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Earthquake-Driven Urban Reconfiguration and Land Use Change: Scenario-Based ANN–Markov Modelling of Post-Disaster Growth

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Abstract

Disasters, either natural or human caused, are significant drivers of land use land cover (LULC) changes. This study analyses the land use change caused by the 6 February 2023 Turkey earthquakes in Malatya and its immediate vicinity. In the study, deep learning and machine learning techniques from integrated artificial intelligence components together with GIS and UA techniques were utilized. Artificial Neural Networks (ANN), Multilayer Perceptron (MLP) and Markov chain methods were used to determine the LULC status before and after the earthquake. The results of the study show that the most dominant land use in the region in 1986 was dry pastures (constituting ~70%). In 2025, this ratio decreased to 6.28 per cent. On the other hand, while built-up areas occupied 9.22% in 1986, it increased to 26.13 per cent in 2025. Our projections show that this ratio will increase to 31.52% in 2050 and 36.88% in 2070. The 2023 earthquakes caused the city to grow horizontally, and this caused a decrease in the proportion of agricultural land on the urban periphery. Distance from the city is the most effective driving force in land use with the Cramer value = 0.456). Therefore, the area most affected by land use is the agricultural lands and pasture areas around the city.

Keywords: Driver variable; land use; artificial neural networks; multilayer perceptron (MLP); Markov chain; earthquake

Introduction

While major disasters, such as earthquakes, are instant humanitarian calamities, their most enduring impact is often engraved in the landscape. The rebuilding process in a post-disaster environment can significantly reconfigure urban form, frequently transferring expansion from dense, vertical patterns to horizontal spread (Kaya & Karadeniz, 2020; Kaya, 2024; Kaya et., al., 2025). While such post-disaster reconfigurations aim to address immediate safety concerns, they also initiate a cascade of land use/land cover (LULC) changes. Importantly, it often drives irreversible transition of peri-urban lands from agricultural and ecological covers to urban built-up areas resulting in long-term impacts (Kang et al., 2022; Chen & Nakatsugawa, 2021). Recognizing and assessing such LULC transformation is thus not only an academic exercise in LULC change detection; it is fundamental to plan resilient cities that are simultaneously safe and sustainable in the wake of disasters.

Earthquakes, being major geological disasters, can lead to significant LULC changes, especially in densely populated cities. After such disasters, sustainable land use planning, along with critical components of urban form such as street systems and building stock can be seriously impacted (Kaya 2024). Recent large earthquakes, such as those in Turkey, have altered LULC in many cities in the country. In this context, GIS, remote sensing, and machine/deep learning are widely used for change detection, monitoring, recovery assessment, and future planning especially in areas vulnerable to disasters (Nath et al., 2018; Aydöner & Maktav, 2009; Karadeniz & Sunbul, 2023; Sunbul et al., 2025). The primary reasons for the widespread use of these approaches include remote sensing datasets being are open access, and deep learning and machine learning methods being developed with artificial intelligence to be robust, reliable, and scalable (Aryal et al., 2023; Adam et al., 2014; Maxwell et al., 2018).

More specifically, advanced methods, such as artificial neural networks (ANN), Support Vector Machine (SVM), Random Forest (RF), decision trees, and Markov Chains (MC) among other models, have attracted interest of researchers over the past decade (Ghosh et al., 2017;

Hirayama et al., 2020; Karadeniz & Sunbul, 2023; Talukdar et al., 2020; Leh et al., 2013). Volke and Abarca-Del-Rio (2020) compared Support Vector Machine (SVM) and Random Forest (RF) classification methods with the Maximum Likelihood (ML) classification to reveal LULC changes following the earthquake and tsunami on February 27, 2010, in the Biobío region of Chile (Volke & Abarca-Del-Rio, 2020). In a similar study, Sheykhmousa et al. (2019) used machine learning to reveal post-disaster recovery activities and LULC changes (Sheykhmousa et al., 2019). Yang et al. (2010) demonstrated land use and land cover changes (LUCC) in Wenchuan city using machine learning techniques (Yang et al.,2010). Karadeniz and Sunbul (2023) employed a multilayer perceptron neural network-based Markov chain model combined with geographic information systems to analyze land cover changes after earthquakes in Düzce (Türkiye) and to make future projections (Karadeniz & Sunbul, 2023). Even though these studies employ methods for LULC projections (e.g., MLP-Markov in Karadeniz & Sunbul, 2023) and other researchers have evaluated post-disaster recovery, such as Ubaura, 2018, there is an absence of a critical integration: how these advance modelling approaches could be exploited to isolate and project the influence of disaster-induced planning shift understanding the reconfiguration of cities in a disaster vs no-disaster situation.

As evident from the above, the primary focus of the existing literature is on immediate impact assessment or recovery in general. This situation results in partial insights regarding quantitative frameworks to estimate how post-disaster shifts in urban planning and policy could be a primary driver of LULC changes that may increase vulnerabilities or create further challenges in the form of compromised resilience. Having such frameworks and assessments could potentially serve as a proxy to urban resilience (i.e., how disasters could drive alteration of peripheral ecological or vegetation lands as a result of re-development and increase built-up areas).

In this context, we here address the critical gap through posing the following research questions:

- how could disasters (specifically earthquakes) alter the patterns of urban growth? (using 2023 earthquake in Malatya as a case),
- to what degree the post-disaster transition from vertical to horizontal development be quantified as a significant influencer in LULC change detection model?

- what are the implications of this disaster-driven horizontal growth for the reduction in vegetation cover and pastorals in the peripheral areas of cities?

To provide answers to such questions, this study proposes and employs a synergistic Artificial Neural-Network Multilayer Perceptron and Markov Chain (ANN-MLP-MC) framework within an earthquake-scenario-based evaluation. The framework is implemented to uniquely evaluate the LUCL changes and prediction under two scenarios (i.e., pre- and post-earthquake changes and prediction for 2050 and 2070). Such comparisons enable us to explicitly assess earthquake's impact not just as a destructive calamity, but as a catalyst of a new urban reconfiguration—with implications for LULC sustainability in cities.

1.1 Study Area

Malatya is a medium-sized Anatolian city in eastern Türkiye. Malatya is located to the east of Türkiye and extends between 38° 21' 19.3032" N and 38° 20' 0.6972' E. Malatya province, located in Malatya plain, is ~ 37 ha has a surface area (Kaya, 2025). The total population of the province is 742,725. Battalgazi and Yeşilyurt districts, which constitute the city Centre, are 556,068. The city Centre has generally developed in the east-west direction around the D-300 highway. Industrialization tendency gains intensity in the west direction where the Organized Industrial Zones are located. In the south of the city Centre, there are the Bey Mountains, which are a topographic threshold for the city, and in the north, there are wide plains (plain) extending to the Karakaya dam lake, where apricot orchards, which have an important structure in terms of urban economy and agricultural pattern, are located (Cengiz & Yılmaz, 2016).

