REPUBLIC OF TURKEY
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GENERAL DIRECTORATE OF COMBATING
DESERTIFICATION AND EROSION

Land Productivity Dynamic For Land Degradation Neutrality in Ilıcak and Kum Çayı Micro Catchments of The Gediz Basin

CASE STUDY REPORT

2015

Forest and Water are Life.

CONTENTS

1 INTRODUCTION

Land degradation is a complex and dynamic phenomenon and, therefore, is difficult to monitor and assess (Sommer et al, 2011). Over the past 50 years humans have changed ecosystems, more rapidly than in past ages, to meet demands for resources. It is increasingly clear that environmental degradation and resource depletion play an important role in creating or exacerbating human insecurities (Dabelko et al., 2002 and Giuseppe et al., 2008).

A main issue in any strategy aimed at the struggle against land degradation and desertification should be based on the new technical and methodological approaches to study environmental degradation process and natural catastrophes through assessing, quantifying and monitoring phenomena and to implement prevention though adequate intervention. Moreover, due to increasing changes of land use, mainly by human activities, detection of such changes, assessment of their trends and analysis of the recent land cover dynamics through the interaction of remote sensing and geographic information system provide base information for documenting land degradation. For this aim, land productivity dynamic is robust approach using new technologies/techniques to get systematic information gathering (mapping, measuring and monitoring) and to reach results which will be submit authorities to take their correct decisions.

Land productivity is here an expression of the bio-productivity resulting of all land components particularly and their interaction particularly for region-wide assessment, not just those related to human activities and direct use. Land productivity is therefore not to be confused with just agricultural productivity. In the main context of this study, land-productivity dynamic is calculated as a combination of long-term changes and current levels of efficiency of factors that define standing biomass conditions (Cherlet, et al., 2013)

In this study after derived from satellite observations between 2001 and 2015, land-productivity dynamic approach is a good reflection of the combined status of the supporting and main regulating ecosystem services that area basis for provisioning and cultural services. This report introduces two adjacent micro catchment' land-productivity dynamics map that is to be a base layer on which issues that influence the biomass condition, such as land use-land cover, vegetation density, and organic carbon, are analyzed. This process of further integrating thematic and/or area specific information, including some soil properties, climate and socio-economic aspects, will ultimately in order to determine land degradation neutrality's targets for a land degradation assessment . The main aims of this study are to determine i-) changing of land use and land cover, ii-) trends in land productivity and iii-) situation of soil organic carbon stocks.

Gediz Havzası

2 MATERIAL AND METHODS

2.1. The Study Field Description

This study was carried out in Ilıcak and Kum Çayı Micro Catchments located at the Gediz Basin. The Gediz Basin lies between northern latitudes of 38004'–39013' and southern longitudes of 26042'–29045'. It covers 2.2% of the total area of Turkey. Larger part of the alluvial plain called under the same name as the river (Gediz Plain) is within the area of Manisa Province and a smaller downstream section within İzmir Province (Figure 1). The basin covers about 18.000 km^2 and approaches a total population of 2 million. The Gediz Basin is significantly important not only agricultural activities but also has high aesthetic values both as naturally attractive environments and as habitats for certain biota.

