.833	442.282	27.436	267.975	31.061	
	Image Difference	42.47	109.20	-23.12	-14.34	-19.36	-22.44	

Fig. 9: Land Use map 1995 (d) | Land Use map 2022 (e) | Land use changes from 1995 to 2022 (f)



Reasons for increased build-up areas; *Phase 3 results*

Building upon the methodology detailed in Section - *Exploring the "Why" through the causes of the land change*, this section explores the drivers of the substantial changes revealed by geospatial analysis *(Phase 2)*. Employing Q methodology, following steps *Selecting the statements* to *Interpreting the results*, the perspectives of participants from three groups – residents, agricultural experts, urban planners, and academic researchers with expertise in UA change– were collected and analyzed, leading to the identification of four key factors. Quotes from semi-structured interviews support interpretations. These four factors are named based on their constituent statements and thematic focus.

Land value change and attraction to urbanized livelihoods

The group has emphasized the significance of "Efficiency of Agriculture" (Codes[16] 7–10), "Local and Macro Economy," "Land Value" (Codes 19–22), and "Lifestyle" (Codes 3–6) as key drivers of UA change in Damavand. They have particularly highlighted low agricultural product prices (Code 10) and the added value of changing the use of UA land (Code 20). One especially experienced local farmer has stated, "It has been ten years since my family and I decided to sell the parts of our garden and agricultural land and use the profits instead of working on the land and planting crops." (Participant 8, September 2022). Another participant has agreed by stating, "Selling our agricultural land is our most stable source of income." (Participant 10, September 2022). Additionally, another local farmer has discussed the growing interest in selling land (Code 9): "For many years, farming has not been worthwhile, and the cost of planting, harvesting, and caring for our products exceeds the income we receive from selling them." (Participant 5, August 2022). The influence of exogenous factors, such as inflation and government policies, has shaped a specific pattern of UA changes (Codes 23 and 24).

[16] Statement codes are referenced in Table 5.

The people in this group have also considered the social roots of land changes (e.g., Code 5). Lifestyle changes, urbanization, and modern occupations also have contributed to the abandonment of UA lands, with one interviewee mentioning, "Because of my age, I could not farm, and my children did not want to continue in this profession. So, I thought of selling the land, my agricultural capital." (Participant 6, June 2022)

Management and Planning Factors

This group has underscored the importance of temporary and cross-sectoral urban policies and has highlighted the lack of comprehensive natural resource management (Codes 39 and 42) as a fundamental driver of UA changes in Damavand. Municipal urban development policies, land regulations, and inadequate oversight are seen as crucial contributing factors to these changes. Municipal employee interviews have revealed their awareness of shortcomings in evaluating and monitoring inappropriate UA changes. One employee has expressed the need for a different monitoring system explicitly tailored to UA lands: "Damavand needs a different monitoring system for UA lands." (Participant 9, June 2022). Furthermore, a manager has highlighted a critical issue: "In our approved plans, there are perfect goals for preserving our agricultural capital and lands, but they do not reach the implementation stage." (Participant 15, June 2022).

Additionally, concerns have been raised about the unauthorized granting of land use change licenses, which can significantly alter UA patterns. One concerned citizen has said, "Many lands are being illegally exchanged. The legal and planning systems need to be evaluated in more detail." (Participant 2, March 2022)

Physical-environmental factor

This group has stressed the physical environment as a critical factor driving Damavand's UA changes. They have emphasized factors like the region's physical and geographical potential, communication network, construction activities, low-density development, and poor urban design as critical determinants of UA changes. The ratio between built-up and barren lands, as well as the distance from the metropolis, is also seen as a crucial factor. One resident has expressed the impact of these changes: "Damavand has a different environment now. Greenness is going away; instead, you see buildings everywhere, even in former farmland." (Participant 4, September 2022)

Additionally, the lower cost of urban land in Damavand compared to Tehran has attracted migrants, resulting in physical growth, expansion, and construction within the city. One study participant has stated, "Roughly five years ago, we migrated to this city with my family because we could not afford the life of the capital. We bought the land that used to be agrarian and built a house after authorization." (Participant 14, August 2022).

