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Research Article

Modeling Future Impacts on Land Cover of Rapid Expansion of Hazelnut Orchards: A Case Study on Samsun, Turkey

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ABSTRACT

Land-use/land-cover (LULC) simulation models predict the long-term effects of LULC changes under various scenarios. Patch-level land use simulation (PLUS) is a recently developed software that uses a rule-mining framework for LULC modelling. With a market share of 76% in the world, hazelnut is a strategic crop for Turkey. The hazelnut orchards have grown in Turkey since the first law was issued on 21 October 1935. This study was carried out to model the hazelnut orchards for 2030, 2042, 2054, and 2066 based on Samsun province and show the future impacts on land use types. Samsun was chosen as a case study due to the rapid expansion of hazelnut groves since 2006. According to PLUS results, by the year 2030, the increase in the hazelnut groves in Samsun is predicted as 9.38%, and hazelnut fields will be formed by the main transformation of open spaces with little or no vegetation, shrub and/or herbaceous vegetation associations, and forest; and this transformation will have severe effects on the ecosystem. The results clearly showed that hazelnut cultivation areas would continue to increase in the future and revealed that policymakers would need to conduct new regulations for environmental sustainability and to maintain Turkey's power in this crop.

Keywords: land use change, hazelnut, modelling, PLUS, simulation

INTRODUCTION

Hazelnut (corylus avellana L.) is one of the most crucial export crops of Turkey (Aytaç, 2021a). Holding down 70% of production and 76% of trade, Turkey is the world's leading manufacturer and exporter of hazelnut (Castro and Swart, 2017). Food and Agriculture Organization of the United Nations (FAO, 2020) statistics indicate that Turkey has an annual production of 420,000 tons, and in 2014 Turkey reached an income of US$ 2.3 billion from hazelnut exportation (Durmaz and Gokmen, 2019). The Black Sea region of Turkey is the main production center of hazelnut, but hazelnut production is growing in Italy, the USA, Georgia, and Azerbaijan (Tas et al., 2019). This crop has a significant influence on the economic and social structure of this region, and thousands of people are directly or indirectly related to this economic activity (Castro and Swart, 2017). Due to these reasons, the hazelnut has massive importance in the economy of Turkey, and some regulations need to be conducted on hazelnut production.

The main objective of policies for hazelnut production in Turkey is, export and manufacturer revenue maximization, inventory, transport, and financing costs minimization, and maintaining the strength in world markets (Kayalak and Ozcelik, 2012). For these purposes, Turkey tried to regulate the hazelnut market with purchase and price warranty, limitation of plantation areas, alternative crop cultivation projects, and direct income support from 1935 to 2014 (Bozoglu and Ceylan, 2007). Nevertheless, despite all the policies to control the supply, hazelnut production fields continued to increase (Bozoglu et al., 2019). Hazelnut fields and hazelnut production between 2004- 2019 in Turkey can be seen in **Figure 1** (TUIK, 2021). This situation weakens the power of Turkey in this strategic crop.

The rising concerns about environmental problems, food security, and loss of biodiversity with excessive cultivation and urbanization have directed researchers to understand the intensity and pattern of land-use/land-cover (LULC) change and to predict future development (Kundu et al., 2017; Liu et al., 2020). Land-use changes occur due to natural and anthropogenic reasons (Kuntoro et al., 2018; Ullah et al., 2019). There is an increasing interest in using computational algorithms for the detection and monitoring of LULC changes in the scientific community, and these algorithms consider various environmental, institutional, economic, and social factors and processes (Ansari and Golabi, 2019; Silva et al., 2020). Accordingly, there is a great necessity to precisely model the LULC changes and understand the spatial-temporal

