

Monitoring and multi-scenario simulation of agricultural land changes using Landsat imageries and future land use simulation model on coastal of Alanya

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Abstract

Anthropogenic activities have adverse impacts on productive lands around coastal zones due to rapid developments. Assessment of land use and land cover (LULC) changes provide a better understanding of the process for conservation of such vulnerable ecosystems. Alanya is one of the most popular tourism hotspots on the Mediterranean coast of Turkey, and even though the city faced severe LULC changes after the mid-80s due to tourism-related investments, limited number of studies has been conducted in the area. The study aimed to determine short-term and long-term LULC changes and effects of residential development process on agricultural lands using six Landsat imageries acquired between 1984 and 2017, and presented the first attempt of future simulation in the area. Average annual conversions (AAC) (ha) were calculated to assess magnitudes of annual changes in six different periods. AACs were used to calculate area demands for LULC₂₀₃₀ and LULC₂₀₅₀, whereby annual conversions from different periods were multiplied by the number of years between 2017, 2030 and 2050 for each scenario. Finally, optimistic and pessimistic scenarios for agricultural lands are simulated using a future land use simulation model. Accordingly, agricultural lands decreased from 53.9% to 31.4% by 22.5% in 33 years and are predicted to change

between 19.50% and 24.63% for 2030, 1.07% and 14.10% for 2050, based on pessimistic and optimistic scenarios, respectively.

Introduction

Coastal zones are one of the most precise areas that usually face rapid and severe changes, due to pressure of extraordinary population, particularly in warm seasons. Mostly, expeditious residential development (RD) results in environmental degradation and land fragmentation in these areas. Investigation of the changes related to RD process is necessary for the maintenance of ecosystem functionality and sustainability of vulnerable ecosystems in such rapidly changing locations (Yaghoobi *et al.*, 2019). Assessment of land use and land cover (LULC) change, a global and continuous trend, known to be an important indicator of such activities since it is predominantly shaped by growing population, economic activities, and political decisions.

As it was mentioned by Roy and Roy (2010), land use term consists of physical or biological cover of the Earth's surface that includes artificial structures, bare soils, water and vegetative covers (Ellis 2007), whereas land use presents the management strategies that humans impose on a certain site that involves social and economic, and thus, has a complicated aspect. Conversion from different LULC types to built-up areas has diverse effects on the Earth's surface. For instance, heavy anthropogenic activities present a common threat to the maintenance of vegetation, especially productive agricultural lands (Leu, 2019), in response to tourism-related socioeconomic development since the construction of roads, airports, and other travel opportunities enhance the accessibility of an area, and it accelerates LULC changes in many touristic locations (Zope *et al.*, 2015). As cited by Modica *et al.* (2012), the Mediterranean region is facing ecosystem loss and fragmentation against urbanization trends (EEA, 2011). Inappropriate and uncontrolled conversions into impermeable structures usually present environmental threats including: flooding, landslide, erosion or urban heat island (UHI) effects, due to increased concrete surfaces. Furthermore, unbalanced alternations triggered by RD negatively contribute to climate change at different scales, which may cumulatively impair biodiversity, and hydrology in further steps. From another point of view, multidirectional changes may occur simultaneously in a certain area, and vegetation areas can be increased although urban areas seem expensed (Pandey *et al.*, 2018). On the other hand, insufficiency of appropriate space for development causes reclamation of land from sea, as was mentioned in China (Sengupta *et al.*, 2019). Therefore, the evaluation of LULC changes has a key role in better understanding human impacts on the environment (Modica *et al.*, 2012; Lodato *et al.*, 2023), whereby multi-temporal change detection presents a basis to understand human-environment interactions (Statuto *et al.*, 2019), and help to collect quantitative information for increasing

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planning efficiency while conserving fragile ecosystems.

Remote sensing technologies have long been used to determine LULC changes at local, regional and global scales. Using remotely sensed data enables analyzing the interactions between population dynamics and LULC changes (Mahmoud and Divigalpitaya, 2019), and availability of cost-free imageries such as Landsat series, which collects data all over the world over 50 years, has increased the number of studies in different regions of the world. Understanding past LULC trends enables forecasting of further replacements, whereby simulation models provide a visual manifestation of possible conditions. Forecasting future conditions assists planners and policymakers in avoiding substantial amounts of productive land or natural vegetation losses against dynamic RD trends (Sakieh *et al.*, 2015), and became an essential tool for maintenance of resources. Different methods have been used for future LULC simulation in recent years within different regions of the world, as well as Turkey. For instance, land change modeler (Leta *et al.*, 2021), cellular automata-artificial neural network (CA-ANN) and multilayer perception (MLP) (Amgoth *et al.*, 2023), CA-Markov model (Hind *et al.*, 2022), MLP-ANN (Çevik-Değerli and Çetin, 2022), Dyna-CLUE (Aydın and Eker, 2022), and future land use simulation (FLUS) (Çağlıyan and Dağlı, 2022) were used to identify the changes in LULC types such as agricultural lands. The present study focused on the identification of past and future agricultural land changes around the main residential site of Alanya City, a popular international tourist location on the Mediterranean coast, Turkey. The area is important not only for tourism but also for agricultural activities due to suitable soil and climatic conditions. The city has been subject to severe alternations after the early 1980s due to an increase in tourism-induced projects, and simultaneously, main income source shifted from the agricultural sector to tourism. Rapid LULC changes have occurred against the shifts due to the appeal of new touristic destinations. However, a limited number of studies conducted around the city to determine changes with different purposes (Sönmez *et al.*, 2016; Özüpekçe, 2020; İşler and Aslan, 2021; Inalpulat and Genç, 2021), and multi-temporal transitions and potential future LULC conditions have not been studied in the area.

The main objectives of the study were to determine short-term and long-term impacts of RD on surrounded agricultural lands, to predict future status according to different conversion scenarios, and to simulate optimistic and pessimistic situations for agricultural lands for manifesting future patterns (LULC₂₀₃₀ and LULC₂₀₅₀) using FLUS model. The scenarios were obtained from average annual conversions (AAC) that occurred in different periods to answer the following questions: i) How was the past LULC change trends in different periods between 1984 and 2017?; ii) Which periods resulted in the lowest and the highest losses in agricultural lands?; iii) What would the LULC pattern be in 2030 and 2050 years if the past trends with minimum and maximum agricultural changes occurred in different periods may eventuate similarly in the future?

Materials and Methods

Study area

Alanya is one of the 20 municipals of Antalya Province with typical Mediterranean climate and vegetation characteristics, and the city center is located at 36° 32' 37" N - 31° 59' 59" E. Due to the existence of sandy beaches, historical and natural places, the city has become a tourist hotspot within the last decades. The study

was conducted around the city center that covers the twelve central neighborhoods, which compose the main residential zone at the coastal part of Alanya with a survey area of approximately 3880 ha (Figure 1, Copernicus, 2018). The specified area was selected due to ecological sensitivity, where rapid LULC changes continuously proceed and agricultural lands are expected to be faced with severe and irreversible changes in the near future against human-induced factors. On the other hand, the ecological zone around Alanya Castle is assumed to remain the same in the future due to its natural and cultural heritage, whereas the General Directorate for Protection of Natural Assets has announced the area as a protected zone since eight endemic plants have been reported in the area (MEUCC, 2018). Therefore, the specified zone is denoted as the restricted zone in the present study and covers an area of approximately 140 ha.