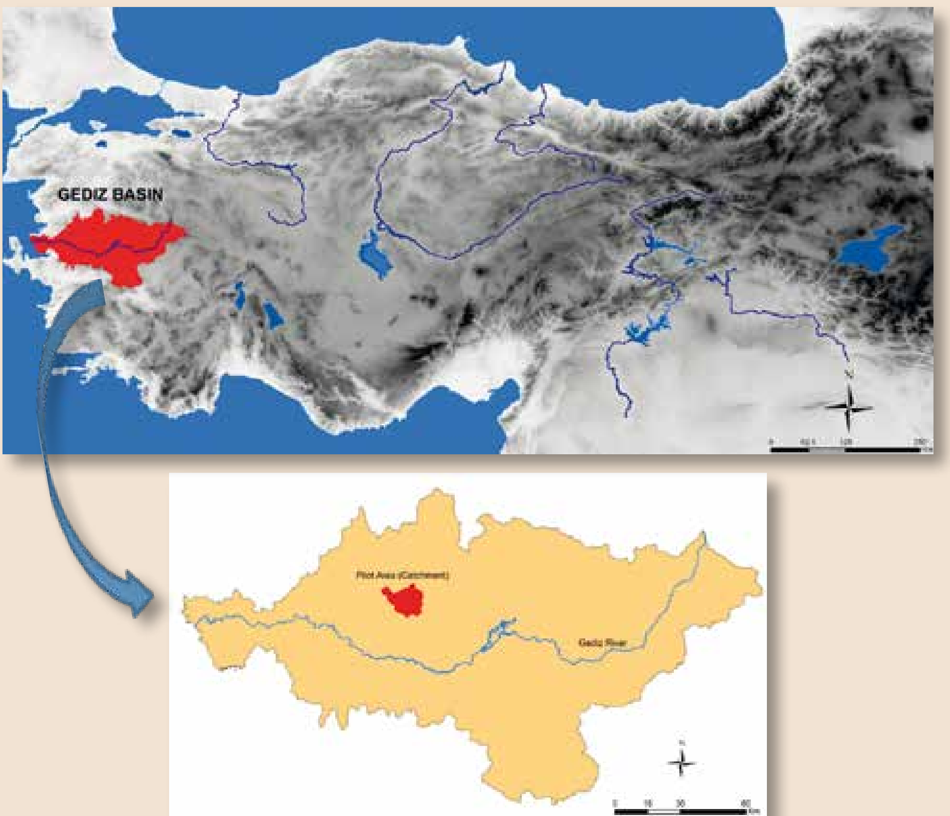


Figure 1. Location map of the selected catchment area of the Gediz Basin in Turkey

Gediz Basin suffer from to rapid demographic changes and cause of economic development particularly in the coastal zone, urbanization, industrialization, tourism and often inefficient agricultural sector as the domain causes of land degradation and also land use problems. Gediz Basin is one of the regions in where intense agricultural activities take place in Western Turkey. Erosion and soil degradation have long been causing serious problems to cultivated fields in the basin.

In order to represent some characteristics of Gediz Basin according to topographic, land use and land cover, climate etc., adjacent two small catchments were selected. It was also observed that in order to supply needs of the people in this region, the increasing pressure on natural resource has lead to the degradations by mismanagement, intensive cultivation, deforestation, overgrazing and poor irrigation practices.

There are two main reasons for selection of this pilot catchment area by taking into consideration of Land Cover-Land Use Change, Land Productivity Dynamics, Soil Organic Carbon Stock in terms of land degradation process. These are i-) artificial effects such as urbanization, industrialization, intensive agricultural activities, forest and rangeland management and so on, ii-) ecological and geomorphological properties and their variations.

Gediz Basin

This pilot area which consists of Ilıcak and Kum Çayı Micro Catchments in Gediz Basin is about 16,647 ha and its elevation changes between 70 m and 760 m from sea level. General land cover and land uses of the pilot catchment area are irrigated agriculture (cotton, grape, maize, tomato, potato, water melon etc), rainfed agriculture (olive, tobacco, wheat, barley etc.), makii, shrub land, forest, settlement and bare and dune lands. In addition, some topographic characteristic maps of this area were also given in Figure 2.

