

Article

Prediction of Greenhouse Area Expansion in an Agricultural Hotspot Using Landsat Imagery, Machine Learning and the Markov–FLUS Model

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Abstract: Greenhouses (GHs) are important elements of agricultural production and help to ensure food security aligning with United Nations Sustainable Development Goals (SDGs). However, there are still environmental concerns due to excessive use of plastics. Therefore, it is important to understand the past and future trends on spatial distribution of GH areas, whereby use of remote sensing data provides rapid and valuable information. The present study aimed to determine GH area changes in an agricultural hotspot, Serik, Türkiye, using 2008 and 2022 Landsat imageries and machine learning, and to predict future patterns (2036 and 2050) via the Markov–FLUS model. Performances of random forest (RF), k-nearest neighborhood (KNN), and k-dimensional trees k-nearest neighborhood (KD-KNN) algorithms were compared for GH discrimination. Accordingly, the RF algorithm gave the highest accuracies of over 90%. GH areas were found to increase by 73% between 2008 and 2022. The majority of new areas were converted from agricultural lands. Markov-based predictions showed that GHs are likely to increase by 43% and 54% before 2036 and 2050, respectively, whereby reliable simulations were generated with the FLUS model. This study is believed to serve as a baseline for future research by providing the first attempt at the visualization of future GH conditions in the Turkish Mediterranean region.



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Keywords: FLUS model; greenhouse; Landsat; machine learning; Markov; simulation

1. Introduction

The majority of land is used for agricultural purposes in many areas of the world [1]. Due to the pressure of rapid population growth, the demand for food is increasing day by day, which is forecasted to increase over 70% in the next 25 years. The situation may lead to an increase in agricultural land in the near future to meet the demand [2]. However, expansion of production areas is known to have limited potential due to restrictions related to the suitability of soil, terrain, and climate conditions for cultivation. Since another important result of population growth is urban sprawl in many regions, increases in agricultural lands may not be possible against urbanization-related political decisions. Therefore, obtaining higher yields from current cultivation areas has become one of the most important aims in agricultural production. In order to achieve this aim, different agricultural production strategies and systems are developed to ensure food safety and sufficiency all over the world. Among the production systems, one of the most widely used type is protected agriculture, mainly greenhouses (GH), which leads to an area of 3×10^6 ha [3].

As is well known, the United Nations (UN) announced their 2030 agenda related to sustainable development in 2015, whereby 17 Sustainable Development Goals (SDG) were introduced [4,5]. On this account, GH cultivation can be especially related to SDG 1, 2

and 3, which aim to ensure access to food, well-being, and health for every individual by contributing to crop yield and increased food quality [4,6], while this type of production may also be linked to other SDGs related to economic growth, infrastructure, and land ecosystems. The largest proportion of the world's GH areas are located in China, which is followed by Mediterranean countries, where the coverage areas of GHs have significantly increased during the 21st century [7]. This type of production has several benefits due to precisely controlled conditions providing a shortened growth period, increased yield and quality, and thus, increased economic incomes. There are also some adverse impacts of the widespread expansion of GHs on the environment [8], such as biodiversity loss, water and soil pollution due to excessive fertilizers, degradation against plastic wastes, and change in regional hydrological process as infiltration or run-off. Hence, monitoring of the long-term dynamics of protected agriculture is essential for promoting sustainable development [9], and the determination of changes in land use and land cover (LULC) status have become a major concern in the last decades for adaptation of more controlled strategies by evaluating the past trends.

In this context, remote sensing technologies have long been used to identify GHs through LULC maps, considering different sensors and various object- or pixel-based algorithms [10]. The distribution of cost-free imagery such as Landsat and Sentinel series has increased the number of studies in the research area of interest. Furthermore, improvements in machine learning (ML) have provided an effective way of information extraction from remotely sensed data [11]. For instance, Landsat images and different ML algorithms were used to obtain multi-temporal GH maps between 1990 and 2018 in the Shouguang region in North China [12]. A ML-based feature extraction method was proposed for GH identification using Sentinel-2 images of different seasons between 2019 and 2020 in Fujian, China [13]. Performances of Landsat 8 and Sentinel 2 for GH delineation were tested through pixel- and object-based ML algorithms in Morocco [6].

In addition, the significance of foreseen and visualized future conditions has increased in recent years [14]. Various models have been developed for the simulation of future LULC patterns based on different potential driving forces [15], whereas the validation of the model presents a key factor [16]. Along with these models, one of the most widely used models is mentioned to be the Cellular Automata-Markov Chain (CA-Markov) hybrid model, due to its capability of evaluating LULC dynamics in complex landscapes by successfully combining ancillary data of biophysical and socio-economic sets with remotely sensed data [14,17,18]. As proposed by [19], the future land use simulation (FLUS) model has different ANN integration to other traditional CA models, and is reported to have higher accuracies than many other models due to improvements in detailed class transitions and occurrence probability [20–22]. Unlike other current models, even non-dominant LULC types with lower probability can be allocated to pixels due to the roulette wheel selection mechanism, which enables reflecting the uncertainties in real-world LULC changes [23]. Moreover, some of the widely used models, such as the Cellular Automata-Markov Model (CA-Markov), Conversion of Land Use and its Effects at Small extent model (CLUE-S), Land Use Scenario Dynamics model (LUSD), Land Change Modeler (LCM) require LULC status for two different times, while Slope, land use, excluded layer, urban extent, transportation, hillshade (SLEUTH) model requires four LULC data at four time points. The lower requirement of the FLUS model with only one LULC map provides an important advantage over other models when land use data is difficult to obtain [24], particularly due to cloudy conditions.

The Turkish Mediterranean region is known to be one of the most important hotspots for agricultural production in the country, where many agricultural products can be grown due to the suitability of climate, soil, and topographic conditions. According to 2022 reports of the Turkish Statistical Institute (TUIK), Antalya takes the first place in controlled production by owning 30,843 ha of area under protective cover [25]. There are some studies that are conducted in the area related to remote sensing of GH characteristics or their temporal coverage (ha) changes using imageries with different spatial resolutions in other

districts [26–34]. Accordingly, many of the mentioned studies were focused on the use of high-resolution satellite imageries for GH identification in the region, and there is limited information on the capability of Landsat [28,29]. Moreover, only one study aimed to predict the amount of near-future GH areas (ha, %) in the Alanya district using Sentinel-2 imageries and MC prediction without simulating future patterns [35]. Therefore, there is a lack of studies on visualizing the probable future conditions for a better understanding of the expansion trends to aid policy and decision-making processes in the area for conservation of resources and prevention of excessive pollution sourced from uncontrolled development of GH areas, whereby more probable simulations are strongly related to the selection of an appropriate classification algorithm in a specified area that has not been evaluated yet.

To fill these gaps in the area, the present study focused on Landsat-based identification of changes between 2008 and 2022 through different ML algorithms and the prediction and simulation of future GH areas (2036 and 2050) based on the Markov–FLUS model considering potential driving factors in the flat areas of the Serik district, Antalya province, Türkiye. This study presents the first attempt of GH-related future simulation in the Turkish Mediterranean region, and seeks to answer the following research questions: (i) Among some widely used ML algorithms, namely, random forest (RF), k-nearest neighborhood (KNN), and k-dimensional trees k-nearest neighborhood (KD-KNN), which presents a more accurate GH classification in the area? (ii) How did GH areas change from 2008 to 2022, and which LULC classes converted to provide space for new GH areas? (iii) Can GH expansions be predicted and reliably simulated via the Markov–FLUS model and ancillary data, and what will the LULC pattern be in 2036 and 2050 years?