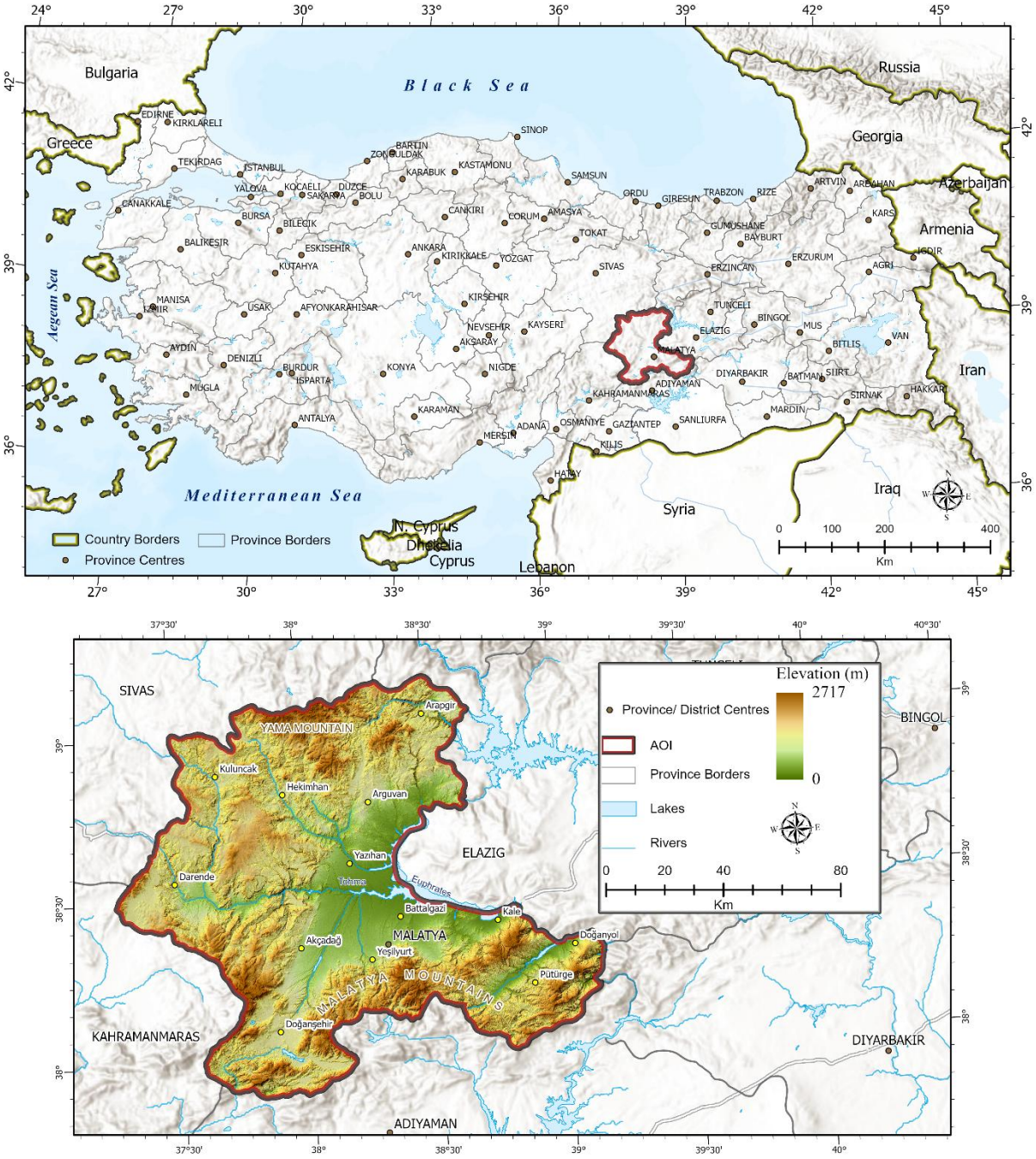


Figure 1: Location of Malatya and its surrounding area.

Malatya, in addition to its morphological and socio-economic characteristics, has been one of the settlements most affected by the series of earthquakes centred in Kahramanmaraş on 6 February 2023. On 6 February 2023, two major earthquakes occurred, with epicentres in the Pazarcık and Elbistan districts of Kahramanmaraş province, measuring Mw 7.7 and Mw 7.6 respectively. Following these earthquakes, another earthquake with a magnitude of Mw 6.4 and its epicentre in the Yayladağı district of Hatay occurred on 20 February 2023. These

earthquakes, occurring in quick succession at short intervals, have not only caused extensive destruction in 11 provinces, but have also brought social and economic life to a standstill. The earthquakes of 6 February 2023, considered one of the greatest disasters of the last century, affected a total of eleven provinces, including Kahramanmaraş, Adıyaman, Hatay, Osmaniye, Gaziantep, Kilis, Şanlıurfa, Diyarbakır, Malatya, Adana and Elazığ, causing widespread destruction.

According to data published by the Disaster and Emergency Management Presidency (DEMA) on 22 April 2023, 50,783 people lost their lives and more than 107,430 were injured as a result of the Pazarcık and Elbistan earthquakes. Furthermore, according to the damage assessment report published on 6 March 2023 (PSB, 2023), 13.6 per cent (232,662 buildings) of the 1,712,182 buildings surveyed after the two earthquakes were destroyed or severely damaged. It is stated that the number of residential buildings destroyed or severely damaged was 518,009. (Özmen et al., 2023).

The settlements most affected by the earthquakes were determined to be Hatay (215,255 homes), Kahramanmaraş (99,326 homes) and Malatya (71,519 homes), respectively. These provinces are followed by Gaziantep (29,155 homes), Osmaniye (16,111 homes), Adana (10,156 homes), Elazığ (8,602 homes), Kilis and Şanlıurfa (PSB 2023). Although it was not the epicentre of the earthquake, the fact that approximately 71,000 homes were destroyed or severely damaged in Malatya, the third most affected province after Hatay and Kahramanmaraş, clearly demonstrates that the city's urban resilience capacity is quite limited.

In this context, Malatya constitutes a critical and priority area of study in terms of examining post-earthquake land use/land cover (LULC) changes, revealing the effects of the disaster on the urban space, and assessing urban resilience dynamics.

2 Data Organization and Methods

The study is based on an experimental scenario to analyze the modifying power of earthquakes on land cover in Malatya city and surrounding area. The first step of the scenario is to simulate how the land cover in and around the city of Malatya will change in 2050-2070 under the condition that the 2023 Kahmaranmaraş earthquakes do not occur. The second stage consists

of simulating the land change between 2050-2070 after the earthquake. All data and software used in the study have been selected to realize this scenario in the most accurate way. In this context, Geographic Information Systems (GIS), Remote Sensing, Artificial Neural Networks (ANN), and Markov Chain techniques were utilized in an integrated manner. In addition, these techniques were utilized through ArcGIS Pro, ERDAS and TerrSet software.

In line with the technique, Landsat satellite images of Malatya City and its surroundings for 3 different summer periods, 1986, 2022 and 2025, when cloudiness is low, were first obtained. Due to the earthquakes in 2023, the image dates were determined considering the target of this study. Images from 1986 and 2022 were used to calculate the land change trends and directions before the earthquake. Images from 1986 and 2025 were used to determine the land change trends and directions from the past to the post-earthquake period. Then, by utilizing these trends, land simulations for two different situations were created. The remote sensing-based Controlled Classification method was used for image processing.

All procedural steps in this study are shown systematically in the workflow diagram below. This diagram provides a clear and organised overview of the entire land use change analysis process, including data collection, land use mapping, trend calculation, driver variable identification and statistical evaluation.

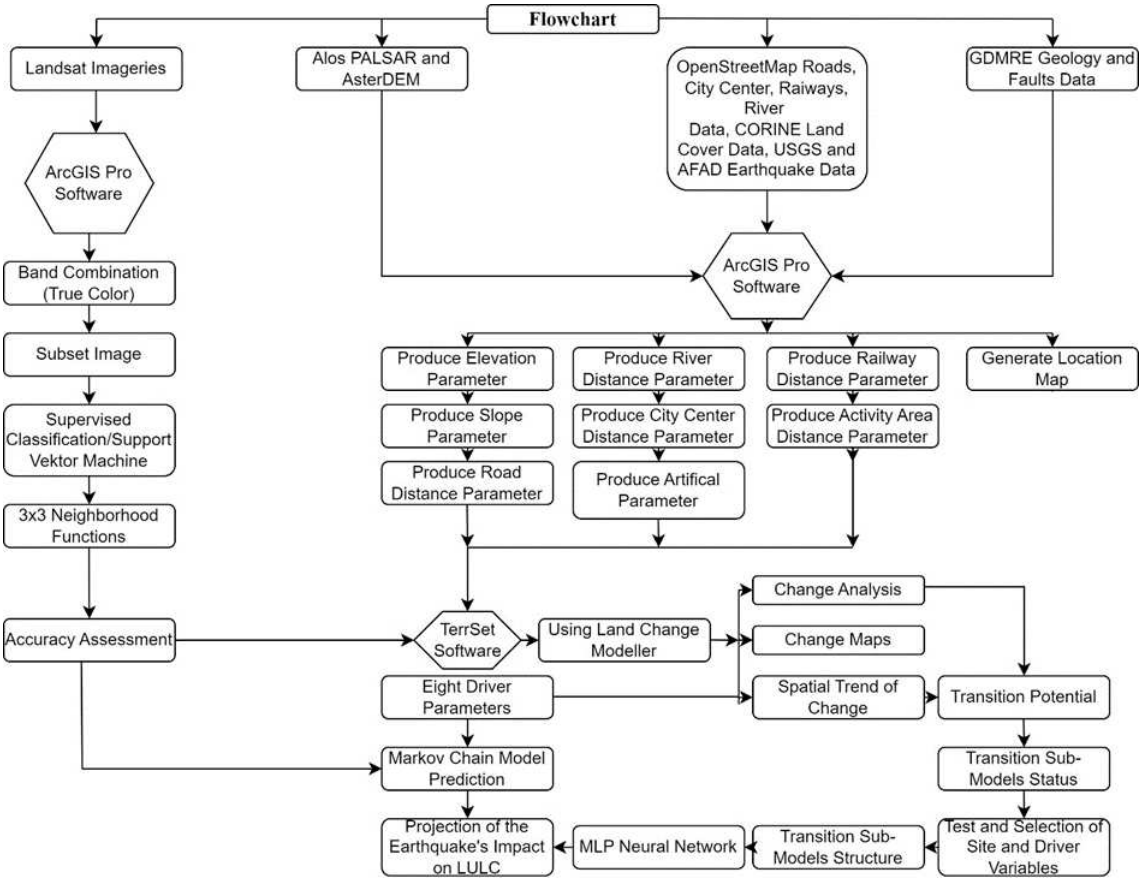


Figure 2. Overall framework, the implemented workflow, and data analysis schematic

The datasets on the LULC in Malatya encompasses a diverse range of public institutions and open source information, all of which are detailed in Table 1.