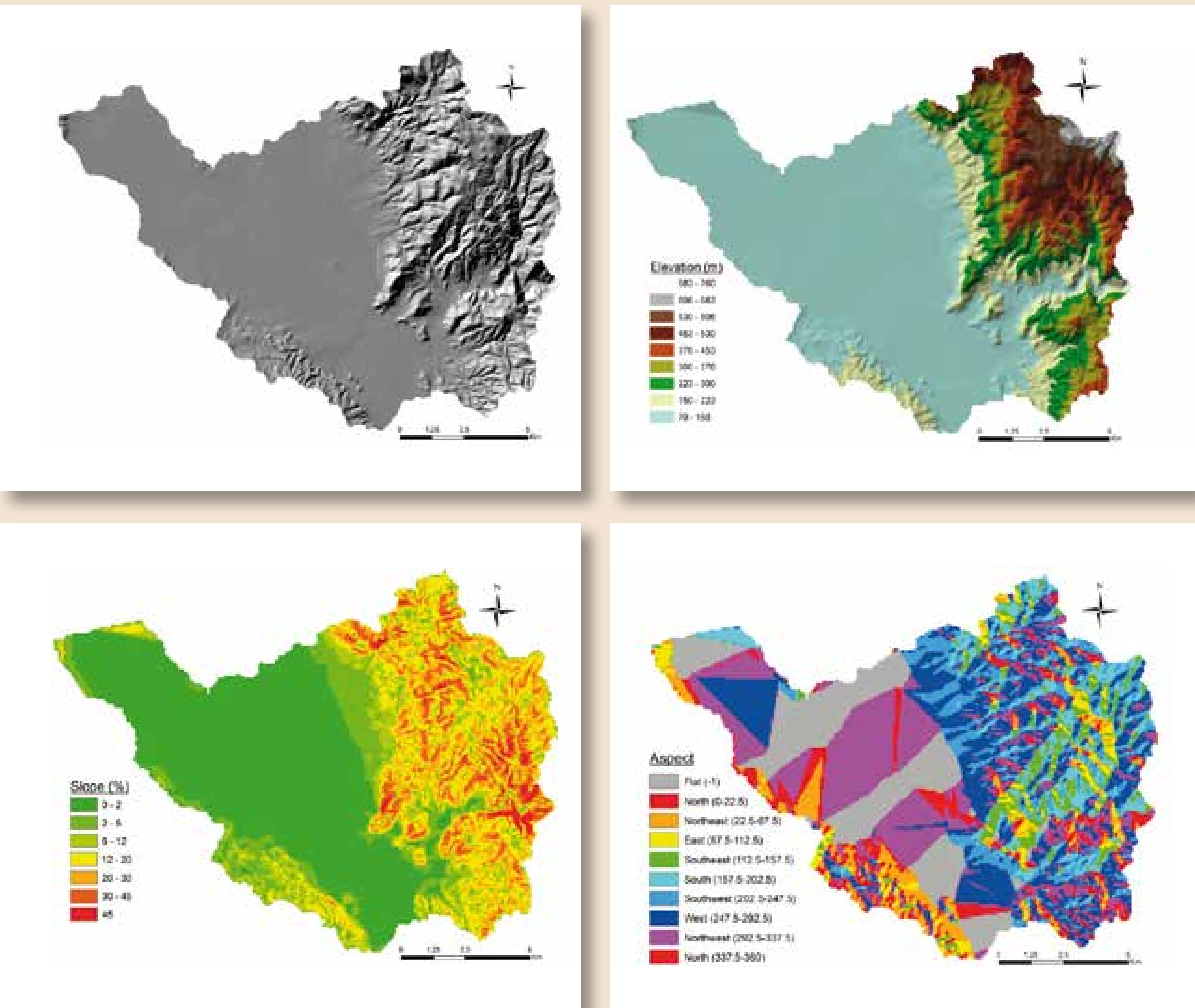


Figure 2. Some topographic properties of the Selected Catchment area

Most of the flat and gently slope area are located on west parts while; east part of the pilot watershed is hilly and mountainous. Slope is undoubtedly one of the most important determinants of soil erosion. Erosion only occurs when slope exceeds a critical angle and it increases with the absence of vegetation cover. Almost half of the study area has moderate, high and very high erosion levels (Table 1 and Figure 3). Particularly hilly and mountainous area covered by forest or pasture has been used for olive cultivation leads to increase soil erosion process.