Image classification and accuracy assessment

Multi-temporal Landsat imageries of Thematic Mapper (TM) (1984, 1990, 1998, 2003, and 2010) and Operational Land Imager (OLI) sensors (2017) with 30 m resolution and path/row number of 177/35, which have been radiometrically corrected and georeferenced, were freely downloaded from United States Geological Survey Earth Explorer website. The COVID-19 pandemic has impacted environmental processes, as well as human activities in many areas. The restrictions on human activities were reported to have improved environmental quality and reduced degradation (Ghosh *et al.*, 2020), and the process may lead to relative increases in especially natural vegetation areas. On the other hand, some of agricultural lands were preferably abandoned or insufficiently processed in many areas of Turkey (Ceylan and Ozkan, 2020; Dogan and Dogan, 2020), while some of the barren lands decided to be used for agricultural purposes with the aid of financial supports to increase yields of strategic products (Uysal and Veziroglu, 2020). Preliminary results of ongoing studies have demonstrated there is a strong link between reduced agricultural activities and LULC change due to the pandemic limitations. In fact, the difficulties

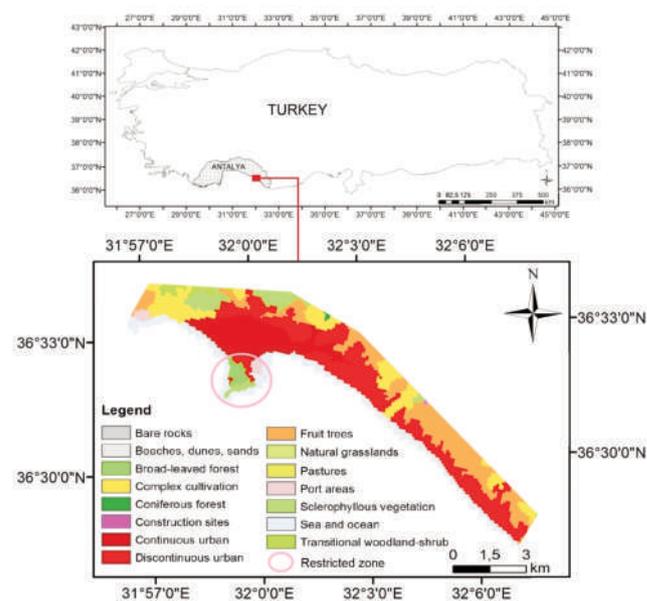


Figure 1. Location of study area, restricted zone, and Corine Land Cover (Copernicus, 2018).

sourced from the limitations have resulted in an abandonment of agricultural lands, which led to the growing of natural vegetation types such as weeds or shrubs in the fields instead of agricultural products. This situation significantly altered the spectral signature in comparison with the previous status of the abandoned pixels, and thus, seemed to have the potential to reach misleading results and overestimations of N class areas for future predictions. Conversely, the conversion of barren lands into agricultural fields as a result of supports may cause an overestimation of future A-class areas and an underestimation of natural vegetation areas. Thence, the period after 2020 has not been involved in the context of the study to prevent misinterpretations for future predictions, while 2018-2020 could not be considered due to intense cloud conditions. Imageries with less than 10% cloud cover and acquired within mid-summer were selected to ensure the similarity in illumination conditions and vegetation pattern, and one image was used to delineate the LULC map of each year. A total of six bands (6-b) covering the visible, near-infrared, and shortwave infrared bands from each TM and OLI imageries were used in the study. The selected bands were stacked to obtain 6-b imageries. The 6-b imageries were clipped based on the study area boundaries. Pixel-based supervised classification maximum likelihood algorithm was adopted for the classification process, which was declared to give satisfactory results for Landsat-based LULC change analysis (Vijay *et al.*, 2016). A classification scheme was composed including four main LULC classes, namely; agricultural land (A), natural vegetation (N), water surface (W), and residential area/bare soil (R-B). The A class covered all types of cultivated fields or orchards. The N class included forest tree species, bushes, shrubs, meadows, pastures, and grasslands. The W class represented coastal water lines and streams. Lastly, the R-B class comprised artificial surfaces like buildings, roads, harbors, and bare areas such as sandy beaches at the coastal line, and rocky hills. Previous studies have revealed that a separate consideration of residential areas and bare soil classes usually led to misclassifications in areas with similar terrain properties and LULC types using imageries with moderate resolutions like Landsat (Inalpulat and Genç, 2016; Inalpulat and Genç, 2017; Awange *et al.*, 2018; Shi *et al.*, 2019), whereby natural areas were underestimated due to their relatively small coverages of beaches, together with fragmented and dispersed structures of particularly rocky areas (Inalpulat and Genç, 2021). Thence, the classes are combined due to their spectral similarities for more precise identification of the change magnitudes. Similarly, meadows and pastures are known to be very rare in the area, and it is difficult to discriminate them from natural vegetation cover, especially in dry season (Xie *et al.*, 2019), and classified within the same class of N to overcome this situation. Alam *et al.* (2020) has mentioned that land use designates the human activities on land that generally cannot be directly observable for satellite

imagery (Lo, 1986), and land cover refers to the vegetation and artificial constructions on the land surface (Burley 1961), which is directly visible. The definitions of 'land use' and 'land cover' terms, on the other hand, vary within different studies in the literature (Nedd *et al.*, 2021), and must be defines considering the specific purposes. The terms 'land use' and 'land cover' denoted to be two of the key observers of the Earth's surface and answer the questions of "What is it for?" and "What is it?", respectively (Duhamel, 2012), as it is cited by Nedd *et al.* (2021). Land use term answers the question of what is it for since it is referred to how humans exploit the land cover for such as, agricultural or residential purposes (Lambin *et al.*, 2000). In the present study, the main research questions are dependent on "What was it in the past?", and "What may it be in the future?", which designate the status of the land cover.

The validation process, which refers to the agreement of classified pixels and reference data representing the actual status, has a key role in LULC studies. Overall accuracy (%) and kappa statistics, the two main well-known indicators, were assessed by controlling a total of 200 stratified random points from each LULC map with a minimum of 10 points per class through the Google Earth application and ground information (Table 1). Kappa values over threshold of 0.75 are denoted to represent good classifications (Bharatkar and Patel, 2013). Classification and accuracy processes were conducted in Erdas Imagine software.

Land use and land cover change detection

The change analysis was conducted in six periods including the changes that occurred in short-term periods between LULC₁₉₈₄-LULC₁₉₉₀, LULC₁₉₉₀-LULC₁₉₉₈, LULC₁₉₉₈-LULC₂₀₀₃, LULC₂₀₀₃-LULC₂₀₁₀, and LULC₂₀₁₀-LULC₂₀₁₇; and long-term period between initial and final years of the study (LULC₁₉₈₄-LULC₂₀₁₇). AAC was calculated for each period, which was used for future pixel demand predictions of each scenario in further steps, to conduct a systematic change analysis by standardizing the past trend comparisons (1). Transformations between LULC classes were determined in hectares (ha) and percentages (%), and changes from each LULC class to another were calculated. With respect to the concept of the study, which promotes the identification of RD effects on other LULC classes, the R-B coverages of each year were subset to highlight conversions (ha) from the previous year's LULC class to R-B area for each period.

$$AAC (ha) = (LULC_{Post-R-B \text{ area}} - LULC_{Prev.LULC \text{ class area}}) / (t_{Post} - t_{Prev}) \quad (\text{Eq. 1})$$

where, $LULC_{Post-R-B \text{ area}}$ represents posterior year's R-B area (ha),

Table 1. Number of control points for accuracy assessments.