Table 1: Data sets used in the analysis

Data Source	Dates	Resolution (m) / Scale	Data Type	Source
Landsat images (TM, ETM+, OLI)	July 17, 1986; July 7, 2022; August 8, 2025	30	Raster	https://earthexplorer.usgs.gov/)
Digital Elevation Model (Slope, Stream network)	November 30, 2013; July 9, 2007	30, 12.5	Raster	https://search.earthdata.nasa.gov https://search.asf.alaska.edu/
Roads	2022-2025	Vector, field scale	Vector	https://www.openstreetmap.org/ ArcGIS StreetMap
Earthquakes	1957 to 2021	Vector, field scale	Vector	https://earthquake.usgs.gov
Active Faults	2013	1:1,250,000	Vector	http://yerbilimleri.mta.gov.tr/
Countries and Maritime Borders, Water Surface	2025	1:1,000,000	Vector	https://www.naturalearthdata.com/
Geology	2019	1:1,250,000	Vector	https://www.mta.gov.tr/en/

2.1 Controlled Classification

In this study, a pixel-based Support Vector Machine (SVM) was employed as a controlled classification tool. SVM, which is effective in processing high-dimensional data, was preferred because it provides high accuracy in land cover classification processes(Huang et al., 2002; Mountrakis et al., 2011). Satellite images have undergone pre-processing steps including atmospheric correction and geometric rectification to improve data quality. Due to the scope of the study, the terrain was categorized into five different classes: artificial surfaces (all human structures such as buildings, roads, mines and excavation sites), agricultural areas, vineyard and garden areas, dry grasslands and water surfaces. In order to train the SVM classifier, 50 training samples for each class representing various land use classes were determined in the Segmentation section. The entire dataset was then classified based on the learnt spectral signatures. Classified images were analyzed to detect temporal changes in land use patterns, providing information about the spatial dynamics of the Malatya area.

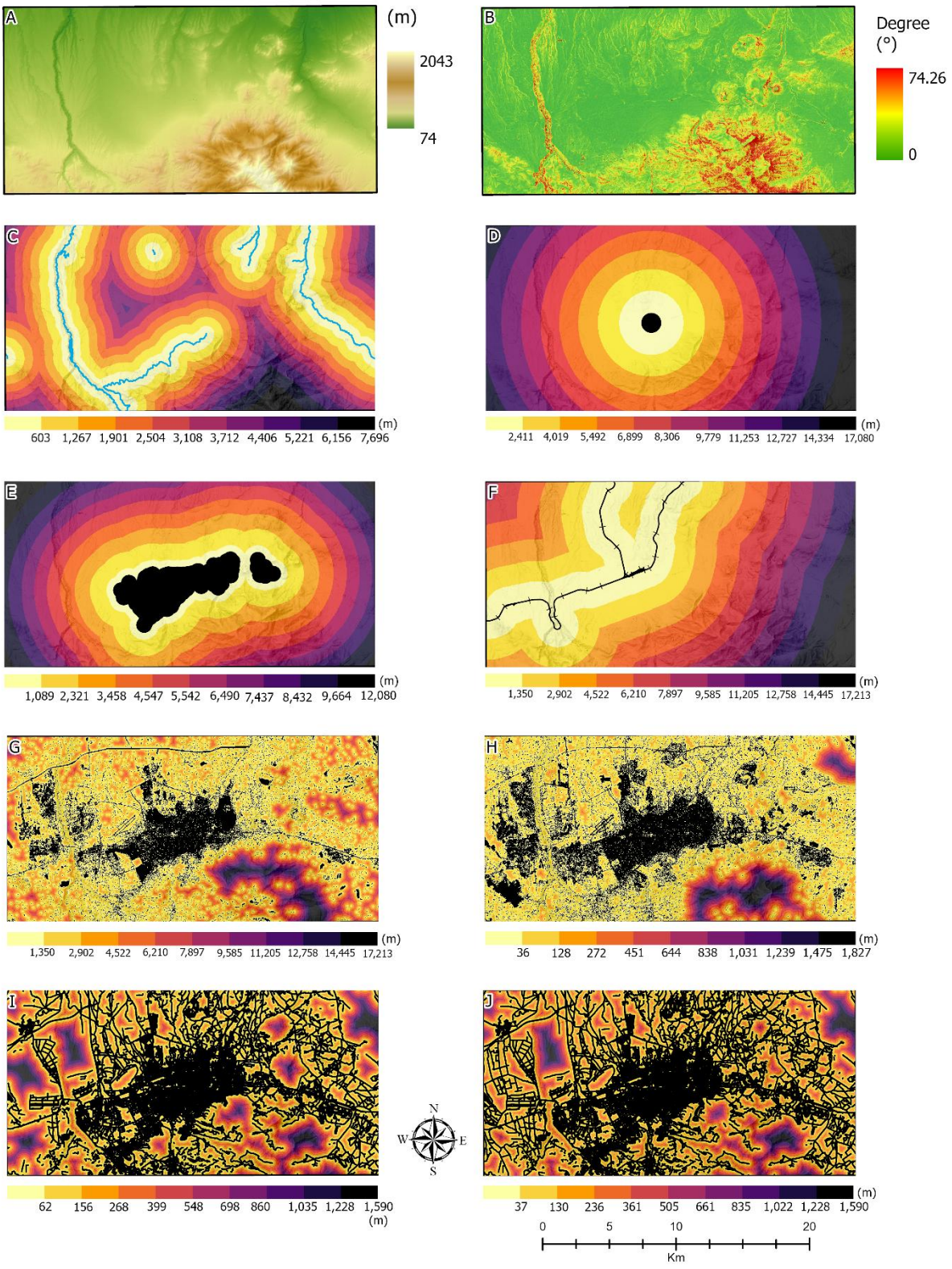
After categorizing the satellite images into five distinct land cover classes, a thorough accuracy assessment was carried out to evaluate the dependability of the classification results. This process involves the creation of an error matrix, also known as a confusion matrix, which is a standard method for assessing classification accuracy in remote sensing studies (Congalton & Green, 2019). A stratified random sampling strategy was implemented by placing 50 random validation points within each land use class, making a total of 250 points in the entire study area. The land use class specified by the user was compared with the actual class observed in the reference data obtained from high-resolution satellite images and ground information at each of these points.

After the image verification process is completed and the desired quality images are obtained, the generation of variables required for future land predictions is initiated. Driver variables (DVs) play an important role in understanding and predicting land use changes by covering various factors affecting spatial change.

In this study, ten basic DVs were selected based on a comprehensive review of the existing literature and specific characteristics of the study area. These variables include dem, slope, distance from steams, distance from city centre, distance from activity centre, distance from railways, settlement area (2022), settlement area (2025), distance from the road (2022),

distance from the road (2025) (figure 3). Each of these factors was selected due to its potential to significantly affect land use patterns in the study area. For example, proximity to urban areas, transportation infrastructure such as highways and railways can facilitate urban expansion and accessibility, while natural barriers such as streams and topographic elements such as slope can restrict this development and direct it differently. In the study, by integrating these driving variables into the analysis, it is aimed to effectively capture the multifaceted effects that shape land use dynamics over time. The produced satellite images and driving variables were processed with the Land Change Models module in the TerrSet software in order to achieve the study goal. In this stage, 2 different analyses were performed with the model in line with two different scenarios. First including 1986-2022 and then 1986-2025 images. After the land cover change analyses between the images were made, land transformations were divided into various groups in the Transition Sub models stage to make them ready for MLP. Later, the impact status of the driving variables was tested again on the model.

The maps produced by LULC analyses are a simulation of real land use (Zheng et al., 2021). LULC maps are produced by the interaction of anthropogenic, abiotic and biophysical factors (Karadeniz & Sunbul, 2023). In this study, ten driving variables were utilized to model LULC dynamics. Among these variables, DEM and slope were treated as static variables, whereas urban areas, roads, rivers, and other spatial factors were considered dynamic variables influencing future land use change (Figure 3).



