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MODELING AND SIMULATING LAND USE/COVER CHANGE USING ARTIFICIAL NEURAL NETWORK FROM REMOTELY SENSING DATA

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HIGHLIGHTS

Applicability of decision support systems in landscape planning.

To reveal the spatio-temporal land use and land cover changes.

Estimation of land use and cover change by human population movements.

Keywords:
Computational intelligence
Human population
Landscape
Forecasting

Historic:
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ABSTRACT

Increasing population, mobility and requirements of human beings have significant effects on the dynamics of land use and land cover. Today, these impacts need to be understood and analyzed for the applicability of decision support systems, which are an important tool in the management of natural resources, urban and rural areas. The aim of this study is to detect the temporal and spatial changes of land cover and human population, in northwest Turkey. For this purpose, using satellite images of 1997-2007 and 2017 years' land cover was estimated for 2027 by ANN (Artificial Neural Network) approach. Kappa values are 93%, 87% and 95% for 1997, 2007 and 2017 respectively. As a result, learning success was 80.6%, and correctness validation value was 90.1% for 2027 simulation. In parallel, the spatial analysis of the population was conducted for 2000-2007-2017. Using the exponential rate of change; the population was predicted to increase by concentrating on the urban area and the rural areas surrounding the urban (with a rate of 2.019%) for 2027. According to the results; rural population, urban population, forest, and built-up areas is estimated to increase by 4.14%, 5.58%, 2.72%, and 0.77% respectively from 2017 to 2027, while the agricultural and water area is estimated to decrease by 3.47% and 0.02% respectively. Consequently, the observation of population movements and the use of the ANN approach in simulations could be suggested for the success of planning in forest and land management.

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INTRODUCTION

The temporal and spatial changes of urban and rural areas and their reasons as regards have been the focus of attention of numerous researchers over the years. Factors that trigger land cover changes can be listed as rapid economic development (Yeh and Li, 2001; Mundia and Aniya, 2005; Pucher et al., 2007), population growth (Mundia and Aniya, 2005; Xiao et al., 2006; Giezen et al., 2018), topographical and geological factors (Lee et al., 2002; Lee, 2005; Metternicht et al., 2005; Lillesand et al., 2014) and climatic factors (Moss et al., 2010). Land use/land cover (LULC) changes in addition to the spatial and temporal change of population in the same area have been examined in this study.

The population growth rate in the world varies regionally, the world population continues to grow and it is foreseen that the world population will reach 8.3 and 8.9 billion people in 2020 and 2030 respectively (United Nations, 2017). Depending on the estimation that the world population will increase; It can be said that the current land use and cover will continue to change with human influence and pressure. Human beings, directly or indirectly, have affected and changed land cover (Entwisle et al., 2005; Harte, 2007; VanWey et al., 2007; Fan et al., 2008; Ningal et al., 2008; Pfeffer et al., 2005; Shi et al., 2010; Zhang et al., 2013; Maimaitijiang et al., 2015). Decision support systems are used/applied in order to analyze LULC changes (Matthews, 1999; De Kok et al., 2001, Fan et al., 2008; West and Turner, 2014; Yu et al., 2018).

Decision support systems, going through a continuous and rapid evolution process, have enabled the use of technology actively in management and planning. Artificial Neural Network (ANN) approach, which is one of the decision support systems, was employed in this study. More stable and successful models compared to traditional approaches can be obtained when the ANN approach (Atkinson and Tatnall, 1997; Hsu et al., 1997) is integrated to GIS (Al-Kodmanyu, 2002; Prasannakumar et al., 2011), which is already capable of producing very powerful solutions (Olden et al., 2004). ANN has a significant structure which mimics the learning architecture of the human brain (Zhang et al., 1998) and transforms it into a very fast process thanks to computer technology (Hopfield, 1988; Yang et al., 2018). ANN is also very frequently used in order to make predictions in numerous different areas just like Remote Sensing (RS) techniques (Benediktsson et al., 1990; Nogueira et al., 2017). RS is complementary to decision support systems of environment-human-related studies in this process (Potapov et al., 2008; Mariano et al., 2018).

