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MARKOV CHAINS BASED LAND COVER ESTIMATION MODEL DEVELOPMENT: THE CASE OF ANKARA PROVINCE

Markov Zincirleri Temelli Arazi Örtüsü Tahmin Modeli Geliştirilmesi: Ankara İli Örneği

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Öz

Arazi örtüsü, başta nüfusun sayısal büyüklüğü ve yoğunluğu olmak üzere, sahip olduğu sosyo-ekonomik özelliklerden teknolojiye, uygulanan arazi politikalarından doğal faktörlere kadar pek çok nedene bağlı olarak değişmektedir. Arazi örtüsü değişiminin büyük bölümü insan kaynaklıdır ve bünyesinde ekonomik, ekolojik pek çok problemi barındırır. Arazinin korunarak kullanılması, bu problemlerin büyümeden çözülmesi ve tedbir alınması açısından büyük önem taşımaktadır. Arazi örtüsü değişimlerinin zamansal izlenmesi ve gelişen Coğrafi Bilgi Sistemleri ile Uzaktan Algılama teknolojileri, bu değişimin geleceği yönünde karar vericilere pek çok imkânlar sunmaktadır. Geliştirilen tahmin modelleri ile arazi örtüsü değişiminin hızı, yönü ve türü ortaya konmakta böylece sürdürülebilir arazi kullanımı için planlamaya altlık oluşturulmaktadır. Arazi örtüsü tahminlerinin yapılmasında pek çok olasılık yöntemi kullanılmakla birlikte yaygın olan uygulamalardan biri de Markov Zincirleridir. Rassal süreçlerin özel bir sınıfı olan Markov Zincirlerinde, tekrarlanan gözlem dizisine bağlı olarak ortaya çıkan iki veya daha fazla sonuç, olasılık kanunları aracılığıyla belirlenebilmektedir. Bu çalışmanın ana hedefi Ankara ili 2018 yılı arazi örtüsünü Markov Zincirleri tekniği ile tahmin etmektir. Bu kapsamda CORINE 1990, 2000, 2006 ve 2012 veri setleri birinci düzey arazi örtüsü sınıflarına göre değerlendirilmiştir. 2012 yılı arazi örtüsü tahmini için modelde, ilk üç veri setine bağlı olarak %92 doğruluk sağlanmıştır. 2012 yılı CORINE verilerinin de modele eklenmesiyle 2018 değerlendirmesi yapılmış, eklenen veri setine bağlı olarak model doğruluğu 2018 yılı için %90 olarak bulunmuştur. Bu son tahmin verilerine göre ildeki arazi örtüsü değişimi yapay alanların lehine, tarımsal alanların aleyhine gelişmeye devam edecektir.

Anahtar Kelimeler: Arazi Örtüsü Tahmin Modeli, Markov Zincirleri, CBS, Ankara İli, Türkiye

Abstract

Land cover changes due to many factors ranging initially from the numerical size and density of the population to socio-economic characteristics and technology, from land policies to natural factors. Most of the land cover change is human-induced and involves many economic and ecological problems. Using the land by protecting it is of great importance to solve these problems before they worsen and to take precautions. Temporal monitoring of land cover changes and improving Geographical Information Systems and Remote Sensing technologies provide decision makers with many opportunities for the future of this change. The speed, direction and type of land cover change are identified with the developed forecast models, thus forming a basis for planning for sustainable land use. Although many probability methods are used to make land cover estimations, one common practice is Markov chain model. In Markov chains, a special class of random processes, two or more results that emerge based on repeated observations can be determined by means of probability laws. The main objective of this study is to estimate the 2018 land cover of Ankara province with Markov chains technique. In this context, CORINE 1990, 2000, 2006 and 2012 data sets were evaluated according to first level land cover classes. In the model for 2012 land cover estimation, 92% accuracy was achieved based on the first three data sets. With the addition of 2012 CORINE data to the model, evaluation for 2018 was made and the accuracy of the model was found to be 90% for 2018 based on the added data set. According to these latest estimation data, the change of land cover in the province will continue to develop in favor of artificial areas and against agricultural areas.

Keywords: Land Cover Prediction Model, Markov Chains, GIS, Ankara Province, Turkey

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INTRODUCTION

Increasing human pressure on land cover has led to a rapid change in this cover and emergence of many economic and ecological problems. For this reason, identifying land cover changes and making estimates for the future is of great importance in terms of sustainable land use. In other words, land cover change occurs as a result of different economic activities and interaction processes of actors at different scales. Today, this process is generally concentrated on the periphery of urban areas and changes the land cover rapidly in these areas. This situation often works against fertile agricultural areas and natural environment in areas where urbanization is rapid and leads to widespread misuse of land. Thus, the identification and modeling of this rapid change is of great importance in terms of the rational use of resources given that natural and cultural resources in these areas are limited (Cengiz and Yılmaz, 2016).

Depending on the improvement in geographical information systems and remote sensing technologies, land cover can be monitored and evaluated in a timely manner, making it possible to estimate and model land cover for the future. Modeling is one of the powerful tools that can be used to analyze the conditions of land cover change and evaluate land use policy (Geist, 2002), and it also constitutes an important basis for planning studies.

The simulation of spatial models based on model analysis and land use can reveal the driving factors of change on one hand and the land use rates on the other, putting forward future demand for use in multiple scenarios (Han, Yang and Song, 2015).

Operational research techniques, which are developed for the decision-makers so that they can make healthy and consistent decisions, use the deterministic model if the model parameters are known in advance and the stochastic (random) model if the parameters are determined according to probability laws. The main objective of this study is to estimate the future land cover of Ankara based on CORINE (Coordination of Information on the Environment data) and using the Markov chains model, which is a special class of stochastic processes. The stochastic process is a repeatable series of observations and two or more results that are obtained are determined with probability laws in this process (Halaç, 2001). The Markov chains model is also an effective and practical estimation technique that enables decision makers to determine the behavioral changes that may occur in the present characteristics of a system drawing on technical matrix algebra and probability laws (Soykan, 2010). With this method, the amount of change in land cover and land use and continuity in cover types can be estimated, and using cross-tabulation, crossover tables and crossover probability matrix can be calculated between land cover categories according to land cover data in different time periods of the same area. Thus, the change or stagnation of each land cover category in the next period is identified.

The Markov matrix can be used alone or by integrating it into various land use models in land cover estimation studies. For example, Iacona et al. (2012) made estimates for the year 2029 for the cities of Minneapolis and St. Paul using the Markov chains method and discussed the strengths and weaknesses of the Markov method. Han et al. (2015) made predictions for 2020 for Beijing using the CLUE-S and Markov model. The fact that the cellular automation method can take into account the reasons for land cover changes has expanded its integrated use with Markov chains, and many researchers have used these two methods together and made future land cover estimates (Mondala, Sharmaa, Kappasb and Gargc, 2013; Halmy, Gessler, Hicke and Salem, 2015; Cengiz and Yilmaz, 2016; Karip Bozkaya and Göksel, 2017; Hamad, Balzter and Kolo, 2018).

The basic principle of the Markov chains model, which is used to estimate future land cover, is that, depending on the degree of model, a value at any given time depends on the values in the same time period before it, and consistent estimates require making some assumptions about variables and behaviors (Kurtuluş, 1989). In brief, with this modeling, estimates are made thinking that past behaviors continue in the future.

In order to establish the Markov chain model, it is necessary to know the different situations in which the system under investigation can be found and the possibility of transition from each of these situations to the other (Levin, Kirkpatrick and Rubin, 1982). In a system with Markov feature, transition from one state to another state is expressed only with conditional probabilities that depend on the previous state (Çetin and Alp, 2016).

The applicability of the Markov model, which is also widely used in ecological modeling (Muller and Middleton, 1994; Brown, Pijanowski and Duh, 2000), in the land cover change model is important because it can determine not only the transformation between land use types but also the rate of transformation. In this study, the Markov chains method was used because it can list all possible situations and can give the transformation between land cover types and rates (Ching, Fung and Ng, 2002; Sang, Zhang, Yang, Zhu and Yun, 2011).

Location of the Study Area, Boundaries and General Land Cover Change

The most important reason for the selection of the province of Ankara, which has a surface area of 25653 km², is that it has the potential for rapid land cover change. The presence of important road routes and intersections connecting the north, south, east and west of Anatolia and the improved socio-economic activity areas due to being the administrative center of the country have made Ankara province an important attraction in every period and led to a rapid increase in population. This increases the human impact on land cover and accelerates change.

Most of the surface area of Ankara, located between the 32-53 east meridians and 39-57 north parallels, is in the Central Anatolia Region, Upper Sakarya section (Figure 1). The land cover which developed depending on the physical geography features of the area has been shaped by the increase in human impact and therefore a large part of the land cover has consisted of agricultural areas and semi-natural areas. Elevation and consequently the increase in precipitation played an important role in the development of forest areas in the north of the province. Ankara has an average altitude of 890 meters above sea level, and its neighboring cities are Kırşehir and Kırıkkale in the east, Eskişehir in the west, Çankırı in the north, Bolu in the northwest and Konya and Aksaray in the south.

