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ORIGINAL PAPER

Predicting climate-based changes of landscape structure for Turkiye via global climate change scenarios: a case study in Bartin river basin with time series analysis for 2050

Merve Kalayci Kadak[1,2] · Sevgi Ozturk[1] · Ahmet Mert[3]

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Abstract
This study was designed to reveal the possible effects of climate change on the landscape structure of the Bartın Stream Basin. Remote sensing (RS) and Geographic Information Systems (GIS) tools and statistical methods were employed throughout the study. Landsat satellite images, which are 30 m × 30 m resolution images produced by Landsat 4–5, Landsat 7, and Landsat 8-Oli satellites, were used. In addition, 42 variables were produced, including 19 bioclimatic variables, plant index data from satellite images, and environmental variables. The effect of the produced variables on land use-land cover (LULC) was investigated. Then, the expected situation in 2050 according to the RCP climate change scenarios was estimated using the R Studio software with time series analysis. The data for 2050 were modeled and mapped using the Maximum Entropy method. As a result, it was revealed that LULC changes within the basin would be in the form of artificialization and increased fragmentation, that bare lands and residential areas would increase, and that agricultural areas and forest areas would decrease by approximately 50%. Planning should be made in order to reduce the breakdown of landscape resistance by predicting the adverse events to be experienced due to climate change in the future. It was concluded that agriculture, which was determined as the development strategy of the region in the current Environmental Plan (EP) of the basin, would not be possible due to the approximately 50% loss in agricultural areas. This study revealed that the effects of climate change, which is the biggest threat of the age, could be revealed with statistical models.

Extended author information available on the last page of the article

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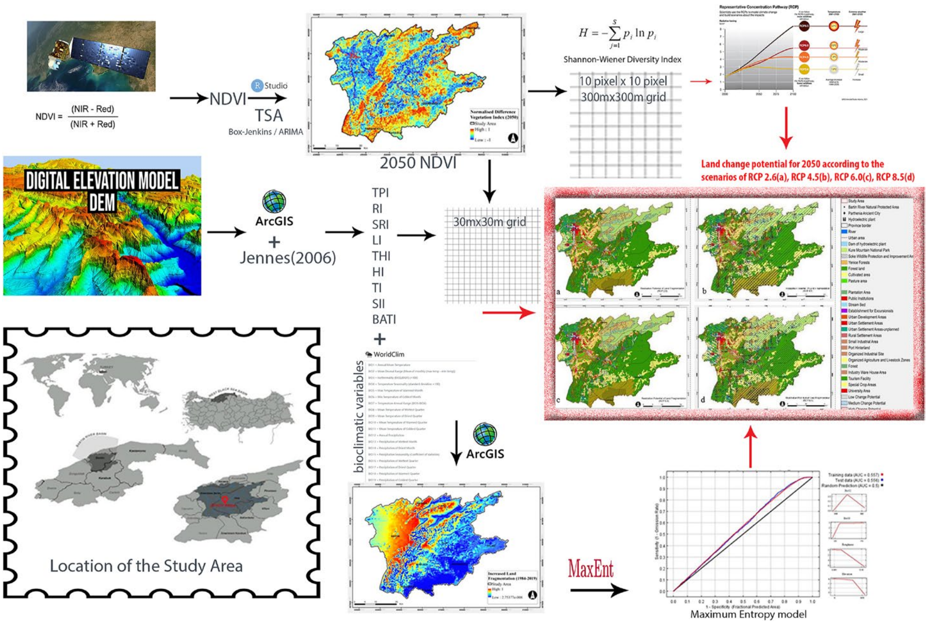
Graphical Abstract



Keywords Climate change mitigation · Adaptation strategies · Climate policy · Geographic information system (GIS) · Land use planning

1 Introduction

The most fundamental factor of climate change, which is one of the biggest threats of the last century, is human (IPCC 2021). Intervention in nature is increasing day by day due to reasons such as energy and food needs, technological developments, employment problems, economic concerns, and increasing intercultural interaction (Tasser et al. 2017). Especially in recent years, there has been an increase in the amount of CO^2 and other greenhouse gases in the atmosphere. Thus, the rays coming from the sun have been kept in the atmosphere more, causing the earth to warm up, and the problem of climate change has consequently become inevitable (Reside et al. 2017). By evaluating the possible consequences of climate change, some climate change scenarios have been created by the Intergovernmental Panel on Climate Change (IPCC) which was established to take measures on a global scale. Based on this approach, in the context of the United Nations Framework Convention on Climate Change (UNFCCC), it is necessary to determine the effects of climate change and take measures at the local level (IPCC 2021; Kirac and Mert 2019; Turkes et al. 2000). Identifying and implementing ways to combat climate change, transferring resource values to future generations, and keeping the world a livable place are among the most important steps to be taken (Aydın 2020). In this context, besides the international conventions to which different countries are a party, there are some measures and plans that they organize within themselves. The common goals of all plans can be listed as reducing or preventing

fragmentation in natural areas; protecting natural areas; preventing environmental factors from having negative effects on the life of all living things, especially human health; and implementing ecologically-based plan decisions as a whole. Considering past and current landscape conditions within the scope of LULC changes makes it possible to make predictions about future landscapes. In this context, LULC changes can be used for forecasting and modeling applications for the European Landscape Convention (ELC)'s objectives of protecting and managing landscapes (Ersoy Mirici 2017). In addition, it has been accepted that land changes caused by human interventions, such as deforestation and conversion of forest into agricultural land, which global climate models deal with, are a factor in climate change on a global scale (Solecki and Oliveri 2004). In addition, Climate change and land cover change have been highly correlated (Hao et al. 2017). Improper land use decisions will lead to land cover fragmentation over time. Therefore, it is necessary to study changes over time (Gulersoy 2013).