The success of planning is directly proportional to the success of estimates realized (Venkatraman and Ramanujam, 1987; Lederer and Sethi, 1996; Jaafari et al., 2015). Therefore, the selection of the criteria used in modeling is very important for the accuracy of modeling. In international literature, in the LULC studies, various criteria used such as distance from roads (Sluiter and De Jong, 2007; Luo and Wei, 2009; Mitsova et al., 2011; Shafizadeh-Moghadam et al., 2017a), distance from streams (He et al., 2005; Chen et al., 2009; Liu et al., 2011; Mouri et al., 2011), distance from buildings (Patarasuk and Binford, 2012), slope (Shafizadeh-Moghadam et al., 2017a), distance to open lands (Shafizadeh-Moghadam et al., 2017b). Besides, the success of the models in these studies is between 70% and 90%.

In this study, LULC changes have been estimated through RS techniques and ANN approach for the year 2027, and temporal and spatial change of the population was analyzed on central district and the villages in close location to the center of Sinop province located in northern Turkey. In the study, LULC change for the year 2027 of the study area was modeled by using satellite images of the past years (1997, 2007, 2017). The urban and rural population data of the region between 2000-2007-2017 were evaluated on a spatial basis and population projection was made so as to reveal the relation between LULC and population movements. Thus, it is planned to contribute to the increase in success rates in revealing the relations between the population and the place.

MATERIAL AND METHODS

Study area

The study area includes the Sinop province central district and its villages (Figure 1). Sinop province is one of the most important provinces in terms of forestry in Turkey and is located in the western Black Sea region between the latitude of 42°01'08'' and 41°57'18'' and longitude of 34°54'39'' and 35°05'17'' and has an area of 42390.16 ha. Images of the study area from 1997-2007 (Landsat 5 TM) and 2017 (Landsat 8 OLI) were obtained from the United States Geological Survey (USGS) web address (USGS 2018). The satellite images used in the study are at L1TP (standard terrain correction) level. This level has downloaded from USGS web site as radiometrically and geometrically corrected. Then, the atmospheric correction was applied.

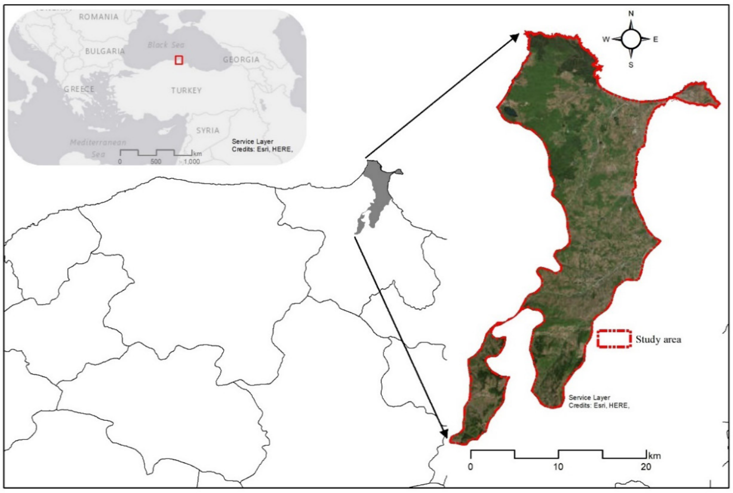

FIGURE 1 Location of the study area in Sinop - Turkey.

Data processing

The provincial border of the study area, highways, village roads, and forest roads and settlements, as well as spatial information data, were received from the database of General Directorate of Forestry and Forestry Regional Directorate of Kastamonu province and reduced to central administrative borders of Sinop province. The central population data of Sinop province were transferred to the created database by taking them from the website of Turkey Statistical Institute (TUIK) (TUİK, 2018). The flowchart of the study is given in Figure 2.

Image analysis and classification

Landsat 5 TM and Landsat 8 OLI 1997, 2007 and 2017 satellite images (Path/Row:176/031) of the study area were used. June and July months were preferred, when the cloud rate was below 10%. Supervised classification was used and image classification was made according to a maximum likelihood algorithm method. The study area was classified into four land cover classes as forest, water, agricultural and built-up areas. Kappa coefficient and overall, producer's and user's accuracy values were calculated to validate the classifications. The classification was performed using 70% the Region of Interest (ROI) and 30% ground true sample.