The remainder of our paper, excluding this introductory section, is structured as follows: Section 2 is concerned with the materials and methods of this study, including the definition of study area, used imagery and ancillary data, as well as tested ML algorithms and steps of this study. Section 3 represents a comprehensive synopsis of study findings. Section 4 includes comparative discussions of the findings with the current literature. Section 5 summarizes the conclusions, implementations, and ongoing efforts in the area of interest.

2. Materials and Methods

2.1. Study Area

This study was conducted in the Serik district of Antalya province (Türkiye) with center coordinates 36°54′59″ N and 31°06′18″ (Figure 1). The district is almost 40 km away from the center of Antalya and is located nearby the Taurus Mountains. The majority of hilly areas are covered by forests, and the secondary natural vegetation type is composed of shrubs. Conversely, agricultural production activities are mainly conducted on flat areas. The district is under the impact of typical Mediterranean climate. The temperature ranges between 6 °C and 34 °C with an average annual value of 18.7 °C, and the average annual precipitation is 807 mm [36]. Many types of vegetables and fruits are grown in the area, especially bananas. The district has great importance to greenhouse cultivation within the province, since it is one of the two major districts in terms of greenhouse coverage area, according to [25]. The greenhouse areas have expanded approximately 115% in the last 15 years. However, as it is well known, the city has great importance in terms of tourism and, thus, it has a complex structure that reflects a mixture of residential and agricultural signatures close to each other. Since GHs are constructed on near-flat areas, the flat land of Serik was selected as the study area, which is given in the red square within Figure 1, where main agricultural activities are currently ongoing. The population in the area was 101,961 in 2008 and reached 139,545 by 2022, with an increase of 36.9%. The survey area covers approximately 50 thousand ha.

2.2. Landsat Imageries and Ancillary Data

Landsat imageries of TM and OLI sensors with 30 m spatial resolution were used as the main data source in the present study, which have been radiometrically corrected and

georeferenced. The images were acquired in the same month of considered years to avoid monthly variations of illumination and production patterns in the area. The threshold for cloud cover was determined to be 10%. Among the images that met the pre-defined cloud thresholds, the ones acquired in July 2008 and July 2022 were selected to ensure a reflection of the actual agricultural patterns, since the harvest of some crops is likely to affect spectral signature properties and likely to increase the overestimation of bare areas or natural vegetation due to dried vegetation or residues after mid-summer. Visible, near-infrared, and shortwave-infrared bands of each scene were stacked to obtain 6-band (6-b) images prior to image classification procedures, and the study area was extracted based on the study area boundaries.

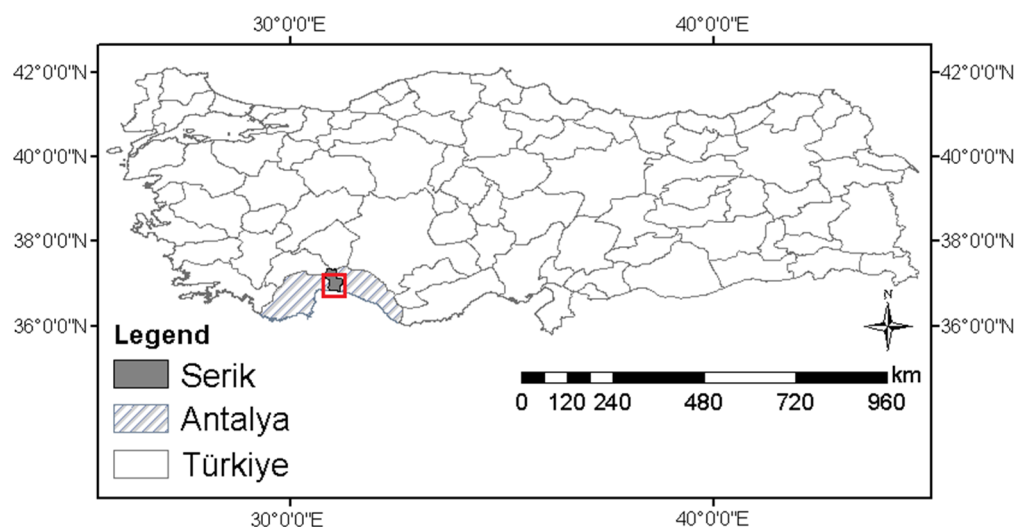


Figure 1. Location of the study area within Antalya province, and Türkiye.

The ancillary data consisted of different layers, including topographic properties, distance to sea, water surfaces, roads, and settled areas. In the context of this study, only six driving forces could be included in simulation procedures due to resolution and data availability concerns, since many socio-economic or policy-related factors are limited to the province level and cannot be obtained at sublevels such as district or village scales. Moreover, use of population data would cause ambiguity in the simulation step due to the fact that demographic variables are collected at the district level, which will not be varied within the study area boundaries. Subsequent to the collection of required data, all datasets were spatially referenced to UTM projection (Zone 36, N) datum WGS84, and spatial resolutions were fixed to 30 m to be consistent with the Landsat data. Topographic properties of the area were obtained from ALOS Global Digital Surface Model [37], and elevation and slope maps were generated in ArcGIS software 10.3.1 to be used in the simulation step. The land use capability class (LUCC) map was obtained from the General Directorate of Village Services. Distances were generated through polyline features for water, sea, and roads, and point features of settlement central point data of building groups based on the Euclidean distance function in ArcGIS [38].

2.3. Steps of This Study

The main steps consisted of image classification, accuracy assessment, change detection, future simulation, and validation in the present study (Figure 2).

2.3.1. Image Classification

Prior to the classification, a LULC classification scheme was composed, including forest (F), natural vegetation (N), agriculture (A), water surface (W), settled area (R), and greenhouse (GH) classes. The ML algorithms of random forest (RF), k-nearest neighborhood

(KNN), and k-dimensional trees k-nearest neighborhood (KD-KNN) were adopted for the image classification step.