In light of this information, the main objective of this study is to predict the LULC situation in 2050 by creating a statistical model as a result of associating potential LULC changes in the Bartın Stream Basin with bioclimatic data and environmental variables. This will, then, help prepare the ground for planning studies by reducing the level of exposure to the negative effects of climate change.

2 Materials and methods

The Bartin Stream Basin covers an area of 211.319 ha and is located between 40° 34' 42"- 41° 27' 52" northern latitudes and 30° 52' 33"- 35° 12' 12" east longitudes (Cengiz 2012; Turoglu 2014) (Fig. 1).

A part of the Küre Mountains National Park (KDMP) and a part of Yenice Forests are located in the study area. These protected areas, which are very important in terms of nature and cultural tourism, are among the 36 hot spots in the world (Habel et al. 2019) and 9 hot spots in Turkey, as determined by the World Wildlife Fund (WWF) (Satar and Gunes 2014). In addition, the fact that Yenice Forests, one of the 122 Important Plant Areas (IPA) in Turkey, are located in the area shows that the study area is also very rich in terms of natural resource values. The work chart of the article method that includes all the steps is as follows (Fig. 2).

The data of a total of 7 stations belonging to 7 districts, which are completely or partially located within the borders of the basin, were obtained from the meteorological bulletins of the General Directorate of State Meteorology Affairs (TSMS 2021). Using these data, vegetation period was determined for each district according to the vegetation period formula of Wiersma (1963). The common vegetation period for the districts in the study area was determined as May-August (Thornthwaite 1948). This is the period in which the amount of reflection from the satellite sensors increases as the amount of chlorophyll in the plants reaches the highest point. The green leaves of healthy plants reflect light well in the near-infrared region of the electromagnetic spectrum (Gungoroglu et al. 2008) because the sunlight reflection and absorption properties of plants result from the plant's activities such as photosynthesis. Due to this feature of plants, their green parts are more easily perceived by satellites, and vegetation data consequently becomes beneficial in terms of creating satellite images (TAGEM 2017). Landsat satellite images were preferred because they had the

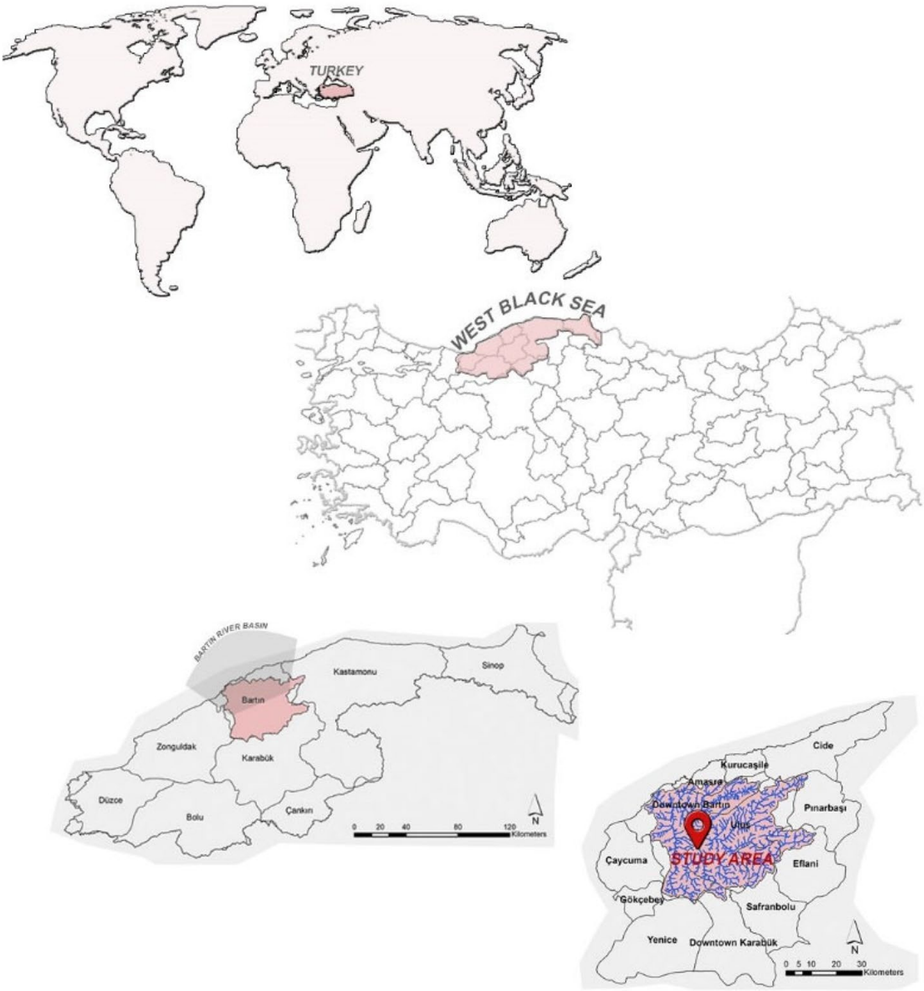


Fig. 1 Location of the study area (Bartin Stream Basin)

necessary resolution and were freely accessible for fragmentation detection. All of the 30 m resolution satellite images produced by Landsat 4–5, Landsat 7, and Landsat 8-Oli satellites (1984–2019) were selected from the vegetation period. There are two factors in determining the year range in which satellite images will be used. These are that the oldest Landsat satellite image of the area reached was in 1984 and that the analysis was started in 2019. The downloaded satellite images were made ready to work in the ArcGIS environment by applying image processing methods. Then, NDVI (Normalized difference vegetation index) was prepared for the determination of species diversity. Like the downloaded satellite images, the digital elevation model (DEM) has a resolution of 30 m. Therefore, the pixel size of the environmental variables created from DEM is 30m × 30m. In this context, a grid size of 30m × 30m was created throughout the study area for a more systematic evaluation.