Class/year	LULC ₁₉₈₄	LULC ₁₉₉₀	LULC ₁₉₉₈	LULC ₂₀₀₃	LULC ₂₀₁₀	LULC ₂₀₁₇
N	64	63	53	51	46	34
A	104	95	84	80	68	59
W	10	10	10	10	10	10
R-B	22	31	53	59	78	97
TOTAL	200	200	200	200	200	200

LULC, land use and land cover; N, natural vegetation; A, agricultural land; W, water surface; R-B, residential area/bare soil.

$LULC_{Prev}$. $LULC$ class area represents previous years LULC class area (ha) (equals to the amount that converted to R-B class in posterior year), and $(t_{Post.}-t_{Prev.})$ represents the time differences between posterior and previous years for all periods.

Scenario generation for LULC₂₀₃₀ and LULC₂₀₅₀

Area (ha) demands for LULC₂₀₃₀ and LULC₂₀₅₀ classes were calculated by extrapolating the past conversion trends depending on AACs for the generation of different scenarios. Accordingly, future LULC class areas of different scenarios were predicted by multiplying AACs of all classes in each period with number of years between 2017 and 2030, and between 2017 and 2050. In this process, the areas of classes within the restricted zone were maintained in the future, which means that even if the class area calculation reaches zero, it would be equal to the restricted part (ha) of LULC₂₀₁₇ class area. The procedure to calculate the future class areas (ca) is given in the equation below (2). Among these scenarios, the optimistic scenario with minimum agricultural land loss (ha) and pessimistic scenario with maximum agricultural land loss were identified for simulation process. Figure 2 represents the scenario generation steps.

$$f(ca) = \begin{cases} ca = (ca_{2017}) \mp (AAC \times (t_{simulation} - t_{2017})), & \text{if } ca_{predicted} > ca_{restricted} \\ ca = (ca_{restricted}), & \text{if } ca_{predicted} \leq ca_{restricted} \end{cases} \quad (Eq. 2)$$

where, ca is class area (ha); ca_{2017} is 2017 ca (ha) of the same class; $t_{simulation}$ is simulated year of 2030 or 2050; $(t_{simulation}-t_{2017})$ represents the number of years between 2017 and 2030 or 2017 and 2050; $ca_{predicted}$ is predicted ca (ha) of same class for 2030 or 2050; and $ca_{restricted}$ is the restricted ca (ha) of the same class.

Simulation of optimistic and pessimistic scenarios

The LULC patterns of optimistic and pessimistic scenarios for

LULC₂₀₃₀ and LULC₂₀₅₀ were simulated based on LULC₂₀₁₇ using ancillary data relating to driving forces via the model of FLUS. In this case, the considered driving forces were elevation, slope and proximity to roads, which were related to LULC classes in ANN step of simulation process. Different models were considered in the training step and the appropriate model with minimum error was selected. Even though different data were also included in the initial steps, such as aspect, land use capability, distance to sea and soil properties, consideration of these data increased the error rates, and thus, excluded from the probability of occurrences (PoO) estimation. Using the FLUS model, the PoOs were obtained by integrated ANN model together with available driving forces of LULC change, and the simulations were conducted through CA model, predicted LULC class area demands, obtained probability of occurrence, in respect to restricted area, and primarily determined conversion costs, which presents the difficulty degree for transformation of current LULC type to another (Zhang *et al.*, 2021). Publicly available FLUS model was downloaded from the Geographical Simulation and Optimization System portal, and used to create simulation maps by distributing a predicted number of pixels within the study area as described by Liu *et al.* (2017) (Figure 3). Therefore, class area demands (ha) were converted into a required number of pixels to be used in simulation software considering 30×30 m size of an individual pixel. ALOS digital elevation data with 30 m spatial resolution was freely downloaded from the Japan Aerospace Exploration Agency website to obtain elevation and slope maps with the same spatial resolution (30 m). ArcGIS (10.3) software was used to create a slope from ALOS digital elevation data. Accordingly, it was seen that the elevation values are ranged from the sea level (0 m) to 467 m, while the slope valued between 0 and 282% in the study area. The major and crossroads were drawn in a Geographic Information System (GIS) environment using base maps provided by ArcGIS software, and proximity to road map was composed using the same software tools with 30 m pixel size to be coherent with spatial resolution of Landsat, elevation, and slope data. Moreover, since the

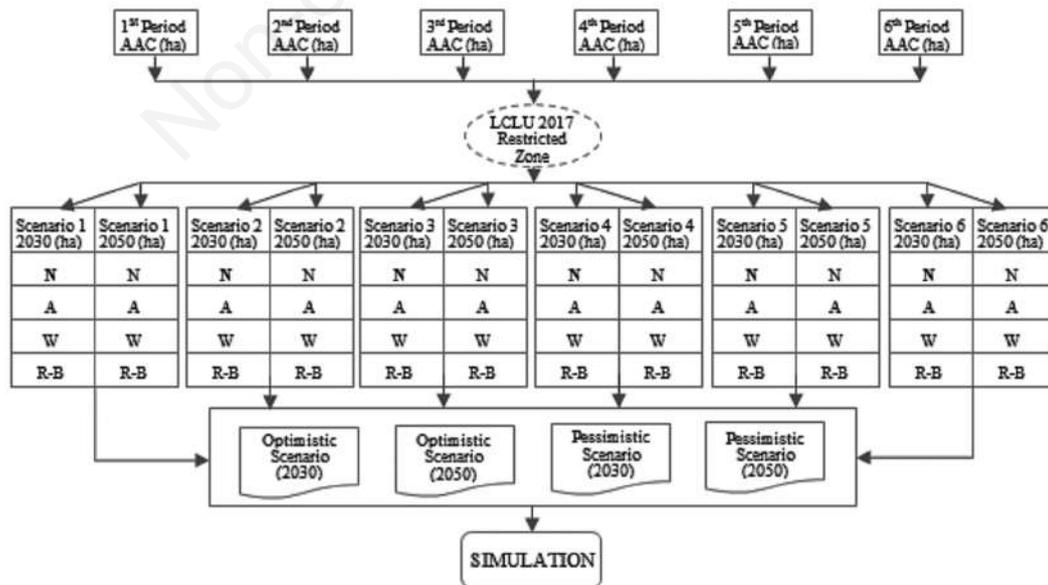


Figure 2. Implemented steps in scenario generation and selection of optimistic/pessimistic scenarios for simulation of N (natural vegetation), A (agricultural land), W (water surface) and R-B (residential area/bare soil) classes.

model simulates future LULC patterns by assessing the initial status of a pixel together with neighborhood effects and transition rules dependent on the pixel value directly instead of a set of different suitability ranges for each dataset, none of the ancillary data was classified into different subgroups of different elevation, slope or distance ranges. Finally, accuracy of simulations was tested by simulating the 2017 year (LULC_{2017simulation}) using actual pixel numbers of LULC₂₀₁₇ as pixel demand, depending on LULC₂₀₁₀ and same ancillary data. Indices of kappa, and figure of merit (FoM), which describe the overlapping rate of actual and predicted change (%), were assessed reliability of LULC_{2017simulation}. Similar to other simulation studies (Guo *et al.*, 2021; Yang *et al.*, 2022; Mamitimin *et al.*, 2023), the accuracy was acknowledged to be valid for all future simulations since there is no future-displaying data for verification.