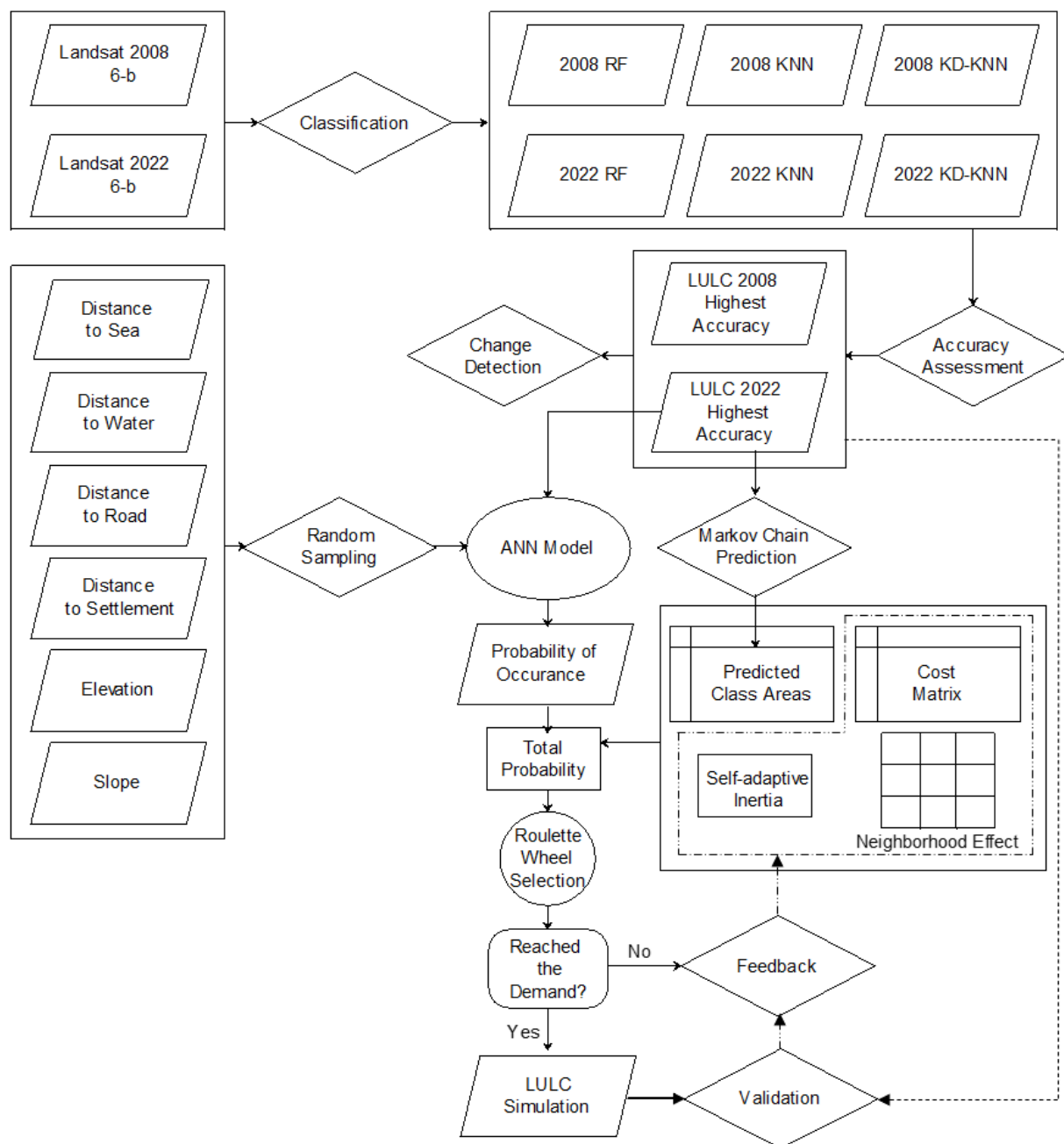


Figure 2. The implemented steps during this study.

The size of the training samples for LULC classification depends on different factors, including the scale of the study area, number of considered classes, magnitudes of these classes, heterogeneity within subclasses, complexity, and variability of the landscape. An increase in training sample size was reported to positively affect classification accuracy [39]. Training samples were randomly collected considering these parameters, and the number of training samples within each year was ranged in relation to the magnitude of each class coverage area according to visual interpretation, whereby a class with a smaller area had a lower number of training samples. For the classification of 2008 and 2022 images, 649 and 676 randomly selected training samples were used, respectively. The same training samples

from each LULC class were used for classification to ensure the differences in classification maps were sourced from the performed algorithm.

2.3.2. Accuracy Assessment

Subsequent to the implementation of different classification algorithms, performances of classifications were compared through accuracy assessment procedures using ground knowledge and high-resolution images of Google Earth. As well as the classification procedures, the same randomized control points were used to assess the accuracy of all LULC maps. Accordingly, accuracies of 278 control points from 2008 and 292 control points from 2022 were checked, respectively. The percentages of training and accuracy samples within the sample totals were 70% and 30%. As previously described in [40], the overall accuracy (OA, %) (1), User's Accuracy (UA, %) (2), Producer's Accuracy (PA, %) (3), and overall Kappa (OK) were compared to understand which algorithm gave the most satisfying result for GH discrimination in the area.

$$OA(\%) = \frac{\sum \text{Correctly Classified Pixels}}{\sum \text{Classified Pixels}} \times 100 \quad (1)$$

$$UA(\%) = \frac{\text{Number of Correctly Classified Pixels}}{\sum \text{Classified Pixelsof Class}} \times 100 \quad (2)$$

$$PA(\%) = \frac{\text{Number of Correctly Classified Points}}{\text{Number of Reference Points of Class}} \times 100 \quad (3)$$

2.3.3. Change Detection

The changes in class areas were calculated based on the initial and the final area values of each LULC class in hectares (ha) and percentages (%) (4). In addition to individual changes in LULC classes, from-to changes were identified for a better understanding of the gains/losses from the classes into each other [41,42]. A post-classification change detection technique was applied for the determination of LULC change, especially related to greenhouse area, using the LULC maps of 2008 and 2022 with the highest accuracy.

$$\text{Change}_{LULC \text{ Area}} = (LULC_{t2} - LULC_{t1}) \quad (4)$$

2.3.4. Markov Chain Prediction and Future Simulation

In remotely sensed modeling processes, the Markov model provides a prediction of LULC change trends through a transition probability matrix based on the initial and final statuses of the LULC pattern in a certain area (5–7). Accordingly, the model predicts change from status L_c to future status L_{c+1} with the transition probability denoted by P_{ij} , whereas L_{c+1} is found depending on L_c [43].

$$\begin{bmatrix} L_{11} & \cdots & L_{1n} \\ \vdots & \vdots & \vdots \\ L_{n1} & \cdots & L_{nn} \end{bmatrix} \quad (5)$$

$$\left(0 \leq P_{ij} < 1 \text{ and } \sum_{j=1}^n P_{ij} = 1, i, j = 1, 2, \dots, n \right) \quad (6)$$

$$L_{(c+1)} = P_{ij} \times L_c \quad (7)$$

For the future simulation, a CA-based ANN model, namely GEOSOS–FLUS software (2.4), was preferred in the present study [44], and the steps were applied as described in [19]. The $LULC_{2036}$ and $LULC_{2050}$ patterns were simulated, based on the best performed $LULC_{2022}$ map with the aid of ancillary data (Figure 3). The pixel values of considered ancillary data were related to the pixels of LULC classes in the ANN training step through different models related to sampling type, rate, and hidden layers. The probability of occurrence (PoO) was generated through this ANN model with the integration of considered

driving forces such as topographic properties or distances, whereby the MC model was used to predict the pixel demands of each LULC class for each simulation year through the transition probability and the matrix. Then, conversion rules were determined based on the matrix, and neighborhood effects were defined subsequently. Then, simulation maps were created based on self-adaptive CA, priorly determined rules for simulation were entered into model through self-adaptive inertia, the CA competition mechanism module, and the probability of a cell determined as a certain LULC class was estimated for all cells based on the equation given below (8) [19]. The CA simulation determines if a cell will be converted to another LULC class, and the simulation criteria may be reconsidered in the feedback step, whereby the demands related to the predicted number of pixels could not be reached.

$$TP_{p,k}^t = P_{p,k} \times \Omega_{p,k}^t \times Inertia_k^t \times (1 - SC_{C \rightarrow k}) \quad (8)$$

where $TP_{p,k}^t$ represents the conversion probability of the p cell from the initial LULC class to the k class at t iteration time, $P_{p,k}$ represents the PoO of LULC k class on p cell; $\Omega_{p,k}^t$ represents the effect of neighborhood of k LULC class on p cell at time t ; $Inertia_k^t$ represents the LULC class k coefficient at time t , and finally, $SC_{C \rightarrow k}$ represents the conversion cost on transition from initial LULC class c to LULC class k .