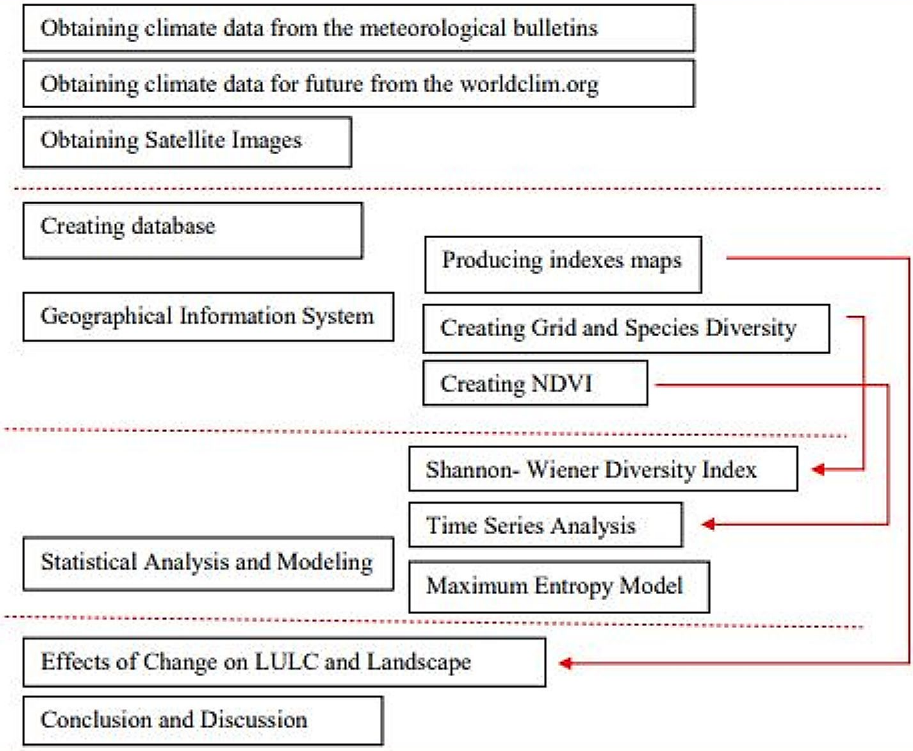


Fig. 2 Work chart of method

As vegetation data, the values of each grid were drawn from the NDVI produced using satellite images from 1984 to 2019, and the NDVI data of 2050 were obtained and mapped with the time series analysis (TSA) method. In addition, bioclimatic data with a resolution of 30 arc seconds was made available in the study area scale (Hijmans et al. 2005).

In order to produce environmental variable maps, first of all, slope, aspect and elevation maps were created by using DEM. Then, by using these maps, topographic position index (TPI), radiation index (RI), solar radiation index (SRI), ruggedness index (RI), roughness index (RI), landform index (LI), topographic humidity index (THI), hillshade index (HI), temperature index (TI), solar illuminance index (SII), Beer's Aspect transformation index (BATI) (Beers et al. 1966) were produced. In this context, the data were spatially created in the ArcGIS software with the add-on prepared by Jenness (2006). In addition to the environmental variables produced, 19 different bioclimate parameters downloaded from online database (Fick and Hijmans 2017) were also included in the study.

Since the effects of climate change can be observed differently depending on the diversity and fragmentation of the landscape structure, the diversity and fragmentation of vegetation in the basin is important. Ecosystems with high structural diversity are more resilient to interventions (Lurette et al. 2020). In this context, plant diversity, which is the biggest indicator of structural diversity, is also an important factor in ensuring the sustainability of ecosystems against adverse effects (Cook-Patton et al. 2021; Ertugrul et al. 2017; Ozdemir et al. 2012; Ozkan 2018; Pittarello et al. 2020; Senturk 2012). In this context, the Shan-

non-Wiener diversity index was calculated to reveal the vegetation diversity of the basin. There is also an ArcGIS software extension for this index. This is one of the reasons why the Shannon-Wiener index is preferred. It is known that as the fragmentation of the land increases, the vegetation and landscape structure in the land become more vulnerable to the interventions of all external factors, especially the effects of climate change (Senturk and Ozkan 2017; Fedor 2018). When the determination of structural diversity is made by field studies, this is quite difficult, long-term and costly. This situation causes the number of researchers, who prefer to use remote sensing methods, to increase (Almeida et al. 2019; Mallinis et al. 2020; Mert 2013; Ozdemir et al. 2012; Tekin et al. 2018). Structural diversity can be examined at different scales with the data obtained by remote sensing methods. In addition, it becomes possible to analyze the changes that occur in the ecosystem over time (Mert 2013). In this context, a grid size of 300 m × 300 m (10 pixels × 10 pixels) was created in the area. By examining the diversity and fragmentation situations in the grid, it was possible to interpret the strength of the landscape structure against pressures.

Then, using the Shannon-Wiener diversity index values between 1984 and 2019, TSA, which can be applied for the data that vary depending on the time dimension, was used to predict the situation in 2050. TSA provides statistical significance of data by designing models. It also creates the possibility of obtaining a model for predicting the future by modeling data in the form of time series. The fact that predictions for the future are statistically based is a great advantage of the TSA method (Brockwell 2010; Cevik and Yurekli 2003; Durbin and Koopman 2013; Goztepe 2018). In this study, the method called Box-Jenkins or ARIMA model, which is frequently used for the analysis of time series, was preferred (Duru 2007; Kara and Cemek 2019; Kaynar and Tastan 2010). The pixels of the study area constitute the area where this estimation was made. The probability distribution in this area is defined based on pixels with known species formation, environmental variables called "characteristics" and their functions (Phillips 2010; Phillips et al. 2006). By using the NDVI values of the previously determined pixels, the pixel values of 2050 were estimated with the R Studio software.