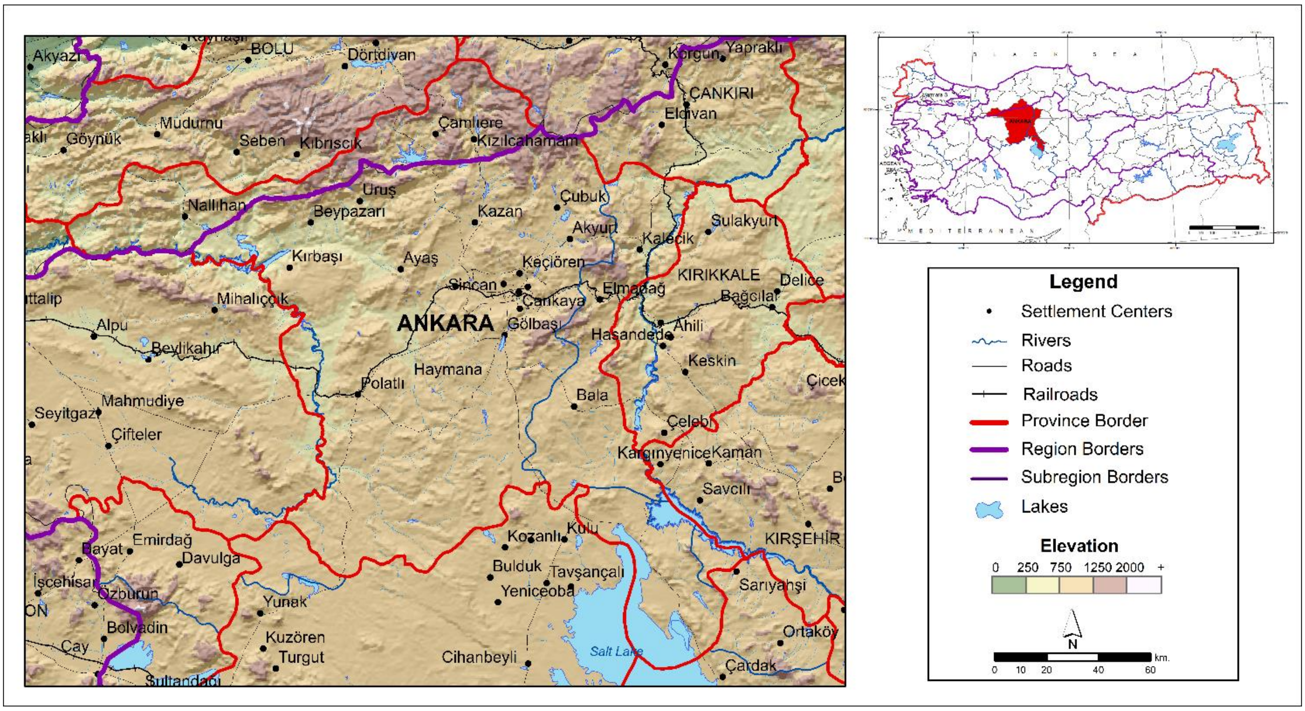


Figure 1: Location of Ankara Province

The CORINE (Coordination of Information on the Environment) program was launched in the European Union in 1985. It was initiated in line with the criteria and classification system set by the European Environment Agency (EEA) to determine the environmental changes in the EEA member countries, to manage the natural resources in a rational way and to establish policies related to the environment by managing the same core data and creating a standard database. CORINE is a non-commercial open access land cover database. It is used as an important data source to compile the basic land use inventories such as agricultural areas, forest areas, wetlands with spatial data, to monitor the destruction of forest areas, to make product estimates, to create agricultural drought action plans, to calculate carbon emissions resulting from land use changes, in studies on erosion control, forest fires and combating against desertification, in the Natura 2000 Project, to monitor wetland changes, to prepare water and waste management plans and watershed action plans, to develop environmental plans, to create city atlas and so on. In line with the land cover classification determined by the EEA, land cover maps on a scale of 1/100.000 were created using the computer-aided visual interpretation method and satellite images. So far, land cover data for the European Union member countries and Turkey for the years 1990, 2000, 2006, 2012, and 2018 and data sets showing the changes between these years have been created. For Turkey, land cover and land cover change data for the years 1990, 2000, 2006, 2012 and recently 2018 have been published.

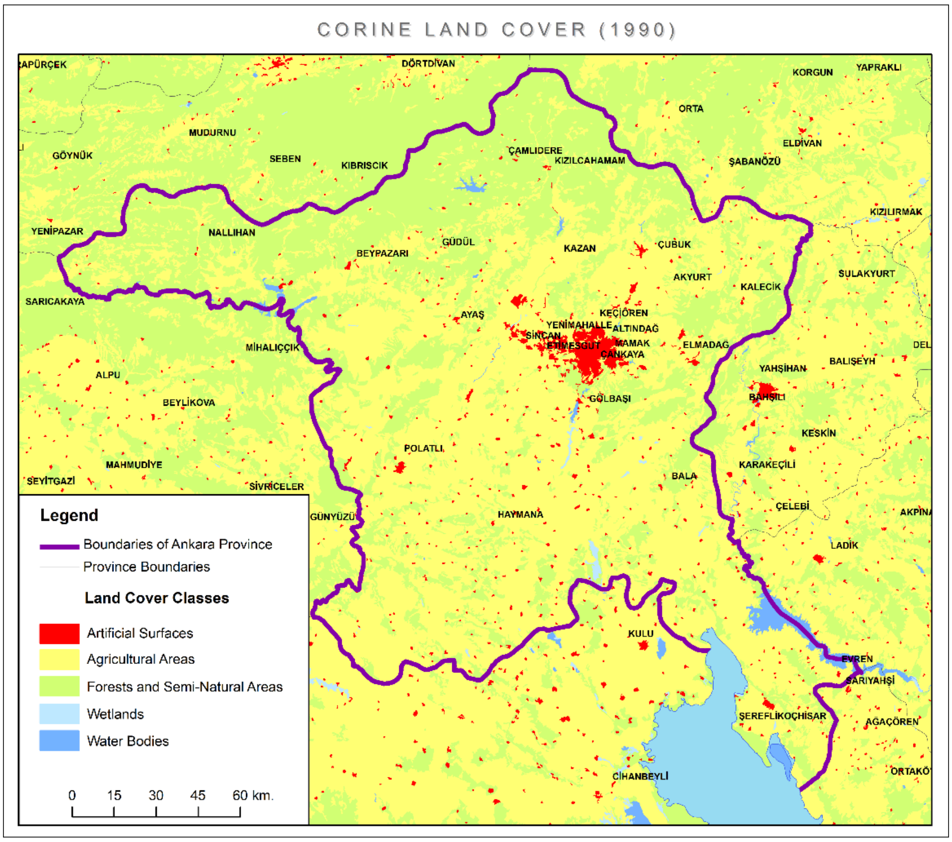
It is possible to monitor the characteristics of and changes in Ankara land cover with CORINE Land Cover 1990, 2000, 2006 and 2012 data. The CORINE land cover data prepared with the criteria and classification system determined by the

European Environment Agency consist of three levels. In this classification, there are 5 sub-land cover classes at the first level, 15 at the second level, and 44 at the third level (EEA, 1995). While the first class designated as artificial surface corresponds entirely to residential areas, the agricultural areas class includes agricultural areas and pastures. The forest and semi-natural areas class covers a wide area from real forest cover to transitional woodland shrub areas, and from natural grassland to moors and heathland. The Wetlands and Water Bodies classes cover the wetlands from inland marshes to salines and to lakes and dams.

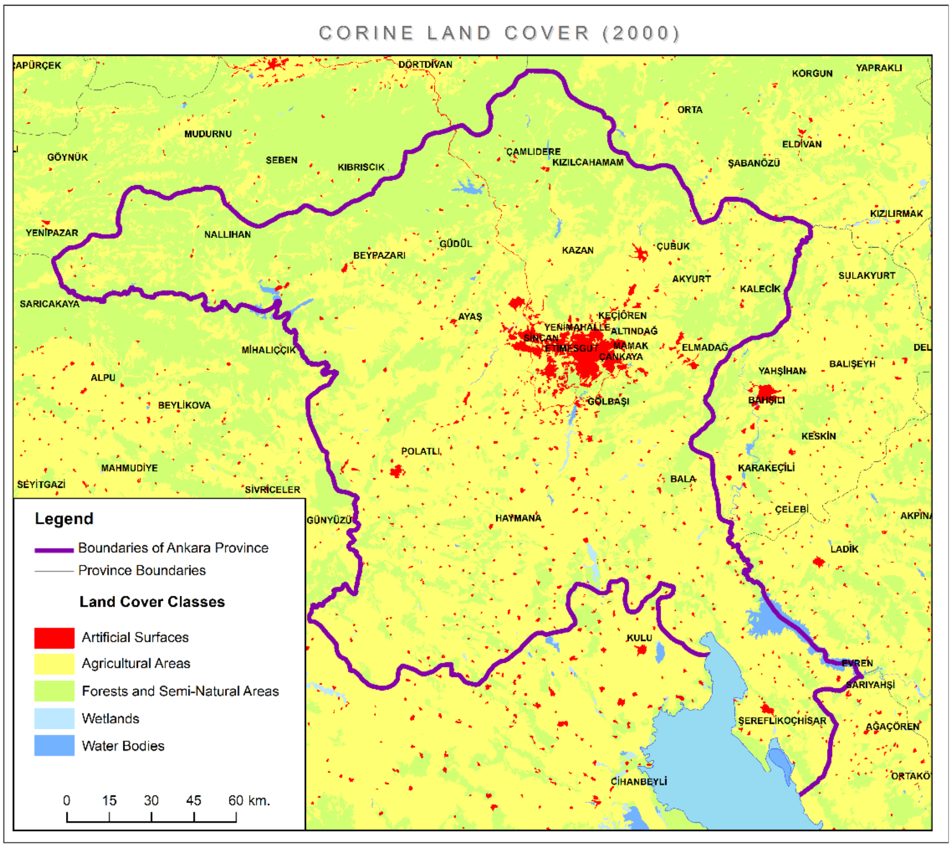
When the change of land cover in Ankara province is monitored within the framework of CORINE main land cover (first level) classes, it is observed that in the 1990-2000 period, the highest increase was in artificial areas with 200.47 km², while the highest loss was in agricultural areas (182.88 km²). The fact that the losses and gains in other land cover areas were not large evidenced that artificial areas developed against agricultural lands in this period (Table 1; Figure 2 a, b, c, d).