Detection of Land use/cover change

Modules for Land Use Change Simulations (MOLUSCE) plugin within QGIS software was used in order to determine LULC changes between the years of 1997 and 2007 and between the years of 2007 and 2017. Distance from roads (highways, village roads, and forest roads) and distance from streams were utilized as spatial variables. These variables are widely used for LULC and provide effective information about the effects of people on LULC. Distance from roads divided into seven zones (50, 100, 250, 500, 1000, 2500, 5000 m) and distance from

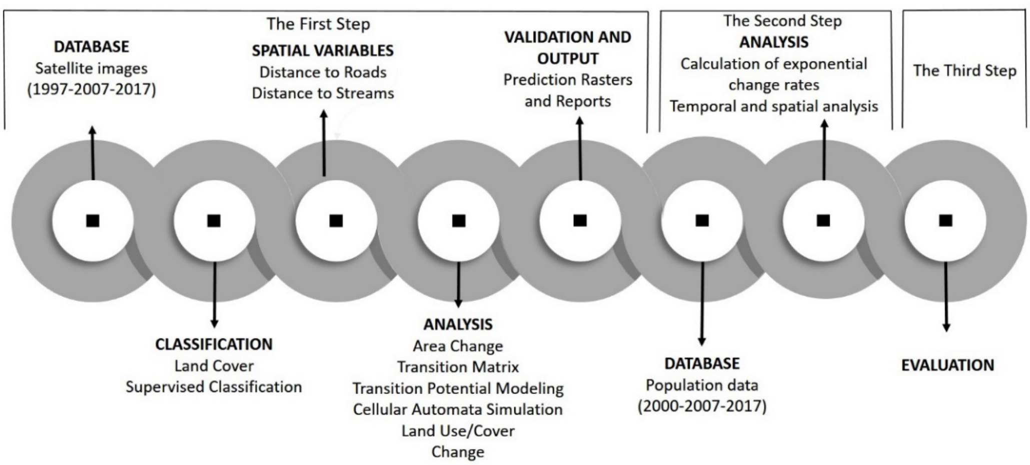

FIGURE 2 The modelling and simulation flowchart of the land cover prediction.

streams divided into six zones (100, 250, 500, 1000, 2500, 5000 m) were recorded by calculating in raster format in order to reveal the land cover changes in this study.

Simulation and validation process

Distance from roads, distance from streams variables and LULC raster (1997-2007-2017) were used as input to the ANN model. Simulation map of 2027 is obtained as output. For the simulation of LULC changes for 2027 year, 100 iterations, neighborhood value 3x3 (9-pixel), learning rate 0.001, 10 hidden layers and 0.050 momentum value were preferred in the ANN learning process. Five iterations were preferred for land cover map validation Cellular Automata (Kerner et al., 2002; Kamusoko et al., 2009). In the calculation of the validation, the change from 1997 to 2017 was determined by comparing the real map obtained from the classification of the current image of 2017 and the simulation map created with by data trained by ANN in the system.

Population data and projection

In this section of the study, the analysis of the spatio-temporal population changes in 1997-2007 and 2017 years was aimed depending on the time interval in LULC. Due to unavailable data for the 1997 population census in Turkey, population data of 2000, which is the most recent available data for the 1997 population census data was used. The data of the urban and rural population of Sinop central district and 42 villages belonging to 2000-2007-2017 were used in the study. The population growth rate between 2000-2007 and 2007-2017 was determined by using exponential rates of change method ($P_n = P_0 \times e^{r.n}$ (P_n: population after n years; P_0: population per period; r: population growth rate; n: the time between two periods) and projection for the year 2027 was made. Spatial analyst tool of ArcGIS 10.3 software was used in the spatial analysis of population data. Pearson Correlation method was applied for LULC change calculation. Because of the distance from roads and distance from streams variables used in this study, it is effective to reveal LULC changes. Markov Chain transition matrices were preferred in the computation of the probability of change from one land to another, and the change maps (1997-2007, 2007-2017) were created.

RESULTS

Image classification

The satellite images were classified into four classes according to the supervised classification method, and land cover overall accuracy and Kappa values of the classified satellite images were calculated (Table 1).

TABLE 1 Land cover overall, producer's, and User's accuracy - Kappa values of the classified satellite images.

Classes	1997		2007		2017	
	producer's accuracy (%)	user's accuracy (%)	producer's accuracy (%)	user's accuracy (%)	producer's accuracy (%)	user's accuracy (%)
Forest areas	99.32	99.72	98.63	91.88	99.8	99.16
Water areas	98.46	100.00	91.85	99.87	96.37	100.00
Agricultural areas	83.4	93.67	82.32	95.64	96.43	97.39
Built-up areas	92.41	82.75	91.61	86.98	96.17	83.53
Overall Accuracy	96.29		90.2		97.02	
Kappa Value	0.93		0.87		0.95	

Forest area, water area, agricultural area, and built-up area classification achievements for the years 1997-2007-2017 have a high acceptance rate, and their Kappa values are 93%, 87%, and 95% respectively.