220

221 **Figure 3**. Driver variables for future LULC predictions. A: Dem, B: Slope, C: Distance from
222 Steams D: Distance from city centre, E: Distance from activity centre, F: Distance from
223 railways, G: Settlement Area (2022), H: Settlement Area (2025), I: Distance from the road
224 (2022), J: Distance from the road (2025)

To measure the effect of each driving variable on land use change in the model, Cramer's V statistic was used, which provides a robust measure of the relationship between categorical variables. This statistical approach allowed the assessment of the strength and significance of the relationship between each driving variable and the observed land use transitions.

2.2 ANN-MLP-MC

Artificial Neural Networks (ANN), particularly the Multilayer Perceptron (MLP), have been utilized for modeling and predicting future land use changes based on satellite imagery data. MLP is a feedforward neural network with an input layer, one or more hidden layers, and an output layer. It can capture complex nonlinear relationships in data. (Haykin, 1998). By training the MLP with historical land use data and relevant driving factors such as socioeconomic variables, environmental conditions, and policy influences, the network is trained based on the underlying patterns that govern land use transitions. This model is trained to predict the probabilities of different land use classes for each pixel, which helps create future land use maps (Pijanowski et al., 2002).

MLPs are effective in applying land use change models due to their superior performance over traditional statistical methods due to their ability to handle nonlinear and complex interactions between multiple variables. (Li & Yeh, 2002). In this study, MLP is used to integrate both spatial and temporal data to increase the prediction accuracy. The flexibility of MLP allows it to include a wide range of input variables, making it a robust tool for simulating various land use scenarios. The predictive information obtained from the MLP model was used to predict land use for the years 2050 and 2070 with an accuracy rate of 78% according to two different cases. After this stage, the Markov chain method was incorporated into the MLP to model the temporal dynamics of land use changes and to predict future land use distributions more accurately.

Markov chains are stochastic models that describe systems that transition from one state to another in a state space. In these models, the probability of each subsequent state depends only on the current state (Weng, 2007). When combined with spatial modeling techniques such as cellular automata or ANN-based models, Markov chains increase the capacity to simulate

realistic land use scenarios by including both spatial and temporal dimensions. Therefore, the integration of the Markov chain method with the MLP model in the study provided important guidance for long-term land use planning and resource management by providing a more comprehensive and accurate prediction of future land use patterns. In the study, the probability of land use transitions between different categories was measured over time by creating transition probability matrices from past land use data through this model. These matrices were applied to current land use data to predict future changes, effectively simulating the temporal evolution of land use patterns.

3 Results

3.1. Spatial-temporal changes in LULC

Malatya and its surroundings constitute the study area, with 70.11% of the total land area consisting of dry pastures (Figure 4). In this period, agriculture areas had an area of ~ 19% and Orchard areas had an area of ~ 2%. Agriculture and Orchard areas were the most expanded areas in 2022 before the earthquake. Agricultural areas comprised 16103 hectares in the same year, making it the largest land class at 41.13% of the total study area. Orchard areas also increased approximately 15 times in this period and reached a total of 14165 hectares. The main reason for this situation is the increasing market share due to apricot production in the region and public support. Dried apricot is the most important export product in Malatya and is marketed to approximately 115 countries. In 2022, Artificial Surface areas expanded and reached 6723 hectares in approximately 35 years. Dry Pasture areas, which cover ~70% of the total land use, decreased to 2,460 hectares in 2025 with 6.28% of the total study area. Pasture areas are the land class that has lost the most area over 40 years, with a total loss of 25,000 hectares. During this period, artificial surface increased by ~ 2 times from 3612 hectares (9.238%) in 1986 to 6723 hectares (17.17%) in 2022 at a positive rate. After the 6 February 2023 earthquake, land use in Malatya changed positively in favor of artificial surface due to the increasing construction in and around the city. Approximately one year after the earthquake, the total area of artificial areas increased by 65.7% to 10,230 hectares. The land use in Malatya from 1986 to 2025 is shown in Table 2 and Figure 4.

Table 2: Land use classification around Malatya between 1986-2022-2025.

	1986		2022		2025	
LU/LC	ha	%	ha	%	ha	%
Artificial Surface	3612	9.22%	6723	17.17%	10230	26.13%
Agriculture Areas	7247	18.51%	16103	41.13%	15453	39.47%
Orchard Areas	805	2.05%	14165	36.18%	10944	27.95%
Dry Pastures	27442	70.11%	2092	5.34%	2460	6.28%
Water Surface	33	0.08%	66	0.16%	62	0.15%
Total	39139	100.00%	39139	100.00%	39139	100.00%

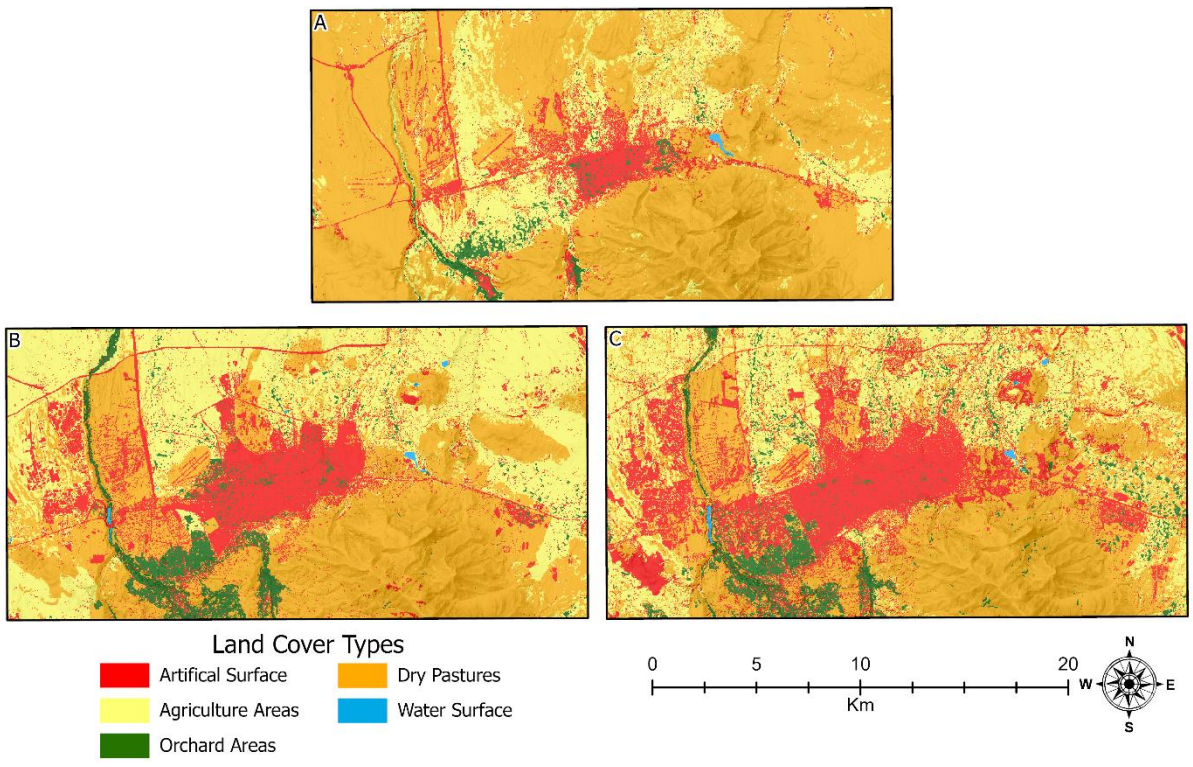


Figure 4: A:1986 Land Use/Cover, B:2022 Land Use/Cover, B: 2025 Land Use/Cover.

The procedures performed for LULC mapping are reliable as our assessment achieved accuracy rates above 90% for most of the classes as well we for all the periods, and the Kappa coefficients yielded similar results (Table 3).

290 **Table 3:** Accuracy rate of LULC classification in Malatya

Land use/land cover classes	1986		2022		2025	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
Artificial Surface	93.75	90.00	92.45	98.00	94.00	94.00
Agriculture Areas	93.18	82.00	93.47	86.00	90.19	92.00
Orchard Areas	95.83	92.00	94.74	90.00	97.80	92.00
Dry Pastures	82.96	100.00	89.09	98.00	90.38	94.89
Water Surface	92.59	100.00	100.00	98.00	100.00	100.00
Overall accuracy (%)	92.40		94.00		94.00	
Kappa coefficient (κ)	0.90		0.92		0.93	

291

292 By calculating Cramer's V for each parameter, it was possible to determine which factors
293 had what level of impact on land use changes in the study area (Table 4-5). The results obtained
294 from this analysis not only emphasize the relative importance of each factor but also provide
295 information for future land use planning and policy making by identifying key impact areas.
296 The process was applied for each scenario. This methodological framework supported more
297 accurate estimations by providing a comprehensive assessment of land use dynamics. After
298 this stage, the MLP stage was initiated to identify land transformation potentials.