Favorable weather conditions also have attracted migrants, resulting in urban sprawl and the development of second homes, as explained by another participant: "Lots of nonlocals build small villas beside their gardens to use just one or two months a year because of the nice weather and beautiful environment." (Participant 7, August 2022). Additionally, improvements in transportation and communication infrastructure, as well as proximity to Tehran, have shaped a diverse future for UA lands.

Urban infrastructure availability factor

This group has highlighted urban infrastructure availability, proximity to commercial centers, and access to urban centers and social services as primary reasons for the increased construction demand in UA land transformations. One real estate agent has pointed out: "In recent years, the sale of land close to infrastructure and facilities, whether agricultural or not, has increased dramatically and seems to be an incentive for farmers to sell their land." (Participant 3, June 2022).

These findings, along with the identification of the four diverse viewpoints (Sections - *Land value change and attraction to urbanized livelihoods* to *Urban infrastructure availability factor*) and interviews, provide the basis for a comprehensive understanding of the factors driving UA changes in Damavand. Further analysis and comparisons with other studies are presented in Section - *Various perspectives on urban agricultural land change* to provide a broader context for the results.

DISCUSSION AND CONCLUSION

Rapid conversion of UA lands to other uses

The observed 109 % increase in built-up area between 1995 and 2022 (Table 12) reflects intense peri-urban development driven by rising land values and population influx. Comparable peri-urban cities have faced similar pressures: As Mulya & Hudalah confirm, Peri-urban agriculture is highly vulnerable to change compared with urban and rural agriculture due to its location in transitional areas. Their research highlights that urbanization in Indonesia is primarily concentrated in major cities and has extended into the main agricultural areas of rural regions (Mulya & Hudalah, 2024). Sridhar & Sathyanathan (2022) also identified areas of sprawl during their study period, revealing that urban sprawl and urbanization are socio-economic and land-use transformations from rural to urban areas, which affect UA (Sridhar & Sathyanathan, 2022). Moreover, Ansari *et al*. (2025) research in Oman shows that rapid urbanization poses significant challenges that can transform the physical and socio-economic environment of a city over the past decades, leading to a built-up area increase from 13.14 % to 14.88 and a vegetation cover decline from 3.93 % to 3.37 % (Ansari *et al.,* 2025).

Additionally, Kanav *et al*. (2024) noted that industrial and economic development has led to the rapid growth of small and medium-sized towns in India. Rewari City has experienced a 69.4 % increase in built-up area at the expense of vegetation and agricultural land between 1989 and 2020 (Kanav *et al*., 2024). Dekolo *et al.* (2015) report that Lagos lost nearly half of its agricultural land over a two-decade period due to urban sprawl. Aubry *et al.* (2012) document a substantial decline in UA over a similar period. Despite the seemingly small 1.31 % direct transition of vegetation to built-up land, these patches coincide with prime agricultural plots, disproportionately undermining UA productivity and ecosystem services. Even marginal losses can sever critical green corridors, diminish pollinator habitats, and reduce local food production capacity, exacerbating food security risks and urban heat island effects. Vrublova (2020) focuses on urban sprawl in the study area of the municipality with extended powers, Třebíč, as the subject of urbanization. The reduction of agricultural land is a widespread issue in Europe, indicating that this challenge extends beyond just Asia.

The analysis of NDVI changes shows a significant transformation of lands previously used for UA in 1995. However, by 2022, these lands had been converted to other uses, including Barren and Sparsely Vegetated land. This transformation poses a threat to the city's identity and its capital, presenting challenges for urban planners and managers. Vegetation loss accelerates further transformations. Moreover, the rapid pace of change over the past two decades hinders the development of tailored solutions to address these evolving conditions. As Alkhaja *et al*. (2025) warn, the interplay between planning regulations and land availability significantly influences farmed land's scope and location, directly impacting UA activities' scale and intensity (Alkhaja *et al*., 2025). Tesema et al. indicate that key challenges, including socioeconomic barriers, limited access to resources, and inadequate extension services, threaten the UA condition (Tesema *et al*., 2025). The challenge, aligning with Maheshwari *et al.* (2016) findings, also underscores the rapid conversion of land from production to consumption. This conversion is occurring at a rate that surpasses the need to accommodate population growth. Much of this conversion is driven by urban dwellers seeking a lifestyle that requires a larger land area than traditional residential lots typically offer. The conversion of UA areas into other land uses is seen as undesirable for several reasons. It results in the loss of valuable land resources, dilutes farming systems, impacts UA efficiency, and contributes to urban sprawl, causing urban development shortcomings (Alterman, 1997). To address these challenges, regulations that prevent land fragmentation are crucial for controlling property speculation and ensuring viable returns on agricultural production, particularly in the face of lucrative non-agricultural alternatives. Effective land use planning is essential, but may not be sufficient. A comprehensive approach is necessary, taking into account environmental preservation, sustaining productive activities, supporting employment, and ensuring stability in UA land markets.

