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ANALYSING THE IMPACT OF URBAN GROWTH ON AGRICULTURAL LANDS USING SLEUTH MODEL AND GOOGLE EARTH ENGINE

[1,*] **Lütfiye KARASAKA**, [2] **Murat GÜNEŞ**

Konya Technical University, Engineering and Natural Sciences Faculty, Geomatics Engineering Department, Konya, TÜRKİYE

[1] lkarasaka@ktun.edu.tr, [2] e208223001012@ktun.edu.tr

Highlights

- SLEUTH is a cellular automaton-based simulation model that determines future land use states and change through probabilistic simulations.
- The SLEUTH model identifies urban growth and this paper examines the impact of urbanisation on agricultural land in the region in the near future.
- The destruction of agricultural land was analyzed by creating simulations for the years 2030 and 2050 using the SLEUTH model and GEE platform.

***Corresponding Author:** Lütfiye KARASAKA, lkarasaka@ktun.edu.tr

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ABSTRACT: In this study, it is aimed to determine the urban growth in the Selçuklu district of Konya, which is the study area with the SLEUTH model based on cellular automata, which is widely used in the modeling of urban growth and land use, and to examine the effect of urbanization on agricultural areas in the near future. In addition to the simulations carried out for the years 2030 and 2050 starting from 2015, which was determined as the last control year in the model, the simulation results of the year 2022 were compared with the terrain classes obtained from the Google Earth Engine (GEE) controlled classification of the 2022 Landsat satellite image. As a result of the creation of simulation models for the years 2030 and 2050, it was concluded that 10428.75-23747.49 hectares of agricultural land will be destroyed, respectively. The SLEUTH model has modeled a total of 56468.26 hectares of agricultural land for 2022. This corresponds to 95% of the classification result for 2022, which is an important factor in examining the accuracy of the model. This study, which aims to guide decision makers and planners, shows that the use of the SLEUTH model has strong implications for the planned examination of future land use.

Keywords: *Agricultural Land, GEE, Remote Sensing, SLEUTH, Urban Growth*

1. INTRODUCTION

Urbanization is generally defined as the process of population flow from rural areas to urban areas [1]. The increasing population around the world day by day leads to urbanization problems and some changes in urban areas. According to [2], while the world's urban population was close to 4.2 billion in 2018, this number is expected to reach 6.7 billion in 2050. According to the report, while 30% of the world's population lived in cities in 1950, this rate was 55% in 2018. In the forecasts for 2050, the urban population is expected to be around 68%. As a result of the urbanization process in the world, urban areas are growing and accordingly, the pressure on the administrative units is increasing. Population migration from rural areas to urban areas has been one of the most important urban problems arising from regional imbalance and causing uncontrolled urban growth [3]. Irregular and unplanned growth in cities leads to the destruction of fertile agricultural and forest areas [4]. Since land is a limited resource, the pressure on it increases with population growth. For this reason, there is a need for studies and planning to increase productivity in land use [5]. The insecurity of access to food, which is felt strongly in the twenty-first century, is mainly due to the decreasing grain productivity and shrinking agricultural areas encountered worldwide [6]. Considering that negative fluctuations in the agricultural sector will also affect vital activities, planning and protection activities in agricultural areas gain importance. In the face of population growth, increasing urbanization rate and rapidly depleting resources, creating urban solutions with the help of developing technologies and creating sustainable cities in all dimensions have made it necessary to develop smart approaches and revealed the idea of 'smartening cities'. The approach that includes these dynamics is called 'Smart City'[7]. This systematic contemporary planning packages such as “sustainable growth”, “smart growth” and “compact city” are opposed to the dispersed and overly focused flexible [3]. New solutions such as sustainable growth and smart growth require comprehensive analysis, fragmentation and modelling of fragmented systems, from which additional pieces of

***Corresponding Author:** Lütfiye KARASAKA, lkarasaka@ktun.edu.tr

information can be generated in response to the causes, effects and chronology of urbanization rates. In addition, in the decision-making process, land managers need to examine the consequences of the urban growth process. Urban growth models meet this demand, and there is a growing number of studies in the literature in the field of modeling urban growth [8], [9], [10], [11]. Despite the disruptions in urban processes, there has been a renaissance in spatial application over the last two decades due to increasing computing power, improved spatial data availability, and the need for planning tools to assist decision services [12]. The main reason for this is; With the technological developments in recent years, traditional methods are insufficient in modeling the complex city structure. When the zoning regulation in our country is analysed, the socio-economic and physical planning process is carried out in the form of regional plans, environmental layout plans, master development plans and implementation growth plans. The application zoning plans included in the local physical plans should be prepared in accordance with the principles of the master zoning plan. Urban simulation results obtained by utilising new technologies such as geographical information systems and remote sensing methods can be taken into consideration at the planning stage, and more realistic and accurate plans can be put forward [13]. In the management of land use, many studies have been carried out using remote sensing method (RMS) with satellite images to analyse large area as well as geographic information system (GIS) technology [14], [15], [16], [17], [18]. With remote sensing, up-to-date data requirements can be met by obtaining data at various resolution levels and at the desired time. GIS, on the other hand, offers important tools in terms of both the assesment of the current situation and planning studies with its powerful analysis capabilities [19]. Models such as Von Thünen Model, Co-centred Zoning Theory Model, Centre Area Theory Model, Sector Area Theory Model are accepted as the first urban growth models. Today, many simulation models such as Cellular Automata (HO), Artificial Neural Networks (ANN), Markov Chains, SLEUTH Model, etc. have been developed in the modeling of urban growth and land use/cover changes [19]. Among the models used to investigate urban growth, cellular automaton (HO) modeling has proven its ability to capture complex land-use dynamics of urban growth [20]. This success of the model has allowed the growth of methods based on HO logic. SLEUTH is an HO-based simulation technique in which model parameters are determined according to the Monte Carlo (M-C) method. It is widely used to simulate the urban growth of many cities around the world [21], [22], [23], [24]. In Turkey, it has been used in urban growth simulations, especially in the provinces of Antalya, Izmir, Tokat, Çorum and Afyon [4], [25], [26], [27], [13]. The aim of this study is to analyze the effects of urbanization dynamics, population growth and uncontrolled urban growth on agricultural areas and environmental sustainability and to investigate the possible effects of this growth on agricultural areas in order to contribute to the implementation of sustainable urban planning in the future. In this context, simulations were created for the years 2030 and 2050 in order to determine urban growth with the SLEUTH model in Selçuklu district of Konya province and to examine the effect of urbanization on agricultural areas in the region in the near future. While creating these simulations, the data required for the SLEUTH model were mainly obtained from Landsat satellite images. The classification of satellite images was performed using Google Earth Engine. GEE is a highly efficient platform that utilises large remote sensing datasets in an online cloud-based method, performing extensive dataset processing and analysis [17], [28]. In order to increase modeling accuracy, high spatial resolution orthophoto and Sentinel satellite imagery were used for city and road data, respectively, as well as Landsat satellite images. According to the results obtained, the agricultural destruction in the study area was evaluated.