The possibility of high correlation between the variables to be used in the modeling was taken into account. At this point, Pearson correlation analysis ($r > 0.80$) was applied to all variables, and it was determined that there was a high correlation between the variables (Kirac and Mert 2019; Suel 2014). Factor analysis was applied to determine the representative variables to be included in the modeling. In this context, the Maximum Entropy (MaxEnt) method, which was developed for models focusing on correlation, was used in the study (Phillips et al. 2006). Maxent is based on a machine learning response designed to make predictions from missing data (Baldwin 2009; Ertugrul et al. 2017; Mert and Kirac 2017; Tekin et al. 2018). The closer the AUC value, which is taken into account in order to evaluate the model performance, to 1, the more descriptive the model is. A value of 0.7 is an acceptable model, while a value of 0.5 means a non-informative model (Mert and Kirac 2017; Phillips et al. 2006).

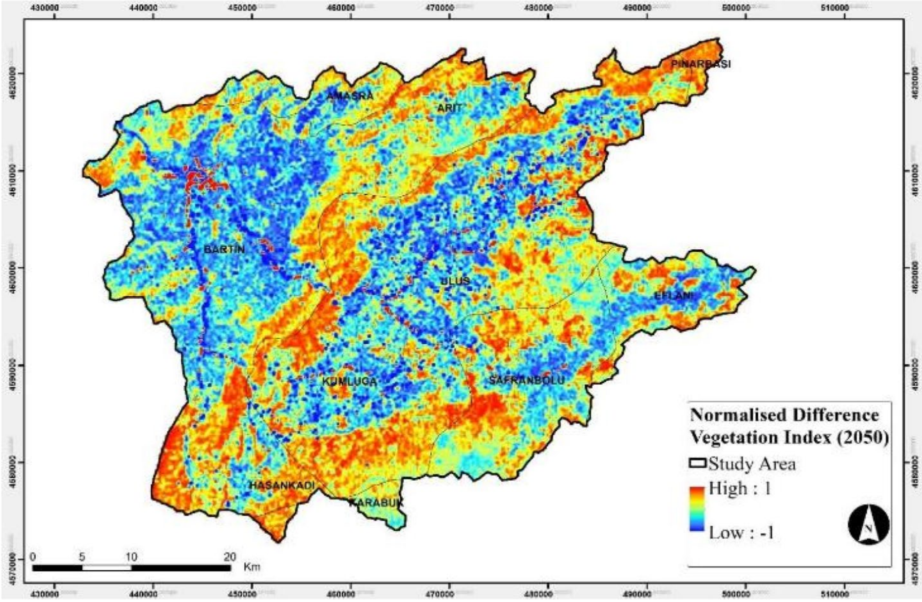


Fig. 3 Year 2050 on the NDVI map

3 Findings

By calculating the NDVI data for the years 1984–2019 in the R Studio program with time series analysis, the NDVI map of 2050 was created in the ArcGIS program (Fig. 3). The NDVI values range from – 1 to 1. These values are shown on the map with a color scale from blue to red. Where vegetation is damaged or fragmentation increases, the value approaches – 1 and is shown in blue on the map. The areas with dense vegetation approach the value of 1 and are shown in red on the map.

It is seen that dense residential areas and agricultural lands in the immediate vicinity of these areas would be lost over time, that the fragmentation in the area would increase, and that the use of land would change. This map is a guide for the vegetation-based measures to be taken regarding the land use-land cover in 2050. Environmental variables, which are likely to affect the landscape structure, were made available for use in the modeling study in the ArcGIS program.

As the fragmentation in the vegetation and landscape structure in the land increases, it will become more difficult to withstand the pressures of all external factors, especially the effects of climate change. In this context, the importance of vegetation diversity and its integrity in landscape structure emerges in terms of the effects of climate change and human intervention. The increase in the Shannon-Wiener Diversity Index value of each of the 300 m × 300 m grids created to determine the determination of this situation in a systematic way means an increase in the fragmentation in the land. The index values changing between 0 and 2.3198 in 2019 and between 0 and 2.61689 in 2050 reveal that fragmentation would increase in 2050 and that naturalness would be damaged.

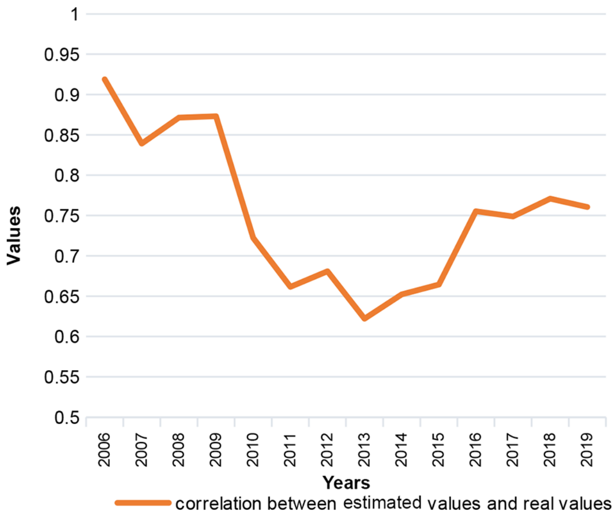


Fig. 4 Correlation coefficients between actual NDVI data and predicted values

For the preliminary determination of the success of the model, 10% of the total dataset was selected with the Arc View Random Point Generator tool and a trial dataset was created. Using the data between 1984 and 2005 from this dataset, estimations were made about the years between 2006 and 2019. Thus, Pearson correlation analysis was performed between the data for the years 2006–2019 and the data obtained as a result of the estimation, and the correlation coefficients were determined (Fig. 4).