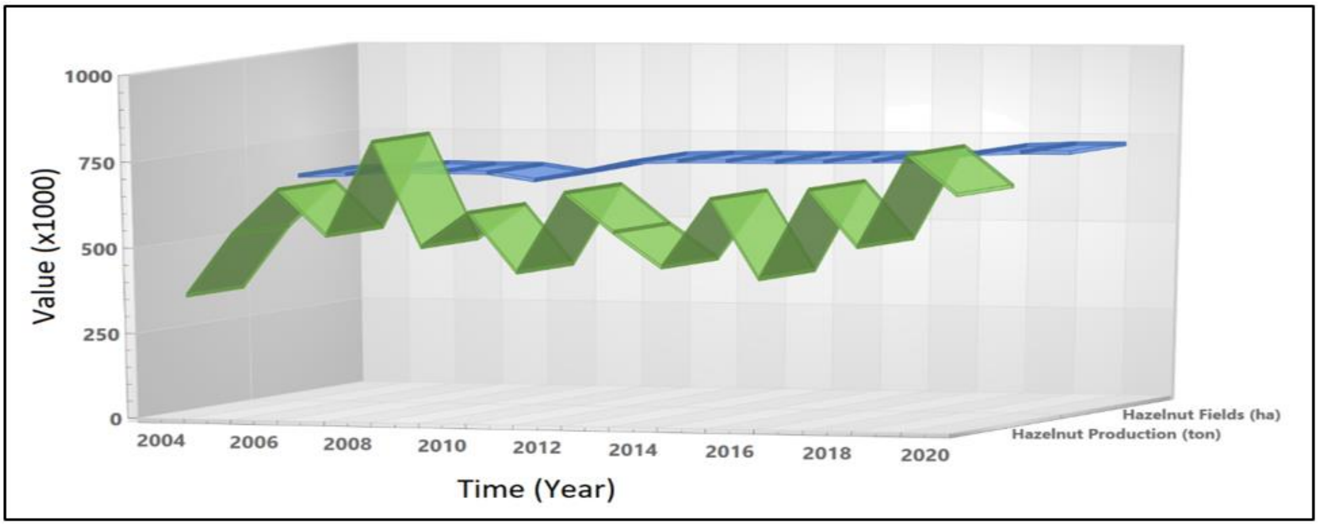

Figure 1. Hazelnut fields and hazelnut production of Turkey

LULC change patterns for land management and urban planning (Xing et al., 2020).

As a significant part of the regional and global change driven by human activities, LULC change has become critical in geography, ecology, and land science (Wang et al., 2019). In the last decade system dynamics (SD) model, cellular automata (CA) model, gray model, linear planning model, neural network model, multi-objective planning model, Markov model, etc. have been developed to simulate and forecast LULC changes (Liu et al., 2020; Sheng et al., 2018).

In 2019, a powerful tool named patch-level land use smulation (PLUS) model (https://github.com/HPSCIL/Patch-level_Land_Use_Simulation_Model) had been introduced for land use/cover simulations. The PLUS model has been developed with a rule-mining framework based on land expansion analysis srategy (LEAS), and a CA model based on multi-type random seeds (CARS). With these integrated features, PLUS helps researchers to understand the driving factors of land expansion and project landscape dynamics. Also, this model has attained a more similar landscape pattern and higher simulation accuracy than the other LULC prediction models. The PLUS algorithm combines knowledge discovery, policy-making, and simulation to provide meaningful information for policy-makers and researchers (Liang et al., 2020).

This study was conducted to model the future hazelnut plantation areas for 2030, 2042, 2054, and 2066 using PLUS. Samsun province, located in the Central Black Sea Region of Turkey, was chosen as a case study due to the rapid expansion of hazelnut groves since 2006.

MATERIALS AND METHODS

Study Area

Samsun is located in Central Black Sea Region of Turkey and has an area about 9,083 km². The geographical position of the city is between 40°50′ and 41°51′ North latitudes and 37°08′ and 34°25′ east longitudes and is between the deltas where Yesilirmak and Kizilirmak rivers run out (Gorur et al., 2011). The study area can be seen in **Figure 2**.

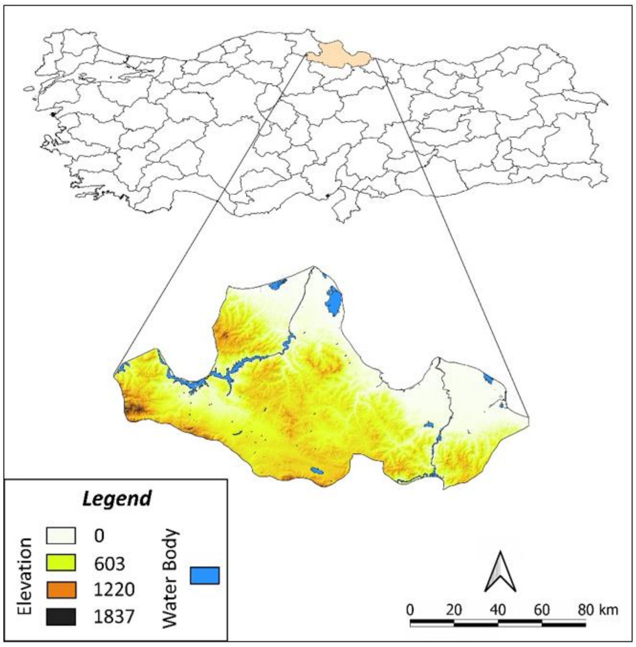

Figure 2. Study area

Samsun's fruit production reached 201,862 tons in 2019. Hazelnut has the highest production rate in tons, with 68.28%. The total amount of hazelnut groves is 1,164.38 km², and this area constitutes 97.40% of the total permanent crops (TUIK, 2021).