The findings of this study, combined with the strategic location of the chosen case study, may serve as a model for understanding development processes in the peri-urban areas of Iranian metropolises and analogous situations, particularly within the Global South. This potential for generalization is supported by the consistency of the observed changes with the national trajectory of urban agricultural land conversion in Iran between 1961 and 2018, as evidenced by FAO statistics (Ritchie & Roser, 2019). These statistics indicate a decrease in the share of agricultural land in Iran, from 39.8 % to 28.21 %, accompanied by a significant decline in per capita agricultural land, from 2.6 to 0.56 hectares per person. Following Keshtkar *et al.* (2022), we believe that the lack of implementation of sustainable land use planning practices in Iran results in an annual rate of soil erosion of 33 tons per hectare, which is 6.5 times higher than international standards, and directly affects UA (Keshtkar *et al*., 2022). Notably, this trend extends beyond Iran, with per capita agricultural land in Asia (excluding China and India) reaching 0.38 hectares in 2016, underscoring the regional significance of this phenomenon.

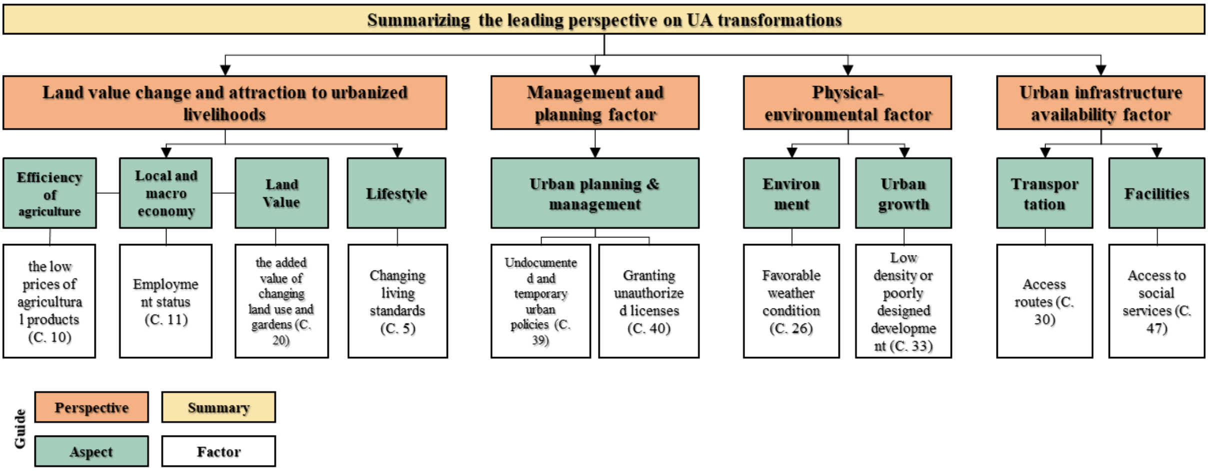
Various perspectives on urban agricultural land change

In this section, we further discuss the four detected perspectives on UA changes, each named after key contributing factors identified through Q-methodology. We present these perspectives using a synthesized framework represented by a diagram (Fig. 10), where “C” refers to the code introduced in Table 5.

The most prominent participants’ group has identified *Land value change and attraction to urbanized livelihoods* as the most critical drivers of UA transformation, attributing these changes primarily to economic and social factors. Economic challenges in UA can be further categorized into two distinct clusters: land value and support for UA.