Results

Identification of land use and land cover changes and average annual conversions

LULC maps were composed and results of accuracy assessments revealed that overall accuracies for LULC maps ranged between 85-91%, while overall and individual kappa values were over 0.80. Furthermore, user's accuracies of individual classes of each LULC map, which represents how classified pixels are coherent with the actual status, ranged between 81.0% and 94.5%. The latest LULC status of the study area (LULC₂₀₁₇) is used for determining the extent of R-B coverage, and for the simulation of future LULC in the study (Figure 4). Accordingly, R-B class covered the

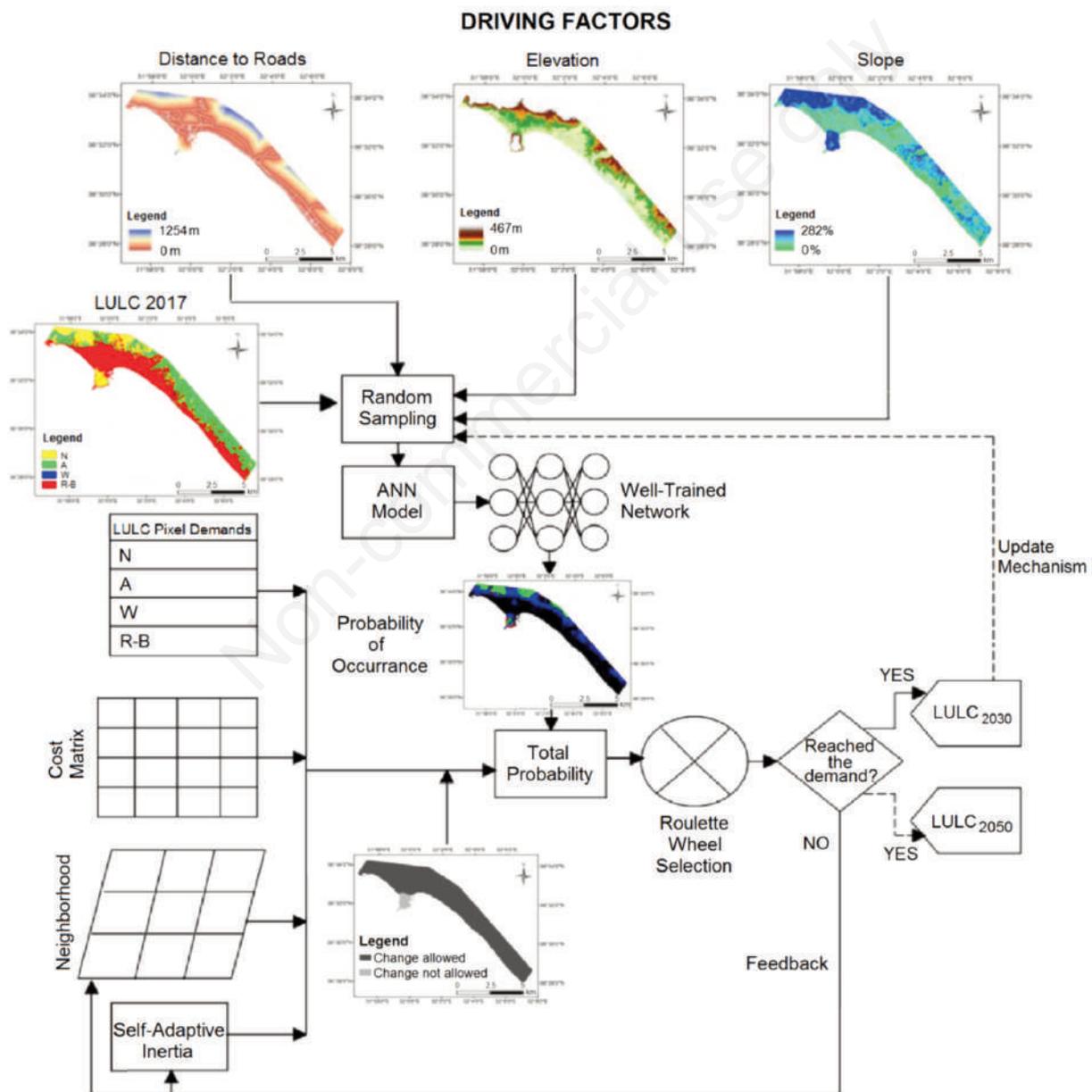


Figure 3. Simulation process for selected scenarios.

majority (50.75%) with 1968.57 ha survey area in 2017, and it was followed by A (31.47%) and N (17.73%) whereas water surfaces covered a small part of the area (0.05%). In addition, areas of the restricted part are found to cover 92.48 ha of N (2.38%) and 4.20 ha of A (0.12%) classes, that should remain unchanged in the scenario-based future simulations. Class area coverages (%) obtained from all past LULC maps are given in Figure 5. It was seen that R-B coverage increased from 10.6% to 50.75% during 33 years between 1984 and 2017. Bare soil areas of R-B class cover the rocky hills around the Alanya Castle, and also the sandy beaches at the coastal line. The coverages of rocky hills and beaches have not changed over time in the area due to their own characteristic situations, and changes in R-B class known to be arisen from the alterations in residential developments within the specified study area. Inventory records of natural areas have shown that approximately 115 ha natural areas of R-B class such as rocky hills or beaches are located within the study (AMM, 2022), revealing that 71.37%, 82.35%, 89.3%, 90.44%, 92.68%, and 94.15% of R-B class were covered by artificial surfaces in studied years, respectively. Despite the increments in residential areas, the coverage of A class decreased by 22.5% within 33 years, as a result of rapid RD. The agricultural lands exhibited a continuous decrease trend in time, whereas the amounts of decrease were varied between periods. In the initial year, the A coverage was 53.9%, and progressively reduced to 48.9% in 1990, to 43.6% in 1998, to 41.9% in 2003, to 35.0% in 2010, and to 31.4% in 2017. Likewise, coverage of N class was obviously reduced from 33.2% to 17.7% against RD, simultaneously. The total decrease in A class cover (22.5%) was higher than the decrease in N class (15.5%).

Depending on the change analysis it was found that the conversions between LULC classes were negligible and mostly sourced from misclassification of individual pixels, except the actual conversions to R-B class. The negligible conversions occurred in more fragmented and small-sized coverages of neighbor classes that exhibit mixed spectral characteristics. Therefore, the AACs from LULC classes to R-B class were considered to predict future demands to prevent the underestimating of RD effects on other LULC classes. The gains of R-B class from other classes can be seen visually in Figure 6 according to the periods. The conversion amounts from all LULC classes to R-B together with AAC (ha) are given in Table 1. Findings have uncovered that the total R-B zone reached 1968.57 ha in 2017 while it was 322.38 ha in 1984, designating that the city has grown by 511% within 33 years. There

were significant conversions from A to R-B class in all periods. In the 1st period, annually 35.63 ha of A class were served as the main source for new R-B areas. The gains from N for RD process were calculated as 9.60 ha, annually in the same period. The annual gains of R-B from A class were slightly reduced in the 2nd period (31.68 ha), while N losses reached to 24.82 ha year⁻¹. The 3rd period presented a more controlled RD process since the gains from A class were observably reduced to 20.42 ha per year. In the same period, annual N losses against RD process were decreased to approximately 12.0 ha. However, annually 35.74 ha of A areas have lost against increasing R-B class areas in the 4th period, whereas the annual losses in N class were considerably lower (13.26 ha) than A class. On the other hand, the N class losses (25.06 ha) in the 5th period seemed more drastic than the other periods in addition to serious agricultural loss (30.71 ha). A rapid increase in R-B class around the main residential site has resulted in considerable losses of N class, as well as A, during the study years. Consideration of the long-term changes between 1984 and 2017 revealed that, annually 17.71 ha N, and 31.35 ha A class areas were lost due to RD activities in the past 33 years. Accordingly, even though the maximum RD rate was obtained from the 2nd period, the maximum gain of R-B areas from A class was eventuated in the 4th period with AAC of 35.74 ha. Furthermore, the minimum conversion from A to R-B class was found in the 3rd period whereas the AAC was 20.42 ha.