Required Data

The PLUS model was used to predict the spatial distribution of future LULC changes. This model consists of three main parts:

1. Extract land expansion,
2. LEAS,
3. CARS.

Each section needs different maps, including LULC, land use constraints, socioeconomic, climatic, and topographic.

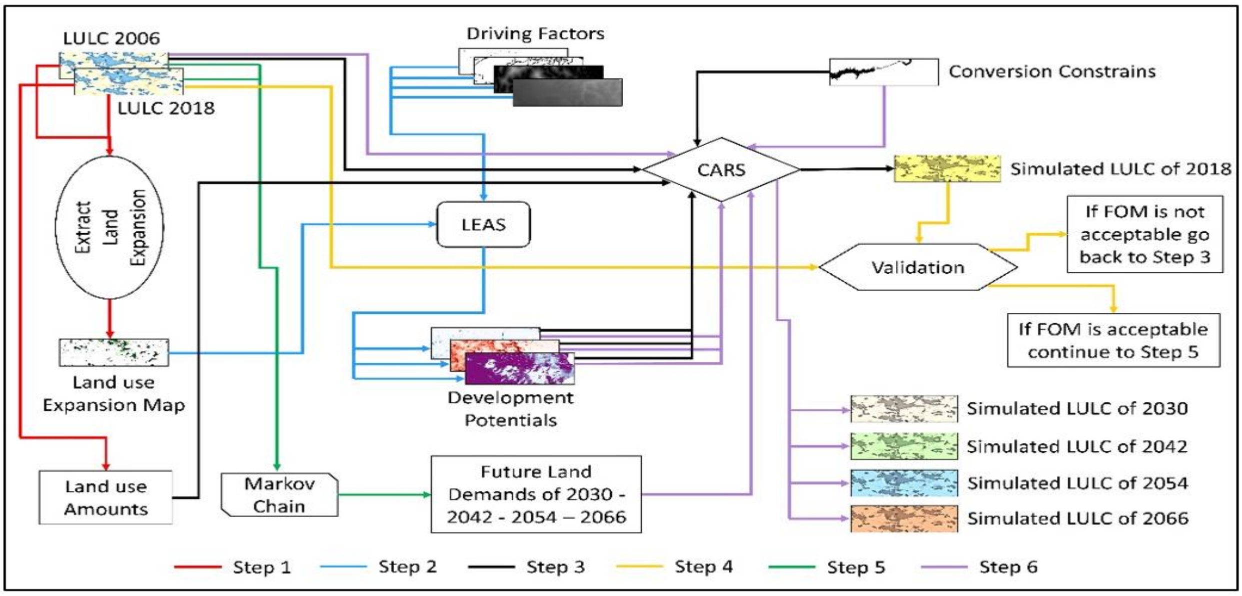

Figure 3. The basic process sequence of PLUS

Table 1. Land use classes used in the study converted from CORINE classification

This study	CORINE classification
Artificial surfaces (AS)	Continuous urban fabric
	Discontinuous urban fabric
	Industrial or commercial units
	Road & rail networks & associated land
	Port areas
	Airports
	Mineral extraction sites
	Dumpsites
	Construction sites
	Green urban areas
	Sport and leisure facilities
Arable land (AR)	Non-irrigated arable land
	Permanently irrigated land
	Rice fields
Fruit groves (97.40% hazelnut groves) (HG)	Fruit trees & berry plantations
Pastures (PS)	Pastures
Heterogeneous agricultural areas (HAS)	Complex cultivation patterns
	Land principally occupied by agriculture with significant areas of natural vegetation
Forest (FST)	Broad-leaved forest
	Coniferous forest
	Mixed forest
Shrub and/or herbaceous vegetation associations (SHVA)	Natural grasslands
	Transitional woodland-shrub
Open spaces with little or no vegetation (OLNV)	Beaches dunes sands
	Bare rocks
	Sparsely vegetated areas
Wetlands (WL)	Inland marshes
	Salt marshes
Water bodies (WB)	Watercourses
	Water bodies
	Coastal lagoons
	Sea and ocean

The basic process sequence to run the model is illustrated in **Figure 3**.