In dynamic cities, whether in developing or developed nations, high urban land costs are a common characteristic, as confirmed by de Zeeuw Drechsel (2015). This poses a significant challenge to implementing intra-urban agriculture, particularly when combined with a lack of supportive policies in planning documents. Additionally, Drescher (2001) has assessed current farmland conversion patterns, which tend to discourage farmers from adopting sustainable practices and long-term perspectives on land value. Nevertheless, as land prices increase, the profitability of production may decrease; farmers may face pressure to sell their land or may even be evicted. This aligns with the findings of Wang *et al.* (2023), who argue that there has been a substantial increase in urbanization, with over half of the world's population now living in urban settlements; low- and middle-income countries experience the highest growth rates. This transformation is characterized by a decline in agricultural labor share and farm exits, resulting in the inefficient use of cultivated land (Wang *et al.*, 2023).

Fig. 10: Leading perspectives on UA transformations



In terms of supporting UA in Damavand, the governing system is aware of the environmental and logistical challenges. It is taking steps to improve land management, promote cultivation, advance mechanization, and empower farmers by reducing the influence of intermediaries and improving their access to finance and insurance. In the agricultural sector, financing has primarily been state-driven, with the state-owned Agricultural Bank of Iran (Bank Keshavarzi) offering low-interest credit loans to farmers. Additionally, the Agriculture Insurance Fund provides pensions and crop insurance coverage. Nonetheless, most UA producers lack access to credit, and current financial systems do not align well with the needs, expectations, and capabilities of farmers. Information about these schemes is also scarce, and there is a need for a deeper understanding of how credit and investment interventions can benefit a larger number of producers.

When considering the impact of modernization on UA abandonment or the social aspects of these changes, it is essential to note that the urban lifestyle has shifted its focus from agricultural pursuits to careers and technology. Additionally, insufficient education about farming practices can deter UA participation, particularly in developing countries. This shift towards convenience and non-traditional careers, as opposed to traditional agricultural practices, influences the dynamics of UA (Magbondé *et al.*, 2023).

The management and planning perspective has stressed the importance of urban planning and its transformative impact on the UA landscape. This perspective aligns with the contemporary evolution of UA, which links UA with modern urban planning principles, sustainable development, technological innovations, and its current relevance. However, it is essential to note that the relationship between urban and agricultural areas has a much longer history, predating the recent surge in urban agriculture since the 1990s (Chenarides *et al.*, 2020).

The physical environment perspective has pointed out the impact of population growth and favorable environmental conditions on increased UA changes. This intensification is closely linked to both current and projected population growth and urbanization in developing nations, such as Iran, which significantly affects UA land availability (de Zeeuw & Drechsel, 2015). Additionally, Malley *et al.* (2023) suggest that land use change is primarily driven by population growth and associated activities, including agricultural production and settlement, with climate change necessitating the expansion of agricultural land for food production.

Group 4, the *urban infrastructure availability* perspective, has highlighted the critical role of service availability in driving UA change. As Hou *et al.* (2023) note, expanding urban land to provide for residents exerts significant pressure on the regional environment. Furthermore, economic factors, including global markets and competitiveness, impact UA due to its proximity to urban areas, which affects farm structure and specialization (Piorr *et al.*, 2018). UA thrives when located near urban centers, providing advantages such as access to a large consumer market, transport cost savings, and the ability to quickly deliver perishable products to markets (Meijerink & Roza, 2007). Simultaneously, the proximity of newly developed residential areas to farms increases the public's demand for environmentally sustainable farming practices (Drescher, 2001).

A basis for policy making

The findings of this study demonstrate that the transformation of UA in Damavand exemplifies broader patterns of peri-urban land conversion observed across Iran. Rapid urban expansion, speculative land markets, weak regulatory oversight, and insufficient integration of UA into statutory planning frameworks pose significant challenges to the sustainability of urban food systems and local livelihoods. Our research provides a foundational understanding of the quantity and quality of UA changes, shedding light on the underlying mechanisms. To mitigate these pressures, a combination of immediate and longer-term measures is required, tailored to the specific governance and socio-economic context of Iran.

Considering the congruence of our research outcomes with national-level recommendations, they should first be structured within the hierarchical national policy system and subsequently tailored for local application.

In the short term, local policymakers and urban planners should:

- *Enhance monitoring and enforcement:* Strengthen local mechanisms for monitoring land use changes and rigorously enforce existing regulations to prevent unauthorized or informal conversions of agricultural land.
- *Introduce targeted incentives:* Provide short-term financial incentives, such as temporary tax relief, subsidies, or preferential credit, to farmers who retain agricultural land use within urban and peri-urban boundaries.
- *Raise community awareness:* Implement outreach initiatives to increase awareness among landowners, residents, and local stakeholders about the economic, environmental, and cultural value of conserving UA land.