Scenario-scenario-based predictions for 2030 and 2050

The predicted class areas (ha, and %) for LULC₂₀₃₀ and LULC₂₀₅₀ according to different AAC-based RD scenarios can be seen in Table 2. Findings revealed that the future area coverage of R-B class is expected to be varied from 61.66% to 69.73% in 2030 and 78.37% to 93.09% in 2050 based on these scenarios. Minimum R-B coverage was obtained from the 3rd scenario, while the maximum coverage was calculated from the 2nd one. Meanwhile, coverage of A class was estimated to be ranged between 19.50% and 24.63% in 2030, and between 1.07% and 14.10% in 2050 years. The maximum and minimum amounts of maintained A class have predicted from the 3rd and the 4th scenarios respectively. Thence, the scenario with minimum A loss is referred as 'optimistic scenario', while the scenario with maximum A loss is named as 'pessimistic scenario' in the study. It was seen that A class coverage is predicted to be decreased by 29.27% between 1984 and 2030, and

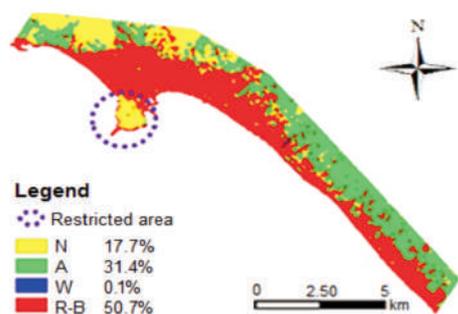


Figure 4. LULC₂₀₁₇ and area coverages (%) of N (natural vegetation), A (agricultural lands), W (water surface), and R-B (residential area/bare soil) classes.

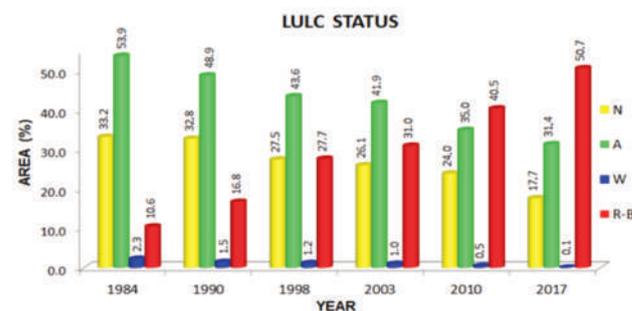


Figure 5. Temporal changes in land use and land cover class areas (%) of N (natural vegetation), A (agricultural land), W (water surface), and R-B (residential area/bare soil). LULC, land use and land cover.

39.8% of initial agricultural land is expected to be lost until 2050 within the specified area in respect to the optimistic scenario for conservation of agricultural lands. In comparison with optimistic scenario, the foreseen decrease of A class area was 34.4 (%) between 1984 and 2017, and a decrease of 52.83% from 1984 to 2050 is predicted to occur depending on the pessimistic scenario with the highest annual A class loss rate. Furthermore, the 3rd scenario seems also promising not only for the conservation of A areas, but also N class coverage with 7.53%. Conversely, although the 1st scenario leads to a higher N area, it can be clearly seen that coverage of A class significantly reduces until 2050, as well as the 4th scenario. As another remarkable result, predicted loss of N class was more than the existent N areas in 2nd and 5th scenarios. However, with respect to the restricted zone, possible R-B area is

considered to be equal to the difference between predicted R-B and restricted part of N class (92.48 ha) for the 2050 year. It was assumed that the R-B area may continue to expand on the areas that were not involved within study area boundaries, if the simulation procedures were implemented for these scenarios.

The expected changes in class areas (%) from 2017 to 2030 and from 2017 to 2050 year are progressively given in Figure 7, as the differences in percent coverage (%) of class areas between given years. The changes in coverage area of R-B class were valued between 10.91% and 18.98% in the first simulation period of 2017-2030. The R-B coverage change estimated to range between 27.62% and 42.34% considering the years between 2017 and final simulation of 2050. The differences between coverages of A class area (%) were ranged between 6.84% and 11.97% within the sim-

Table 2. Conversion amounts (ha, %) and average annual conversions (ha) of each land use and land cover class to R-B class in periods.

LULC class		LULC ₁₉₈₄ class to LULC ₁₉₉₀ R-B (ha)	R-B (%)	AAC (ha)
1 st period (1984 & 1990) short-term	N	57.60	9.59	9.60
	A	213.75	35.62	35.63
	W	6.39	1.02	1.07
	R-B	322.38	53.72	46.29
	TOTAL	600.12	100.00	
LULC class		LULC ₁₉₉₀ class to LULC ₁₉₉₈ R-B (ha)	R-B (%)	AAC (ha)
2 nd period (1990 & 1998) short-term	N	198.52	18.77	24.82
	A	253.46	23.97	31.68
	W	5.31	0.51	0.66
	R-B	600.12	56.75	57.16
	TOTAL	1057.41	100.00	
LULC class		LULC ₁₉₉₈ class to LULC ₂₀₀₃ R-B (ha)	R-B (%)	AAC (ha)
3 rd period (1998 & 2003) short-term	N	59.93	4.89	11.99
	A	102.09	8.34	20.42
	W	4.75	0.39	0.95
	R-B	1057.41	86.38	33.35
	TOTAL	1224.18	100.00	
LULC class		LULC ₂₀₀₃ class to LULC ₂₀₁₀ R-B (ha)	R-B (%)	AAC (ha)
4 th period (2003 & 2010) short-term	N	92.84	5.90	13.26
	A	250.20	15.91	35.74
	W	5.53	0.35	0.79
	R-B	1224.18	77.84	49.80
	TOTAL	1572.75	100.00	
LULC class		LULC ₂₀₁₀ class to LULC ₂₀₁₇ R-B (ha)	R-B (%)	AAC (ha)
5 th period (2010 & 2017) short-term	N	175.45	8.91	25.06
	A	214.96	10.92	30.71
	W	5.41	0.28	0.77
	R-B	1572.75	79.89	56.55
	TOTAL	1968.57	100.00	
LULC class		LULC ₁₉₈₄ class to LULC ₂₀₁₇ R-B (ha)	R-B (%)	AAC (ha)
6 th period (1984 & 2017) long-term	N	584.34	29.68	17.71
	A	1034.46	52.55	31.35
	W	27.39	1.39	0.83
	R-B	322.38	16.38	49.88
	TOTAL	1968.57	100.00	

LULC, land use and land cover; AAC, average annual conversions; R-B, residential area/bare soil; N, natural vegetation; A, agricultural land; W, water surface.