Table 1: Ankara Province Land Cover Areas (km²) and Gain-Loss (km²)

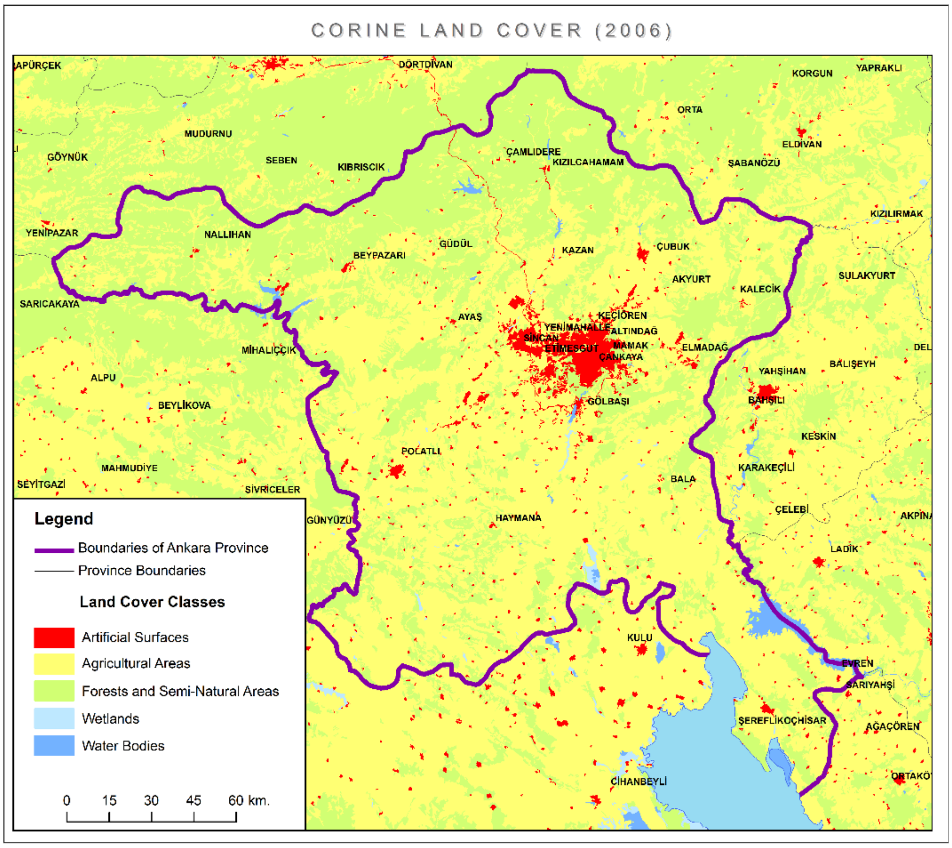
Land Cover Classes	Land Cover Area (km²)				Gain and Loss (km²)		
	1990	**2000**	**2006**	**2012**	**1990-2000**	**2000-2006**	**2006-2012**
Artificial Surfaces	550.37	750.84	831.01	892.41	200.47	80.17	61.4
Agricultural Areas	15008.8	14825.9	14453.5	14389.1	-182.88	-372.41	-64.35
Forests and Semi-Natural Areas	9356.74	9343.79	9477.17	9467.1	-12.95	133.38	-10.07
Wetlands	83.07	93.08	257.32	257.17	10.01	164.24	-0.15
Water Bodies	654.53	639.88	634.5	647.67	-14.65	-5.38	13.17
Total Area	**25653.46**	**25653.46**	**25653.46**	**25653.46**			



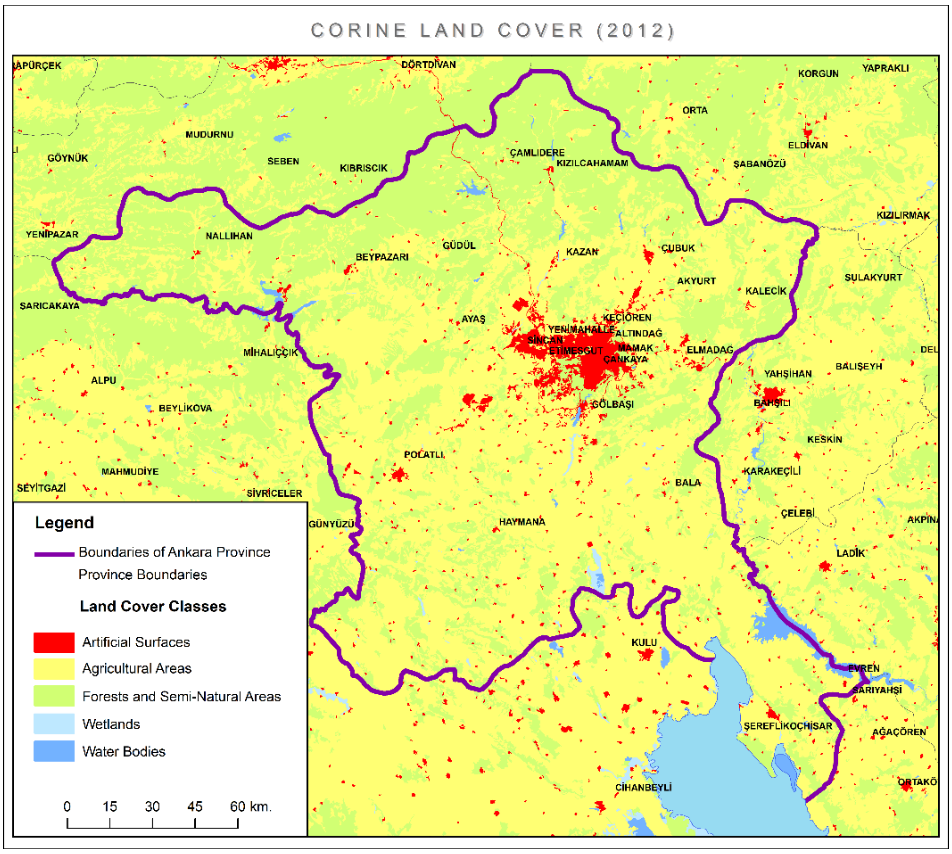
a. CORINE Land Cover 1990



b. CORINE Land Cover 2000



c. CORINE Land Cover 2006



d. CORINE Land Cover 2012

Figure 2: CORINE land cover classification of Ankara province according to different periods

In the 2000-2006 period, the highest losses were observed in agricultural areas, while the highest gains were observed in wetlands (Figure 3). The main reason for this is that despite being low compared to the previous period, artificial areas developed against agricultural areas and some drinking water and irrigation ponds were put into service. The highest increase in forest and semi-natural areas was also observed in this period. The increase in forestation activities and the conversion of vacated agricultural areas into forests and semi-natural areas were effective in the emergence of this situation (Table 1 and 2; Figure 3).

The period of 2006-2012 was relatively stable for all land cover types. The highest gains were in artificial areas and the highest losses were in agricultural areas (Table 1 and 2; Figure 3).

Taking 1990 as the reference year, in the periods until 2012, the highest increase was observed in artificial areas, and artificial areas increased by 342.04 km² in 2012, while agricultural areas decreased by 619.64 km². This increase in artificial areas was mostly met by agricultural, forest and semi-natural areas (Figure 3).

Table 2: Change of Area by 1990 Reference Year (km²)

Land Cover Classes	**2000**	**2006**	**2012**
Artificial Surfaces	+200.47	+280.64	+342.04
Agricultural Areas	-182.88	-555.29	-619.64
Forests and Semi-Natural Areas	-12.95	+120.43	+110.4
Wetlands	+10.01	+174.25	+174.1
Water Bodies	- 14.65	- 20.03	- 6.86

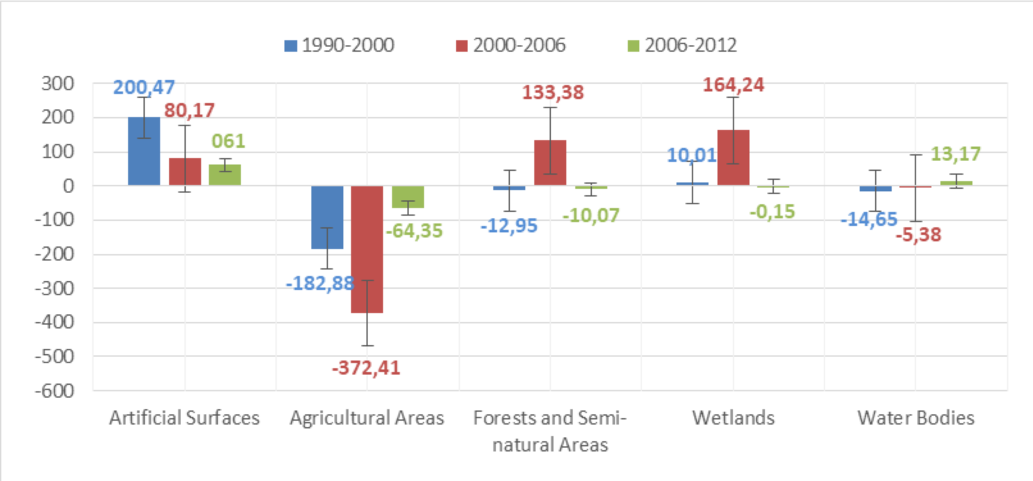


Figure 3: Land Cover Gain and Loss by Periods (1990-2012)

The total land cover change accounted for about 2% of the province area in 1990-2000, while this rate increased to 4% in the 1990-2006 period and to 5% in the 1990-2012 period. The rate of change gradually increased, and the areas that remained stable within the provincial area had a significant value in each period (Table 3). From 1990 to 2012, 91% of agricultural areas, forests and semi-natural areas, 77% of wetlands and 94% of water bodies were steady. Artificial areas, on the other hand, continued to change positively in each period (Table 3; Figure 4).