Land use/cover change and validation

Transitions of four classes in the change map were expressed as the pixel transition of the classes with each other. Each class had different primary colors for easy understanding of the change, and the change to the other classes was shown by lightening these primary colors form dark colors to light colors (Figure 3).

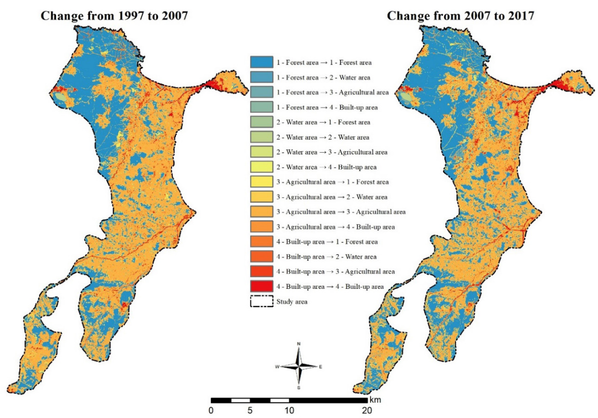

FIGURE 3 LULC change map (1997 to 2007 and 2007 to 2017).

The temporal variation of the distribution of the study area to land cover classes is provided in Table 2. It was determined that the forest and built up areas increased while the agricultural areas decreased between 1997-2007 and 2007-2017 in the study area. The water area has increased by 0.5% between 1997 and 2007, whereas it has decreased by 0.6% between 2007-2017. It is thought that this change in water area may be related to issues such as climate, annual rainfall, and river replications and etc. LULC maps for 1997, 2007 and 2017 are shown in Figure 4.

TABLE 2 Distribution of land cover into classes of 1997-2007 and 2017 years and changing rate of land cover from 1997 to 2017 and 2017-2027.

Classes	1997		1997-2007	2007		2007-2017	2017	
	ha	%	Δ (%)	ha	%	Δ (%)	ha	%
Forest area	15639.98	35.23	5.49	18076.31	40.72	6.17	20816.91	46.90
Water area	160.95	0.36	0.05	185.01	0.42	-0.06	160.11	0.36
Agricultural area	26506.16	59.71	-5.93	23874.52	53.78	-6.21	21116.88	47.57
Built-up area	2083.07	4.69	0.39	2254.32	5.08	0.09	2296.26	5.17
Total area	44390.16	100.00	0.00	44390.16	100.00	0.00	44390.16	100.00

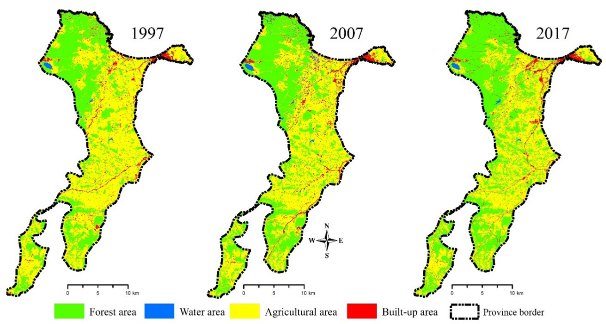

FIGURE 4 LULC maps for the years 1997-2007-2017.

Simulation process

For the estimation success of 2027 LULC with the ANN approach, primarily, the map of 2017 LULC is simulated with classified images from 1997 and 2007 (Figure 5a). The learning process was completed by the ANN approach, to reveal the learning process of LULC for 2017 years and with 100 iterations, 3x3 (9 pixels) neighborhood value, 0.001 learning rate, 10 hidden layers and 0.050 momentum value. In the learning process, the Min Validation Overall Error was 0.09982 and Current Validation Kappa was 84% for 2017 and a simulation map was created. In the validation phase, using Cellular Automata method, Real-LULC map of 2017 satellite image was compared with the LULC simulation map estimated by the ANN approach. At the end of the validation, the ANN approach made estimation with 90.1% success was determined.

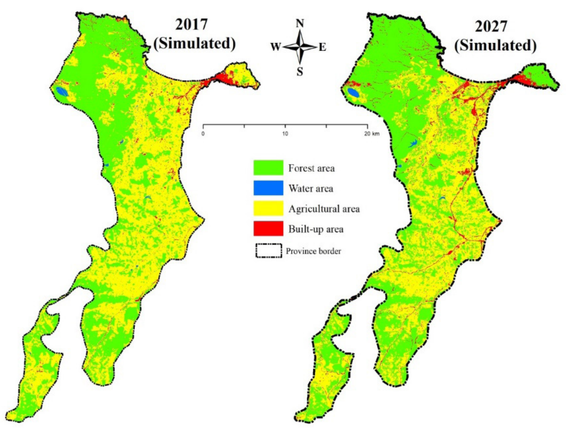

FIGURE 5 a) LULC map of 2017 year simulation (CA); b) Prediction of 2027 LULC map.