299 **Table 4:** Cramer's value of the driving variables for Malatya in 2022.

Class	Distance to city	Distance to roads	Distance to downtown	Distance to Railways	Distance to Activity Center	Distance from streams	Dem	Slope
Overall value	0.2174	0.1595	0.2862	0.1951	0.2878	0.2032	0.2120	0.1733
Artificial Surface	0.3153	0.2567	0.4557	0.2812	0.4272	0.1489	0.1384	0.1601
Agriculture Areas	0.2010	0.2318	0.3583	0.1323	0.4064	0.1881	0.3132	0.1963
Orchard Areas	0.1200	0.0864	0.2542	0.1744	0.1717	0.2525	0.3551	0.2640
Dry Pastures	0.3372	0.0389	0.1826	0.2683	0.2713	0.3062	0.3880	0.3151
Water Surface	0.0246	0.0155	0.0678	0.0689	0.0613	0.0921	0.0701	0.0322

Table 5: Cramer's value of driving variables for Malatya (2025).

Class	Distance to city	Distance to roads	Distance to downtown	Distance to Railways	Distance to Activity Center	Distance from streams		Class
Overall value	0.1759	0.1555	0.2353	0.1937	0.2565	0.2050	0.1901	0.1643
Artificial Surface	0.3458	0.2447	0.3925	0.2870	0.4054	0.2013	0.1384	0.1744
Agriculture Areas	0.2133	0.0817	0.2568	0.0903	0.3339	0.1622	0.3132	0.1987
Orchard Areas	0.1272	0.0662	0.1551	0.1343	0.1481	0.2013	0.1133	0.1106
Dry Pastures	0.0815	0.2281	0.2212	0.3171	0.2386	0.3326	0.2178	0.2862
Water Surface	0.0135	0.0251	0.0896	0.0689	0.0789	0.1207	0.0456	0.0322

Figure 5 quantitatively captures the post-earthquake urban transformation processes observed in Malatya by means of machine-learning-derived transition potential surfaces. The ANN–MLP–Markov framework reveals that the conversion of agricultural and pasture lands into artificial surfaces is not spatially random, but instead follows distinct patterns that align with post-disaster planning interventions, relocation strategies, and the expansion of urban infrastructure. The concentration of high transition potential values along the urban periphery corresponds closely with areas where post-earthquake development has shifted towards low-rise and horizontally expanding settlements. This spatial configuration directly supports the central argument of the study regarding the transition from vertical to horizontal urban growth following the 6 February 2023 earthquakes. In this context, the earthquake functions not only as a destructive event but also as a structural driver that reorients long-term urban development trajectories.

Moreover, the transition potential surfaces illustrate how historical land-use trends, when combined with spatial driving variables such as proximity to existing settlements and transportation networks, amplify the likelihood of artificial surface expansion in the post-earthquake period. These findings indicate that earthquake-induced planning adjustments have intensified development pressure on agricultural and pasture lands, thereby raising critical concerns for land-use sustainability and urban resilience in earthquake-prone regions.

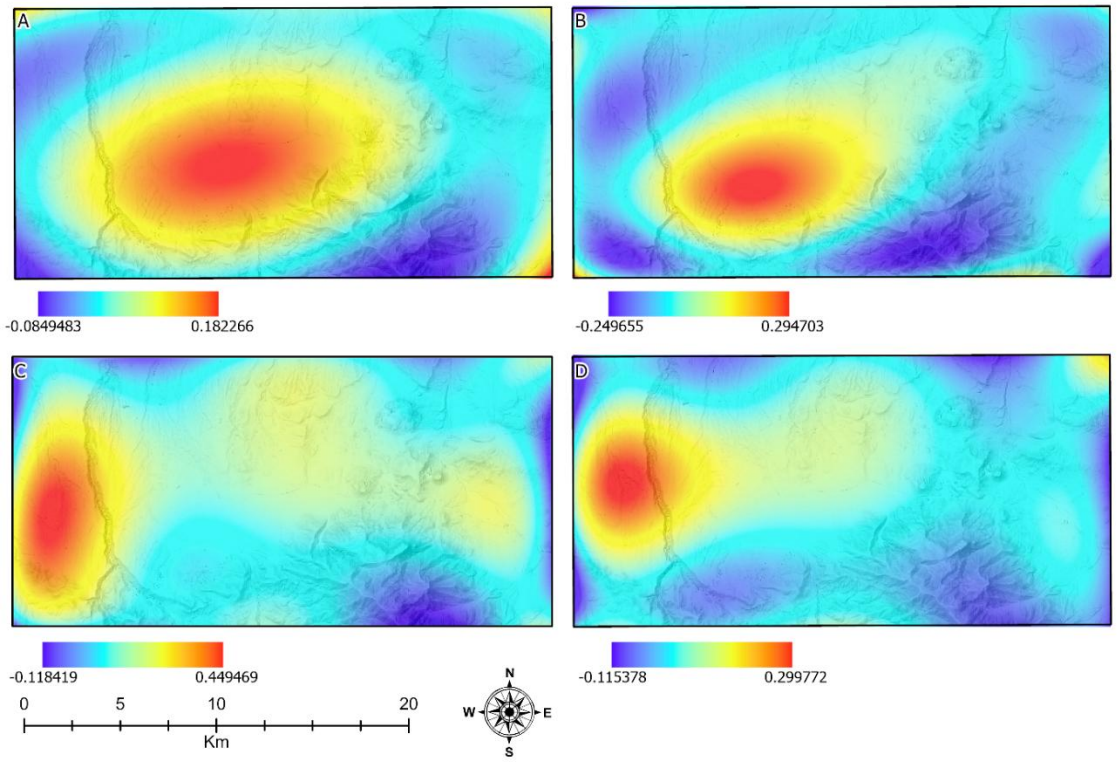


Figure 5: A: 1986-2022 change from agricultural land to artificial surfaces focal center, B: 1986-2022 change from pasture land to artificial surfaces focal center, C: 1986-2025 focal center for change from agricultural land to artificial surfaces, D: 1986-2025 change from pasture land to artificial surfaces focal center

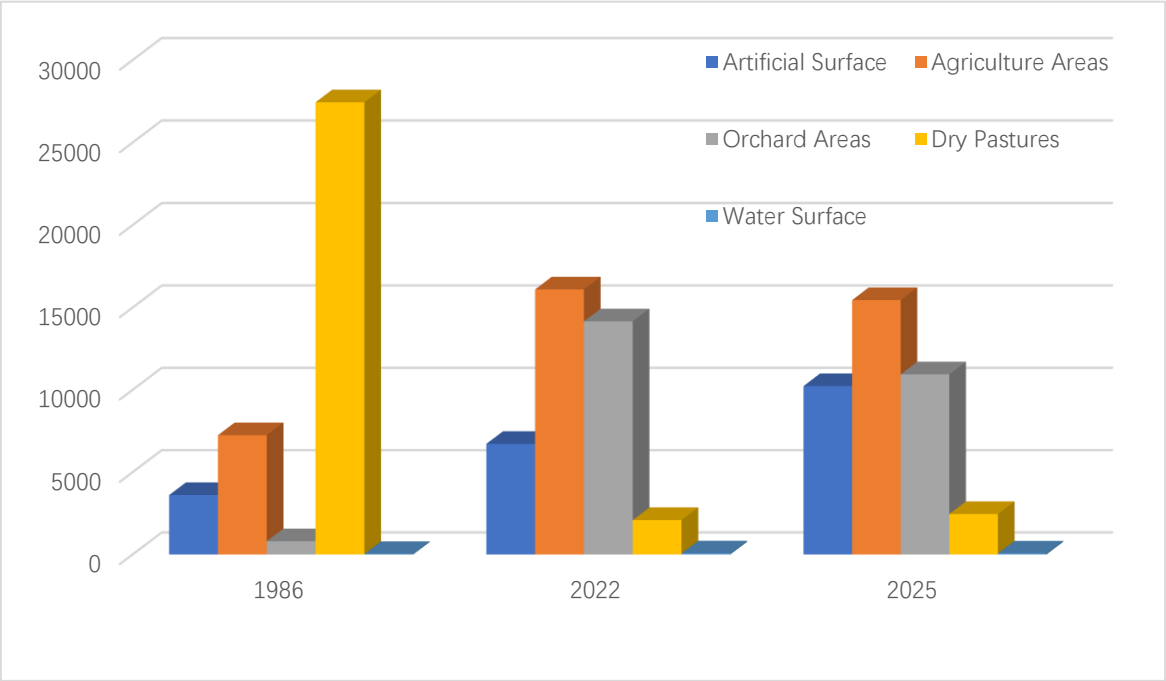


Figure 6: Land use classification around Malatya between 1986-2022-2025.