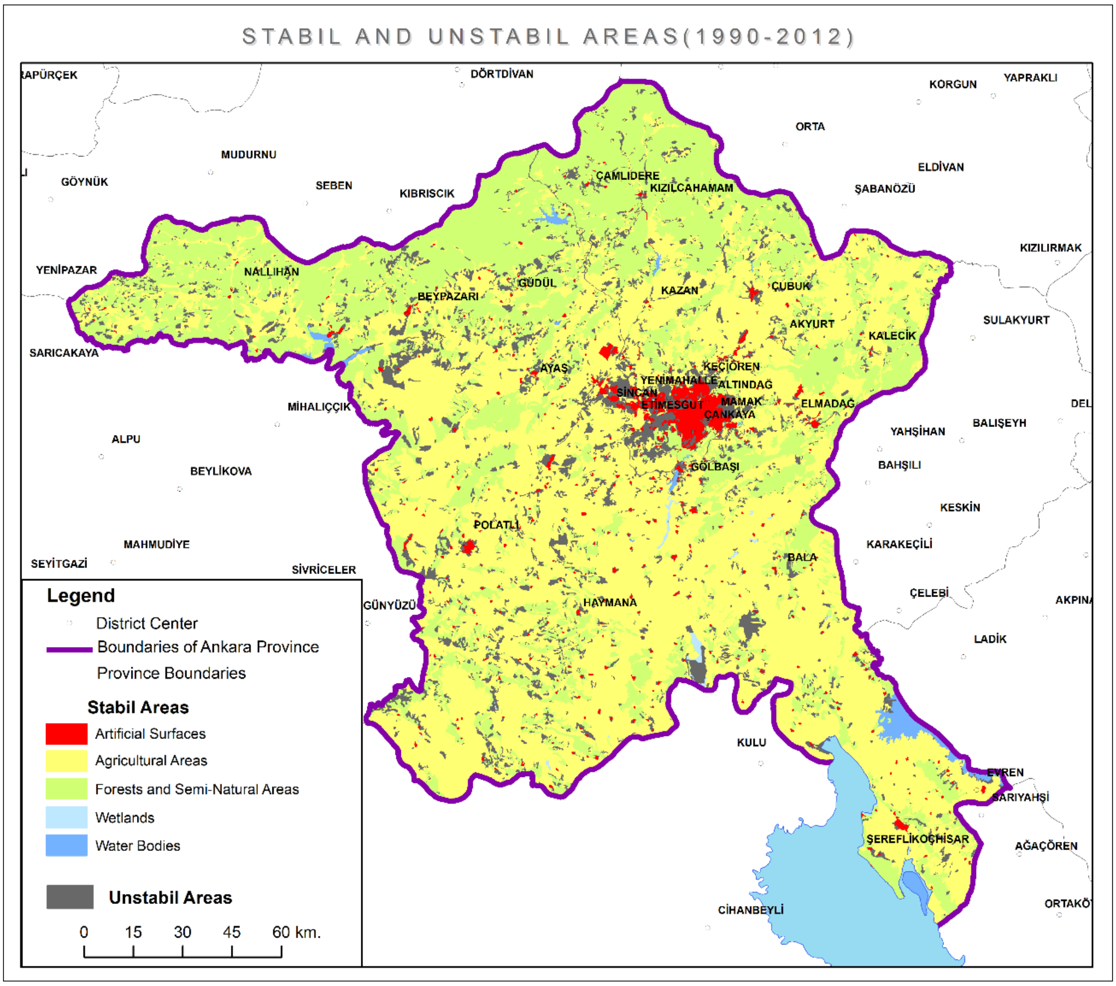


Figure 4: Stabil and Unstabil Areas

Table 3: Stabil Areas

Land Cover Classes	Corine 1990 (km²)	Stabil 2012 (km²)	Stabil 2012 (%)
Artificial Surfaces	550	458	83
Agricultural Areas	15.009	13.751	92
Forests and Semi-Natural Areas	9.357	8.591	92
Wetlands	84	70	83
Water Bodies	655	623	95
Total	**25.655**	**23.493**	**92**

In all periods, the biggest land cover change in Ankara was seen as the transformation of agricultural areas around the city into artificial areas depending on the development of the city (Bayar and Karabacak, 2017; Table 1 and 3, Figure 2). This trend of land cover classes provides important clues that the change will continue to accelerate in the future (Figure 5). This shows that there is a need for some planning studies in order to prevent the conversion of the areas suitable for tilled agriculture to residential areas and the misuse of the land. Therefore, it is of great importance to estimate the future land cover of Ankara so that attention could be drawn to wrong land use and a basis for planning can be formed.

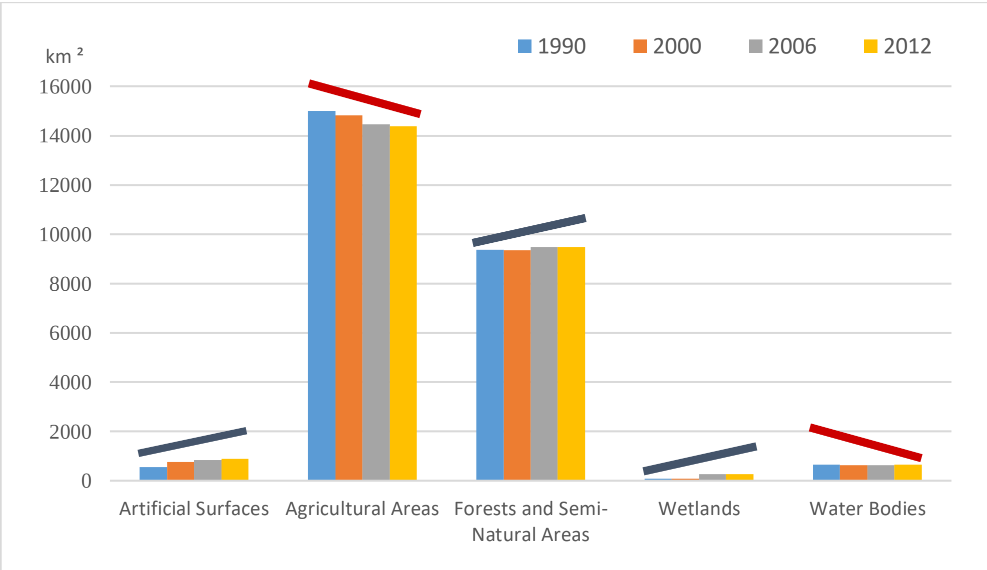


Figure 5: Land Cover Change Tendency (1990-2012)

Data and Method

CORINE 1990, 2000, 2006 and 2012 data used to monitor the land cover change in Ankara and make estimates for the future were taken into consideration within the scope of Level 1 data in order to show the entire Ankara province as the scale of the study. The data were organized according to Ankara provincial borders and analyzed using the ArcGIS 10.1, Interchange (EEA), Microsoft.Net C#, Ms SQL, Ms Access and Ms Excel software.

To use of the model, first, the CORINE data for the years 1990, 2000, 2006 and 2012 was sorted according to the land cover classes using ArcGIS 10.1, the Geographic Information Systems software, and written on the Ms Access database. In the Geographical Information Systems environment, these vector datasets were processed and converted into raster datasets with a resolution of 100x100 pixels, and a table of value attributes was created for the classification of land cover. In order to estimate the land cover class possibilities of the constructed Markov Chain model in the future, point data was obtained by retransforming raster data using the ArcGIS 10.1 Geographic Information Systems software and 2,565,346 points were obtained as a result of this transformation for an area of 25,653.46 km². Land cover classes of 1990, 2000, 2006 and 2012 for each point were listed according to years and the new data set was written on an MS SQL database table. A program was developed using the C # programming language in Microsoft.NET environment for the development and operation of the Markov Chain Model. With this program, the probability of occurrence of each Pj case at sample points at any time for the land cover classes at each point was calculated with V0 (initial probabilities) vector. Thus, land cover classification for each period was found, and the P "transition probability matrix" of the Markov Chain Model was created for each criterion using this data. According to the data sets taken into account, prediction maps were produced for Ankara, and accuracy tests were evaluated using the Ms Excel software. In this way, changes or stationarity in each land cover category for the following period were revealed.

According to the data sets taken into consideration, an estimation map of Ankara was produced for 2012, accuracy tests were conducted and real data for 2012 were included in the model and consequently, the land cover of Ankara in 2018 was estimated and mapped (Figure 6). With geographical information systems and spatial analysis field tabulation tools (Tabulate Area), land use capability classes in 2018 forecast map and digital soil maps were evaluated together and how the estimated land cover change was distributed in areas suitable for tilled agriculture (Figure 6).