Table 2. Details of the fetched data used in the study

Category	Data	Year	Data source
Socioeconomic	Population	2018	(LandScan, 2020)
Terrain	LULC	2006-2019	(CORINE, 2020)
	DEM		(USGS, 2020)
	Aspect		Calculated from DEM
	Slope		Calculated from DEM
Climatic	Proximity to water bodies	2019	(OSM, 2020)
	Annual precipitation		
	Annual mean temperature		
Soil	Soil type	2019	(FAO, 2020)
Human influence	Proximity to primary roads	2019	(OSM, 2020)
	Proximity to secondary roads		
	Proximity to tertiary roads		
	Proximity to trunk		
	Proximity to railways		
	Proximity to city center		
	Proximity to districts		

Data preparation consisted of LULC maps, driving factors, and conversation constraints. In the study, Coordination of Information on the Environment (CORINE) LULC maps of 2006 and 2018 were used (CORINE, 2020). Considering the operability of the study, level two land-use types were selected. However, some land-use types were unified at level one because the ones lower than the allocated number of samples, cause problems. So, ten major classes were created by merging CORINE (2020) classes can be seen in **Table 1**.

The driving factors used in the study were mainly socio-economic, climatic, and environmental data collected from different publicly available vector and raster data (**Table 2** indicates details of the fetched data).