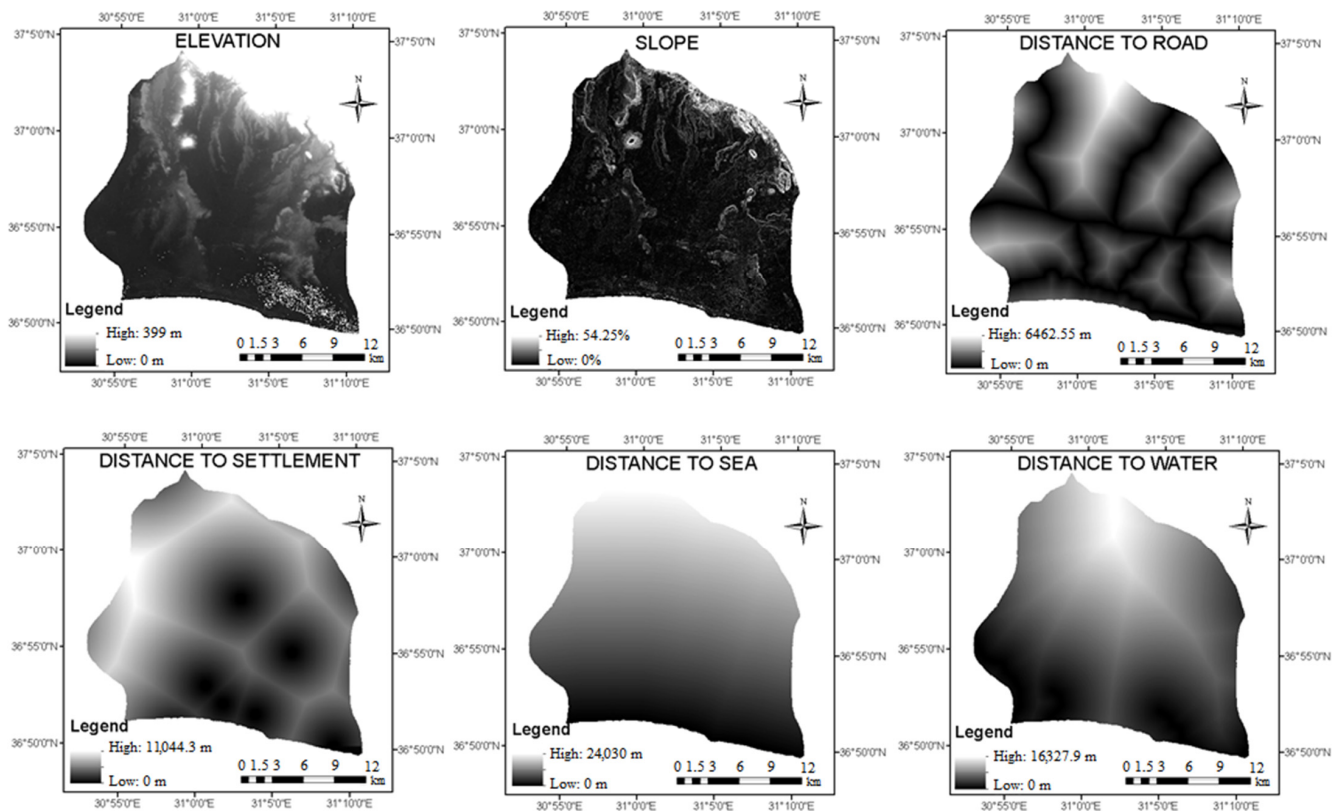


Figure 3. The ancillary data used in the ANN training step.

Accordingly, simulation maps representing 2036 and 2050 conditions were generated. Moreover, to understand the reliability of simulations, 2022 LULC status was simulated based on LULC₂₀₀₈ and the actual number of pixels from each class of the best-performed LULC₂₀₂₂, together with the same ancillary data to compare the coherency between classified and simulated situations to understand the distribution capability of the model for class demands through K and Figure of Merit (FoM) values, where FoM represents the obtained and simulated change overlap (%) [45]. Like other simulation studies [46–48], the accuracy of the simulated LULC₂₀₂₂ was acknowledged to be same for LULC₂₀₃₆ and LULC₂₀₅₀ since there are no other products showing the future status of the area to be compared.

3. Results

3.1. Produced LULC Maps of 2008 and 2022

The $LULC_{2008-RF}$, $LULC_{2008-KNN}$ and $LULC_{2008-KD-KNN}$ are given in Figure 4a–c, while, $LULC_{2022-RF}$, $LULC_{2022-KNN}$ and $LULC_{2022-KD-KNN}$ are given in Figure 5a–c, respectively. Moreover, the areas of classes that were obtained from the produced maps are given in Figure 6. As can be seen from the figures, the order of class area magnitudes was similar in both years, while the amounts of W surface have relatively small values in 2008 and 2022. However, there are considerable differences between class areas, especially in A and N classes, although the same training samples were used in the classification step. The GH area seemed to range between 2760 ha and 3026 ha in 2008, while the values were varied from 4775 ha to 6124 ha in 2022. There was a difference of 9.6% in 2008 and 33.9% in 2022 year between GH areas obtained from RF and KD-KNN, which corresponds to 266 and 1349 ha, respectively. Due to the considerable number of differences, it is highly important to determine which classification algorithm gave more reliable results, especially in terms of GH classification for obtaining more precise results for precise evaluation of past situations, as well as for more accurate simulation of future status.

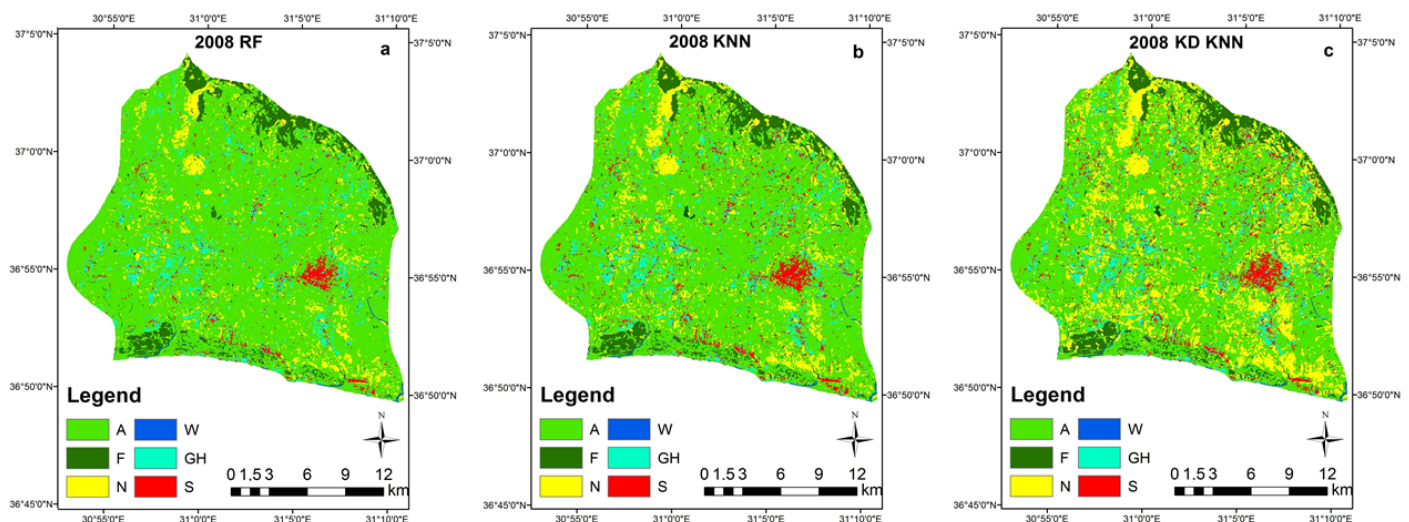


Figure 4. Produced LULC maps of 2008 (a) $LULC_{2008-RF}$, (b) $LULC_{2008-KNN}$, and (c) $LULC_{2008-KD-KNN}$.