2. MATERIAL AND METHODS

SLEUTH is a cellular automata-based simulation model that determines future land use situations and change with probabilistic simulations with gridded data [29]. Modeling of urban growth with the SLEUTH model can be done on the desired date for the near or distant future. SLEUTH, an open source software, has been tested and implemented with a number of changes since its growth. Simulation methods using statistical interpretation techniques are generally based on random sampling. Monte Carlo (MC) simulation basis is one of the most preferred simulation methods. It has also affected the models in which urban growth and sprawl are determined, and simulation and prediction models have been used in many studies [3]. The MC method was also adopted in the SLEUTH model based on HO. The SLEUTH model consists of the initials of the names of the input data of slope, **Landuse**, **Exclusion zone**, **Urban**, **Transportation**, **Hillshade** input data [26]. In order for the system to function smoothly, at least four urban data, at least two each of transport and land use data, and one each of slope data, excluded layer and hillshade data are required. Land use data are required if land use changes are to be modelled in addition to urban growth. The model is based on three main stage: "Test", "Calibration" and "Forecasting". The test phase is the stage where the suitability of the input data for simulation is tested (Figure 1). The calibration phase is the most time-consuming part of the model and is completed in four steps. These are coarse calibration, fine calibration, final calibration and prediction phase. At each step, the resolution of the input data in the data sets is increased, and "the relationships between the modeled and the current state are determined with thirteen different metric values using Pearson *(r^2)* statistics [13]. These metrics are Product, Compare, Population, Edges, Clusters, Cluster Size, Lee-Sallee, Slope, %Urban, X-Mean, Y-Mean, Rad and F-Match [30]. The OSM (Optimum SLEUTH Metric) method multiplies seven of the thirteen metrics calculated at each step of the calibration to obtain a value in each iteration. With the help of the values obtained, growth coefficients are determined. In the study of [30], it is stated that if land use is to be modeled as well as urban growth, the F-match metric should be included in the method, and that the OSM method will provide strong results for SLEUTH calibration. Lee-Sallee is the ratio of the intersection and confluence of simulated and real urban areas. The highest values of this value, which is one of the thirteen calculated metrics, have an important place in determining the growth coefficients. In terms of modeling success, the value is expected to be as close to one as possible.

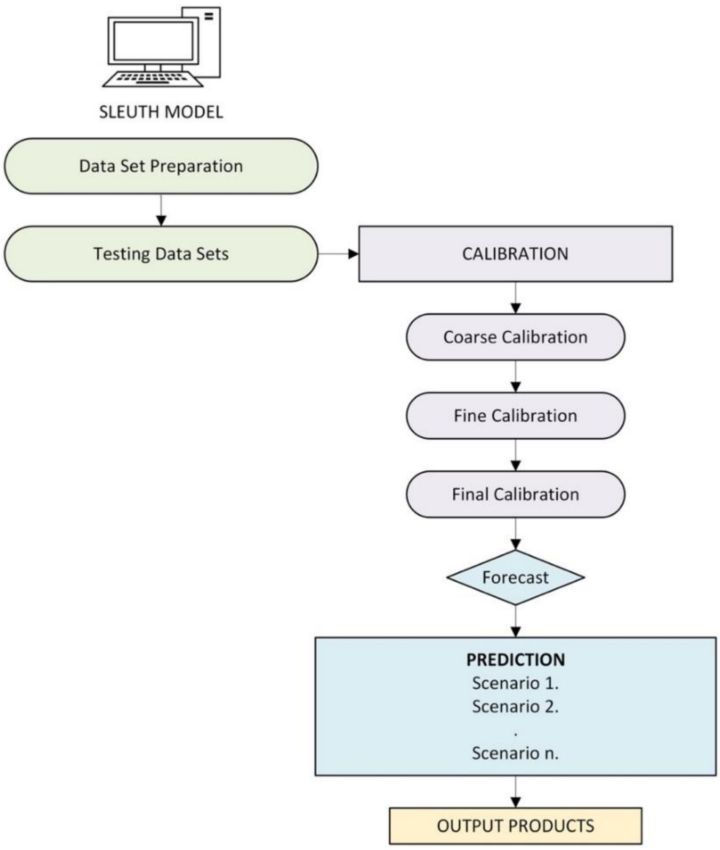

Figure 1. Basic workflow of the model

$$OSM= Compare *Pop*Edges*Cluster*Slope* X\text{-}mean*Y\text{-}mean \quad (1)$$

The final growth coefficients obtained as a result of the calibration phase are important for modeling urban growth. At this stage, the model tries to determine the parameters that are critical to be able to predict growth with the help of input data. After the parameters are determined, the estimation phase is started for urban growth simulation. The final growth coefficients obtained as a result of the calibration phase are important for modeling urban growth. Urban growth maps for the desired year are created at the estimation stage of SLEUTH with the help of growth coefficients based on the city data of the last control year. At this stage, SLEUTH establishes growth cycles for each developed year with growth coefficients. After analyzing the desired year of modeling of urban growth, the growth cycles will stop and provide statistical and visual outputs to the user.

2.2 Study Area and Data

Selçuklu district of Konya province is located between 36°52' north latitude and 32°29' east longitude. The average height of the district above sea level is 1016 meters (Figure 2). The area of the district is 1836.3 km^2 (Mevka, 2019). There are partially mountainous areas on the west side of the district, which is generally established in a plain area. In 1990, the population of the district covered about twelve percent of the provincial population, but by 2022, this rate has reached thirty percent.