3.2 Transition potential sub-model

Various models are utilized to analyze LULC changes. The most widely used model among these models is MLP (Abbas et al., 2023). MLP is generally based on networks of neurons and generates multiple hashes based on simple computations. MLP creates a set of connection network relationships between driving factors and other classes (change and persistence) with the help of neuron networks (Mozumder et al., 2016). In the sub-model for converting agricultural areas to artificial surfaces based on satellite images from 1986 to 2022, the skill measure is 0.7952. The conversion from pasture to artificial surfaces is 0.8670, and the conversion from agricultural areas to artificial surfaces based on satellite images from 1986 to 2025 is 0.8935. Additionally, the conversion from pasture to artificial surfaces based on images from 1986 to 2025 is 0.8495.

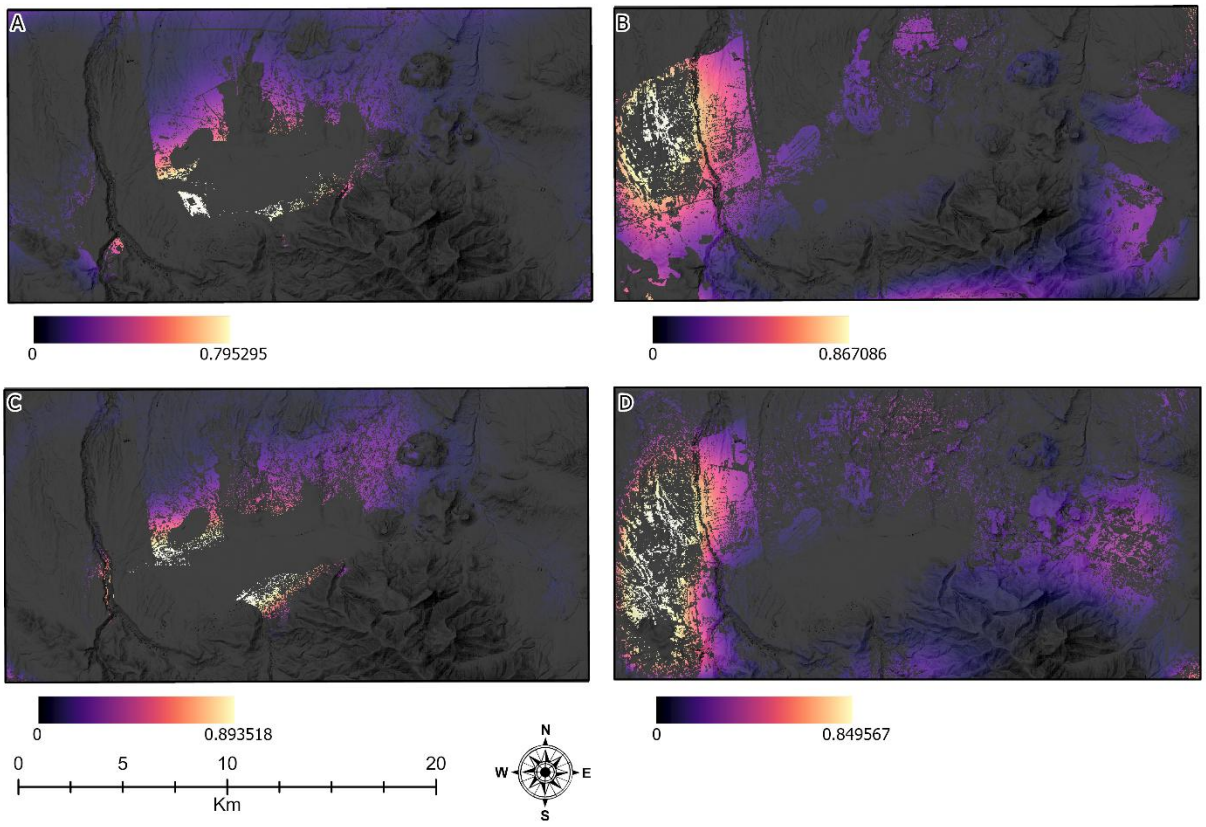


Figure 7. MLP Transformation potential results: A: From agricultural areas to artificial surfaces according to 1986-2022 images, B: From pasture to artificial surfaces according to 1986-2022 images, C: From agricultural areas to artificial surfaces according to 1986-2025 images, D: 1986-2025 from pasture to artificial surfaces.

3.3 LULC transition modelling in Malatya

The MLP-MC and Transition Sub-Model models used in the study were employed to simulate the land use situation in Malatya. The analysis maps created with these models sought to answer the question of what kind of land use scenario would have developed if an earthquake had not occurred. Subsequently, post-earthquake land use development scenarios were created. In constructing these scenarios, predictions for land use in 2050 and 2070 were calculated and mapped. The analysis models used are based on trend forecasts. If the influence levels of existing factors remain unchanged, land use outcomes change incrementally. However, this process is viewed as a tendency to reach equilibrium in the long term (Rahnama & Wyatt, 2021). Within the scope of the research, various transition analysis maps were produced using

the Transition Sub-Model method. To determine the impact of the earthquake on land use change, the transition potential from "areas with high agricultural potential to artificial surfaces" and "pastures to artificial surfaces" was selected. Here, artificial surfaces generally represent urban structures (Figure 7).

After completing these procedures, we analyzed MC probability models in the assessment of land use classes using temporal data. Markov chain analysis utilizes the probabilities of past and present satellite images to reveal their potential for future change. It thus determines the amount of land use in the future using specific satellite imagery (Rahnama & Wyatt, 2021). The transition probability matrix is the probability that each land use class will be invaded by another. In the study, transition analyses based on scenario models are determined for the years 2050 and 2070, 2022 pre-earthquake and 2025 post-earthquake (Tables 6-10). 2022 land cover data before the 6 February 2023 earthquake were analyzed and Marcov chain transition matrix results were obtained (Figure 7). A similar process was performed using the satellite image obtained after the 6 February 2023 earthquake. Thus, land use changes in 2022 (pre-earthquake) and 2025 (post-earthquake) were compared. Thus, the validity of the models used was tested thanks to the findings determined with different scenarios.

Table 6: Matrix of probability of conversion of land use categories (2022-2050).

	Artificial Surface	Agriculture Areas	Orchard Areas	Dry Pastures	Water Surface
Artificial Surface	0.6463	0.0654	0.0641	0.2241	0.0000
Agriculture Areas	0.1957	0.5323	0.1109	0.1595	0.0016
Orchard Areas	0.2780	0.0901	0.5714	0.0430	0.0175
Dry Pastures	0.1886	0.2494	0.0077	0.5540	0.0003
Water Surface	0.0072	0.2421	0.0350	0.0094	0.7062

Table 7: Matrix of probability of conversion of land use categories (2022-2070).

	Artificial Surface	Agriculture Areas	Orchard Areas	Dry Pastures	Water Surface
Artificial Surface	0.6261	0.1098	0.0852	0.1783	0.0007
Agriculture Areas	0.2602	0.4451	0.1363	0.1550	0.0034
Orchard Areas	0.3485	0.1349	0.3866	0.1073	0.0227

Dry Pastures	0.1564	0.3993	0.0431	0.4007	0.0006
Water Surface	0.0482	0.3055	0.0647	0.0384	0.5431

Table 8: Matrix of probability of conversion of land use categories (2025-2050).

	Artificial Surface	Agriculture Areas	Orchard Areas	Dry Pastures	Water Surface
Artificial Surface	0.7336	0.0972	0.0494	0.1192	0.0005
Agriculture Areas	0.2436	0.4099	0.1525	0.1938	0.0001
Orchard Areas	0.3161	0.0627	0.5597	0.0437	0.0178
Dry Pastures	0.1809	0.2791	0.0124	0.5272	0.0003
Water Surface	0.0719	0.2136	0.0636	0.0131	0.6378

Table 9: Matrix of probability of conversion of land use categories (2025-2070).

	Artificial Surface	Agriculture Areas	Orchard Areas	Dry Pastures	Water Surface
Artificial Surface	0.6595	0.1144	0.0717	0.1532	0.0012
Agriculture Areas	0.3326	0.2652	0.1665	0.2333	0.0024
Orchard Areas	0.4053	0.0964	0.3708	0.1054	0.0222
Dry Pastures	0.2697	0.2894	0.0560	0.3847	0.0003
Water Surface	0.1435	0.2420	0.1068	0.0569	0.4508

Table 10: Land use classification around Malatya between 1986-2022-2025.