In the long term, more structural interventions should be prioritized:

- *Institutionalize UA within statutory plans:* Integrate designated UA zones into urban master plans and regional development strategies, ensuring legal protection against speculative conversion.
- *Reform land governance frameworks:* Strengthen national and municipal regulations to curb speculative land transactions and unauthorized developments, supported by clear, enforceable penalties. Urban planners and policymakers must craft evidence-based policies for UA growth management, necessitating a thorough understanding of the causes and consequences of urbanization and the ability to anticipate future urbanization patterns (Lee & Lee, 2023).

- *Promote intersectoral coordination:* Foster closer collaboration between urban planning authorities, agricultural ministries, and regional governance bodies to align urban development policies with sustainable agricultural objectives.

Taken together, these recommendations offer a practical framework for local and regional stakeholders to preserve urban agriculture as a vital element of urban sustainability, food security, and socio-economic resilience. Aligning local action with Iran's broader national goals for sustainable land use and agricultural self-sufficiency will be essential to counteract the accelerating loss of valuable urban and peri-urban farmland.

Research limitations

Our research has some limitations. Due to data accessibility constraints, the analysis is limited to data from 1995 onward. Furthermore, there may be inaccuracies in the classification process. Despite the efforts to enhance data granularity, the inherent spatial resolution limitation of 30 meters associated with the acquired Landsat imagery should be acknowledged as a potential constraint within this study. Additionally, the limited number of participants is another constraint. These limitations should be taken into account when interpreting our results.

Also, the participant selection for this study was intentionally focused on residents with firsthand experience of UA land-use change, practicing urban farmers (included in the agricultural experts group), and professionals with direct expertise in UA studies and urban planning. While we acknowledge that engaging a broader range of stakeholders, such as local administrations or NGOs, could have added additional perspectives, practical constraints related to time, resources, and accessibility limited our capacity to reach these groups during this research. Future studies could expand the scope by incorporating a wider range of institutional and civil society actors to build on these findings.

Suggestions for further studies

Future research can build upon the policy implications, identified patterns, and investigated factors to delve into exploring the land market dynamics, modeling urban growth, and collecting valuable data in this field. Moreover, the integrated approach of quantitative and qualitative methods can serve as a framework for researchers in geography and earth science. Future research should evaluate the significance of UA through targeted questionnaires directed at various groups, such as farmers, those who cultivate these plots, and urban residents not engaged in agricultural activities. This approach will help investigate the role of UA in food security, the provision of diverse ecosystem services, cultural value, and agrobiodiversity.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