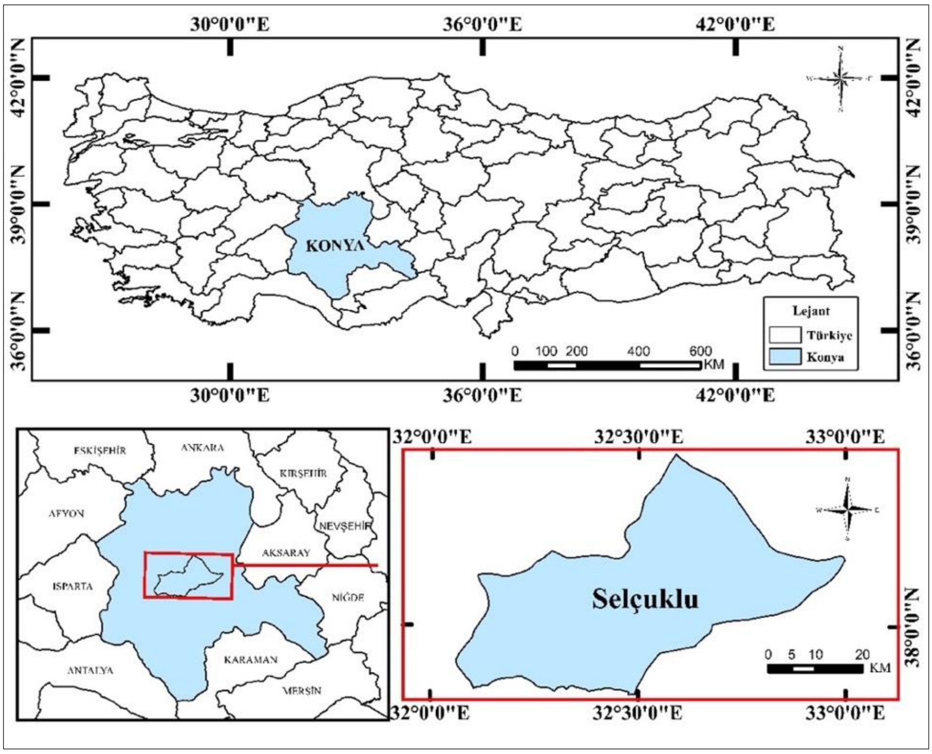

Figure 2. Study area

The nomenclature standards of the input data produced for the SLEUTH model and the sources from which they were obtained are shown in Table 1. is also shown. In addition, it is aimed to increase the accuracy to be obtained as a result of the simulation by using orthophoto and Sentinel satellite images in high spatial resolution. While creating the urban growth and land use simulation, all data were prepared in the same datum and projection, at the same spatial resolution and in the same nomenclature standard, taking into account the SLEUTH rules. The Google Earth Engine (GEE) platform, which is available for free access, was used to obtain Landsat satellite images. The data were exported in "GeoTIFF" format and evaluated as SLEUTH model input data in ArcGIS software. While preparing all the input data, a rectangular frame was drawn that enclosed the working area, so that the data contained an equal number of pixels on the basis of row*column. Blank fields that are outside the study area but included in the frame content are not included in the simulations. The frame size is 2848*1800 pixels at 30 meters, which is the best spatial resolution in the study, and the spatial resolution is 1424*900 pixels when reduced to 60 meters, and 712*450 pixels when reduced to 120 meters. All standards have been prepared with ArcGIS software in 8-bit radiometric resolution and '.gif' format.

Table 1. Input Data

Land Class	Source
Urban	GEE -Landsat 5 TM
	Landsat 7 ETM+
	Ortofoto
	GEE - Landsat 8OLI/TIRS
Transportation	Landsat 5 TM
	Sentinel 2 MSI
Land-use	GEE - Landsat 5 TM
	GEE -Landsat 8 OLI/TIRS
Slope	Alos Palsar DEM
Hillshade	Alos Palsar DEM
Excluded	Municipality – (Areas to Protest)

2.3 Input Data Processing

2.3.1. Landuse data

The SLEUTH model requires two different types of land use data. 1991 was chosen for the core year and 2015 for the last control year. The main reason why 2015 was chosen as the last control year is that the forecast simulations, which will start from 2015, are intended to be compared with the 2022 data and today's real data and used in accuracy analysis. Therefore, it was ensured that the modeled data and the actual data were compared over a 7-year time period. The choice of the year 1991 is basically the desire for the time period between the input data to be as minimal as possible. This will affect the accuracy of the products as a result of the simulations. In order to obtain land use data, controlled classification of Landsat satellite images for the relevant years was performed on the GEE platform. In this classification, the "Random Forest" algorithm was used. In the classification, five different classes are considered: forest, water, agriculture, empty and urban area. While collecting training data during the classification phase, the relevant line of code was added on the GEE platform and a total of 5000 points were marked in the class. Similarly, 20% of the training data, i.e. 1000 points, were marked automatically to test the classification accuracy.

2.3.2. Urban data

In order to create urban growth simulations with the SLEUTH model, urban data for four different years are needed. In addition to the core year 1991 and the last control year 2015, urban data for the years 2000 and 2010 were also included in the model. The reason for choosing these data is to divide the 24-year time period between the core year and the last control year into as equal intervals as possible and to consider urban growth in similar time intervals for the simulations to be created. Urban data for the years 1991 and 2015 were obtained by subtracting urban classes from land use data containing five different land classes on the GEE platform. For the city data for the year 2000, the Landsat satellite image was digitized with the help of ArcGIS software. Similarly, for the year 2010, urban areas were digitized from orthophoto at 40 cm spatial resolution. While evaluating the images of 2000 and 2010, all details that could be considered within the scope of urban areas such as buildings were subjected to digitization. For the city data for the year 2000, the Landsat satellite image was digitized with the help of ArcGIS software. Similarly, for the year 2010, urban areas were digitized from orthophoto at 40 cm spatial resolution. While evaluating the images of 2000 and 2010, all details that could be considered within the scope of urban areas such as buildings were subjected to digitization. The urban areas obtained as vector data were converted into raster data and the input data were resampled to spatial resolution standards and three different urban data were obtained.