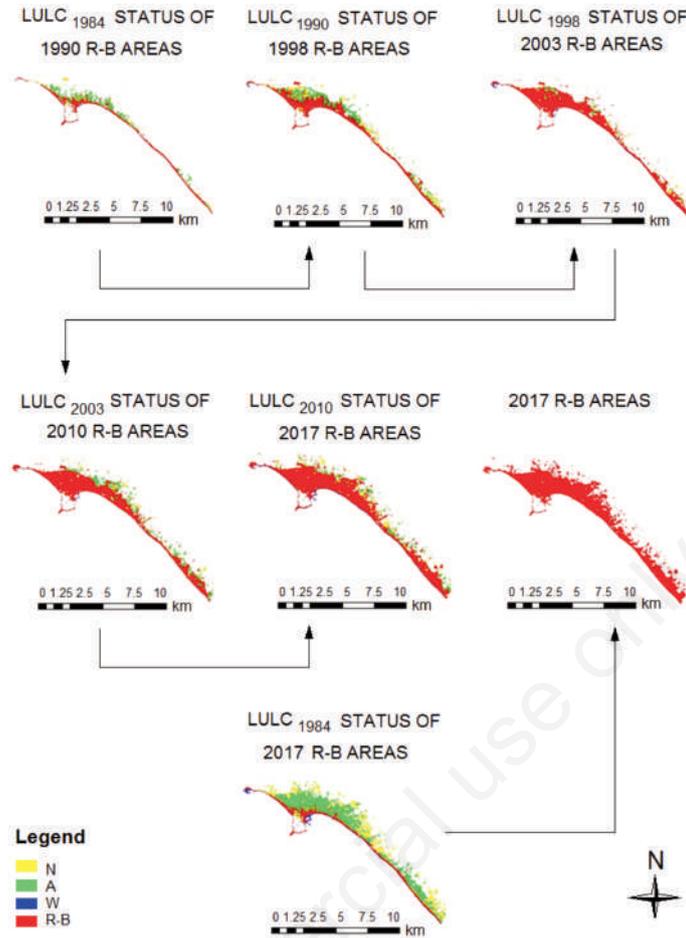


Figure 6. Progressive transformations from previous year’s N (natural vegetation), A (agricultural land), and W (water surface) classes to posterior year’s R-B (residential area/bare soil) class.

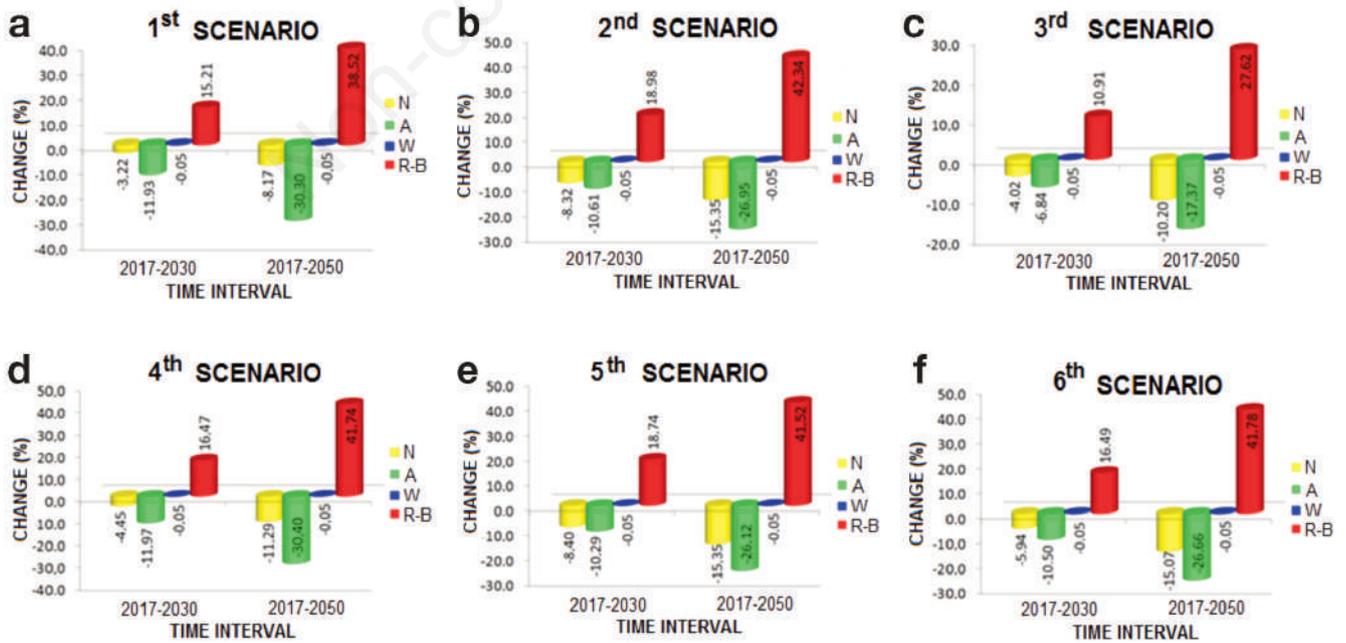


Figure 7. Changes in N (natural vegetation), A (agricultural land), W (water surface), and R-B (residential area/bare soil) class areas (%) in respect to different scenarios (a) 1st scenario; (b) 2nd scenario; (c) 3rd scenario; (d) 4th scenario; (e) 5th scenario; (f) 6th scenario.

ulation period of 2017 and 2030, dependent on optimistic and pessimistic scenario predictions, while the differences predicted to reach 17.37% and 30.40% at the end of 33 year period between 2017 and 2050. No matter which scenario may be approached, gained amounts (ha) from A to R-B class were higher than from N, as evidence for agricultural lands that are serving as the major source for new residential areas in all periods (Table 3).

Simulations of optimistic and pessimistic scenarios for agricultural lands

Prior to simulation of future status, the reliability of a simulation process was verified by assessing the coherency between LULC₂₀₁₇ and LULC_{2017simulation}. Accordingly, both kappa and FoM vales were over 0.70, indicating that the simulation is within the reliable thresholds. The pixel demands of the 3rd and 4th scenarios were simulated to present the possible distributions of the predicted number of pixels for LULC classes in the future (Figure 8). Depending on Figure 8, which shows the optimistic scenario for 2030 and 2050, it was seen that a considerable part of the agricultural lands is predicted to be conserved in the area. As it can also visually seen from Figure 8a-b, if more controlled and environment-friendly annual conversions eventuate in the near future, as it occurred between 1998 and 2003 years, the excessive losses in both agricultural lands and vegetative cover can be prevented in the specified area. On the other hand, it can be seen that there are remarkable differences even in the first simulation year, when Figure 8c is investigated. Moreover, almost all agricultural lands would convert to residential-related surface in 2050 (Figure 8d) if RD may eventuate annually identical to the 4th period, which covers the years between 2003 and 2010. Additionally, since the optimistic and pessimistic scenarios for A class were not obtained from the 2nd and 5th scenarios, all the pixel demands were within the

changeable amount of pixel numbers in the study area, which means that all demands were distributed with the aid of restricted zone in the simulation step.