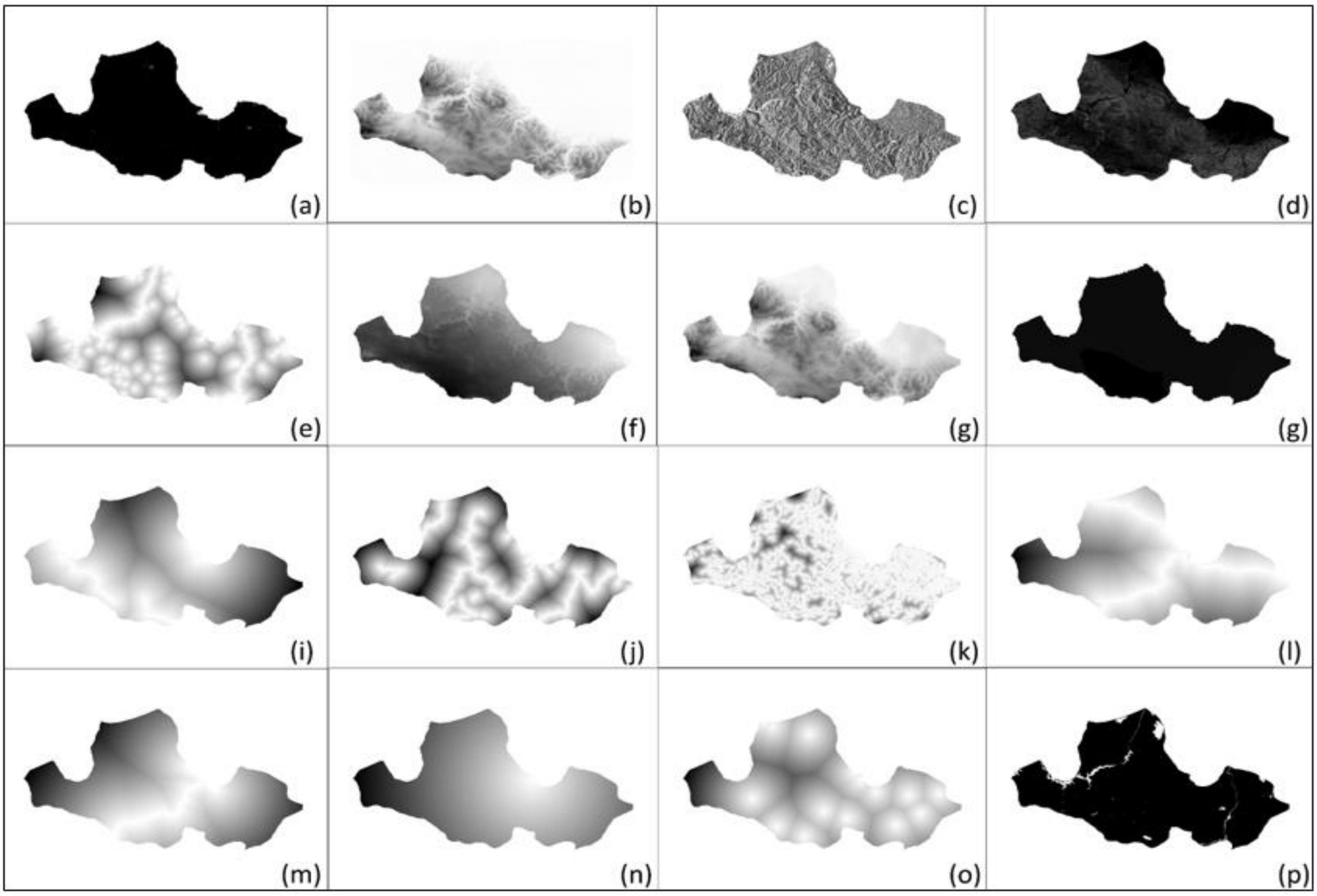

Figure 4. Driving factors: (a) population density, (b) digital elevation model (DEM), (c) aspect, (d) slope, (e) proximity to water bodies, (f) annual precipitation, (g) annual temperature, (h) soil types, (i) proximity to primary roads, (j) proximity to secondary roads, (k) proximity to tertiary roads, (l) proximity to trunk, (m) proximity to railways, (n) proximity to city center, (o) proximity to districts and conversation constraint, and (p) open water bodies

An open water body map was defined as the conversation constraint to the model. The required driving factors and conversation constraint .tiff images fetched from different publicly available sources for the PLUS model can be seen in **Figure 4**.

RESULTS AND DISCUSSIONS

Extracting Land Expansion

The model primarily extracts the land expansion map to execute the development potentials of different land-use types in the LEAS step. A land expansion map is also essential to understand the neighborhood weights and transition matrix, two of the inputs to be used in CARS. LULC maps of 2006 and 2018 were used in extracting land expansion. **Figure 5** shows generated land expansion map and LULC maps of 2006 & 2018.

Training the Model

The land expansion analysis strategy menu is the step for training the model. The model reveals the development potential of each land-use type using random forest regression (RFR) in this stage, and the development potential maps created here will be used in the CARS step. Random forest regression, which was developed by Leo Breiman, is a tree-based machine learning regression method (Babar et al., 2020). Machine learning seeks to anticipate outcomes by extracting patterns from huge datasets, typically in the form of a code (Aytaç, 2020, 2021b). RFR has high robustness performance against outliers and has the ability to well-approximating variables with non-linear relationships (Li et al., 2018). This method is based on the bootstrap aggregation (bagging) strategy (Aytaç, 2022; Zhao et al., 2019). In the bagging approach, random samples (weak learners) from the training data are generated. Then the method is trained on the average of the weak learners to output the learning results using Eq. 1.

$$\hat{f}_{avg}(x) = \frac{1}{B}\sum_{b=1}^{B}\hat{f}^{b}(x) \quad (1)$$

where B is the number of weak learners and $\hat{f}^{b}(x)$ is the result of the weak learner (James et al., 2017). There are two critical parameters while tuning and optimizing the performance of the RFR, and these parameters are nTree and mTry. nTree represents the number of regression trees to grow, and mTry is the number of variables at each split determined by using a randomized subset of the variables (Zhao et al., 2019). The nTree value was chosen as 20, and the mTry value was set as 15, equal to the number of driving factors. The sampling rate was selected as 0.10. After the training process, ten development potential maps were created, and the calibration and validation process step followed the creation of development potentials.