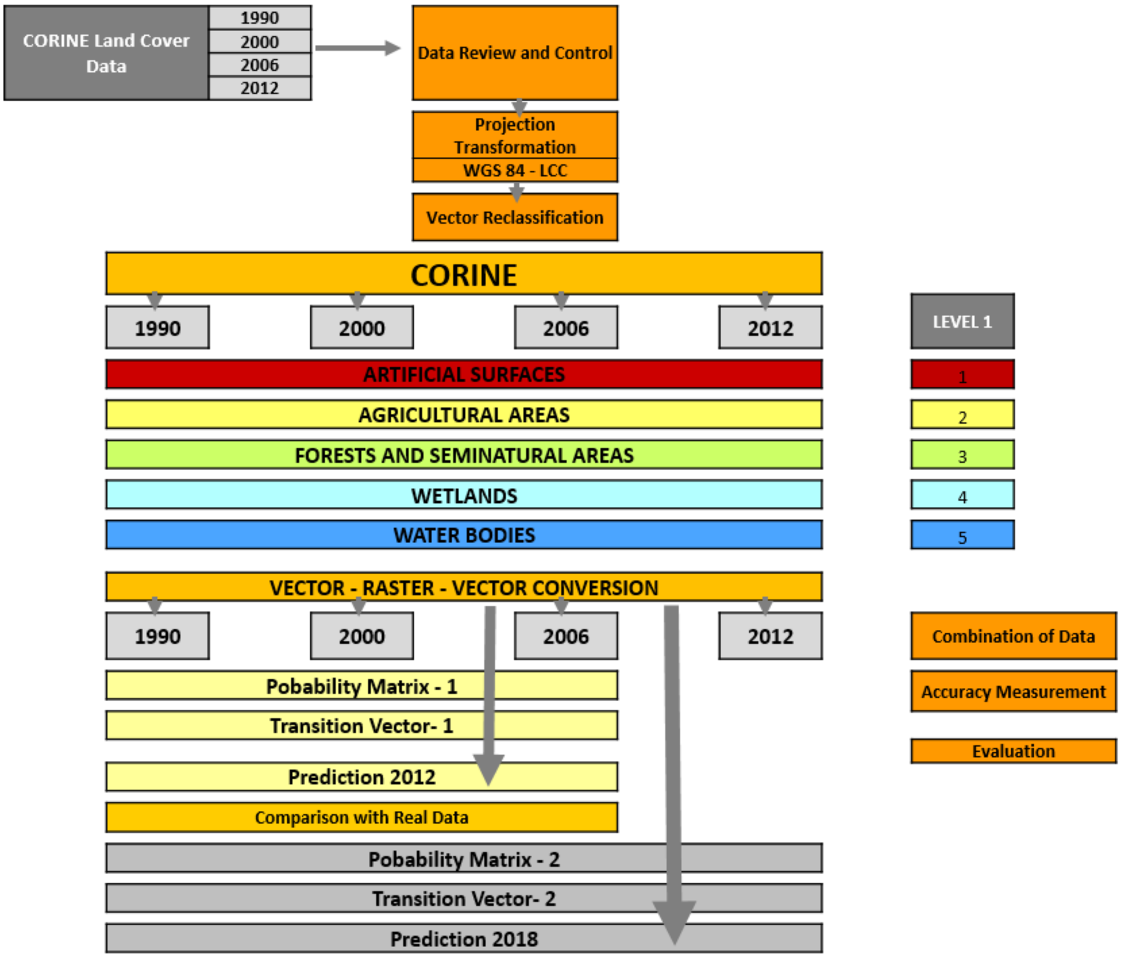


Figure 6: Graphic Description of Used Method

Data organization and implementation of the model

In order to use the model, firstly, CORINE data for 1990, 2000, 2006 and 2012 were sorted according to land cover classes and these vector data sets were converted to raster data sets at 100m × 100m pixel resolution. These raster datasets were processed in the geographical information systems environment, and a value attributes table was created for the land cover classification. Thus, the land cover classification for each period was put forward, and the P "transition probability matrix" of the Markov chain model was created for each criterion using these data (Table 4). Since the land cover classes were independent from each other at different times, the model was stationary.

Each land cover class is represented by a different PJ symbol in the Markov chain model. The value of J (J = 1, 2, 3, 4, 5) indicates the index values of the CORINE land cover classes (Table 4).

Table 4: Symbol of Land Cover Types	
Symbol	***Land Cover Type***
P_1	Artificial Surfaces
P_2	Agricultural Areas
P_3	Forests and Semi-Natural Areas
P_4	Wetlands
P_5	Water Bodies

In order to estimate the land cover class probabilities in the future periods of the Markov chain model, the data was converted from raster data to point data by means of geographical information systems software and 2565346 points were obtained for 25653.46 km² area. The 1990, 2000, 2006 and 2012 land cover classes for each point were sorted by years and the new data set was written to a SQL database table (Table 5).

Table 5: 1990-2000-2006-2012 Sample Pixels		
Pixel No	**Year**	**CORINE level 1**
1	1990	P_3
1	2000	P_3
1	2006	P_2
1	2012	P_2
2	1990	P_3
2	2000	P_2
2	2006	P_2
2	2012	P_1
3	1990	P_2
3	2000	P_5
3	2006	P_3
3	2012	P_2

In 4-year periods (1990, 2000, 2006 and 2012), based on the land cover classes in each period, Vº (initial probabilities) vector was created for all points prepared, and each component of this vector indicated the possibility of occurrence of different situations represented by the symbol "PJ" in the land cover class at that point. The Markov chain Model was run and the results revealed the probabilities of emergence of future land cover classes. The probability of occurrence of land cover classes for any desired period was determined using the following equations:

$$V^n = V^{n-1} * P = V^0 * P^n$$

$n =$ n years after the last year taken into account when developing the model (number of steps),

V^n = Probability vector in year n (step),

V^0 = Initial probabilities vector,

P = Transition probability matrix (Mckee et al., 1993).

For example, the general equation given above will turn into the following figure when the probability is written respectively for the first two terms (years) to be estimated.

$V^1 = V^0 * P$

$V^2 = V^1 * P = V^0 * P^2$

In this study, the probability vector for the next period (2018) is shown with V^1 from 2012, which is the last year considered in the development of the model. In these equations, the numbers ($_{1,2, \dots n}$) on the V vectors represent the number of steps in the model. Each component of these probability vectors reveals the probability of occurrence of $P_1, P_2, \dots . P_5$ situations in Ankara for the period analyzed.

A program has been developed using C# programming language in Microsoft.NET environment to develop and run the Markov chain model. With this program, the probability of occurrence of each P_j situation at any time for the land cover classes at each point was expressed by the vector V^0 (initial probabilities) (Table 6).

Table 6: V0 (Beginning Possibility) Vector						
Pixel No		**P_1**	**P_2**	**P_3**	**P_4**	**P_5**
1	**V^0**	0	0.5	0.5	0	0
2	**V^0**	0	0	1	0	0
3	**V^0**	**0**	**0.5**	**0.25**	**0**	**0.25**

The P (transition probabilities) matrix of the Markov Chain Model was calculated for the land cover classes at each point (Table 7).

	Table 7: Transition Probability Matrix in Sample Points						
	Piksel No		**P_1**	**P_2**	**P_3**	**P_4**	**P_5**
$P =$	1	**P_1**	0	0	0	0	0
	1	**P_2**	0	0.5	0	0	0
	1	**P_3**	0	0.5	0.5	0	0
	1	**P_4**	0	0	0	0	0
	1	**P_5**	0	0	0	0	0
	2	**P_1**	0	0	0	0	0
	2	**P_2**	0	0.5	0.5	0	0
	2	**P_3**	0	1	0	0	0
	2	**P_4**	0	0	0	0	0
	2	**P_5**	0	0	0	0	0
	3	**P_1**	0	0	0	0	0
	3	**P_2**	0	0	0	0	0.5
	3	**P_3**	0	1	0	0	0
	3	**P_4**	0	0	0	0	0
	3	**P_5**	0	0	1	0	0

As a result of running the Markov chain model for 2018, V^1 probability vector results of each point were obtained (Table 8). For example, the probability of occurrence of class 2 for pixel 1 was found to be 50%; the probability of occurrence of class 1 for pixel 2 was calculated as 25%; and the probability of occurrence of class 2 was 50%, and the probability of occurrence of classes 2, 3 and 5 for pixel 3 was calculated as equal (25%). As a result of these operations for 2565346 pixels, 2018 land cover estimates were calculated and mapped.

Table 8: V1 Possibility Vector						
Piksel No		**P_1**	**P_2**	**P_3**	**P_4**	**P_5**
1	**V^1**	0	0.5	0.25	0	0
2	**V^1**	0.25	0.5	0	0	0
3	**V^1**	0	0.25	0.25	0	0.25

In order to evaluate the accuracy of the study, 2012 CORINE data of Ankara were taken as a reference and compared with 2012 estimation data and an error matrix was produced. Then, the accuracy of the study was tested and 2018 land cover data were produced.

The creation of an error matrix is of great importance to determine overall accuracy, omission errors, commission errors, user's accuracy, producer's accuracy and accuracy statistics. In this study, according to the error matrix based on 1990, overall accuracy for the classification was calculated by first adding the values along the diagonal and then dividing this value into the total area $[GA = (ASAS + AAAA + FSNAFSNA + WW + WBWB)/TT]$ (Table 10 and 11).

Producer's accuracy is the map accuracy from the point of view of the map maker (the producer) $[Producer\ accuracy = 100\% - Omission\ error]$.

$[PA = ASAS/T \gg 458.19/550.37 = 0.83]$ (Table 11).

Omission errors occur by subtracting or omitting the actual type of land cover from the classified map. The class above and below the correctly classified values of the main diagonal is located in the column cells. The sum of these cell values is the absolute value of the class assignments. By dividing this sum by the total value, the relative assignment error value is found. For example, for the artificial areas column, $[(AA + FSNA + W + WB)/T][(72.43 + 19.17 + 0.29 + 0.29)/550.37 = 0.17]$ this value was calculated as 17%.

The User's Accuracy is the accuracy from the point of view of a map user, not the map maker. The User's accuracy essentially tells use how often the class on the map will actually be present on the ground $[User's\ Accuracy = 100\% -$

$Comission\ Error$]. It is complementary to assignment errors. User's accuracy is calculated based on the total number of correct classifications for a given class and divided by the total of rows. For example, for the artificial areas class:

$[UA = ASAS/TT \gg 458.19\ /892.41 = 0.51]$ (Table 11).