2.3.3. Transportation Data

While preparing the road data, two separate digitisations were performed in ArcGIS software for the core and final control year. The digitisation process was ensured to cover only the main roads in the region. While obtaining this data, the main roads that can be distinguished in satellite images were obtained as vector data and then converted to raster format. If more than one road network is to be used, each of them should have a different pixel brightness value. Thus, when creating simulations with the SLEUTH model, it is possible to consider more than one scenario using the road network variable. Landsat 5 TM satellite image was used for 1991 data, and Sentinel-2 MSI satellite image at 10 meter spatial resolution was used for 2015 data to increase accuracy. After digitization, the data were included in the model in ".gif" format with spatial resolutions of 30, 60 and 120 meters. The Road Gravity coefficient, which is one of the five growth coefficients that the model tries to determine during the calibration phase, controls the realisation of urban sprawl with the effect of the road network. For the 2015 input data, Sentinel satellite image, which provides higher spatial resolution than Landsat, has been preferred. In this data with a frame size of 2848*1800 pixels, the pixels belonging to the road network were adjusted to have a brightness value of 255 and the pixels not belonging to the road network were adjusted to have a brightness value of 0 pixels and included in the model.

2.3.4. Slope, Exclusion Zone, and Shading Data

A digital elevation model is needed to produce slope and hillshade data. In this context, the data obtained from Alos Palsar DEM data were produced as 30, 60 and 120 metres resolution. The pixel brightness values of the generated slope data are in the range of 0-100. In addition, it is aimed to prevent the destruction that may occur in the archaeological sites in the study area. While obtaining external region data, it is aimed that the military zone in the district in addition to these protected areas is not included in the urban growth simulation. External region input data in GIF format and 2848*1800 pixels in size was obtained. External region data were weighted in the range of 0-100 and included in the modeling.

3. RESULTS AND DISCUSSION

After six different input data were obtained in three different data sets as 30, 60 and 120 meters resolution, the test phase of the SLEUTH model was started. At this stage, the suitability of the inputs obtained for model calibration is tested.

3.1. Calibration Process

Since the aim here is to determine the growth coefficients, in addition to the increase in spatial resolution, the coefficient ranges are narrowed at each stage and the optimum coefficient values for urban growth simulation are obtained. Another factor that is important here is the MC iterations. Even if gradually increasing the number of MC iterations at each stage of the calibration provides a disadvantage in terms of temporal factors, it will affect the simulation probabilistically in terms of bringing the coefficients closer to the most appropriate value. In the coarse calibration process, it is necessary to use the input data set with a lower spatial resolution at a ratio of 1/4 of the full resolution. Therefore, since lower resolution and larger pixel sizes are processed in the coarse calibration phase, the coefficients are determined in a shorter time than in other calibration stages. At this stage, each growth coefficient; It is tried to be determined in a total of five steps with 25-unit increments (0-25-50-75-100) in the range of 0-100. The system will perform a total of 3125 (5^5.) operations to determine the five growth coefficients. Under normal conditions, since 3125 operations are performed at this stage, the result values consist of the same number of rows. However, since land use is also modeled in this study, it is aimed to determine the growth coefficients according to the top five values of OSM values, which are the product of eight metrics. There are also studies in the literature based on the first three or top ten values of OSM values. In the study, thirteen metrics and five growth coefficients were determined in 5 hours and 14 minutes. After the coefficients were obtained, the coefficient ranges to be processed in the scenario file were determined for good calibration and the fine calibration phase was started. According to the fine calibration stage, it is aimed to bring the coefficients closer to the most appropriate value by processing at higher spatial resolution and shorter coefficient intervals. For example, the "Spread" coefficient, which is expected to take a value in the range of 0-100 units, is seen to take values in the range of 75-100 units as a result of coarse calibration. According to these results, the start and end values of the relevant coefficient should be set to 75-100 in the fine calibration phase and appropriate "Step" values should be determined to ensure that this interval is completed in five or six steps. After the coefficient ranges determined according to the coarse calibration results were processed into the scenario file, good calibration was started with 60 meter of data. Table 2 shows fine calibration result values. In the study, thirteen metrics and five growth coefficients were determined in 20 hours and 45 minutes. According to the fine calibration results, after the coefficient ranges shown in Table 3 were processed into the scenario file, the final calibration was started with 30 meters of data. In the study, metrics and growth coefficients were determined in 3 days, 6 hours and 47 minutes. It should be taken into account that if satellite images are used at high spatial resolution, hardware needs will increase linearly, otherwise it may take weeks for the final calibration phase to be concluded.

3.2 Forecast and ve Prediction

The coefficient ranges obtained in the last calibration and the input data set with full spatial resolution are used in the estimation phase (Table 4). This is where SLEUTH's self-modification comes into play and leads to changes in the coefficient values obtained from the last calibration. Table 5 shows the forecast phase result values. Accordingly, for example, although the "Breed" coefficient received the value of "9" as a result of the last calibration, it was determined as the final "11" with the self-modification feature. On the other hand, there was no change in the "Road Gravity" coefficient.

*Table 2. The highest r^2 values according to factor 1 class

	Product	Compare	Pop	Edges	Clusters	Clusters Size	Lee-Scale	Slope	%Urban	X-mean	Y-mean	Rad	F-match
Coarse	0.01240	0.85846	0.67216	0.84197	0.81858	0.54851	0.15418	0.95013	0.74539	0.90896	0.94688	0.65977	0.91705
	0.01372	0.92967	0.67640	0.89620	0.81805	0.58852	0.15749	0.79674	0.75222	0.92180	0.95578	0.66164	0.91875
	0.01372	0.92967	0.67640	0.89620	0.81805	0.58852	0.15749	0.79674	0.75222	0.92180	0.95578	0.66164	0.91875
	0.01230	0.85410	0.67389	0.83256	0.87684	0.55475	0.15280	0.88551	0.74634	0.91774	0.93796	0.66114	0.91797
	0.01122	0.95589	0.66587	0.92030	0.85003	0.52682	0.15787	0.68744	0.74611	0.92164	0.95514	0.65286	0.91884
Fine	0.01606	0.87579	0.68885	0.82983	0.99043	0.58852	0.14295	0.96742	0.75392	0.92103	0.92954	0.67260	0.91688
	0.01552	0.82264	0.70682	0.81444	0.97791	0.58741	0.14101	0.98364	0.76441	0.91447	0.93514	0.68661	0.91620
	0.01495	0.86806	0.68954	0.76031	0.96352	0.58795	0.14273	0.99962	0.75335	0.93376	0.93638	0.67217	0.91792
	0.01487	0.84829	0.69308	0.79540	0.96892	0.59939	0.14172	0.97724	0.75476	0.91229	0.92771	0.67481	0.91694
	0.01359	0.87200	0.66575	0.79512	0.99832	0.57925	0.14361	0.97155	0.73482	0.90397	0.91674	0.65255	0.91863
Final	0.01031	0.7329	0.71839	0.74135	0.99264	0.56752	0.12875	0.99995	0.7648	0.84751	0.87863	0.69884	0.91527
	0.00964	0.73173	0.71633	0.73282	0.99537	0.55149	0.12911	0.97322	0.76287	0.84969	0.88086	0.69677	0.91480
	0.00992	0.72540	0.71737	0.73565	0.99643	0.56752	0.12884	0.98275	0.76341	0.84535	0.87940	0.69771	0.91396
	0.00991	0.73892	0.71668	0.73544	0.99513	0.56752	0.12905	0.97448	0.76372	0.83838	0.87716	0.69747	0.91484
	0.00914	0.71476	0.71673	0.73682	0.99648	0.53813	0.12839	0.99044	0.76212	0.83503	0.87574	0.69675	0.91465