	1986		2022		2025	
LU/LC	Hectare	Percentage	Hectare	Percentage	Hectare	Percentage
Artificial Surface	3612	9.22%	6723	17.17%	10230	26.13%
Agriculture Areas	7247	18.51%	16103	41.13%	15453	39.47%
Orchard Areas	805	2.05%	14165	36.18%	10944	27.95%
Dry Pastures	27442	70.11%	2092	5.34%	2460	6.28%
Water Surface	33	0.08%	66	0.16%	62	0.15%
Total	39139	100.00%	39139	100.00%	39139	100.00%

3.4 LULC Prediction for 2050 and 2070

Land use simulations for the years 2050 and 2070 in Malatya were created using Marcov

chain prediction results and MLP neural network analysis data. The land use change results obtained within the scope of the study are shown in Figure 7, Tables 11 and 12. Thus, four different scenario maps were created to determine the LULC change in Malatya. These maps show how land use is shaped after a disaster such as an earthquake. Of course, this is a scenario created using today's data. It is a fact that it does not reflect the reality. However, the analyses made by using past data roughly give information about the land use that will occur in the future.

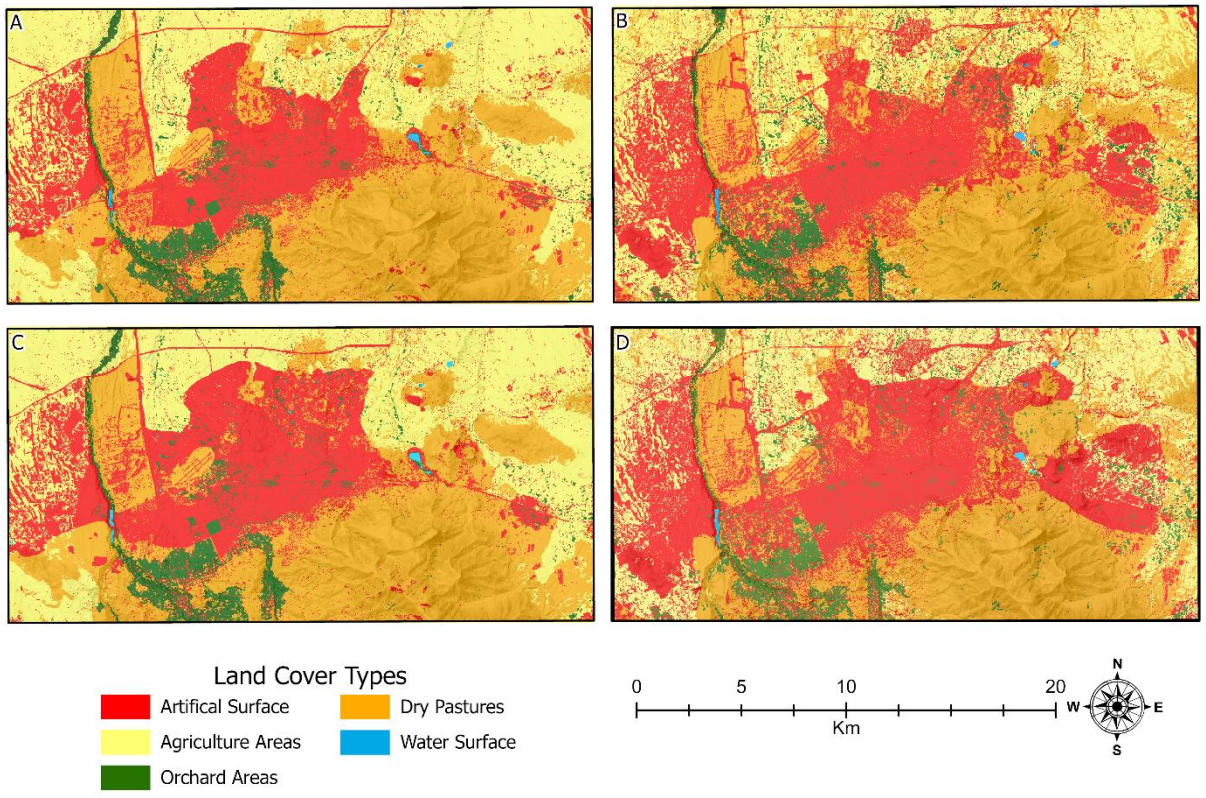


Figure 8: Land use status: A: 2050 without earthquake, B: 2050 with earthquake, C: 2070 without earthquake, D: 2070 with earthquake**.**

Figures 9 A and C show that if the earthquake had not occurred on 6 February 2023, the development direction of the city would have been more towards the north and southwest. These areas are important agricultural lands around the city. Construction on these lands is very dangerous due to the earthquake risk. After the 7.7 and 7.6 magnitude earthquakes centred in

Kahramanmaraş, 4,655 buildings and 12,83 independent sections collapsed in Malatya. The number of emergency, medium, heavy and collapsed buildings was determined as 42 thousand 821, the number of independent sections as 130 thousand 530 and the number of houses as 104 thousand 713 (21) (Figure 10). If the earthquake had not occurred, vertical construction would have continued in unsuitable areas around the city. In 2022, agricultural lands will cover 41.13%, while this rate is predicted to decrease to 33.75% in 250 and 31.29% in 2070. In 2022, Artificial Surface covered an area of 17.17%, while this rate was predicted to increase to 23.55% in 250 and 26.48% in 2070. This is evidence that vertical construction will continue.



Figure 9: Post-earthquake urban destruction in Malatya city (Türkiye), where severe damage occurred to buildings with low earthquake resistance located in the city centre. The images illustrate the structural vulnerability created by unplanned land-use transformation in urban environments exposed to high seismic risk. The photographs were provided by the Anadolu Agency (AA https://www.aa.com.tr/).

Table 11: Land Use Classes and Proportions across Pre-Earthquake (2022), Post-Earthquake

(2025), and Projected (2050) Time Periods

	2022 (Pre-Earthquake)		2025 (Post-Earthquake)	
	Hectare	Percentage	Hectare	Percentage
Artificial Surface	9218	23.55%	12338	31.52%
Agriculture Areas	13211	33.75%	10331	26.39%
Orchard Areas	2116	5.40%	2453	6.26%
Dry Pastures	14528	37.11%	13961	35.67%
Water Surface	66	0.16%	56	0.14%
Total	39139	100.00%	39139	100.00%

Table 12: Land Use Classes and Proportions across Pre-Earthquake (2022), Post-Earthquake (2025), and Projected (2070) Time Periods

	2022 (Pre-Earthquake)		2025 (Post-Earthquake)	
	Hectare	Percentage	Hectare	Percentage
Artificial Surface	10367	26.48%	14435	36.88%
Agriculture Areas	12250	31.29%	9273	23.69%
Orchard Areas	2124	5.42%	2450	6.25%
Dry Pastures	14332	36.61%	12925	33.02%
Water Surface	66	0.16%	56	0.14%
Total	39139	100.00%	39139	100.00%

With the 6 February 2023 earthquake, horizontal construction has been replaced by laws instead of vertical construction in the city and its immediate surroundings. This situation has led to an increase in Artificial Surface areas in and around the city. The ratio of artificial surface, which was 17.17% in 2022, increased by approximately 9% in 2025 and rose to 26.13%. In the projections, the percentage of artificial surface is expected to rise to 31.52% by 2050 and 36.88% by 2070. It is estimated that the expansion of transportation networks and the relocation of

settlements to areas with lower earthquake risk will lead to significant changes in agricultural areas.

4 Discussion

Urban settlements in Turkey are not only areas of population concentration but also areas with high disaster risk. Seventy-five per cent of Turkey's population lives in cities located in areas with active fault zones. (Görür & Yıldız 2026). This situation should be considered an integral component of sustainability, as incorporating resilience knowledge into urban planning, design and urban policies in Turkish cities has yielded significant results in reducing disaster risk. (Sajjad et all., 2021). Increasing resilience in Turkish cities with high earthquake risk is essential to minimise negative social and economic impacts and to minimise loss of life and property. The reconstruction phase of the disaster cycle is a process involving the management and procedures related to the repair of damaged buildings and the construction of permanent housing, as well as the social dimensions of these activities (Vanclay, 2020). In this context, increasing the resilience of buildings after an earthquake by constructing housing with high earthquake resistance on solid ground is the first step towards creating a resilient society.