Commission errors are related to classified results. For any class, it occurs when pixels are assigned to a particular class that does not actually belong to it during the classification process. It is located in the class row cells to the right and left of the correctly classified values of the main diagonal. The sum of these cell values is the absolute value of the class assignments. By dividing this sum by the total value, the relative assignment error value is found. For example, for the artificial areas line, $[(AA + FSNA + W + WB)/T][(372.49 + 61.49 + 0.00 + 0.24)/892.41 = 0.49]$ this value was calculated as 49% (Table 11).

In order to evaluate the accuracy of the classification as well as the accuracy values calculated for the study area, the Kappa test was performed because it is a statistical measure of the reliability of concordance between two or more observers. Kappa only assesses how good the classification is compared to randomly assigned values. Cohen acknowledges that the Kappa test may be a coincidence between observers, and therefore the percentage between the two observers yields a stronger result than that found in proportion (Cohen, 1960; Kılıç, 2015). Kappa value can take a value between $(-)\ 1$ and $(+)\ 1$ and the value found is interpreted as follows (Dawson and Trap, 2004; Sim and Wright, 2005):

$\kappa = +1$ The results found by the two observers are completely consistent.

$\kappa = 0$ The concordance between the two observers depends only on chance.

$\kappa = -1$ The two observers evaluate exactly the opposite of each other.

FINDINGS

With the implementation of the Markov chains model for 2012, the value assignment for each point estimated a 67% probability at some points, while in others there was an assignment to two classes with a 33% probability. For this reason, in the model, the areas estimated with a 67% probability in which each point was assigned to a single class were considered. Other probabilities were determined as the unpredictable areas. According to the Markov chains method, which was implemented with reference to 1990, a change was estimated for each land cover class in 2012 as shown in Table 9, where the difference between the actual 2012 data and the forecast data came from this 33% (Table 9; Figure 7).

Table 9: Result Comparation (2012)

Land Cover Classes	**Corine 2012 (km²)**	**Markov 2012 (km²)**	**Markov Predict (%)**	**Difference (km²)**	**Difference (%)**
Artificial Surfaces	892	633	71	259	29
Agricultural Areas	14389	13774	96	615	4
Forests and Semi-Natural Areas	9467	8584	91	883	9
Wetlands	257	81	32	176	68
Water Bodies	648	626	97	22	3
TOTAL	**25653**	**23698**	**92**	**1955**	**8**

When these results are examined, it is seen that 23698 km² of the total area of 25653 km² was estimated. This amount corresponds to 92% of the total area. Given the consistency of estimation, the wetland class was estimated at a low rate of 32%, while water bodies (97%), forests and semi-natural areas (91%) and agricultural areas (96%) were predicted with high level of consistency (Table 9; Figure 7).

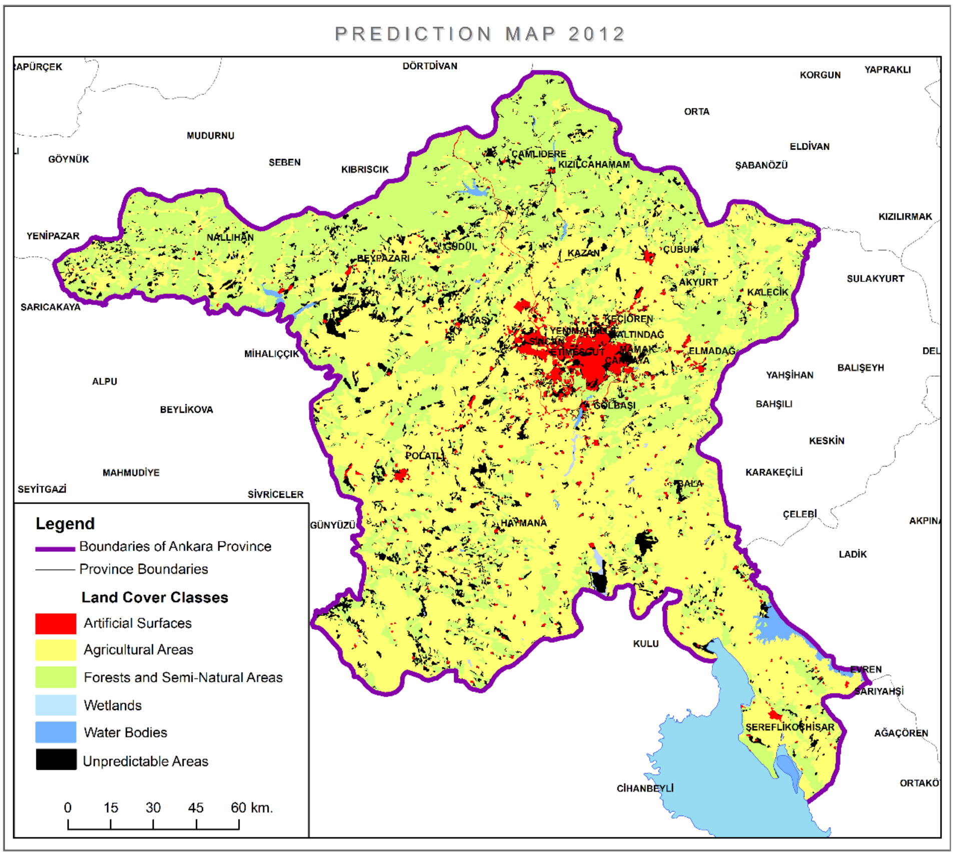


Figure 7: Predicted Land Cover of Ankara Province (2012)

According to the error matrices obtained by comparing the 1990 and 2012 data, the elements along the diagonal represent the values classified correctly for that class (Table 10).

Table 10: Error Matrices (1990-2012)

	1990											
	Artificial Surfaces		Agricultural Areas		Forests and Semi-Natural Areas		Wetlands		Water Bodies		TOTAL	
2012	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**
Artificial Surfaces	458.19	0.83	372.49	0.02	61.49	0.01	0.00	0.00	0.24	0.00	**892.41**	0.03
Agricultural Areas	72.43	0.13	13750.65	0.92	554.93	0.06	6.58	0.08	4.52	0.01	**14389.11**	0.56
Forests and Semi-Natural Areas	19.17	0.03	855.22	0.06	8591.20	0.92	0.00	0.00	1.51	0.00	**9467.10**	0.37
Wetlands	0.29	0.00	15.11	0.00	146.62	0.02	69.98	0.84	25.17	0.04	**257.17**	0.01
Water Bodies	0.29	0.00	15.28	0.00	2.50	0.00	6.51	0.08	623.09	0.95	**647.67**	0.03
TOTAL	**550.37**	**1.00**	**15008.75**	**1.00**	**9356.74**	**1.00**	**83.07**	**1.00**	**654.53**	**1.00**	**25653.46**	**1.00**

According to these error matrices, the overall classification accuracy was found to be 92% for the period 1990-2012, while the Kappa coefficient was found as 0.843 (Table 11). Kappa only evaluates how good the classification is compared to randomly assigned values. The obtained Kappa value explains that the data are compatible with each other. However, according to the calculated error matrices, the total area estimated incorrectly is 81.63 km². The largest erroneous estimation value was observed in the classes of agricultural (64.87 km²) and forest and semi-natural areas (14.75 km²). In other classes, this value was observed below 1 km² (Table 12).

Table 11: Validation (1990-2012)

	Artificial Surfaces	Agricultural Areas	Forests and Semi-Natural Areas	Wetlands	Water Bodies
Producer Accuracy (%)	**0.83**	**0.92**	**0.92**	**0.84**	**0.95**
Omission (%)	**0.17**	**0.08**	**0.08**	**0.16**	**0.05**
Commission Eror (%)	**0.49**	**0.04**	**0.09**	**0.63**	**0.04**
User Accuracy (%)	**0.51**	**0.96**	**0.91**	**0.27**	**0.96**
General Accuracy (%)	**0.92**				
Kappa Factor	0.842832284				

Table 12: Incorrectly Predicted Areas According to Error Matrices

Incorrectly Predicted Areas	**m²**	**km²**
Artificial Surfaces	237225	0.24
Agricultural Areas	64874689	64.87
Forests and Semi-Natural Areas	14748360	14.75
Wetlands	985859	0.99
Water Bodies	788515	0.79
TOTAL	**81634648**	**81.63**

DISCUSSION

This study aimed to establish a model that analyzes the distribution of a value taken at any time over time dimension depending on the values in the same time period before it based on the basic principle in the Markov chains method, i.e., depending on the degree of the model. It was further aimed to estimate the CORINE 2018 Level 1 classes across Ankara with the constructed model and to evaluate its accuracy. The acquisition and release of real 2018 CORINE data during the study enabled the comparison of the results obtained with the Markov model. As explained in the conclusion part, comparisons with the 2018 Corine data showed that satisfactory results were produced with the Markov Model. During the study, erroneous estimation or unpredictability emerged. It was determined that this was statistically due to the assignment of the same probability values to more than one pixel at the same time. It is thought that the model can be integrated with methods that take into account spatial proximity and neighborhood principle to guide other researchers who will make land cover estimations with the Markov Model and to increase estimation consistency.

The development and accuracy of land cover prediction studies is of great importance in terms of ensuring early detection of both economic and ecological problems and taking necessary measures. Therefore, there is a direct correlation between the sustainability of land and its correct use. For this reason, modeling studies will be an important base for those who are engaged in land use planning and for decision makers.