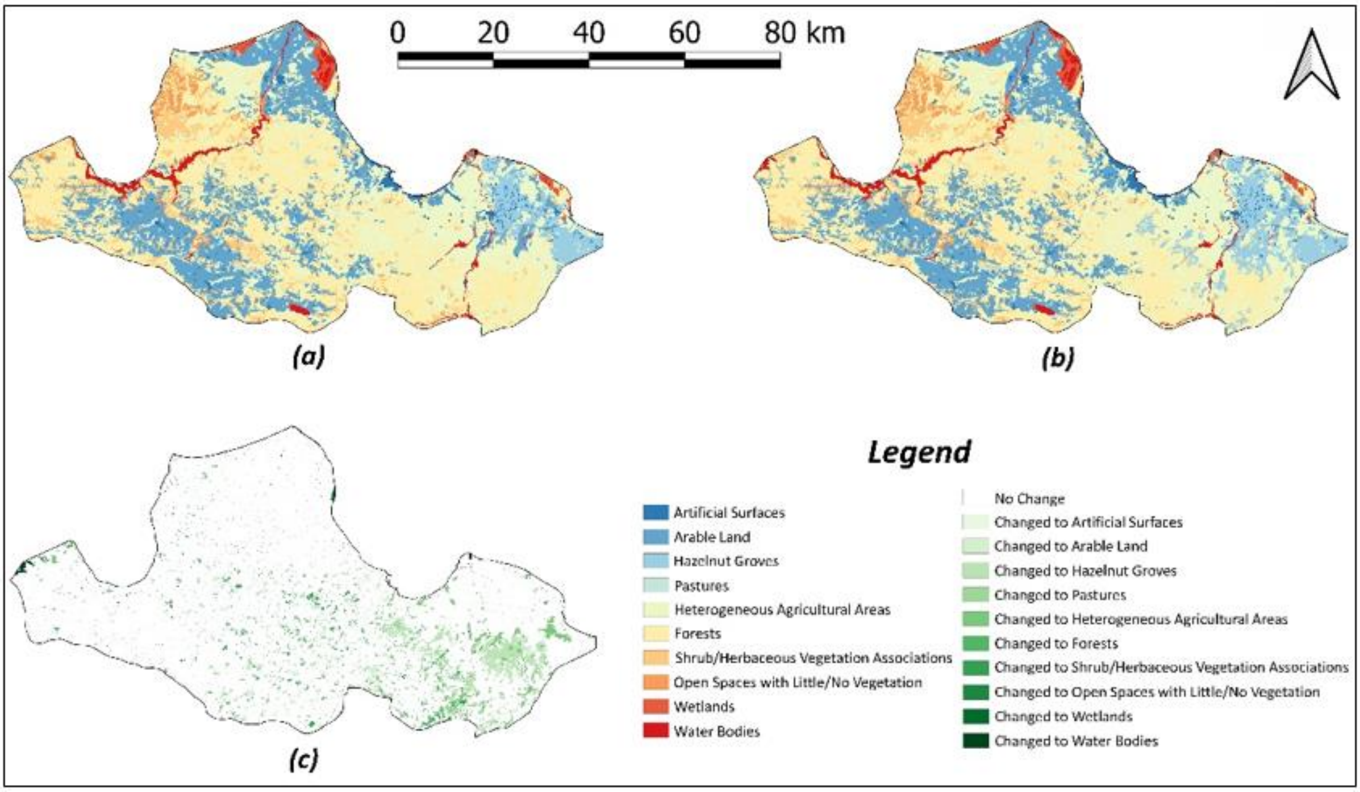

Figure 5. LULC maps of (a) 2006, (b) 2018, & (c) land expansion between 2006 and 2018

Table 3. Neighborhood weights

	AS	AL	HG	PS	HAS	FST	SHVA	OLNV	WL	WB
Start pixel number (2006)	14,204	155,102	31,358	6,699	202,129	256,443	48,854	15,612	7,611	17,481
Future pixel number (2018)	15,358	154,435	49,030	6,831	194,788	249,605	45,915	13,735	7,824	17,972

Table 4. Land-use amounts of 2006 and 2018

	AS	AL	HG	PS	HAS	FST	SHVA	OLNV	WL	WB
Value	0.03814	0.11517	0.28540	0.01831	0.29826	0.13483	0.07931	0.00731	0.00670	0.01653

Calibration and Validation

The CARS step is to simulate the future LULC. However, calibration and validation of the modelling process were required before simulation. So, the first time use of this step was for the calibration of the model. CARS process uses a cellular automata model, which also incorporates a patch-generation mechanism based on multi-type random seeds of land uses (Liang et al., 2020). The cellular automaton is a method where each cell interacts with neighboring cells based on a set of predefined rules simulating self-replicating complex systems that discretize both space and time that was proposed by von Neumann and Ulam in the late 1940s (Fuyong et al., 2020; Liao et al., 2019; Uzuna et al., 2018).