The correlation coefficient value ranges from −1 to +1. Regardless of the sign, values less than 0.30 can be interpreted as low correlation, values between 0.30 and 0.69 as medium correlation, and values above 0.70 as high correlation (Cokluk et al. 2014). In this context, the correlation coefficients in Fig. 4 were examined, and it was determined that there was a medium-level correlation between 2011 and 2015 and a high-level correlation in other years. The fact that the relationship between the estimated values found using the model and the actual values was at an acceptable level led to the conclusion that the model was usable in the first place.

Then, 15 representative variables were determined by factor analysis among 42 variables that were found to have multicollinearity problems. The multicollinearity problem arises from the strong relationships between the independent variables ($r>0.8$). In this case, the method of elimination should be used among the variables that are the source of the problem (Cokluk et al. 2014). The representative variables to be used for modeling include slope, aspect and elevation variables obtained from DEM; 8:00 solar illuminance (SI); 12:00 SI; total SI; landform index (LI); roughness index (RI); Bio18 (precipitation of the warmest three months); Bio12 (annual precipitation); Bio9 (Average temperature of the driest three months); temperature index (TI); topographic humidity index (THI); topographic position index (TPI); and hillshade index (HI).

In order to create the model to be used for the prediction of 2050, the changes between 1984 and 2019 were determined by Maxent. These are the changes that increase fragmentation in the study area and can be described as negative according to the protection-utilization balance approach. The increase in fragmentation and artificiality in the area means that natural areas are damaged (Fig. 5).

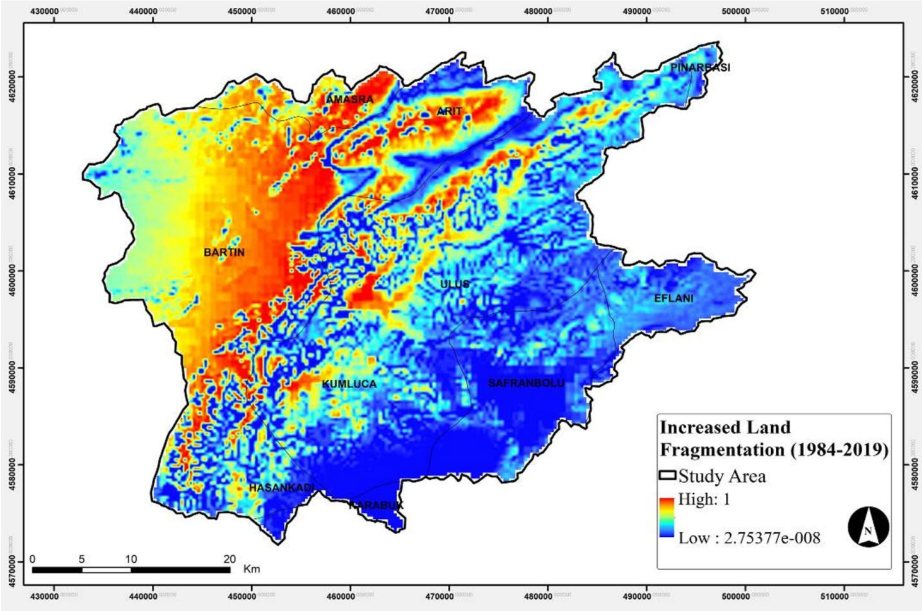


Fig. 5 Fragmentation between 1984–2019

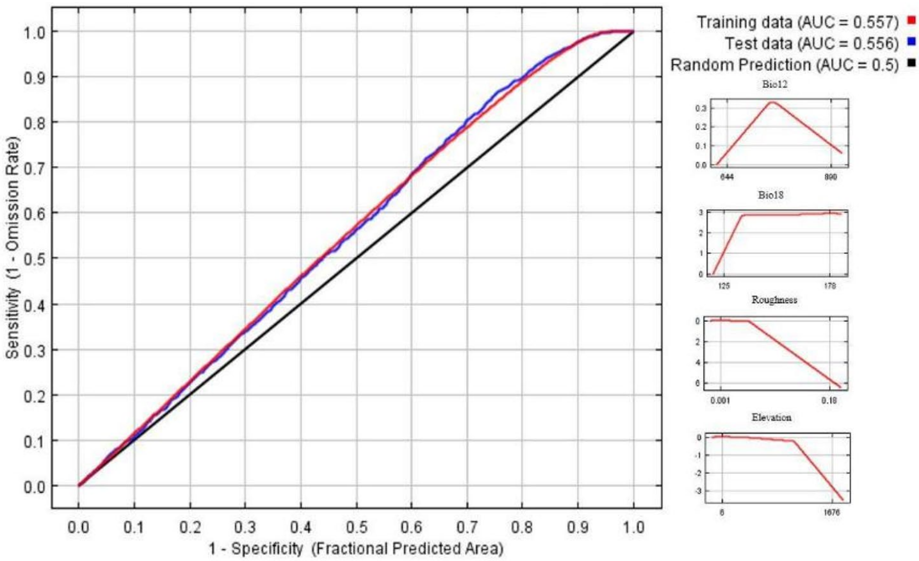


Fig. 6 Fragmentation and effective variables between 1984–2019

Table 1 Contribution rates of variables to the model

Variable	Percent contribution	Permutation importance
Roughness	55.7	57.7
Elevation	28.3	30.7
Bio18	14.1	6.6
Bio12	1.9	4.9

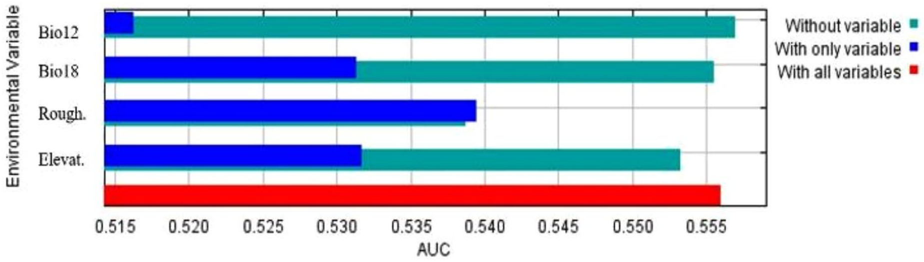


Fig. 7 Jackknife statistical findings on fragmentation (1984–2019)

According to the Maxent model, fragmentation is high in the northwest of the area. In the modeling study, which was conducted with 10 repetitions, it was only possible to reach the model, which was formed by the most effective variables and gave the highest explanatory value, in the second repetition of the third model. The ROC (Receiver Operating Characteristic) curve of the model and the effect of the representative variables, which are the inputs for the model, on the model are given in Fig. 6. The part under this curve gives the AUC (Area Under Curve) value.