***Description of Metric Name**

Product; All other scores multiplied together , **Compare;** It is the ratio of the number of all modeled urban cells of the last year and the current number of urban cells of the last year, **Population**; Least squares regression score for modeled urbanization compared to actual urbanization for the control years, **Edges;** Least squares regression score for modeled urban edge count compared to actual urban edge count for the control years, **Clusters;** Least squares regression score for modeled urban clustering compared to known urban clustering for the control years, **Cluster Size ;** Least squares regression score for modeled average urban cluster size compared to known average urban cluster size for the control years, **Lee-Scalle**; A shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years, **Slope;** Least squares regression of average slope for modeled urbanized cells compared to average slope of known urban cells for the control years, **% Urban;** Least squares regression of percent of available pixels urbanized compared to the urbanized pixels for the control years, **X-Mean**; Least squares regression of average x_values for modeled urbanized cells compared to average x_values of known urban cells for the control years, **Y-Mean;** Least squares regression of average y_values for modeled urbanized cells compared to average y_values of known urban cells for the control years, **Rad;** Least squares regression of standard radius of the urban distribution, i.e. normalized standard deviation in x and y, **F-Match**; A proportion of goodness of fit across landuse classes [30].

Table 3. Calibration result values

	Calibration interval values			Cofficient name					
	Start	Step	Stop	Diffusion	Breed	Spread	Slope	Road Gravity	OSM
Coarse	0	25	100	1	1	100	25	75	0.298240
	0	25	100	1	1	75	1	50	0.297321
	0	25	100	1	1	75	1	75	0.297321
	0	25	100	1	1	100	25	1	0.294008
	0	25	100	1	1	75	1	1	0.276863
Fine	0	5	20	1	10	75	1	80	0.376536
	0	5	20	1	15	75	5	20	0.356902
	75	5	100	1	10	75	5	60	0.351793
	0	5	25	1	15	75	10	20	0.343628
	0	20	100	1	5	85	20	20	0.340829
Final	0	5	20	5	9	75	20	35	0.2640575
	5	2	15	5	9	75	20	50	0.2547713
	75	2	85	5	9	75	15	35	0.2547018
	0	5	20	5	9	75	20	20	0.2540900
	20	15	80	5	9	77	20	20	0.2491760

Table 4. Forecast result values

Coefficients	Interval		
	START	**STEP**	**STOP**
Diffusion	5	1	5
Breed	9	1	9
Spread	75	1	75
Slope	20	1	20
Road Gravity	35	1	35
Monte Carlo Iteration	**100**		
Resolution	**30 meter (2848*1800 Pixel)**		

Table 5. Forecast result values

Year	*X-mean*	*Y-mean*	*Diffus.*	*Breed*	*Spread*	*Slp*	*RG*	*Grw_rate*
2000	1382.86	1345.05	5.41	9.75	81.21	19.60	35.04	9.74
2010	1422.77	1210.59	5.98	10.77	89.71	18.50	35.15	6.83
2015	1437.41	1155.15	6.29	11.31	94.29	17.61	35.24	6.20

The final growth coefficients obtained as a result of the forecasting phase, which was completed in a short time, were Diffusion:6; Breed:11; Spread: 94; Slope:18; Road Gravity: 35. These coefficients were used in the analysis of urban growth and modeling of land classes. With the estimation phase, it is aimed to create simulation models for the years 2030 and 2050. Thus, starting from 2015, the last control year, simulation models were created for each year with the growth coefficients determined and the desired forecast year was modeled.

As a result of the SLEUTH estimation phase, two different visual outputs were obtained: urbanization and land use. Figure 3 and Figure 4 show the result of urbanization simulation. The result of the spread and road gravity coefficients, which are the growth coefficients determined as a result of the calibration, was higher than the other coefficients, and the output was reflected in the products. Accordingly, the pixels of urban areas have developed around the road network and urban growth has been realized.