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APPENDIX

Appendix A: NDVI Computation Algorithm in GEE

```
var City = table;
Map.centerObject(City);
Map.addLayer(City);
// 1995
var dataset = ee.ImageCollection('LANDSAT/LT05/C02/T1_L2')
    .filterBounds(City)
    .filterDate('1995-07-01','1995-10-01')
    .filter(ee.Filter.lessThan('CLOUD_COVER', 45))
    .median()
    .clip(City);
// ndvi1
var Landsat_1 = ee.ImageCollection('LANDSAT/LT05/C02/T1_L2')
.filterBounds(City)
.filterDate('1995-01-01','1995-05-01');
var ndvi1 = Landsat_1.map(function(img){
  return img.normalizedDifference(['SR_B4','SR_B3']);
});
var ndvi_max_1 = ndvi1.max().clip(City).rename('ndvi1');
// ndvi2
var Landsat_2 = ee.ImageCollection('LANDSAT/LT05/C02/T1_L2')
.filterBounds(City)
.filterDate('1995-05-01','1995-09-01');
var ndvi2 = Landsat_2.map(function(img){
  return img.normalizedDifference(['SR_B4','SR_B3']);
});
var ndvi_max_2 = ndvi2.max().clip(City).rename('ndvi2');
// ndvi3
var Landsat_3 = ee.ImageCollection('LANDSAT/LT05/C02/T1_L2')
.filterBounds(City)
.filterDate('1995-09-01','1995-12-01');
var ndvi3 = Landsat_3.map(function(img){
  return img.normalizedDifference(['SR_B4','SR_B3']);
});
var ndvi_max_3 = ndvi3.max().clip(City).rename('ndvi3');
//ndvi stack
var ndvistack1995 = ndvi_max_1.addBands(ndvi_max_2).addBands(ndvi_max_3);
print(ndvistack1995);
Map.addLayer(ndvistack1995);
// ndvi mean
```

```
// Select the bands to calculate the mean for
var selectedBands = ndvistack1995.select(['ndvi1', 'ndvi2', 'ndvi3']);
// Calculate the mean of the selected bands
var meanImage = selectedBands.reduce(ee.Reducer.mean());
// Rename the band
meanImage = meanImage.rename('mean_value');
// Visualize the mean image
Map.centerObject(meanImage, 10);
Map.addLayer(meanImage, {min: 0, max: 255, palette: ['blue', 'green', 'red']}, 'Mean Image');
// Export
Export.image.toDrive({
 image: meanImage,
 description: 'NDVI-meanImage-1995',
 region: City,
 scale: 10,
 maxPixels: 1e9
});
Export.image.toDrive({
  image: ndvistack1995,
  description: 'ndvi_map_1995',
  region: City,
  scale: 10,
  maxPixels: 1e9
});
//2022
var Landsat_2022 = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
.filterBounds(City)
.filterDate('2022-07-01','2022-10-01')
.filter(ee.Filter.lessThan('CLOUD_COVER', 45))
.median()
.clip(City);
// ndvi111
var Landsat_111 = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
.filterBounds(City)
.filterDate('2022-01-01','2022-05-01');
var ndvi111 = Landsat_111.map(function(img){
  return img.normalizedDifference(['SR_B5','SR_B4']);
});
var ndvi_max_111 = ndvi111.max().clip(City).rename('ndvi111');
// ndvi222
var Landsat_222 = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
```

```
.filterBounds(City)
.filterDate('2022-05-01','2022-09-01');
var ndvi222 = Landsat_222.map(function(img){
  return img.normalizedDifference(['SR_B5','SR_B4']);
});
var ndvi_max_222 = ndvi222.max().clip(City).rename('ndvi222');
// ndvi333
var Landsat_333 = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
.filterBounds(City)
.filterDate('2022-09-01','2022-12-01');
var ndvi333 = Landsat_333.map(function(img){
  return img.normalizedDifference(['SR_B5','SR_B4']);
});
var ndvi_max_333 = ndvi333.max().clip(City).rename('ndvi333');
//ndvi stack 2022
var ndvistack2022 = ndvi_max_111.addBands(ndvi_max_222).addBands(ndvi_max_333);
print(ndvistack2022);
Map.addLayer(ndvistack2022);
// ndvi mean
// Select the bands to calculate the mean for
var selectedBands2 = ndvistack2022.select(['ndvi111', 'ndvi222', 'ndvi333']);
// Calculate the mean of the selected bands
var meanImage2022 = selectedBands2.reduce(ee.Reducer.mean());
// Rename the band
meanImage2022 = meanImage2022.rename('mean_value2');
// Visualize the mean image 2022
Map.centerObject(meanImage2022, 10);
Map.addLayer(meanImage2022, {min: 0, max: 255, palette: ['blue', 'green', 'red']}, 'Mean Image2022');
// Export
Export.image.toDrive({
 image: meanImage2022,
 description: 'NDVI-meanImage-2022',
 region: City,
 scale: 10,
 maxPixels: 1e9
});
Export.image.toDrive({
  image: ndvistack2022,
  description: 'ndvi_map_2022',
  region: City,
  scale: 10,
```

```
  maxPixels: 1e9
});
// Calculate the absolute difference between the two NDVI images
var ndviDifference_Main = meanImage2022.subtract(meanImage).abs();
// Visualize the NDVI difference
var visParams = {
  min: 0,
  max: 0.5,
  palette: ['blue', 'white', 'red']
};
Map.centerObject(ndviDifference_Main, 10);
Map.addLayer(ndviDifference_Main, visParams, 'NDVI Difference');
// Optionally, you can also calculate the ratio between the two NDVI images
var ndviRatio = meanImage2022.divide(meanImage);
// Visualize the NDVI ratio
var ratioVisParams = {
  min: 0.5,
  max: 1.5, // Adjust this range based on your specific data
  palette: ['blue', 'white', 'red'] // Adjust colors as needed
};
Map.addLayer(ndviRatio, ratioVisParams, 'NDVI Ratio');