Discussion

The determination of LULC change has become essential for many research areas as well as city planning studies (Abbas *et al.*, 2021), since inappropriate and uncontrolled conversions from all kinds of vegetative covers to impervious surfaces may present significant issues for the residents in a certain area. On the other hand, productive usage of geo-data depends on reliability (Rwanga and Ndambuki, 2017). Findings have demonstrated that produced LULC maps were reliable since overall classifications, user accuracies, and kappa values were over the threshold value of 0.75 (Bharatkar and Patel, 2013). Depending on these past maps, it was seen that rapid RD trends eventuated in all periods. The dominant LULC class was comprised of agricultural lands in 1984, owing the majority of the study area while the residential area became the dominant class after 2003 by converting fertile lands to impervious surfaces. A similar situation was mentioned in the wider area of Alanya city, where the residential-related class was reported to have expanded 3 times between 1984 and 2018, and reached almost 2600 ha which was initially 650 ha (Özüpekçe, 2020). Several factors can play a role in such transformations from agricultural lands, natural vegetation cover to residential class including, economic development, developments in infrastructure, uncontrolled growth of urban population or migration, and rapid urban expansion, which may lead to scarcity in natural resources in the area (Fu and Weng, 2018). Many researchers agreed on the idea of tourism investments as the major responsibility for serious

Table 3. Scenario-based predictions for land use and land cover class areas (ha, %) in 2030 and 2050 years.

Scenario	LULC Class	LULC ₂₀₃₀ (ha)	LULC ₂₀₃₀ (%)	LULC ₂₀₅₀ (ha)	LULC ₂₀₅₀ (%)
1 st scenario	N	562.80	14.51	370.80	9.56
	A	757.82	19.54	45.32	1.17
	W	0.00	0.00	0.00	0.00
	R-B	2558.57	65.96	3463.07	89.27
2 nd scenario	N	365.01	9.41	92.48	2.38
	A	809.07	20.86	175.42	4.52
	W	0.00	0.00	0.00	0.00
	R-B	2705.11	69.73	3611.28	93.09
3 rd scenario	N	531.78	13.71	292.06	7.53
	A	955.51	24.63	547.15	14.10
	W	0.00	0.00	0.00	0.00
	R-B	2391.89	61.66	3039.97	78.37
4 th scenario	N	515.18	13.28	249.93	6.44
	A	756.28	19.50	41.43	1.07
	W	0.00	0.00	0.00	0.00
	R-B	2607.71	67.22	3587.83	92.49
5 th scenario	N	361.76	9.33	92.48	2.38
	A	821.73	21.18	207.56	5.35
	W	0.00	0.00	0.00	0.00
	R-B	2695.69	69.49	3579.14	92.27
6 th scenario	N	457.41	11.79	103.26	2.66
	A	813.43	20.97	186.48	4.81
	W	0.00	0.00	0.00	0.00
	R-B	2608.35	67.24	3589.44	92.53
Total class areas from each scenario		3879.18	100.00	3879.18	100.00

LULC, land use and land cover; N, natural vegetation; A, agricultural land; W, water surface; R-B, residential area/bare soil.

reductions in A and N areas after the 1980s in the Mediterranean Region. The depletion of vegetative areas together with increased residential areas affects the ecosystem services, health and thermal conditions of the city in the further steps (Kafy *et al.*, 2021). Concurrently, Alanya city centre were declared to be vulnerable against threat of flooding (Gökçe *et al.*, 2018), while past RD process and loss from permeable surfaces like agricultural fields to R-B class seemed probable to be strongly linked with this vulnerability status. In fact, the study conducted in Gazipasa, the Eastern neighbor of Alanya, has revealed that residential area has expanded by approximately 80% between 2013 and 2019, and the situation is expected to increase the peak flood value and flood volume by $10.1 \text{ m}^3\text{sec}^{-1}$ and 18%, respectively (Mehr and Akdeğirmen, 2021). Another environmental issue has been reported to be the increased UHI effect as a result of high building density (Gökçe *et al.*, 2018), since extinction of agricultural fields in the rural-urban fringe may arguably lead to the increase of surface temperature due to increase of concrete structures and decrease of cooling effects of both vegetative cover and depleted irrigation practices against agricultural loss. Therefore, Alanya city is one of the most precise areas within the central Mediterranean region due to ongoing RD trends, and depletion of such resources would be inevitable in the area unless more environment-friendly development strategies are adopted in the near future.

On the other hand, the amounts of LULC conversions seemed strongly relevant to different numbers of years within periods, which means that the lowest RD between two successive LULC maps was found for the periods with narrower time intervals due to lack of cloud-free imageries, and may lead to difficulties in interpretation of the change magnitudes. Seasonal and phenological effects can be captured only if the LULC maps of the same season can be generated, whereby they present a great challenge due to cloud contamination (Lu *et al.*, 2019), and methods for accurate interpretation of these unsystematically captured changes are crucial. Researchers implement different methods for eliminating these problems, such as spatiotemporal data fusion operations. In the present study, the situation was overcome by calculation of AACs (ha) for each period to standardize the change comparison process for identifying the annual impacts of RD in different periods. In addition, the AAC may provide a better understanding of the change trends even within equal time intervals since the growth rates may differ instantaneously depending on unforeseen events such as political decisions or natural events within a certain period. According to past changes and estimations from AAC scenarios, the drastic decreases in agricultural lands around the residential zone are predicted to continue in the future. Although the prediction of future areas provides valuable information and basis, it is not individually sufficient for demonstrating the severity of the

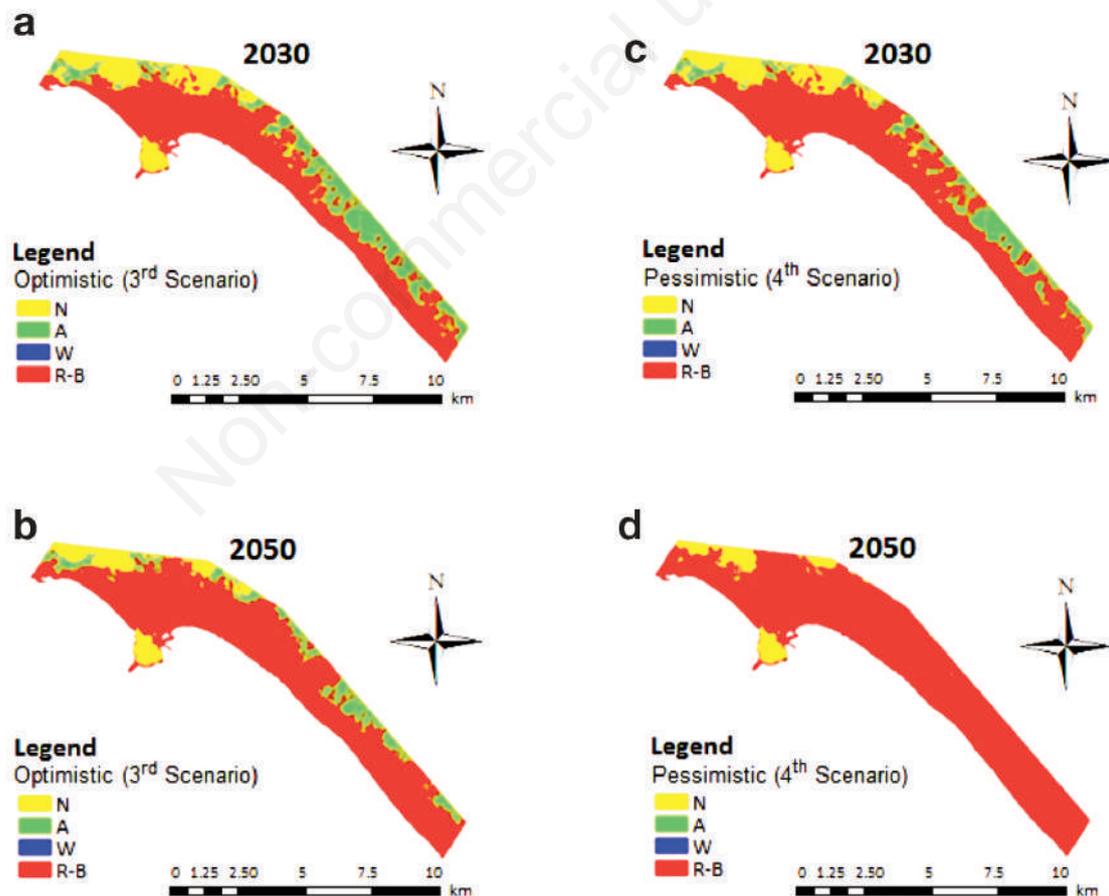


Figure 8. Simulations for N (natural vegetation), A (agricultural land), W (water surface), R-B (residential area/bare soil) classes. (a) Optimistic scenario LULC₂₀₃₀; (b) optimistic scenario LULC₂₀₅₀; (c) pessimistic scenario LULC₂₀₃₀; (d) pessimistic scenario LULC₂₀₅₀.