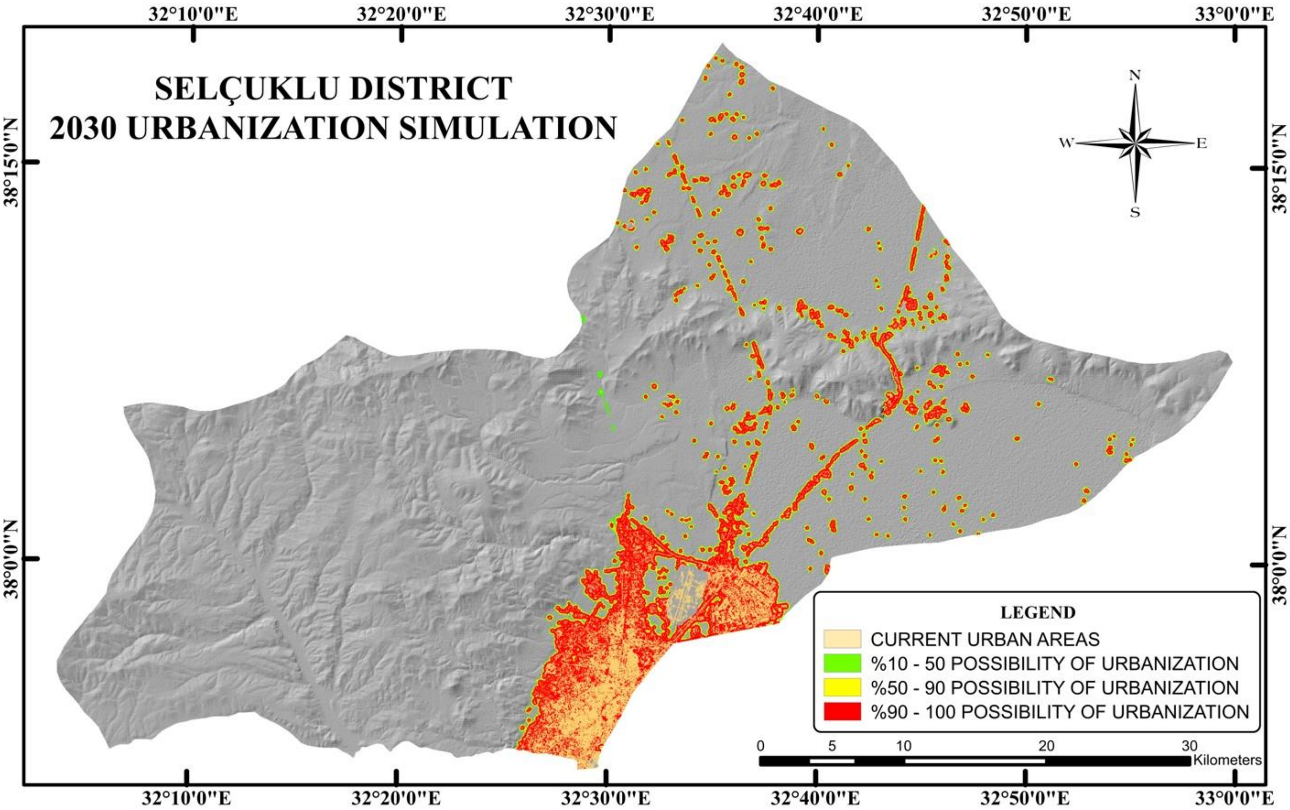

Figure 3. 2030 Urbanization Simulation

These output products, which are obtained as a result of simulations carried out for each year using growth coefficients starting from 2015, the last control year, until 2050, deal with urban sprawl probabilistically. Figure 4. shows the urbanization situation that will occur with a probability of 10-50%, 50-90% and 90-100%. These probabilistic distributions are organized in the scenario file of the SLEUTH model. If desired, these intervals can be arranged with a 10% increase. However, it has been evaluated in three different possible ranges, both because of the confusion that may occur in the visual output and because it is desired to deal with the urban sprawl situation in a more general way. Even if urbanization occurs with a 90-100% probability in the boundaries of the military zone, which is one of the areas excluded from growth during the preparation of input data, the fact that no urbanization was seen within the area increased the confidence in the external region layer.