It is seen that fragmentation increases where the roughness is less than 5%, the elevation is less than 1500 m, the Bio18 is between 0 and 130 mm, and the Bio12 is in the range of 0 to 700 mm. In the light of this information, the contribution rates of each effective variable to the model are given in Table 1.

The variable that contributes the most to the model is RI, and the variable that contributes the least is Bio12. Figure 7 shows the results of the jackknife test.

The model obtained by using the bioclimatic data of the HadGEM2-ES RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 scenarios for the year 2050, instead of the bioclimatic variables affecting the model, is shown in Fig. 8.

In Fig. 7, as we move from the RCP 2.6 scenario to the RCP 8.5 scenario, it is seen that the fragmentation in the northwest of the study area increases due to the change in the bioclimatic data. In the light of this information, the percentage ratios of the fragmentation level in the model according to the RCP scenarios are given in Table 2. The level classification according to change potentials was arranged according to model performance evaluation intervals and expert opinions.

It is thought that the estimated changes in the areas with low change potential in Table 2 would be realized at a rate of 50%, that the estimated changes in the areas where the change potential is at a medium level would be realized at the rate of 70%, and that the predicted changes would take place almost 100% in the areas with high change potential. Also, the size of the change area in hectares according to fragmentation level is given in Table 3.

RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 maps, in which the fragmentation potential is classified, are given below, respectively (Fig. 9, Appendix A, B, C, D).

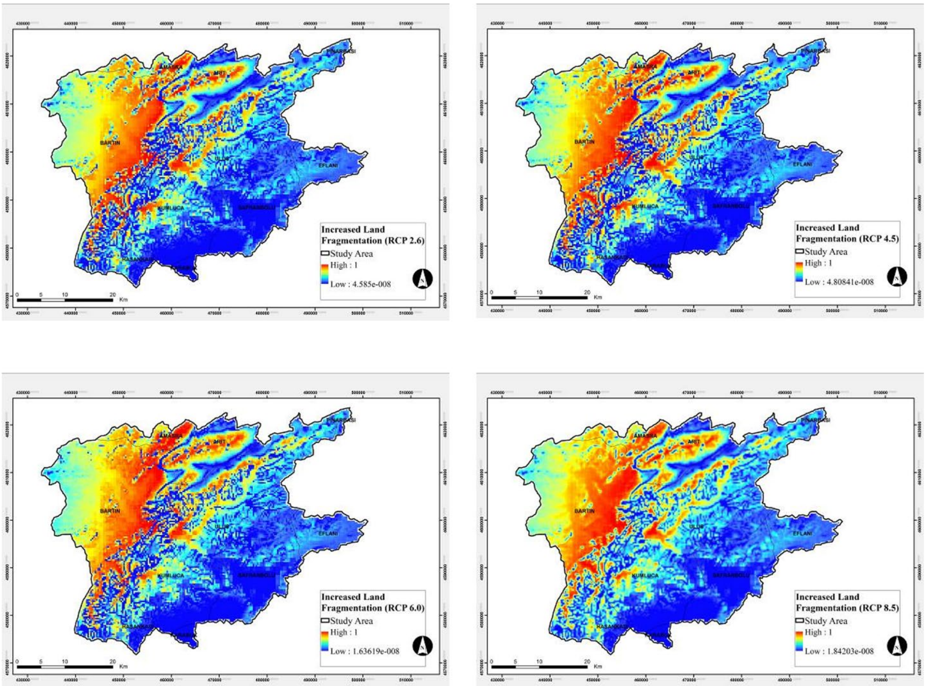


Fig. 8 Increasing fragmentation/artificialization for 2050 according to RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5 scenarios

Table 2 Percentages of land change (%)

Level	1984–2019	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Low change potential	61.9	61.8	61.6	61.2	60.4
Medium change potential	15.0	15.2	15.3	15.5	15.8
High change potential	23.1	23.0	23.1	23.3	23.8

Table 3 Sizes of the change area (ha)

Level	1984–2019	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Low change potential	130.806	130.595	130.172	129.323	127.647
Medium change potential	31.698	32.120	32.332	32.757	33.378
High change potential	48.815	48.604	48.815	49.239	50.294

In the maps above, the classification of the fragmentation potentials over the existing land use-land cover is shown in red, blue, and black. It is seen that the changes expected to be experienced with high potential increase as one moves from the most optimistic RCP 2.6 (a) scenario to the most pessimistic RCP 8.5 (d) scenario. In case of the realization of the RCP 8.5 scenario, the possibility of changes, in which the agricultural lands near the