Because of rapid population growth, the change in land cover is also rapid in Ankara. Especially, the spreading of urban areas on the natural cover makes it necessary to make planning in terms of land use. Otherwise, agricultural and natural areas will gradually turn into urban areas, which will create many irreversible problems. For this reason, the prediction map developed with the model created in the conclusion part of the study was compared with land use capability to draw attention to possible problems.

CONCLUSION

The Markov chain model was re-run by re-applying the transition matrices calculated by adding them to the data set of 2012 for 2565346 points, and the 2018 land cover of Ankara was estimated. With the developed Markov chain model, the amount of land cover change and continuity in cover types were estimated in the period from the reference year 1990 to 2018. In this way, the change in the next period or stagnation of each land cover category was presented. The emergence of areas in which the model made more than one assignment for a point (unpredictable areas) is thought to be due to inaccuracies in the CORINE database. Thus, when the Markov chain model is evaluated with high resolution satellite images in different time periods, unpredictable areas are thought to be lower and more accurate predictions can be made on a spatial basis. In this study, which is considered within the scope of CORINE Level 1 class, the added time periods allowed the system to estimate with a higher probability. In fact, in 2018 land cover estimation, the probability of one point to turn into more than one land cover decreased to 25% and an accurate estimate could be made with 75% probability. According to this estimate, of the 25653 km² province area, 828 km² consists of artificial areas, 14454 km² of agricultural areas, 9472 km² of forests and semi-natural areas, 258 km² of wetlands and 635 km² of water bodies (Table 13). The 6 km² area in the southwest and periphery of Ankara could not be predicted by the developed model (Table 14; Figure 8). However, the results were in line with the general tendency of the change of land cover in the province from 1990 to 2012.

Table 13: Result Comparation (2018)

Land Cover Classes	**Corine 2018 (km²)**	**Markov 2018 (km²)**	**Markov Predict (%)**	**Difference (km²)**	**Difference (%)**
Artificial Surfaces	1007	828	82	179	18
Agricultural Areas	14334	14454	101	-120	-0,8
Forests and Semi-Natural Areas	9393	9472	101	-79	-0,8
Wetlands	283	258	91	25	9
Water Bodies	636	635	100	1	0,2
TOTAL	**25653**	**25647**	**100**	**6**	**0,02**

Table 14: Prediction Results

Land Cover Classes	**Real Data 1990**	**Predict 2018**	**Difference (km²)**
Artificial Surfaces	550	**828**	+278
Agricultural Areas	15009	**14454**	-555
Forests and Semi-Natural Areas	9357	**9472**	+115
Wetlands	84	**258**	+174
Water Bodies	655	**635**	-20
UNPREDICTABLE		**6**	
TOTAL	25653	**25653**	

CORINE 2018 real data was published after the completion of this study. For this reason, we found the opportunity to test the accuracy of the 2018 land cover estimation model. In this study, the overall accuracy was 90%, and the kappa value was found to be 0.82 (Table 15 and 16).

Table 15: Error Matrices (1990-2018)

	1990											
	Artificial Surfaces		Agricultural Areas		Forests and Semi-Natural Areas		Wetlands		Water Bodies		**TOTAL**	
2018	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**	**(km²)**	**(%)**
Artificial Surfaces	451,28	82,00	479,37	3,19	75,71	0,81	0	0,00	0,31	0,05	**1006,67**	3,92
Agricultural Areas	77,69	14,12	13552,52	90,30	690	7,37	8,84	10,64	5,05	0,77	**14334,1**	55,88
Forests and Semi-Natural Areas	20,31	3,69	934,89	6,23	8436,16	90,16	0	0,00	2,18	0,33	**9393,54**	36,62
Wetlands	0,73	0,13	17,45	0,12	148,79	1,59	67,72	81,52	48,69	7,44	**283,38**	1,10
Water Bodies	0,36	0,07	24,52	0,16	6,08	0,06	6,51	7,84	598,3	91,41	**635,77**	2,48
TOTAL	**550,37**	**1,00**	**15008,75**	**1,00**	**9356,74**	**1,00**	**83,07**	**1,00**	**654,53**	**1,00**	**25653,46**	**1,00**

Table 16: Validation (1990-2018)

	Artificial Surfaces	Agricultural Areas	Forests and Semi-Natural Areas	Wetlands	Water Bodies
Producer Accuracy (%)	0.82	0.90	0.90	0.82	0.91
Omission Error (%)	0.18	0.10	0.10	0.18	0.09
Commission Eror (%)	22.42	0.05	0.10	0.76	0.06
User's Accuracy (%)	0.45	0.95	0.90	0.24	0.94
Overall Accuracy (%)	0.90				
Kappa Factor	0.82				

In addition, the 2018 real land cover data proves that the overall trend was well predicted. Although the gains and losses showed slight differences in terms of periods, the general tendency remained the same from 1990 to 2018 (Table 14 and 17).

Table 17: Land cover Gain and Loss by Periods (1990-2018)

	Land Cover Gain and Loss by periods (km²)			
Land Cover Classes	**1990-2000**	**2000-2006**	**2006-2012**	**2012-2018**
Artificial Surfaces	200.47	80.17	61.40	114.26
Agricultural Areas	-182.88	-372.41	-64.35	-55.01
Forests and Semi-Natural Areas	-12.95	133.38	-10.07	-73.56
Wetlands	10.01	164.24	-0.15	26.21
Water Bodies	-14.65	-5.38	13.17	-11.9

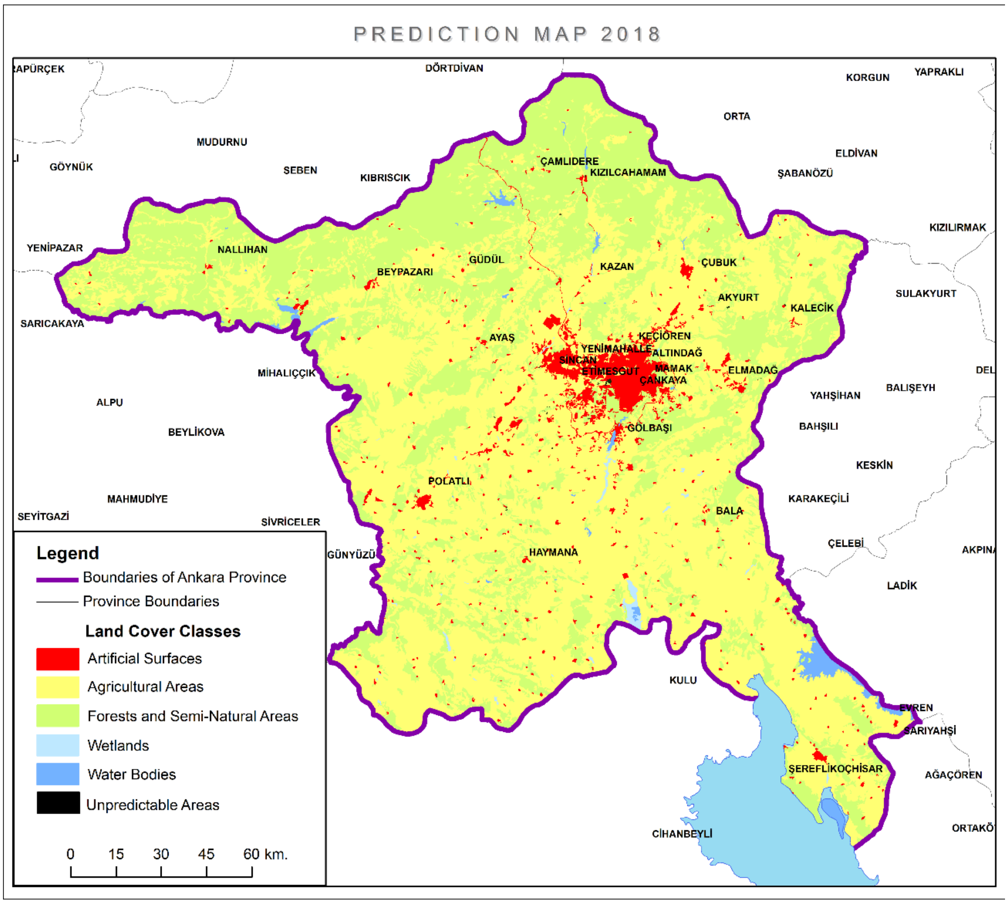


Figure 8: Predicted Land Cover of Ankara Province (2018)

Considering the land cover change since 1990, which is the basis of the study, it can be stated that the artificial areas corresponding to the residential areas have constantly been spreading, while the agricultural areas have been decreasing to a great extent. It is possible to observe the same situation in the distribution of the first four classes of land. Artificial Areas will begin to spread more and more over the areas suitable for agriculture (Table 17).

When the estimated 2018 land cover data of Ankara were evaluated, it was seen that artificial areas, forest and semi-natural areas and wetlands grew against other land cover, which is noteworthy on the periphery of residential areas and especially in the city of Ankara. This situation leads to the misuse of agricultural areas to the west and partly south of the city. The evaluation of the agricultural areas in this area according to land use capability classes may reveal the impact of the growth of the settlement areas on agricultural areas more clearly. When the land use capability classes and 2018 estimation data are evaluated together, it is seen that 3% of the first four classes of land suitable for tilled agriculture, which constitutes approximately 45% of the province surface area, are allocated to artificial areas. According to the 2018 land cover estimate, 36% of the artificial areas will actually develop on this group, which is suitable for agricultural activities.