The LULC simulation map of 2027 was created after the training with ANN of the data we obtained by RS (Figure 5b). The learning phase was completed by virtue of the ANN approach, to reveal the learning process of LULC map of 2027 year, and with 100 iterations, 3x3 (9 pixels) neighborhood value, 0.001 learning rate, 10 hidden layers, and 0.050 momentum value. Min Validation Overall Error was 0.07136 and Current Validation Kappa was realized as 86.2% for the LULC simulation map of 2027.

Land cover classes in the 2027 LULC simulation map and 2017 classes were compared (Table 3). It is estimated as a result of the comparison that by 2027 forest areas and built-up areas will increase by 2.72% and 0.77% respectively while agricultural areas and water areas will decrease by 3.47% and 0.02%.

TABLE 3 Estimated exchange of LULC from 2017 to 2027 years.

	2017-year (ha)	2027-year (ha)	Change Δ (ha)	2017-year (%)	2027-year (%)	Change Δ (%)
Forest areas	20816.91	22022.45	1205.54	46.9	49.61	2.72
Water areas	160.11	150.66	-9.45	0.36	0.34	-0.02
Agricultural areas	21116.88	19577.52	-1539.36	47.57	44.1	-3.47
Built-up areas	2296.26	2639.53	343.27	5.17	5.95	0.77

Population and projection

Exponential change rates of the population of 42 rural and one urban area in the study area between 2000-2007-2017 were calculated (Figure 6).

90% of the population shown negative change rate in the range of 0.29-13.16% and 10% of the population shown positive change rate in the range of 0.35-4.34% was found, in the rural settlement between 2000 and 2007. Also between 2007 and 2017 years, 76% of the population shown negative change rate in the range of 0.14-6.22% and 24% of the population shown positive change rate in the range of 0.19-9.61% was found.

The population of the year 2027 was predicted by using population change rate of 2007-2017. Temporal and spatial change of the obtained projection results and the population of 2000-2007 and 2017 are given in Figure 7.

According to the results, the population in the southern part of the study area decreases, whereas the population increases towards the north-eastern part where the city center located.

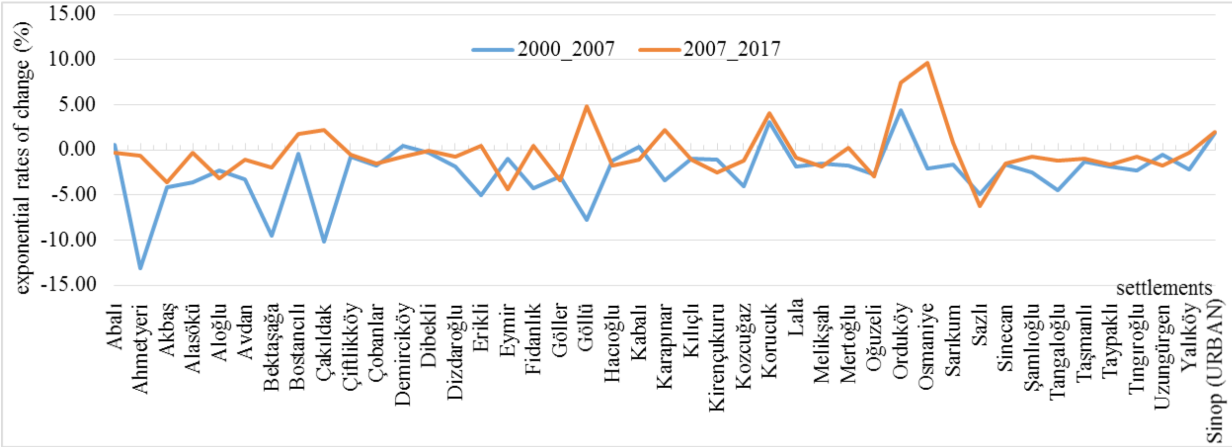

FIGURE 6 Exponential change rates of the population of 42 rural and one urban area in the study area between 2000-2007-2017.