// Compute the difference between two NDVI maps 1995 & 2022
var ndviDifference = ndvistack2022.subtract(ndvistack1995);
// Threshold the difference to identify significant changes
var changeThreshold = 0.1;
var significantChanges = ndviDifference.gt(0.1);
// Visualize the significant changes
Map.addLayer(significantChanges)
print(significantChanges);
// Export the image to your Google Drive
Export.image.toDrive({
  image: ndviDifference,
  description: 'ndviDifference',
  region: City,
  scale: 10,
  maxPixels: 1e9
});
// Export the image to your Google Drive
Export.image.toDrive({
  image: significantChanges,
  description: 'significantChanges2',
```

```
  region: City,
  scale: 20,
  maxPixels: 1e9
});
// Calculate statistics for the difference image
var stats = ndviDifference.reduceRegion({
  reducer: ee.Reducer.mean().combine({
    reducer2: ee.Reducer.stdDev(),
    sharedInputs: true
  }),
  geometry: City,
  scale: 30,
  maxPixels: 1e9
});
// Convert the statistics to a Feature
var statsFeature = ee.Feature(null, stats);
// Export the statistics as a CSV
Export.table.toDrive({
  collection: ee.FeatureCollection([statsFeature]),
  description: 'change_detection_stats',
  fileFormat: 'CSV'
});
// Display the statistics in the Console
print('Change Detection Statistics:', stats);
// Calculate statistics for the difference image / significant
var stats = significantChanges.reduceRegion({
  reducer: ee.Reducer.mean().combine({
    reducer2: ee.Reducer.stdDev(),
    sharedInputs: true
  }),
  geometry: City,
  scale: 30,
  maxPixels: 1e9
});
// Convert the statistics to a Feature
var statsFeature = ee.Feature(null, stats);
// Export the statistics as a CSV
Export.table.toDrive({
  collection: ee.FeatureCollection([statsFeature]),
  description: 'significant_change_detection_stats',
  fileFormat: 'CSV'
```

```
});
// Display the statistics in the Console
print('S Change Detection Statistics:', stats);
// Define a function to calculate zonal statistics
var calculateZonalStats = function(image, aoi) {
  var stats = image.reduceRegion({
    reducer: ee.Reducer.mean().combine({
      reducer2: ee.Reducer.stdDev(),
      sharedInputs: true
    }),
    geometry: City,
    scale: 30,
    maxPixels: 1e9
  });
  return ee.Feature(null, stats);
};
// Calculate zonal statistics for both NDVI images
var statsImage1 = calculateZonalStats(ndvistack1995, City);
var statsImage2 = calculateZonalStats(ndvistack2022, City);
// Create a FeatureCollection from the calculated statistics
var statsCollection = ee.FeatureCollection([statsImage1, statsImage2]);
// Export the zonal statistics as a CSV
Export.table.toDrive({
  collection: statsCollection,
  description: 'zonal_stats_ndvi',
  fileFormat: 'CSV'
});
// Define NDVI value ranges ndvistack1995
var valueRanges = [
  { min: 0.2, max: 0.5, label: 'Low' },
  { min: 0.5, max: 0.7, label: 'Medium' },
  { min: 0.7, max: 1.0, label: 'High' }
];
// Calculate the area for each value range
var areaStats = ee.FeatureCollection(valueRanges.map(function(range) {
  // Calculate a binary mask for the current range
  var mask = ndvistack1995.gte(range.min).and(ndvistack1995.lte(range.max));
  // Calculate the area within the AOI for the current mask
  var areaDict = mask.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: City,
```

```
    scale: 30,
    maxPixels: 1e9
  });
    // Print the area dictionary to the console to inspect its keys
  print('Area dictionary:', areaDict);
  // Get the computed area from the dictionary
  var area = ee.Number(areaDict.get('ndvi1')).divide(10000);
  return ee.Feature(null, {
    label: range.label,
    area: area
  });
}));
// Export the results as a CSV
Export.table.toDrive({
  collection: areaStats,
  description: 'ndvi_area_stats',
  fileFormat: 'CSV'
})
// Define NDVI value ranges ndvistack2022
var valueRanges = [
  { min: 0.2, max: 0.5, label: 'Low' },
  { min: 0.5, max: 0.7, label: 'Medium' },
  { min: 0.7, max: 1.0, label: 'High' }
];
// Calculate the area for each value range
var areaStats = ee.FeatureCollection(valueRanges.map(function(range) {
  // Calculate a binary mask for the current range
  var mask = ndvistack2022.gte(range.min).and(ndvistack2022.lte(range.max));

  // Calculate the area within the AOI for the current mask
  var areaDict = mask.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: City,
    scale: 30,
    maxPixels: 1e9
  });
    // Print the area dictionary to the console to inspect its keys
  print('Area dictionary:', areaDict);
  // Get the computed area from the dictionary
  var area = ee.Number(areaDict.get('ndvi1')).divide(10000);
  return ee.Feature(null, {
```

```
    label: range.label,
    area: area
  });
}));
// Export the results as a CSV
Export.table.toDrive({
  collection: areaStats,
  description: 'ndvi_area_stats',
  fileFormat: 'CSV'
})
```