Table 1. Soil erosion levels of the study area

Class	Area (ha)	Ratio (%)
Very low	1351.08	8.11
Low	7379.86	44.26
Moderate	2485.51	14.93
High	4456.62	26.75
Very high	992.25	5.95
Total	**16,647.32**	**100.00**

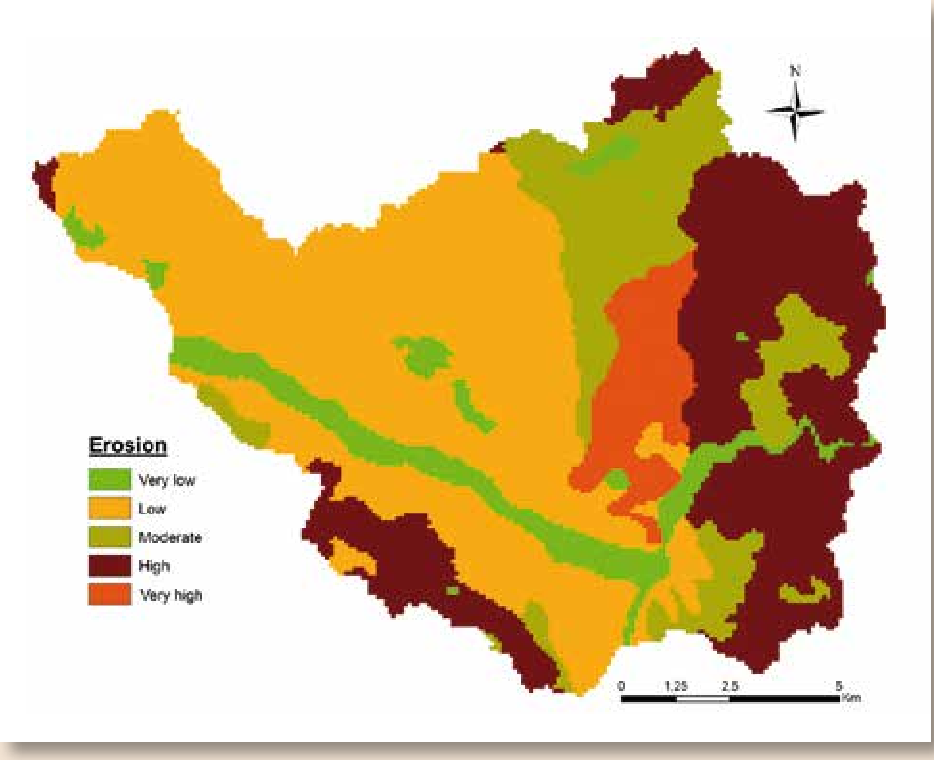


Figure 3. Soil water erosion map of the study area

2.2. Methods

2.2.1. Changing of Land Cover/Use

The detection of the multi-temporal land cover/use changes (LUC) was carried out in the case study area. This study was performed thanks to the integration of geographical information systems and remote sensing. For this purpose, Landsat7 ETM+ (Enhancement Thematic Mapper Plus) and Landsat8 OLI/TIRS (The Operational Land Imager/Thermal Infrared Sensor) satellite images that belong to May 2001 and May 2015 years and have about 30m resolution (Figure 4) were used as base data processed using ENVI 5.0v and ArcGIS 10.2v softwares.

Imagery for use in LUC should be prepared so that the before and after images match each other as closely as possible spatially, spectrally and radiometrically. In this way, the only differences detected will be those that have actually occurred on the ground. All images were rectified to UTM zone 36 N, WGS 84 using the rectified Landsat images as the reference source for image to image registration and also 1:25.000 scale digital topographic maps and 200 ground control points. Image processing procedure includes geometric and radiometric correction, image enhancement, supervised classification and accuracy assessment stages. Supervised classification was performed using the Maksimum Likelihood provided by ENVI 5.1v. In addition, for performing supervised classification, field work was applied to collect coordinate samples by using GPS tool for each land use and land cover types.

The land cover changes are coded in the 2001-2015 LUC processing following a 2 digits system based on Table 2 (Retiere et al., 2014). The first one is the class code for 2001 and the second is the class code for 2015.