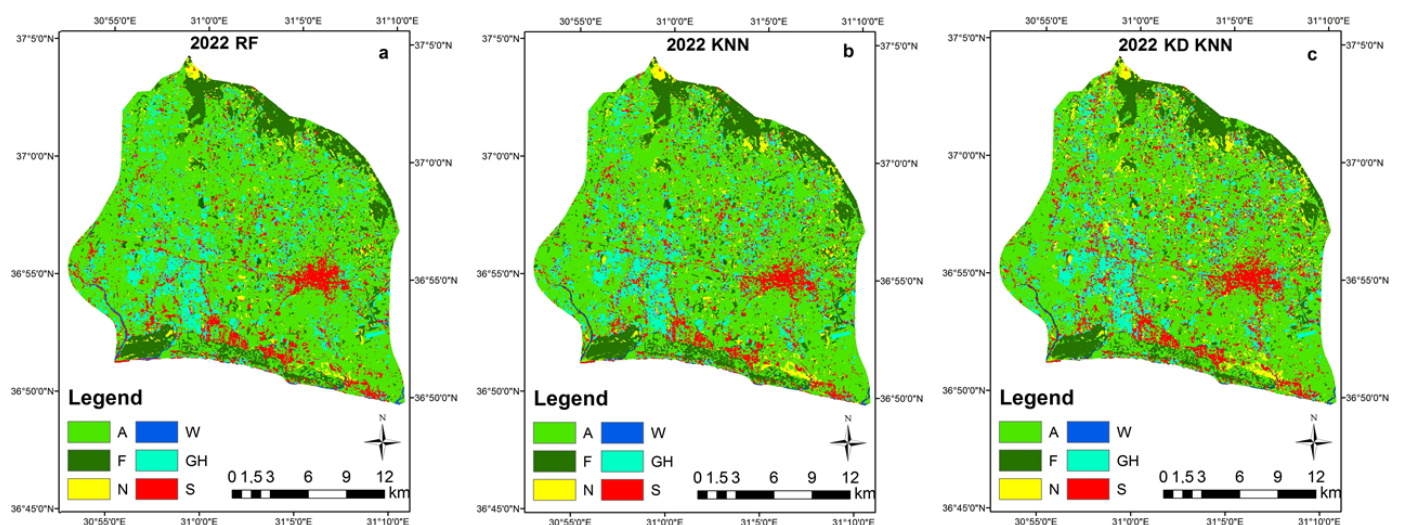


Figure 5. Produced LULC maps of 2022 (a) $LULC_{2022-RF}$, (b) $LULC_{2022-KNN}$, and (c) $LULC_{2022-KD-KNN}$.

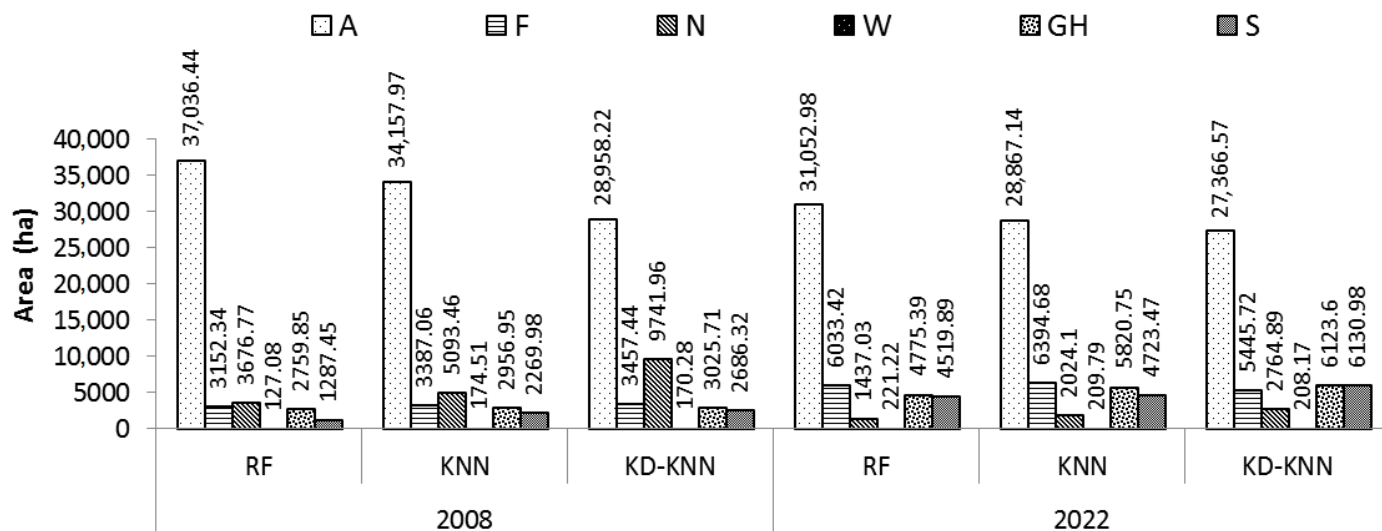


Figure 6. LULC class areas (ha) of $LULC_{2008-RF}$, $LULC_{2008-KNN}$, $LULC_{2008-KD-KNN}$, $LULC_{2022-RF}$, $LULC_{2022-KNN}$, and $LULC_{2022-KD-KNN}$.

3.2. Accuracies of LULC Maps

The error matrices were produced through accuracy assessments and given in Tables 1 and 2 for LULC maps of 2008 and 2022, respectively. As it can be clearly seen from the tables, the OA and OK values of 2008 LULC maps were lower than 2022 LULC maps in all classifications. The individual comparisons of 2008 and 2022 classifications have shown that the highest OA and OK values were obtained from RF classification in both years. The OA and OK values for $LULC_{2008-RF}$ were 89.9% and 0.8680, whereas the values were calculated as 92.5% and 0.9032 for $LULC_{2022-RF}$. The accuracy of RF classification was followed by KNN classification in each year. Accordingly, the values were 87.4% and 0.8354 for $LULC_{2008-KNN}$, and 90.1% and 0.8723 for $LULC_{2022-KNN}$. The lowest accuracies were obtained from KD-KNN with OA and OK 80.9% and 0.7521 for $LULC_{2008-KD-KNN}$, and 88.0% and 0.8466 for $LULC_{2022-KD-KNN}$. On the other hand, OA and OK values are not individually sufficient for evaluating the potential use of compared ML algorithms in greenhouse classification. Thus, the UA and PA values were compared to identify a more reliable algorithm to achieve the aim of this study. The GH class accuracies presented similar performances with OA values, whereby the highest GH accuracies were obtained from the RF algorithm in both years. The UA and PA of $LULC_{2008-RF}$ were 92.2% and 90.4%, while they were found to be 96.2% and 94.9% for $LULC_{2022-RF}$. Accordingly, 47 of 52 control points in 2008, and 75 of 79 control points in 2022 were accurately classified for GH class using RF. On the other hand, even though the GH accuracy of $LULC_{2008-KD-KNN}$ was within acceptable thresholds [49], the use of this algorithm for future simulation may cause misestimating of F, N and S classes, which were under the reliability threshold in terms of individual accuracies. As can be seen from the table, there were especially confusions between A and N or S classes with increased levels in KNN and KD-KNN classifications. Moreover, relatively young trees in the forest areas are classified in the N class instead of F, due to the spectral similarity sourced from more apparent soil reflectance below the canopy low coverage of tree branches and leaves in early stages. These may affect the accuracy of prediction and probably leads to overestimation of N areas and underestimation of A and F areas. Therefore, $LULC_{2008-RF}$ and $LULC_{2022-RF}$ with UA and PA over 90% were used for determining the LULC changes and future simulation in the latter steps based on these situations.