Appendix B: Q-Methodology participants

Table B-1: Q-Methodology participants

Factor	Participants ID	Interview Date	Occupation/Description
2	P1	20 June 2022	Municipality Employee
2	P2	28 March 2022	Local resident
4	P3	20 June 2022	Local resident / Expert in Land selling
3	P4	13 Sep 2022	Local resident
1	P5	18 August 2022	Local farmer
1	P6	12 June 2022	Former Farmer
3	P7	10 August 2022	Local resident
1	P8	10 Sep 2022	Local farmer, with a decade experience
2	P9	20 June 2022	Municipality employees
1	P10	10 Sep 2022	Local farmer
1	P11	12 August 2022	Local farmer
1	P12	18 August 2022	Local farmer
1	P13	14 September 2022	Local farmer
3	P14	23 August 2022	Resident
2	P15	20 June 2022	City Manager

Appendix C: Annual NDVI maps

A stack of NDVI images for 1995 and 2022 represents different seasons. This stack is visualized, providing insights into seasonal variations in vegetation health within the Damavand region.

Fig. C-1: Change trends of NDVI of the Damavand in three periods of one year/1995 (a-c)

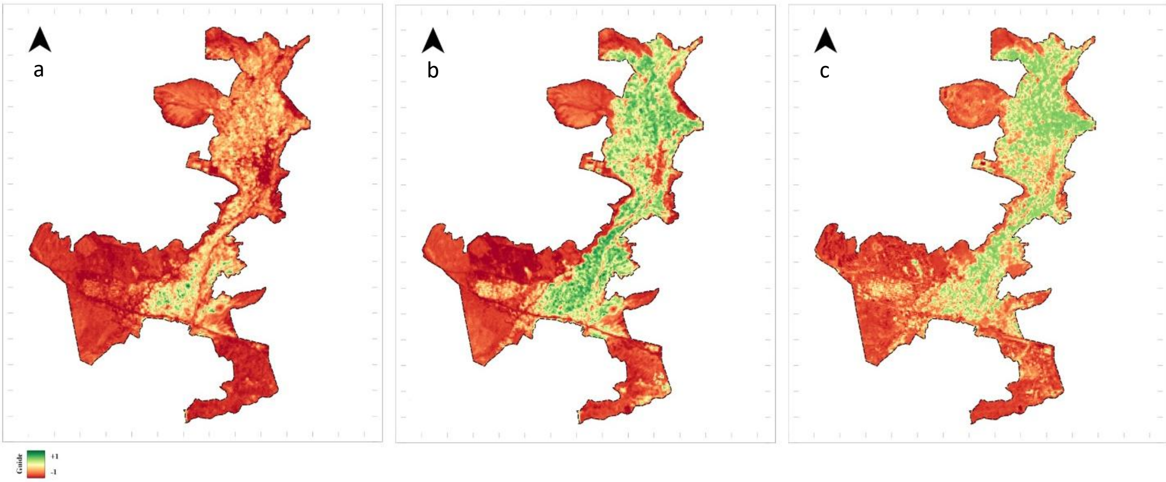

Fig. C-2: Change trends of NDVI of the Damavand in three periods of one year /2022 (e-g)