Recent studies have shown significant changes in the resilience paradigm in earthquake-related resilience assessments. The fundamental reason for this situation stems from the actions of the survivors (Rashed& Weeks 2003, Shafapourtehrany et all., 2022). After devastating disasters such as earthquakes, the most important expectation of survivors is to increase their resilience in a wide variety of ways, including individual, social, institutional and structural aspects (Doğulu et all., 2016). Following the earthquakes centred in Kahramanmaraş and Hatay on 6 February 2023, work has begun on strengthening the existing urban building stock as the first stage of building societal resilience. This has directly impacted urban land use, altering the direction of urban development. As a result of changes in urban planning and design policies, particularly in earthquake-prone areas, development plans have been amended. According to the revised zoning plans, priority has been given to imposing height restrictions on newly constructed residential buildings, followed by the creation of new urban patterns in geologically safe areas with low earthquake risk. This situation has led to a complete change

in urban land use. The research findings support this situation. The findings of this study showed that without the earthquake, artificial surfaces would have risen by 23.55% in 2050 and 26.48% in 2070. This situation indicates that vertical construction will be common especially in urban area growth. However, with the earthquake, artificial surfaces increased by 26.13% in 2024 and this ratio will increase to 31.52% in 2050 and 36.88% in 2070. After the earthquake, the emphasis on horizontal construction in land use has clearly changed the LULC situation in Malatya. The main reason for this is the change in zoning plans in rural and urban areas and the prevention of multi-storey construction in areas with high earthquake risk. For this reason, while the area of agricultural areas and pastures in and around Malatya decreases, there is a great increase in the proportion of artificial surfaces.

4.1 The impact of earthquakes on urban sprawl and LULC change

Turkey's urbanisation process was shaped more by urban rent than by taking disaster risks into account. Industrial areas, which became widespread particularly after the 1950s and 1960s, densifying shanty town structures, and urban planning amnesties, plans and applications based on the 1980s and later urban planning laws, and the impact of real estate development-focused urban projects that came to the fore in the 2000s. As a result, the morphological structure and typological characteristics of cities reflecting Turkey's geographical and cultural diversity have undergone and continue to undergo a significant transformation process (Sınmaz& Özdemir 2016). However, following the earthquakes, legislation was introduced to address this situation. Although it is difficult to draw universal conclusions from a single factor, the earthquakes of 6 February 2023 led to the emergence of new settlement areas on the outskirts of cities due to their spatial and functional diversity. In this context, the earthquakes of 6 February 2024 caused significant destruction in the old urban fabric of Malatya city centre (Figure 10). Following the earthquake, the process of rebuilding housing, accompanied by population movements, accelerated the dynamics of urban sprawl in an unorganised manner. Areas located on the outskirts of cities rather than city centres have been opened for settlement in the 11 provinces affected by the earthquakes of 6 February 2023. These areas have been shaped largely outside the existing planning hierarchy and with the guidance of public resources. The research results

support this situation. The findings of this study showed that without the earthquake, artificial surfaces would have risen by 23.55% in 2050 and 26.48% in 2070. This situation indicates that vertical construction will be common especially in urban area growth. However, with the earthquake, artificial surfaces increased by 26.13% in 2024 and this ratio will increase to 31.52% in 2050 and 36.88% in 2070. After the earthquake, the emphasis on horizontal construction in land use has clearly changed the LULC situation in Malatya. The main reason for this is the change in zoning plans in rural and urban areas and the prevention of multi-storey construction in areas with high earthquake risk. For this reason, while the area of agricultural areas and pastures in and around Malatya decreases, there is a great increase in the proportion of artificial surfaces.

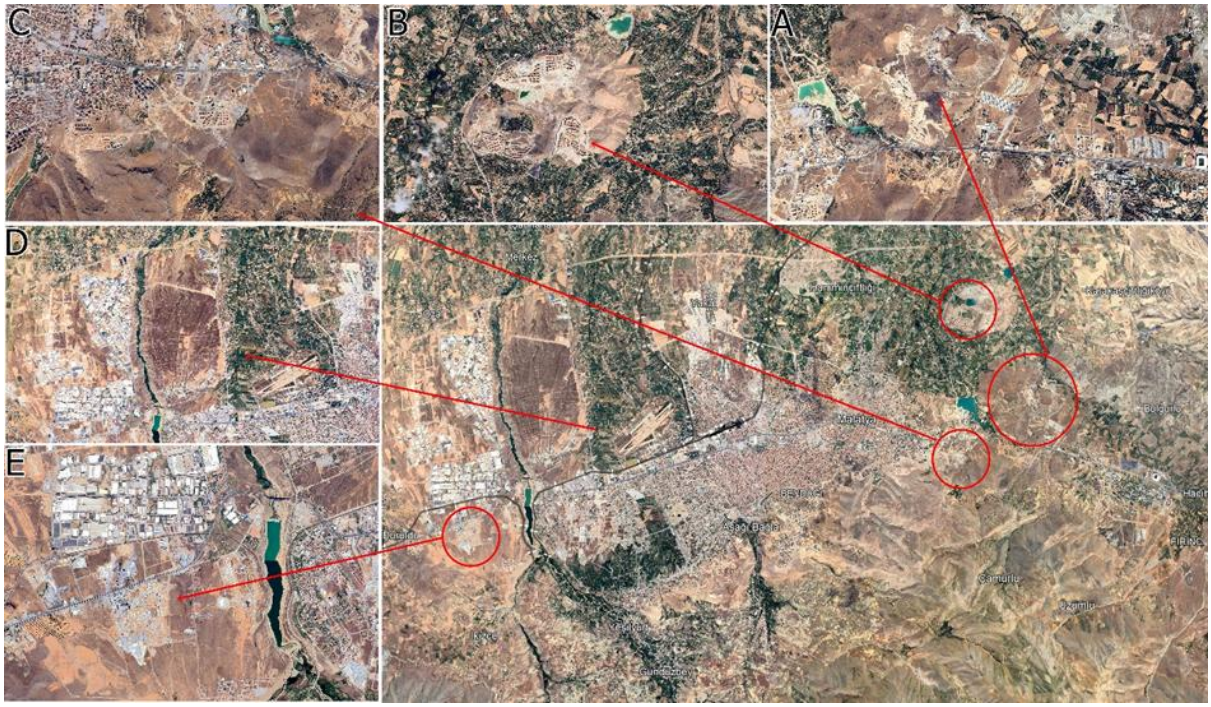


Figure 10: New housing areas after the earthquake in the study area 2025.

4.2 Limitations and Future work

While this study effectively captures the drastic shift from vertical to horizontal urban growth in Malatya following the 2023 earthquakes, it is important to recognize the constraints imposed by the timeline of the analysis. Since the post-disaster data is drawn from 2025, the study essentially examines a city still in the midst of emergency recovery rather than one that has completed its reconstruction. Consequently, some of the land use changes identified as "urban

expansion" may currently reflect temporary housing or debris management sites, meaning the landscape is likely to evolve further as permanent rebuilding plans take full effect.

Furthermore, while the 30-meter resolution of the Landsat imagery provided an excellent perspective for tracking four decades of change, it inevitably glosses over finer details. This resolution limits the ability to detect smaller-scale structural damages or subtle shifts in housing typologies that a higher-resolution analysis might reveal. Similarly, it must be acknowledged that the predictive models used in this study rely heavily on historical trends, which makes it challenging to fully account for abrupt, human driven interventions, such as the sudden implementation of new zoning laws or strict height restrictions, that override past behaviors. Looking ahead, future research could bridge these gaps by integrating higher resolution data and socio-economic indicators, potentially extending this framework to compare regional impacts across other severely affected provinces like Hatay and Kahramanmaraş.

5 Conclusion

UA and GIS technologies provide important opportunities to reduce and manage disaster risk with the opportunities they provide before, after and during disasters. UA and GIS methods also provide convenience in making spatial decisions and creating future plans. In this study, the change in LULC of Malatya between 1986, 2022 and 2025 after the 6 February 2023 earthquake was analysed by using RS and GIS techniques and the effects of disasters on LULC were compared. The ANN-MLP-MC approaches used in the research make important contributions to the literature in determining the land use change after the earthquake (Karadeniz & Sunbul, 2023). Satellite images of 1986, 2022 and 2025 were used to measure the future land use prediction ability of ANN-MLP and MC methods.

Implementation of land use policies and planning depends on the quality of the spatial and non-spatial data used for the implementation and the targeted results (Aydöner & Maktav, 2009). The destruction caused by the earthquakes that occurred on 6 February 2023 reveals the current land use situation. Our current research reveals this situation. Especially if there was no earthquake, it indicates that vertical construction will continue in urban areas rather than artificial construction. This situation shows that it will cause greater loss of life and property

in a future disaster. Of course, there are differences between simulations and real land use. However, current simulations show roughly how the land use will be. Thus, LULC change provides important information for decision makers for sustainable, resilient settlements.

As a result, the earthquakes of 6 February totally changed the LULC in Malatya. Considering this situation, more resilient planning principles can be developed by using LULC models in settlements with high disaster risk.

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Availability of Data and Materials: The data will be made available on request by contacting the corresponding author, (Sajjad M): mah.sajjad@hotmail.com

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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