Table 1. Error matrices of LULC_{2008-RF}, LULC_{2008-KNN}, and LULC_{2008-KD-KNN}.

LULC _{2008-RF}									
Class	A	F	N	W	GH	S	Total	UA	PA
A	97	4	4	1	3	1	110	95.1	88.2
F	1	35	1	0	0	0	37	83.3	94.6
N	2	2	41	0	0	1	46	85.4	89.1
W	0	1	0	9	0	0	10	90.0	90.0
GH	2	0	1	0	47	2	52	92.2	90.4
S	0	0	1	0	1	21	23	84.0	91.3
Total	102	42	48	10	51	25	278		
OA (%)	89.9								
OK	0.8680								
LULC _{2008-KNN}									
Class	A	F	N	W	GH	S	Total	UA	PA
A	95	2	6	1	4	2	110	95.0	86.4
F	2	33	1	0	0	1	37	84.6	89.2
N	1	3	40	0	1	1	46	81.6	87.0
W	0	0	0	10	0	0	10	90.9	100.0
GH	2	1	2	0	45	2	52	86.5	86.5
S	0	0	1	0	2	20	23	80.0	87.0
Total	102	39	49	11	52	25	278		
OA (%)	87.4								
OK	0.8354								
LULC _{2008-KD-KNN}									
Class	A	F	N	W	GH	S	Total	UA	PA
A	83	8	12	1	3	3	110	86.5	75.5
F	6	30	1	0	0	0	37	73.2	81.1
N	5	2	39	0	0	0	46	72.2	84.8
W	0	0	0	10	0	0	10	90.9	100.0
GH	2	1	2	0	43	4	52	87.8	82.7
S	0	0	0	0	3	20	23	74.1	87.0
Total	96	41	54	11	49	27	278		
OA (%)	80.9								
OK	0.7521								

3.3. Temporal Changes between 2008 and 2022

The LULC changes were determined through LULC_{2008-RF} and LULC_{2022-RF} (Table 3). As can be clearly seen, the areas of A and N have reduced while F, W, GH and S class areas have increased within the considered period. The coverages of A class decreased from 77.10% to 64.64% and N class from 7.65% to 4.66%. A difference of 6.0% was found in F areas due to forestation activities, while a part of the increase in F areas is due to the spectral changes in reflectance of young trees due to increased maturity level in time, which led these younger trees to be accurately classified as F. Similarly, the reduction in N class areas is related to the same situation. The relatively small increase in W areas is believed to have arisen from meteorological conditions, since small water bodies can be dried at higher air temperatures. The GH areas were increased from 2759.85 to 4775.39, corresponding to a 73% increase, whereas the 15 year difference in coverage area was found to be 4.20%. Finally, it was seen that there was a considerable increase in S class area starting from 1287.45 ha in 2008 and reaching 4519.89 ha, with an increase of 3232.44 ha.

Table 2. Error matrices of LULC2022-RF, LULC2022-KNN, and LULC2022-KD-KNN.

LULC ₂₀₂₂ -RF									
Class	A	F	N	W	GH	S	Total	UA	PA
A	85	3	4	0	0	1	93	96.6	91.4
F	1	22	1	0	0	0	24	81.5	91.7
N	1	1	35	0	0	0	37	85.4	94.6
W	0	1	0	10	0	1	12	100.0	83.3
GH	0	0	1	0	75	3	79	96.2	94.9
S	1	0	0	0	3	43	47	89.6	91.5
Total	88	27	41	10	78	48	292		
OA (%)					92.5				
OK					0.9032				
LULC ₂₀₂₂ -KNN									
Class	A	F	N	W	GH	S	Total	UA	PA
A	86	2	2	0	1	2	93	94.5	92.5
F	1	21	2	0	0	0	24	84.0	87.5
N	1	1	33	0	1	1	37	80.5	89.2
W	0	0	1	10	0	1	12	100.0	83.3
GH	2	1	2	0	70	4	79	94.6	88.6
S	1	0	1	0	2	43	47	84.3	91.5
Total	91	25	41	10	74	51	292		
OA (%)					90.1				
OK					0.8723				
LULC ₂₀₂₂ -KD-KNN									
Class	A	F	N	W	GH	S	Total	UA	PA
A	82	2	5	0	1	3	93	0.953	0.882
F	1	21	1	0	0	1	24	0.778	0.875
N	0	2	32	0	2	1	37	0.800	0.865
W	0	0	0	11	0	1	12	1.000	0.917
GH	2	2	2	0	68	5	79	0.919	0.861
S	1	0	0	0	3	43	47	0.796	0.915
Total	86	27	40	11	74	54	292		
OA (%)					88.0				
OK					0.8466				

Table 3. Changes in LULC areas (ha, %).

Class	2008 Area		2022 Area		LULC Area Change		Direction
	ha	%	ha	%	ha	%	
A	37,036.44	77.10	31,052.98	64.64	5983.46	12.46	—
F	3152.34	6.56	6033.42	12.56	2881.08	6.00	+
N	3676.77	7.65	1437.03	2.99	2239.74	4.66	—
W	127.08	0.26	221.22	0.46	94.14	0.20	+
GH	2759.85	5.74	4775.39	9.94	2015.54	4.20	+
S	1287.45	2.68	4519.89	9.41	3232.44	6.73	+
Total	48,039.93	100.00	48,039.93	100.00			

In addition to class area changes, it is important to determine the conversion directions and amounts from one class to another to understand the transition trends (Figures 7 and 8). Figure 7 represents the magnitudes of conversions from one class to another, which does not include values for remaining in the same class in both years. The reliability of the values is directly related to accuracies of LULC₂₀₀₈ and LULC₂₀₂₂. The highest conversion occurred from A to GH class areas (3916.47 ha), showing that agricultural lands comprised

the majority of new GH class areas. The secondary source for GH class areas was N class areas, with a 200.51 ha conversion amount. The conversions from S to GH class areas were highly probable to arise from the ongoing construction process in 2008 due to the incomplete status of GHs without coverage on the top changing the spectral signature and the concrete bases interpreted as S class areas. The conversions from F and W class areas to GH class areas were considerably low. Another considerable change was the conversion of A to S class areas (2260.13 ha) due to the expansion of settled areas, especially around agricultural fields. Conversion of A to F class areas were particularly close to hilly areas (2711.25 ha), and A to N class areas were mostly caused by changes in spectral harvested plants (905.45 ha). Moreover, conversion from N to A class areas (2199.01 ha) mostly occurred for balancing the reductions in A class areas, since agricultural lands are vital elements for ensuring food security. With the increase in the maturity level of young trees, previously misclassified F areas as N class areas could be accurately classified as F class areas in the latter year, leading to a virtual conversion from N to F class areas (697.68 ha). A conversion from GH to A class areas is expected to be the source of the elimination of damaged GHs against natural disasters. The gains of S from GH class areas seemed to occur around settled areas against the requirement of space for settlement expansion.