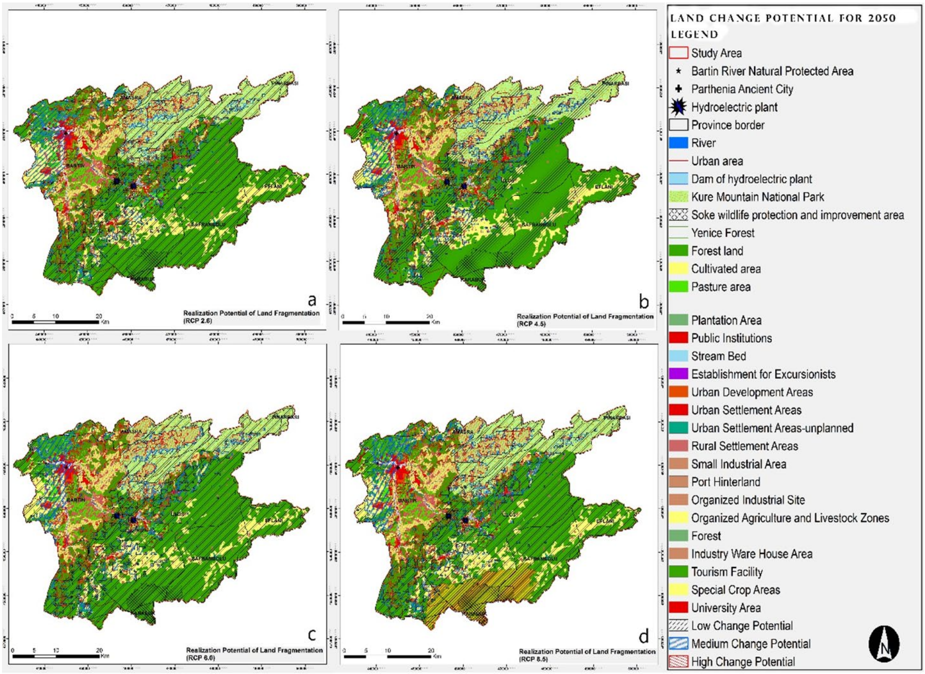


Fig. 9 Land change potential for 2050 according to the scenarios of RCP 2.6 (**a**), RCP 4.5 (**b**), RCP 6.0 (**c**), RCP 8.5 (**d**)

residential areas and the agricultural lands close to the forest border become fragmented and turn into bare land, increases. The RCP 8.5 (d) scenario shows that land fragmentation is likely to occur at a higher rate even in the buffer zone of the protected area, the Küre Mountains National Park. In addition, it is estimated that the possible adverse changes in the hydroelectric power plants in the basin and their immediate surroundings would increase as they approach the RCP 8.5 (d) scenario. In the context of these maps, the realization rate of possible fragmentation in the area towards the pessimistic scenario would also increase. The fragmentation, which is predicted to occur mainly in agricultural areas and forests, would cause the resistance of the landscape structure to be broken.

4 Results and discussion

This study was planned in order to model potential LULC changes, which could occur due to climate change in the Bartin Stream Basin, with the maximum entropy method and to determine the possible state of the landscape structure in the Bartin Stream Basin in 2050. Some researchers stated that modeling studies at the regional scale would be more guiding in terms of determining the local effects of climate change on LULC (Kirac and Mert 2019; Mert 2013; Pitman et al. 2012). They mentioned that it would be more possible to protect ecological values by using the basin scale, not administrative borders, in the planning studies to be carried out, and that the steps to be taken in terms of adaptation would be more realistic (Pitman et al. 2012). In this context, the study was carried out on a sub-basin scale

in Turkey (IPCC 2021; Kirac and Mert 2019; Sert et al. 2021), which is expected to be heavily affected by global climate change due to its location in the Mediterranean Basin. In addition, with the development of technology, it has become more possible to perform models by using predictions and simulations for the future (Ersoy Mirici 2017). In this study, a model was created with the maximum entropy method in order to make LULC estimation using bioclimatic factors and future climate change projections. Besides, time was used more efficiently with remote sensing and Geographical Information Systems (Heymann et al. 1994; Mert 2013; Ozdemir et al. 2012) tools which are important application tools in studies on climate change projections. In this context, the study revealed that the effects of climate change on land use-land cover were predictable with statistical-based models. It was proven by the model that the river, forest and protected areas in the study area would deteriorate due to climate change and that the resources would be damaged (Zhan et al. 2014). When the environmental variables were examined, it was determined that the temperature index value was high in the residential areas concentrated in the northwest of the area. It is thought that the main reason for this situation is the formation of urban heat islands due to the reduction of green areas and evaporation surfaces in areas where urban settlements are dense (Adiguzel et al. 2020; Shashua-Bar et al. 2011). It was observed that the roughness increased linearly with dry and wet streams where the altitude was low compared to the residential areas. This means that the susceptibility to natural events, such as landslides, increases. In the areas with increased altitude, solar illuminance appears to be higher. However, it was determined that the areas covered with forest would receive less light because it is known that the density of tree cover increases hillshading and that it is therefore difficult for the sun to enter the parts of the forest (Turk and Ozen 2014, 2016).

In addition, the Shannon-Wiener diversity index values, which were calculated based on the knowledge that there is a close relationship between biodiversity and landscape structure (Cook-Patton et al. 2021; Ozkan 2018; Senturk 2012), were used to determine the landscape structure diversity and fragmentation in the area. According to these calculations, the fragmentation, which increased from 1984 to 2019, was mostly concentrated in the settlements, whereas according to the land use-land cover prediction for 2050, it was observed that the fragmentation increased not only in the settlements, but also in the agricultural areas, forest areas and natural areas.