CA was used widely to simulate systems such as the behavior of land, rivers, and topographies, crystal growth, the behavior of gases, the spread of fires, bacterial or viral behavior, population development, and forecast of plant growth (Silva et al., 2019). A cellular automaton (A) that can be thought of as a tuple (d, S, N, f), where d is the dimension of space, S is a finite set of states, N is a finite subset of Z^d is the neighborhood and $f:S^N \rightarrow S$ is transition function, or the local rule (Ortigoza et al., 2020). The inputs of CARS were the 2006 LULC map, development potential maps produced in the LEAS step, and the conversion constraints map. The neighborhood size was selected as three, similar to that of traditional models (Liang et al., 2018). The patch generation value was set to 0.5, and the expansion coefficient was selected as 0.1 as the parameters. The land demand values were determined from 2006 and 2018 LULC maps, and the neighborhood weights were determined with the land expansion map and can be seen in **Table 3** and **Table 4**, respectively.

The simulation of 2018 LULC demands was conducted after the required data has been implemented into the model for calibration and validation.

The simulation results were validated using the figure of merit (FoM). FoM is an excellent indicator of cell-level agreement and pattern similarity (Liang et al., 2018). FoM value can be calculated with Eq. 2.

$$FoM = \frac{B}{A+B+C+D} \tag{2}$$

where A is the area of error due to observed change predicted as persistence, B is the area of accuracy due to observed change predicted as change, C is the area of error due to observed change predicted as changing to an incorrect category, and D is the area of error due to observed persistence

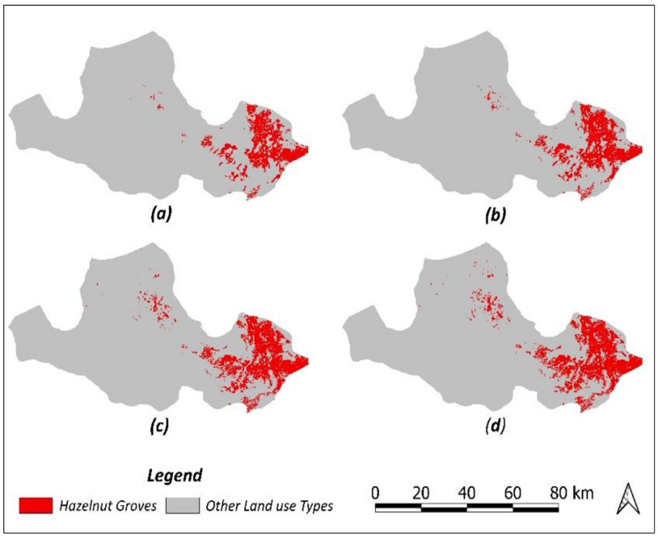

Figure 6. Projected hazelnut plantation areas for the years (a) 2030, (b) 2042, (c) 2054, & (d) 2066

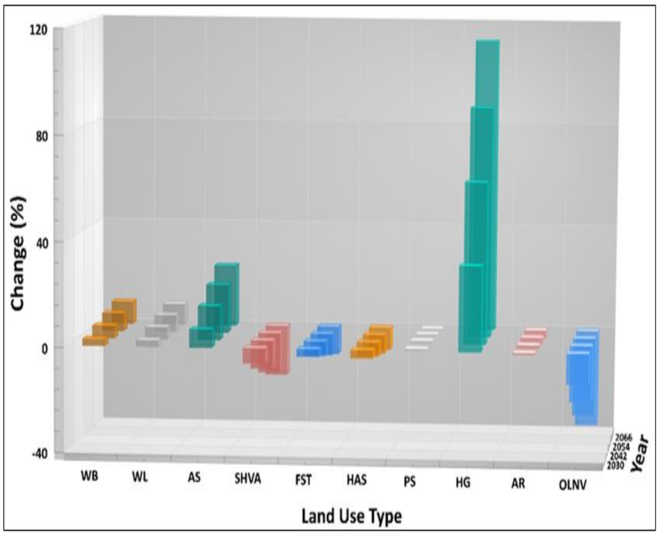

Figure 7. Predicted land-use changes (%) from 2030 to 2066

predicted as change (Liu et al., 2017). The calculated FoM value was 15%. This value showed that the predicted outcome was in an acceptable range, similar to the results in other papers (Chen et al., 2014; Li et al., 2017; Pontius et al., 2008).