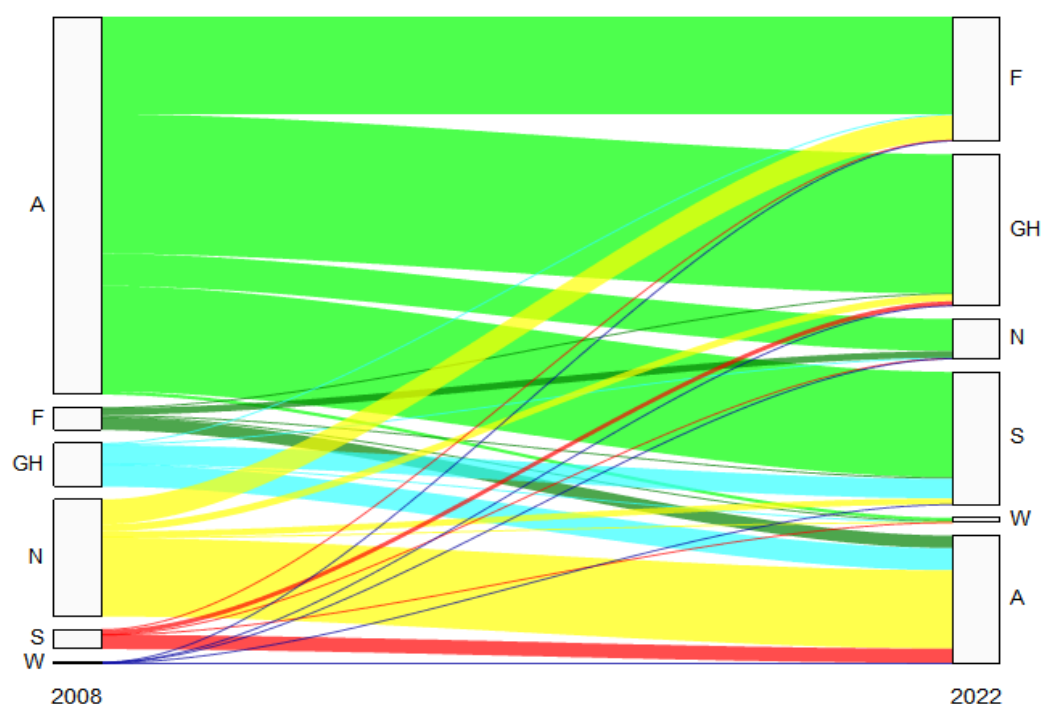


Figure 7. LULC conversions from one class to another between 2008 and 2022.

3.4. Future LULC Class Demand Prediction

In the MC prediction step, the future class demands were determined in terms of the number of pixels per class to be used in the simulation step of the FLUS model for 2036 and 2050, then converted to area (ha, %) (Figure 9). This step depends on a conversion probability matrix that represents the probability of conversion from one class to another. Based on the obtained results, the area of the A class is expected to reduce significantly, while a slight decrease is predicted to occur in the N class area. Conversely to this situation, the S and GH class areas are foreseen to continue their process of expansion. The GH class areas are predicted to reach from 2759.85 ha to 6943.05 ha in 2036 and 7322.40 ha in 2050, compared to their initial status in 2008, with increases of 4183.20 and 4562.55 ha, respectively. Another important predicted change is the continuing expansion in settlement area that reaches to 7030.26 ha, which was calculated as 1287.45 ha in 2008.

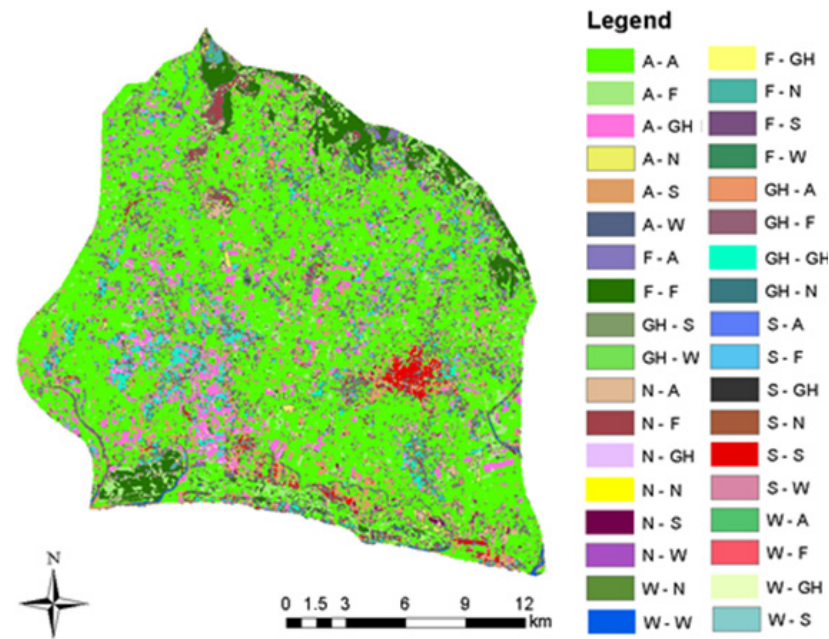


Figure 8. LULC conversion map representing converted pixel locations.

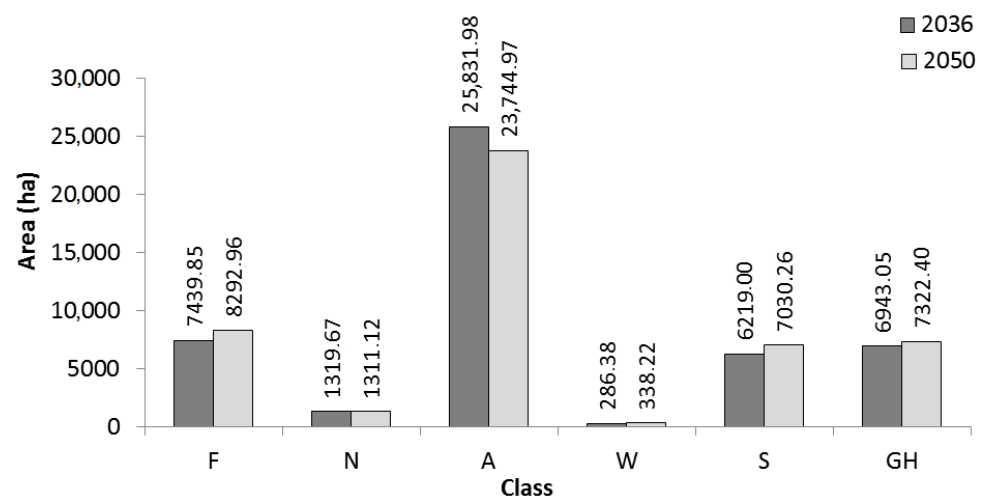


Figure 9. Predictions for class areas (ha) of LULC₂₀₃₆ and LULC₂₀₅₀.

3.5. Simulation and Validation of LULC₂₀₃₆ and LULC₂₀₅₀

Subsequent to the MC prediction, the module of self-adaptive inertia and competition mechanism CA was used based on determined rules for simulation, based on conversion probabilities, whereby a cost value of 0 represents no conversion between the two classes and 1 represents possible conversions. Similarly, the neighborhood effect ranges between 0 and 1. Then, the simulation step was implemented based on the PoO that was composed in the ANN training step, using the possible variables as the ancillary data. The spatial distribution of MC-based predicted pixel demands was performed through trained ANN. The actual numbers of pixels from all LULC classes in LULC₂₀₂₂ were used as the future pixel demand, and LULC_{2022simulation} was simulated based on the 2008 values for comparing the overlap between the simulated and classified status of the 2022 values. The K and FoM values were calculated for this purpose, and both values were found to be over 0.70. Moreover, the UA and PA values for the simulation were 0.75 and 0.77, respectively. The accuracies of A, W and S were similar with GH, while the lowest values were obtained from the N class. Since the values are coherent with the literature and, thus, acceptable, MC-based predictions of LULC₂₀₃₆ and LULC₂₀₅₀ pixel demands were

simulated in the final step using an RF-based LULC₂₀₂₂ map, and simulation maps were given in Figure 10a and Figure 10b, respectively. New GH areas seemed to be located close to each other, mainly on the open agricultural areas of LULC₂₀₂₂. Moreover, new S areas are distributed around the current residential areas, as well as the main roads. The impacts of such change should be evaluated from different perspectives including points of views related to agriculture, environment, tourism and economy to conserve the ecological and economical balance while reducing the negative impacts.