Table 18: 2018 Prediction Classes and Land Use Capability Classes

Land Use	**Land Use Capability Classes (%)**																	
Classes (1990 and2018)	**I**		**II**		**III**		**IV**		**V**		**VI**		**VII**		**VIII**		**Other***	
	1990	**2018**	**1990**	**2018**	**1990**	**2018**	**1990**	**2018**	**1990**	**2018**	**1990**	**2018**	**1990**	**2018**	**1990**	**2018**	**1990**	**2018**
Artificial Surfaces	7	9	9	11	7	9	6	7	0	0	5	7	9	11	0	1	58	45
Agricultural Areas	13	13	19	20	21	21	15	16	0	0	11	11	18	17	1	1	2	1
Forests and Semi-Natural Areas	1	1	2	2	4	4	6	6	0	0	12	12	72	73	2	2	2	1
Wetlands	10	4	5	4	7	2	12	5	9	3	11	6	16	6	1	0	29	70
Water Bodies	1	1	0	1	0	0	0	0	0	0	0	0	2	4	1	1	95	93
Total (%)	8	8	12	12	14	14	11	11	0	0	11	11	37	37	1	1	6	6

* Bare rock surface, flood plain etc.

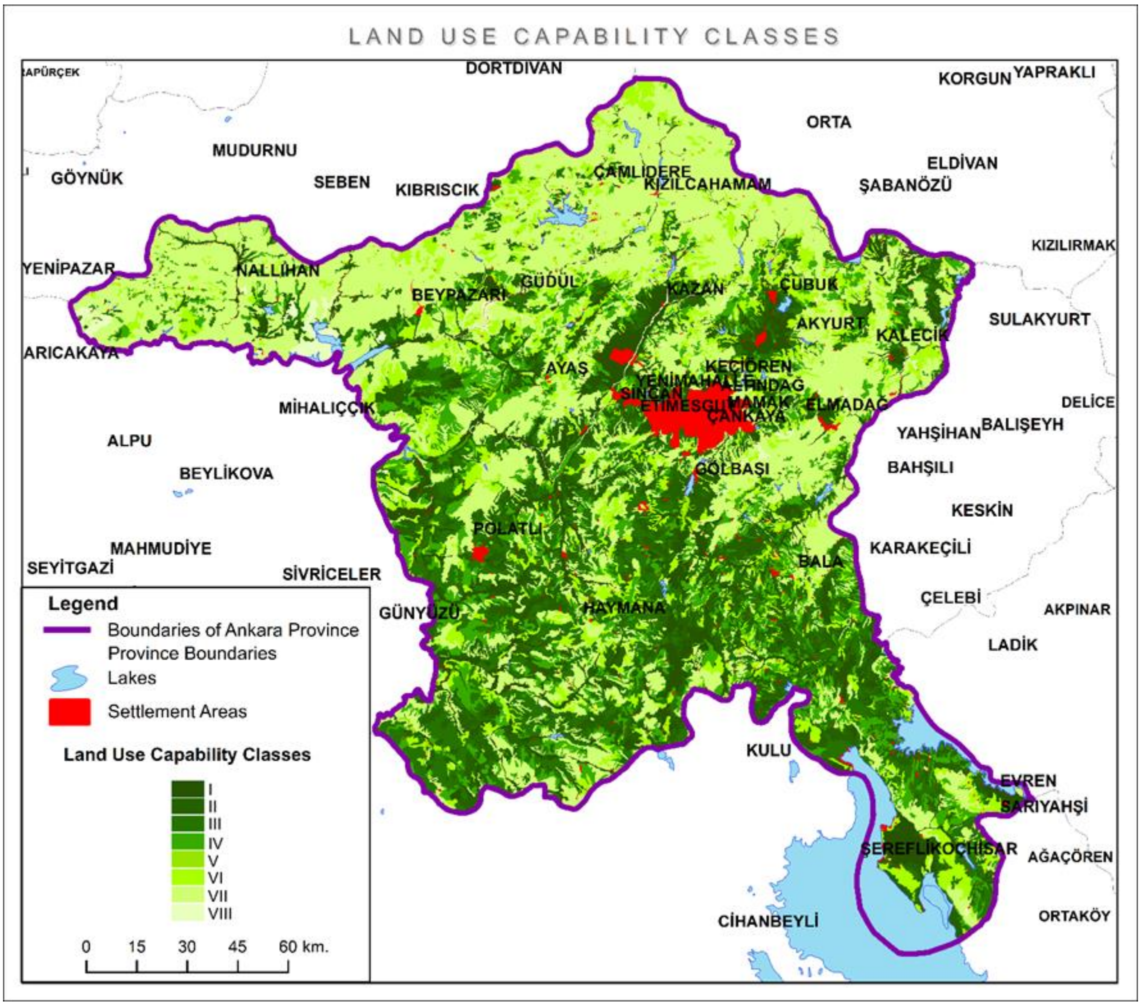


Figure 9: Land use Capability Classes of Ankara Province

While the estimated agricultural areas in 2018 constituted 56% of the province surface area, 67% of these areas will develop on areas suitable for tilled agriculture and 33% will develop on other classes which are not very suitable for agricultural activities. When we examine the west and partly south of Ankara, which is the biggest artificial area in the province, it is possible to say that these areas suitable for agricultural activities will rapidly turn into artificial areas (Figure 9; Table 18). In order to minimize the impact of this transformation on agricultural areas, this situation must be taken into consideration in the development plans of the residential areas and the improper use of agricultural lands should be prevented.

Kaynakça / References

Bayar, R. & Karabacak, K. (2017). Ankara ili arazi örtüsü değişimi (2000-2012). *Coğrafi Bilimler Dergisi,* 15(1), 59-76.

Brown, D. G., Pijanowski, B. C. & Duh, J. D. (2000). Modeling the relationships between land-use and land-cover on private lands in the Upper Midwest, USA. *Journal of Environmental Management,* 59, 247-263.

Cengiz, S. & Yılmaz, B. (2016). Malatya'da arazi kullanımı/örtüsünün modellemesi, 2025-2045 arazi kullanımı/örtüsü simülasyonu. D. Maktav & S. Berberoğlu (Ed.), *UZAL-CBS 2016 Sempozyumu Bildiriler Kitabı* içinde (s. 49-57). Adana.

Çetin, N. G. & Alp, S. (2016). Cep telefonu marka tercihlerinin Markov zincirleri ile analizi. *Erzincan Üniversitesi Fen Bilimleri Enstitüsü Dergisi*, 9(3), 126-138.

Ching, W. K., Fung, E. S. & Ng, M. K. (2002). A multivariate Markov chain model for categorical data sequences and its applications in demand predictions. *IMA Journal of Management Mathematics,* 13, 187–199.

Cohen, J. (1960). A Coefficient of agreement for nominal scales. *Educational and Psychological Measurement,* 20(1), 37-46.

Dawson, B. &Trapp, R. G. (2004). *Basic and clinical biostatistics.* (4th ed.). New york: McGraw-Hill.

EEA. (1995). CORINE land cover. Retrieved January 15, 2020, from *https://www.eea.europa.eu/publications/COR0-landcover.*

Geist, H. J. (2002). Causes and pathways of land change in Southern Africa during the past 300 years: Moving from simplifications to generality and complexity. *Erdkunde*, 56, 144-156.

Halaç, O. (2001). *Kantitatif karar verme teknikleri (yöneylem araştırması).* (5. Baskı). İstanbul: Alfa Basım Yayım Dağıtım.

Halmy, M. W. A., Gessler, P. E., Hicke, J. A. & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography,* 63, 101-112.

Hamad, R., Balzter, H. & Kolo, K. (2018). Predicting land use/land cover changes using a CA-Markov model under two different scenarios. *Sustainability*, 10, 3421.

Han, H., Yang, C. & Song, J. (2015). Scenario simulation and the prediction of land use and land cover change in Beijing, China. *Sustainability*, 7, 4260-4279.

Iacona, M., Geneldy, E. A. M. & Rania, W. (2012). Markov chain model of land use change in the Twin Cities. *Journal of Land Use, Mobility and Environment*, 8(3), 1-24.

Karip Bozkaya, A. G. & Göksel, Ç. (2017). İğneada koruma alanının arazi örtüsü/arazi kullanımının zamana bağlı değişiminin Markov zincirleri ile modellenmesi. *Journal of Geomatics,* 2(2), 94-105.

Kılıç, S. (2015). Kappa testi. *Journal of Mood Disorders,* 5(3), 142-144.

Kurtuluş, K. (1989). *İşletmelerde Araştırma Yöntembilimi (Araştırma Yöntemleri)*. İstanbul: İstanbul Üniversitesi İşletme Fakültesi Yayınları.

Levin, R. I., Kirkpatrick, C. A. & Rubin, S. D. (1982). *Quantitave Approaches to Management* (5th ed.). Newyork: McGraw-Hill.

Mckee, T. B., Doesken, N. J. & Kleist, J. (1993). The relationship of drought frequency and duration of time scales. *Proceedings of eighth conference on applied Climatology American Meteorological Society* (pp. 179-186). California.

Mondala, M. S., Sharmaa, N., Kappasb, M. & Gargc, P. K. (2013). Modeling of spatio-temporal dynamics of land use and land cover in a part of Brahmaputra River basin using geoinformatic techniques. *Geocarto International*, 28(7), 632–656.

Muller, M.R. & Middleton, J. (1994). A Markov model of land-use change dynamics in the Niagara region, Ontario, Canada. *Landscape Ecology,* 9, 151-157.

Sang, L., Zhang, C., Yang, J., Zhu, D. & Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA-Markov model. *Mathematical and Computer Modelling*, 54, (3-4), 938–943.

Sim, J. & Wright, C.C. (2005). The Kappa statistic in reliability studies: Use, interpretation, and sample size requirements. *Physical Therapy*, 85, 257-268.

Soykan, Y. (2010). Markov zincirleri ile pazar payı araştırma modeli ve otomobil lastiği pazarında bir uygulama. *Dumlupınar Üniversitesi Sosyal Bilimler Dergisi,* 27, 95-108.