changes and highlighting the importance of appropriate management strategies, since the distribution of predicted numbers of pixels is a more significant indicator of vulnerability in a certain area. Various models were developed for simulation of future LULC statuses including equations, statistics, Markov and cellular models as it is cited by Baig *et al.* (2022). The models have benefits and drawbacks while hybridizing of prediction models may help to overcome the weakness of each other. For instance, CA-Markov model is acknowledged to be one of the most frequently used models and reported to produce reliable results, whereby such models can be used with multi-criteria AHP method (Omar *et al.*, 2014), multiple linear regression (Seto *et al.*, 2011), logistic regression (Hamdy *et al.*, 2016), and ANN (Grekousis *et al.*, 2013) for including triggers of LULC changes, as it is cited by Mohamed and Worku (2020). The FLUS model is reported to be one of the widely used simulation models in different areas of interest, especially in terms of constructed areas, whereas the research on agricultural lands is denoted to be lacking (Xiang *et al.*, 2022). In addition to the lack of agriculture-related studies in the literature, the model was selected since it has improvements over traditional cellular automata allocation models. For instance, the simulation model is based on the recent LULC pattern instead of the changes that occurred between two terms that allow predicting the future at the same time interval, and thus, preventing the accumulated errors sourcing from the disagreements of two-term LULC maps. Depending on the causal links between past LULC and recent LULC statuses, class area demands and probable distributions reported to be computed for simulating future patterns in respect to different scenarios (Noszczyk, 2019; Zhu *et al.*, 2023). At this point, the study believed to provide reliable simulations since the verification results were confidential for LULC₂₀₁₇simulation, even though many factors such as socioeconomic indicators could not be evaluated due to a lack of available data. The produced simulation maps exhibit precious manifestations of the possible optimistic and pessimistic statuses for agricultural lands, and have enabled interpretation of the most probable areas for future RD, which presented information on the severity of process in different parts of the study area. In comparison with a significant decrease in agricultural lands, RD is predicted to continue and increase in all directions, even in hilly areas, particularly after 2030. Comparable outcomes were noted in the literature (Inalpulat and Genç, 2017; Yattoo *et al.*, 2020), whereby, agricultural land areas have been predicted to be decreased against residential area expansion in different areas of the world, and as a general result, natural ecosystems, as well as biodiversity losses declared to be more fragile since the process continues. Moreover, RD on hilly areas due to increased accommodation needs has resulted in adverse environmental consequences in different touristic locations (Vijay *et al.*, 2016; Dey *et al.*, 2018; Mehr and Akdeğirmen, 2021), and preventions should be carefully stated in the area of interest before the consequences occur. Hence, being the first simulation study in Alanya city, the results are believed to provide valuable information for researchers and planners by indicating the necessity for more controlled and well-planned approaches to avoid severe transformations.

As another important point of view, the underlying reasons or triggers of ongoing trends should also be considered for preventing from the undesirable effects of ongoing RD trends in the near future. Researchers emphasized that increasing tourism activities rather than other socioeconomic factors overwhelmingly prompt rapid LULC changes in various coastal areas. Extinction of agriculture lands may reduce yielding potentials and interruption in agriculture-related economic sectors (Martellozzo *et al.*, 2018). Specifically, agricultural activities were known to be the main

income source in the Mediterranean region before the tourism boom. Increasing demand for tourism-related needs resulted in loss of agricultural lands, whereby farmers with less incoming profits have preferred to quit agricultural activities, sold their arable fields instead of cultivating them. Therefore, convention and valorization of agricultural uses in the area seem significant. As a suggestion for conserving agricultural lands, consideration of urban agriculture possibilities may present an alternative approach which is getting wider in developed countries, and may help to overcome some environmental, socioeconomic and sociocultural problems by reducing ecological footprints by preventing undesired levels of urban expansion (Yenigül, 2016). Investigating feasibility of small-scaled agri-tourism in the current agricultural areas may also be a supportive tool, that embraces various benefits in different aspects, and knows to be accelerating local economic situations while protecting the agricultural activities within the residential development zone (Akşit-Aşık, 2016).

In brief, agriculture became one of the priority initiatives for planners and decision-makers as the food demand increases especially in still-developing countries and the importance of forecasting future conditions has become a significant procedure (Radwan, 2019). Thus, the study may serve as a basis for researchers, not only by being the first simulation study in the area, but also by representing more than one probable future condition in the simulation step. However, there were some limitations while conducting the research, and they were mainly related to data availability. Especially socio-economic driving factors could not be assessed due to lack of desired level data. In addition, the LULC types were combined to reduce spectral similarities between some classes, sourced from relatively low-resolution of Landsat datasets, and complex structure of the surface properties. Thence, the performance of the analysis method was tested on a small scale within the context of the study, since the main alternations eventuate around main residential zone of the city.

Conclusions

Mediterranean landscapes are significant areas particularly in land use types, whereby LULC changes eventuate against interactions of anthropic activities and natural events. Forecasting the future status is vital in such areas for maintenance of valuable ecosystems. Rapid RD trends seemed eventuated in continuously developing urban-rural fringe zone of Alanya city, in South-Central Mediterranean coast of Turkey. As the most remarkable result, agricultural lands served as the main source for the new residential-related structures in all periods. Also, it was seen that consideration of short-term changes became a powerful predictor since using only long-term changes concluded to result in misestimating of future LULC status due to fluctuating changes in RD rates in the area. The AAC method found to be practical for comparison of change rates and prediction of future demands in similar studies. In addition, simulation of alternative scenarios provided manifestation of multiple possible consequences for researchers, planners or decision makers in the local authorities. More controlled future growth is recommended in the area to reach environmental-friendly and sustainable conditions while avoiding from adverse consequences before irreversible effects became occur. On the other hand, there were some limitations in the study. First, intense cloud cover comprised a limitation for selection of years due to relatively low temporal resolution of Landsat imageries with 16 days of revisit interval of Landsat TM, while COVID-19

presented the secondary limitation due to the extraordinary stability in many activities in the area. In order to overcome these issues, the dates between 2018 and 2022 have not been considered within the context of the study. Moreover, a study is currently ongoing in pilot hotspots within Aegean-Mediterranean coast to determine the COVID-19 effects on agriculture using different remotely sensed imageries with higher resolutions. In conclusion, being the first simulation attempt in the specified area, the study has stated the drastic changes through optimistic and pessimistic situations for agricultural lands for 2030 and 2050 years, and has great potential to provide useful information on future LULC changes.

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