Simulating Future Hazelnut Groves

The simulation process initially started with determining future land demands; the PLUS model uses the Markov chain for this procedure. Markov chain models are class-dependent transition matrices, and they have been widely used to determine the probabilities of LULC change between two time periods (Nery et al., 2019). The basis of the Markov chain model is to predict the state of the future time based on the state of the current time and the transition probability between states (Jia et al., 2020). Using the Markov model results, LULC simulations were carried out. The projected hazelnut grove areas for 2030, 2042, 2054, and 2066 can be seen in **Figure 6**.

Figure 6 shows that the hazelnut cultivation areas will continue to increase in the coming years. The cultivation areas will develop primarily in the coastal fields of the city and towards the Western Black Sea region. The increase in hazelnut areas in 2030, 2042, 2054, and 2066 is predicted as 32.46%, 61.79%, 88.37%, and 112.54%, respectively, compared to 2018. Despite all the regulations, farmers did not comply with the decisions and continued to keep their production in hazelnuts, and the process of transforming different land-use types into hazelnut fields will continue increasingly. The changes in the land use types for 2030, 2042, 2054, and 2066 by percentage are shown in **Figure 7**.

When **Figure 7** is examined, four land-use types will expand their lands that are artificial surfaces, hazelnut groves, wetlands, and water bodies. After hazelnut groves, the most increasing land use type was predicted as artificial surfaces, which will be increased by 6.76%, 12.87%, 18.40%, and 23.44% for 2030, 2042, 2054, and 2066, respectively. The remaining six land use types will lose fields. Among these, the most decreasing land-use types stand out as open spaces with little or no vegetation, shrub and/or herbaceous vegetation associations, and forests. These results show that policy-makers will not be able to prevent the increase of hazelnut lands with regulations, and forests and other vegetation areas will be negatively affected by the transformation of these land-use types into hazelnut groves. By 2066, the decrease in open spaces with little or no vegetation, shrub and/or herbaceous vegetation associations, and forest in Samsun is predicted to decrease 36.82%, 19.11%, and 10.52%, respectively.

Land cover change is the process through which anthropogenic activities alter the natural landscape, referring to how the land has been utilized, emphasizing the functional use of land for economic output (Kanti and Harun, 2017). The increase in population and growing GDP causes the clearing of broad areas for agriculture, the land expansion for urban development, and tree cutting for wood fuel generation (Mzuza et al., 2019). Land cover changes occur at various levels and have particular and cumulative consequences on water bodies, air, habitats, climate, and human health. According to Environmental Protection Agency (EPA, 2022) land, development and agricultural usage are two major areas of concern. Land development involves the creation of impermeable surfaces such as highways, parking lots, and other structures. Impermeable surfaces affect ground water aquifer recharge, contribute to nonpoint source water contamination by reducing soil's ability to filter runoff, increase the erosion potential and stormwater runoff. Agricultural uses have a huge impact on the quality of water and watersheds, result in habitat loss or increased wind erosion and dust, and may hasten or worsen the spread of invasive species (EPA, 2022). The results clearly indicate that the future expansion of hazelnut orchards will have a huge impact on natural land cover and the associated ecosystem.

CONCLUSIONS

Turkey is the leading hazelnut producer globally, and hazelnut has strategic importance in the Turkish economy. The laws and regulations implemented by governments did not achieve their purposes, and hazelnut areas increased every year. Therefore, understanding the development of future land use areas can promote a more efficient and targeted land use policy. This study used the PLUS model to simulate the future hazelnut groves in Samsun province as a case study. PLUS is a recently developed model used to project the dynamics of land use patches and landscape patterns and to identify the drivers of land growth. The LULC changes were simulated for 2030, 2042, 2054, and 2066.

The results of the PLUS model indicate that by the year 2066, the hazelnut groves will approximately double their area. The hazelnut groves will expand notably in the city's coastal lands and toward the Western Black Sea region. In 2030, 2042, 2054, and 2066, hazelnut areas are expected to rise by 32.46%, 61.79%, 88.37%, and 112.54%, respectively, compared to 2018. Despite all of the laws, farmers did not follow the choices and continued to produce hazelnuts, and the process of converting diverse land-use categories into hazelnut fields will continue. It is also clear that the new hazelnut fields will be formed by transforming LULC types, mainly as open spaces with little or no vegetation, shrub and/or herbaceous vegetation associations, and forest, and this transformation will have severe effects on the ecosystem. Besides artificial surfaces will expand as well in the coming years. The results of this study are significant and noteworthy as they show the urgent need to balance new regulations with long-term strategies in designing effective hazelnut policies.

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