When the LULC changes related to climate change were modeled, it was revealed that bare lands and residential areas would increase and that agricultural areas and forest areas would decrease by approximately 50% in 2050. Due to the increase in construction and fragmentation, the natural structure would be damaged (Akten et al. 2009; Balcik et al. 2011; Doygun 2017; Doygun and Erdem 2012), thus reducing the resistance of the landscape structure to the effects of climate change. Considering all these LULC changes, it is considered that it is not possible for the development strategy specified in the environmental plan for this region to be agriculture-oriented. If the development strategy is not revised in the environmental plan created for the study area, it is thought that the food safety problem, which is one of the biggest problems in the world, would be the inevitable end for this region as well. In addition, according to the IPCC (2014) food safety report, factors such as decreased accessibility of fresh water, loss of soil fertility, and changes in the rates of greenhouse gases in the atmosphere threaten food safety. In order to prevent this, it is necessary to protect the agricultural areas which are revealed to be potentially reduced by almost half in 2050 within the scope of the study. With the development of agroforestry systems,

food insecurity and equal access to food should be optimized in order to provide superior land use at global, regional and watershed scales (Izac and Sanchez 2001). Thus, the necessity of taking measures to ensure equal access to food and food safety is emphasized once again with the results of this study. However, the predictions show that forest areas would decrease very seriously as well as agricultural areas. This does not change the fact that more than 20% of the world's population directly needs agroforestry products and services in their rural and urban areas (Leakey and Sanchez 1997).

As a result, it is thought that the resistance to the effects of climate change would decrease due to the fragmentation that would occur in the Bartin Stream Basin. It would consequently be difficult to realize sustainable resource management of natural resources. In this context, the complexity in the landscape structure would increase and it would not be possible to transfer resources to future generations (Festus et al. 2020; Huang et al. 2020).

The highest contribution to the model, which was created by the maximum entropy method in order to estimate all the LULC changes, is roughness with 55.7%. It is thought that the main reason for this situation is that settlements are not preferred by people in areas where there are many hills and high slopes (Doygun and Erdem 2012). Thus, these areas are not directly exposed to human intervention.

According to the RCP scenarios, the LULC change status of the Bartın Stream Basin was classified as low, medium and high in terms of change potential. As we go from the RCP 2.6 scenario to the RCP 8.5 scenario, it is possible to say that the artificialization potential increases, especially in the northwest of the area, and that the landscapes have potential to become vulnerable to the effects of climate change with the increase of fragmentation. The part of the Yenice Forests located in the south of the Bartın Stream Basin, which falls within the study area, and the Bartin Ulus Söke Wildlife Development Area within it are estimated to have low potential for change, even according to the RCP 8.5 scenario, which is the most pessimistic scenario. This means that even the expected low-intensity fragmentation would occur with a 50% probability. It is also thought that the positive relationship between the protection of landscapes and the high biodiversity contributes to the protection of the Yenice Forests and the natural areas in the buffer zone of the Küre Mountains National Park, another protected area. This is an indication that the effects of climate change would have much less impact on protected areas. In this context, it is thought that the planning of protected areas should be conducted very sensitively and that more areas with resources should be given the status of protected area.

According to the most pessimistic scenario, which is the RCP 8.5 scenario, about 30% of the existing agricultural areas would definitely be lost (high change potential) and that about 40% would be lost with a probability of over 70% (medium change potential). It is also predicted that the forest areas would decrease by about half and that approximately 40% of these areas would be lost definitively (high change potential). Thus, a sustainable life in the Bartın Stream Basin would become impossible.

It is thought that the main reasons why the margin explanation of the model used is not high is that the study area is too large, that there is too much field diversity, and that too many external factors consequently come into play (Rittenhouse et al. 2007; Suel 2014). In addition, despite the cloudiness and scan line error in the satellite images of some years, it is not possible to reach the original satellite image accuracy, although corrections have been made. In addition, due to the changing satellite technology since 2013 (transition from Landsat 7 to Landsat 8-Oli), it is thought that the increase in resolution from 8 bits to 16

bits has also reduced the margin explanation. Despite the conversion of 16-bit images to 8-bit (Value Range: 0-255) within the scope of the study, it was not possible to capture the sensitivity of the original satellite image produced by the satellite itself. It is known that the accuracy values will increase as the spatial resolution increases and that the cloudiness/scan line error problems are, then, eliminated (Kaya and Kaplan 2021). In this context, it should not be forgotten that the size of the area and the diversity of the structure of the area are very important in the modeling studies to be created for the purpose of LULC change detection. In addition, it was determined that the satellite images to be used should be error-free and of the same technology, which is actually a very important selection criterion.

5 Conclusion

In this article, the effects of climate change on the existing landscape structure and its expected effects in the future were revealed via LULC changes. For this purpose, the statistical relationships between climate change and environmental variables were focused, and the expected changes in 2050 were examined in the context of global climate change scenarios. It was determined that there would be a large loss of forest assets and agricultural areas in the natural structure of the landscape structure of the Bartin Stream Basin. These results show that the Bartin Stream Basin would experience a loss of almost 50% in just 30 years and would be damaged so much that it would not combat climate change. It is of great importance that decision-makers and authorized institutions make decisions based on the results of this study, which could help ensure the protection-utilization balance. Research results emphasize the important of relationships between resilience and adaptation for the sustainability of the landscape. In addition, it is thought that all of the methods used in the study contribute to the literature since they differ from those used in similar studies. Modeling climate change is a significant study area for all ecologic-based researchers. Because climate parameters are essential input data for ecological planning. It will also guide other studies planned later, especially at the basin scale, by providing a different method proposal.

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Declarations

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Authors and Affiliations

Merve Kalayci Kadak[1,2] · **Sevgi Ozturk**[1] · **Ahmet Mert**[3]

Merve Kalayci Kadak
mkalayci@kastamonu.edu.tr; merve.kalayci_kadak@uconn.edu

Sevgi Ozturk
sozturk@kastamonu.edu.tr

Ahmet Mert
ahmetmert@isparta.edu.tr

1 Department of Landscape Architecture, Faculty of Engineering and Architecture, Kastamonu University, Kastamonu 37150, Turkey

2 Department of Plant Science and Landscape Architecture, College of Agriculture, Health and Natural Resources, University of Connecticut, Storrs, CT 06269-4067, USA

3 Department of Wildlife and Ecology Management, Faculty of Forestry, Isparta University of Applied Sciences, Isparta 32260, Turkey