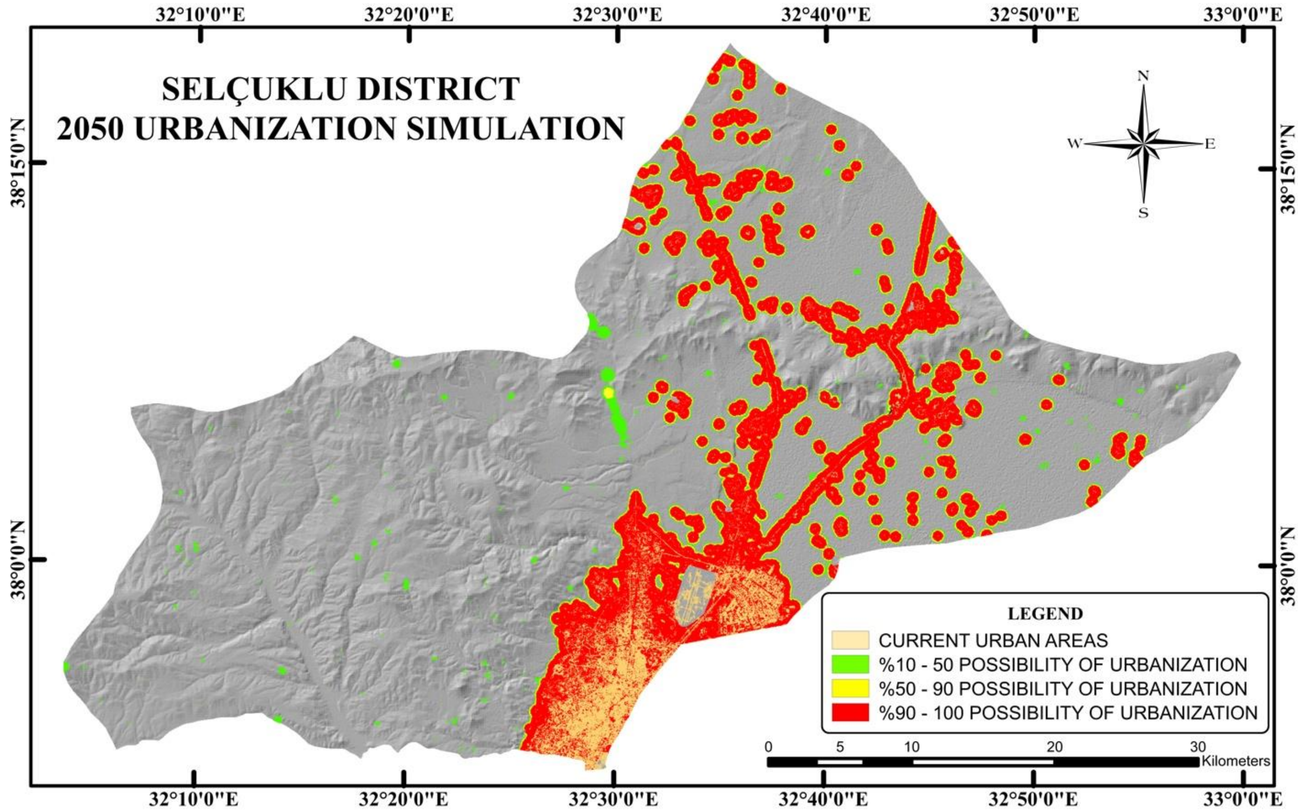

Figure 4. 2050 Urbanization Simulation

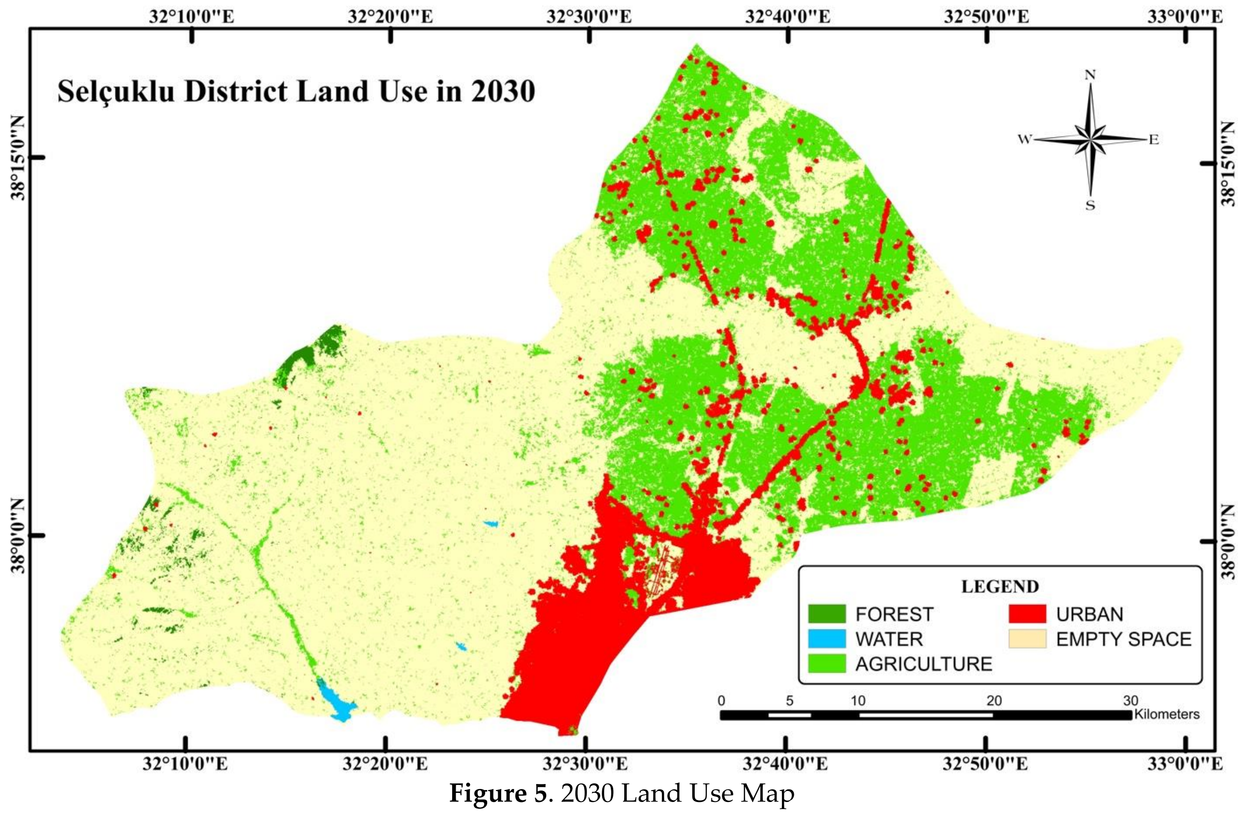

Figure 5. 2030 Land Use Map

The land use maps obtained as a result of the estimation phase are shown in Figure 5 and Figure 6. SLEUTH modeled the land class transitions based on pixel neighborhoods with the help of determined growth coefficients on land classification input data as a result of simulations.