DISCUSSION

In order to reveal the change in LULC in the study area, using Land cover maps obtained from the Landsat satellite images of 1997, 2007 and 2017, land cover maps obtained by supervised classification technique which is an RS technique was created. LULC change of 2027 year was simulated by the Multi-Layer Perceptron-ANN approach. Furthermore, the spatial and temporal changes of the population between the years of 2007-2007-2017 were determined in 43 settlements. As a result of the analysis, between 2000 and 2017, while the population is decreasing in the south of the study area, the population increases in the city center and the rural areas around the city center in the northeast, as in the studies of Verburg et al. (1999), Zhang et al. (2013), and Maimaitijiang et al. (2015). This phenomenon called as "*population shift*" (Zhang et al., 2013) is thought to occur both in the Sinop district center and in the province in this study. Sure enough, in another study (Erkan Buğday and Özden, 2017) conducted in the Kastamonu province which is adjacent to the study area, similar migration movements were observed. Instead of the decrease in the presence of forests in the LULC studies in the literature, the increase of forest land in this study similar to the studies of Pfeffer et al. (2005) has been associated with the decrease of the rural population.

When the LULC change maps obtained as a result of the study were compared with the spatial distribution maps of the population, it is clearly observed that both the built-up areas and the population are increasing in rural settlements surrounding Sinop. Increase even more in built-up areas around the center of the province in LULC map of 2017 year is an expected result in line with the population growth trend in the world (United Nations, 2017). The event observed on the sub-urban around the metropolis has occurred on the rural areas surrounding ordinary district center. At the same time, this event could be described as the causes of LULC change.

Similar to the study of Sinabell and Schmid (2003), the land cover changed from agricultural areas to forest areas was identified. Besides, changing from the agricultural areas near roads to built-up areas was observed. As a result, in the LULC exchange model (1997-2027) for the area of Sinop central districts and villages; forest and built-up areas will increase by 14.8%

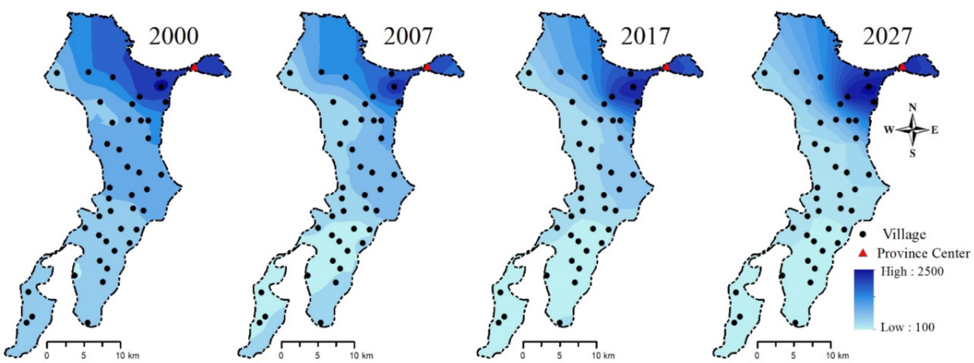

FIGURE 7 Temporal and spatial change of population for 2000-2007-2017 and 2027 projection.

and 1.25% and agricultural and water areas will decrease by 15.61% and 0.02% respectively (86.2% success rate).

The preferred ANN method, Cellular automata simulation technique and use of Markov Chain approach in transition matrices could be affected by the increase in modeling success. In addition, the success of the classification has increased the success of the model (Kassawmar et al., 2018). For this reason, along with main roads, village and forest roads have been added as spatial variables.

CONCLUSIONS

In this study, in order to reveal the change in LULC in the study area, using land cover maps obtained from the Landsat satellite images of 1997, 2007 and 2017, land cover maps obtained by supervised classification technique which is an RS technique was analyzed. And also, using population data of these years, the population changes of 43 settlements in the study area were calculated for 2000-2007-2017. The population has been predicted to increase by concentrating on the urban area and the rural areas surrounding the urban (with a rate of 2.019%) for 2027. Also, rural population, urban population, forest, and built-up areas are estimated to increase by 4.14%, 5.58%, 2.72%, and 0.77% respectively from 2017 to 2027, whereas the agricultural and water area is estimated to decrease by 3.47% and 0.02% respectively. Modeling methods used in this study can be improved by using different criteria and land cover change estimation achievements can be increased. In the subsequent studies, to improve the predictive power of the model, high-resolution and more sensitive satellite images could be used. Consequently, for the planning of management of forest and land can be suggested both evaluating population movements and using the ANN approach for simulations of LULC change.

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