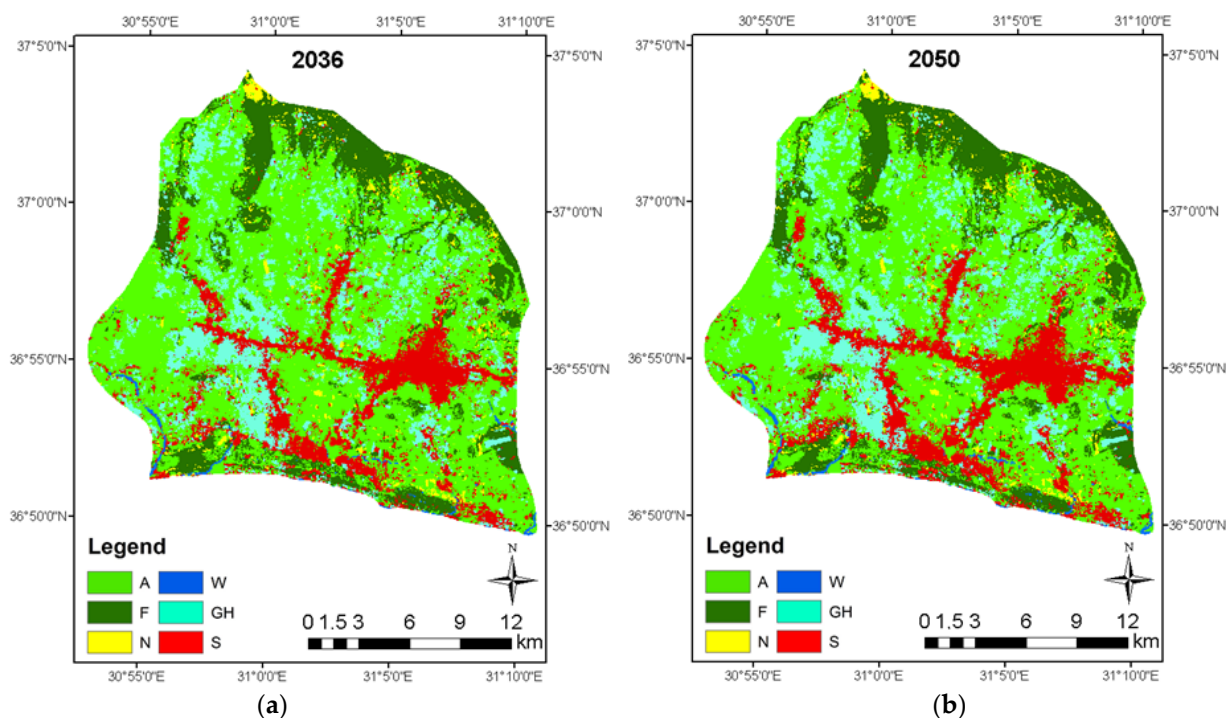


Figure 10. Simulation of predicted class areas (a) LULC₂₀₃₆ and (b) LULC₂₀₅₀.

4. Discussion

In the center of the Turkish Mediterranean region, both GH and settlement expansion trends rapidly occur. The increase in settled areas can present another threat to agricultural and environmental perspectives, whereby a major part of this increase is known to originate from tourism-related initiatives in the area. Therefore, the magnitudes of these changes are required to be evaluated. LULC maps provide rapid and valuable information, whereas accuracy presents the main concern since the further use of classified data is possible only if they are reliable [50]. On this account, different thresholds were given in the literature for quantifying the reliability of classified maps by grading the performances based on overall and class-based accuracies and Kappa values [49,51]. The selection of a more appropriate classification technique for a specified area is a significant process, especially in areas with complex structures due to the small patch size of some LULC classes. Based on the results of the present study, it can be confidently said that, although accuracies of all classifications were over the threshold values, the reliability of LULC maps obtained through RF was considerably higher overall for both LULC and GH classifications.

Despite the benefits to the producers in the Antalya province, especially in terms of economic profits, the increase in GHs should be precisely evaluated due to potential adverse effects, since previous studies have shown that the requirements of new areas for GH construction are mostly met from productive agricultural fields [28]. Results of this study were coherent with those obtained from Aksu, Finike, and Kumluca districts in different years [27–30,32,34]. For the maintenance of the balance between different production systems and environmental health, more controlled and well-planned strategies are required to be adapted in the area since rapid and inappropriate transitions may result

in serious environmental issues [52]. For instance, an increase in such surfaces within a certain area accelerates vulnerability against natural disasters. The Antalya province is known to be vulnerable against tornado and flooding impacts, where the phenomena mostly lead to serious damages on GH coverage materials and growing products [53,54]. The monitoring of GH areas in narrower periods can be helpful for disaster management and more rapid determination of the locations of effected GHs. From another point of view, thermal conditions of the area can be changed due to the increased area of GHs, which have a strong potential to contribute undesired UHI impacts in the future, which may also be assessed using thermal bands of Landsat imageries via appropriate algorithms.

On the other hand, the evaluation of previous statuses seems insufficient without forecasting possible short- and long-term future conditions. Unfortunately, only one study was conducted in our country [35], and the findings of the present study have shown that the increasing trends in predictions were coherent with the previous one [35]. Beyond the estimation of change amounts (ha, %), the allocation of predicted pixel demands for the spatial representation of the most probable future statuses is of importance. Hence, the use of land use simulation models has widely increased. However, the simulation studies related to GH identification have been lacking for the whole region. The simulation maps of LULC₂₀₃₆ and LULC₂₀₅₀ were successfully generated with Kappa and FoM values based on MC-based estimated number of pixels for each LULC class using the FLUS model that was denoted to have successful results [55].

5. Conclusions

One of the two important economic income sources in the Mediterranean coast of Türkiye is agriculture, where the other one is tourism. Initiatives in tourism activities have accelerated the expansion of settlement areas, together with the growth of local population. These situations also affected the agricultural sector due to increased food demand. The process has led to a significant increase in GH areas within the last two decades. Therefore, the expansion amounts should be evaluated to avoid undesired further impacts. In this study, performances of three different ML algorithms for Landsat-based GH classification were compared for obtaining more accurate evaluation of past conditions, as well as the prediction and simulation of future LULC statuses for 2036 and 2050.

Results showed that Landsat images can be confidentially used for GH determination in areas with similar production patterns and climate conditions, together with the RF algorithm, with over 90% accuracy. The most remarkable result was found to be rapid and considerable conversions from open agricultural lands to GH and S areas within the considered period. The serious increases in GH areas, as well as S, are expected to continue in the next decades. In fact, GH areas are predicted to increase by 165% from 2008 to 2050 according to the Markov–FLUS model simulations with acceptable accuracy.

Based on the findings, well-planned and more environmentally friendly strategies are recommended as essential in the area for prevention from adverse effects before irreversible effects come into the frame. For sustainable development, this includes taking precautions against potential environmental consequences that may arise from uncontrolled growth, especially in GH areas. Since GH production interacts with UN SDGs, the contributions of different GH production types to relevant SDGs are recommended to be investigated to avoid undesired results while ensuring positive impacts. The potential of images with higher spatial and temporal resolutions may trigger an increase in the mentioned efforts in the area.

In brief, by being the first simulation attempt in our country, this study is believed to provide a baseline for researchers and decision-makers in the local authorities since the development process is acknowledged to be still ongoing. Our current study is focused on understanding the future effects of the changes on the environment from different point of views within the whole Mediterranean region of Türkiye and investigating how local communities perceive the process and behave against these changing dynamics.

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