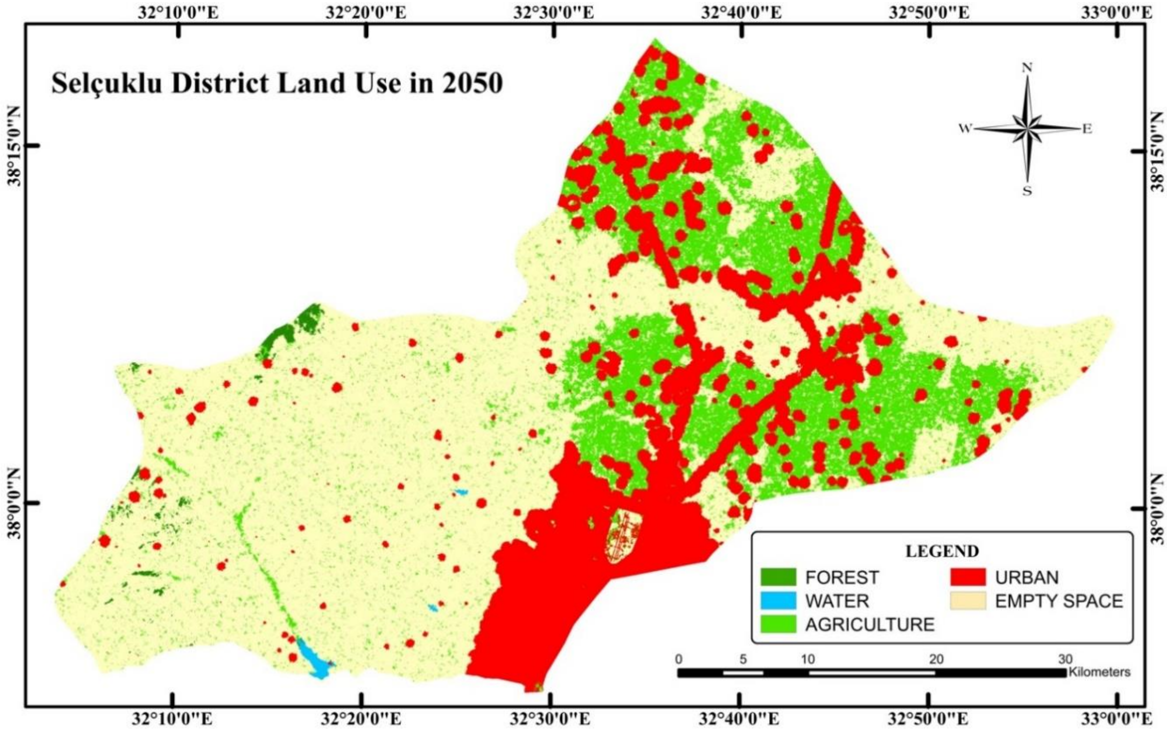

Figure 6. 2050 Land Use Map

Land use maps were evaluated on a pixel basis in ArcGIS software and change analysis of land classes was made for two different years, modeled as shown in Table 6 and Table 7. Based on the fact that each pixel is 30*30 meters in the output products, the change in the areas corresponding to all land classes is handled in hectares (ha). As in the land use input data, five different classes were evaluated. Accordingly, a class can be assigned to the class it belongs to, or it can be converted into different classes. Thus, it can be interpreted as the areas that turn into different classes are destroyed. In this context, while there were 62042.94 hectares of agricultural land in 2015, according to the modeling results of 2030 and 2050, these areas have mostly turned into urban areas. In 2030, a change of 15.22% can be mentioned with 9445.95 hectares in agricultural lands that have turned into urban areas. By 2050, the change of 21862.44 hectares corresponds to 35.24% of the existing agricultural areas. Similarly, while it is predicted that the existing vacant lands will be transferred to agricultural activities in 2030, it has been determined by the model that the areas to be transferred to agricultural activities in the twenty-year period between 2030 and 2050 will lag behind those that will be converted into urban areas. This will be one of the factors affecting the production of agricultural products in Selçuklu district.

Table 6. Destruction analysis for 2030

		2030						
	Land classes(ha)	Empty	Urban	Forest	Water	Agriculture	Other	Total
2015	Empty	112772.70	4756.32	59.67	10.08	4811.22		122409.99
	Urban		6858.63					6858.63
	Forest	163.17	7.11	1139.04	2.34	12.87		1324.53
	Water	6.21	1.98	0.18	348.57	0.18		357.12
	Agriculture	5795.55	9445.95	10.44	1.08	46789.92		62042.94
	Other						268382.79	268382.79
	Total	118737.63	21069.99	1209.33	362.07	51614.19	268382.79	**461376**

Table 7. Destruction analysis for 2050

		2050						
	Land classes(ha)	Empty	Urban	Forest	Water	Agriculture	Other	Total
2015	Empty	103641.93	12217.14	117.18	21.33	6412.41		122409.99
	Urban		6858.63					6858.63
	Forest	342.00	59.94	892.53	7.56	22.50		1324.53
	Water	9.45	9.45	0.09	337.77	0.36		357.12
	Agriculture	8293.50	21862.44	25.83	0.99	31860.18		62042.94
	Other						268382.79	268382.79
	Total	112286.88	41007.60	1035.63	367.65	38295.45	268382.79	**461376**

3.3. Testing model accuracy

There are two different evaluations for accuracy analysis. The first of these is the analysis of the accuracy of the controlled classifications obtained with the "Random Forest" algorithm on the Google Earth Engine platform while obtaining input data. Producer and user accuracies were calculated from the error matrices. At the same time, the Kappa Statistical values of each classification are shown in Table 8.

Table 8. Accuracy analysis

Classification	**1991/1**	**1991/2**	**2015**	**2022**
Kappa	0.93	0.96	0.94	0.96

The year 2022 was considered appropriate for the investigation of model accuracy. Thus, the accuracy analysis was carried out for a 7-year time period starting from 2015, the last control year. Table 9 shows the comparison of the land classification performed on the GEE platform for the year 2022 and the SLEUTH model predictions for the same year on the basis of area. When the table is examined, it is seen that there are 59594.88 hectares of agricultural land according to the classification result and 74% of these lands and 43978.32 hectares are modeled by SLEUTH. In addition, SLEUTH modeled that there will be a total of 56468.26 hectares of agricultural land for 2022, including those that have converted from other land classes to agricultural land classes. This corresponds to approximately 95% of the classification result for 2022. It should not be forgotten that factors such as the realism of the classification made on the GEE platform and the temporal and spatial resolutions of the input data may affect this accuracy analysis.

Table 9. Model accuracy forecast for 2022

		2022 SLEUTH Model Prediction					
	Land classes(ha)	Empty	Urban	Forest	Water	Agriculture	Total
2022 GEE Classification	Empty	107357.16	2030.28	652.63	6.49	10919.32	120965.88
	Urban	1414.02	8410.84		0.72	1561.52	11387.10
	Forest	67.32	0.54	590.93	0.27	7.03	666.09
	Water	12.80	11.52	9.99	342.88	2.07	379.26
	Agriculture	11919.26	3668.31	18.09	10.90	43978.32	59594.88
	Total	120770.56	14121.49	1271.64	361.26	56468.26	192993.21

5. CONCLUSIONS

In the early 19th century, the process of analysing and planning urban growths, which started with agricultural factors, continued towards the end of the 20th century with the modelling of the growth of compact cities. Today, urban growth models are widely used by decision makers and urban planners as future planning is based on more solid foundations in the light of technological developments. In this study, using the SLEUTH urban growth model, simulations were created for the years 2030 and 2050 in the Selçuklu region and the destruction of agricultural areas was analysed. According to the 2015-2030 simulation result, 15253.02 ha of agricultural land will be destroyed by turning into different classes. On the other hand, 4824.27 ha of land will be transformed into agricultural land of different classes. Therefore, it is concluded that there will be a total of 51614.19 ha of agricultural land in 2030 and 10428.75 ha of agricultural land will be destroyed with a rate 16.81% compared to 2015. According to the 2015-2050 simulation result, 30182.76 ha of agricultural land will be destroyed by transforming into different classes. On the other hand, 6435.27 ha of land will be turning into agricultural land of different classes. Therefore, it is concluded that there will be 38295.45 ha of agricultural land in total in 2050 and 23747.49 ha of agricultural land will be destroyed with a ratio of 38.28 % compared to 2015.

DECLARATION OF ETHICAL STANDARDS

The authors declare that study complies with all applicable laws and regulations and meets ethical standards.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Author 1: Investigation, Software, Validation, Visualization, Writing- review and editing,
Author 2: Resources, Investigation, Software, Formal analysis, Writing –original draft

DECLARATION OF COMPETING INTEREST

The authors declare that have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY

Data available on request from the authors.

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