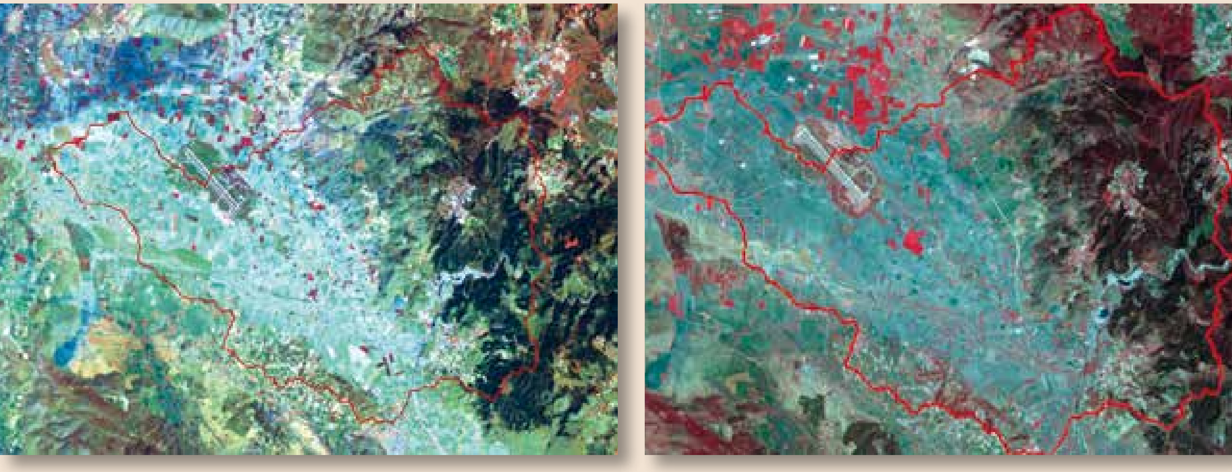


Figure 4. Landsat satellite images (2001 and 2015)

For example:

11, 22, 33, 44, 55 and 66 mean no change between 2001 and 2015;

13 means a change from forest (code 1) to cropland (code 3) between 2001 and 2015;

45 means a change from wetland (code 4) to artificial area (code 5) between 20001 and 2015.

Table 2. Land categories

Value	Categories	Short description
1	Forest	Geographical areas dominated by natural tree plants with a cover of 15% or more. This class also includes: - mosaic tree and shrub (>50%) / herbaceous cover - seasonally or permanently flooded with fresh water
2	Shrubs, grasslands, and sparsely vegetated area	Geographical areas dominated by: - natural shrubs; or - natural herbaceous plants; or - sparse natural vegetation with a cover of 15% or less; This class also include: - mosaic natural vegetation (>50%) / crops - mosaic herbaceous cover (>50%) / tree and shrub
3	Cropland	Geographical areas dominated by: - herbaceous crops; or - woody crops; or - mixed herbaceous and woody crops; This class also include: - mosaic crops (50%) / natural vegetation
4	Wetlands and water bodies	Geographical areas dominated by: - shrub or herbaceous vegetation, aquatic or regularly flooded; or - mangroves or - water bodies
5	Artificial areas	Geographical areas dominated by artificial surfaces, including urban and associated areas (e.g. urban parks), transport infrastructures, industrial areas, burnt areas, waste deposits, extraction sites.
6	Bare land and other area	Geographical areas dominated by : - bare areas or - snow and glaciers

2.2.2. Accuracy assessment of land cover/use

Classification accuracy assessment is necessary for comparing the performance of various classification techniques. A most common and typical method used by researchers to assess classification accuracy is the use of an error matrix. It can be also called as a contingency table. This table produce many statistical measures of thematic accuracy including "overall classification accuracy", percentage of "omission error", "commission error" by category, and KHAT coefficient (an estimate of the Kappa coefficient, an index that relays the classification accuracy after adjustment for change agreement) (Congalton and Oderwal, 1983)

The importance and power of the Kappa analysis is that it is possible to test if a land use and land cover map is significantly better than if the map had been generated by randomly assigning labels to area (Congalton, 1996). Kappa coefficient lies typically on a scale between 0 and 1, where the latter indicates complete agreement, and is often multiplied by 100 to give a percentage measure of classification accuracy. Kappa values are also characterized into 3 groupings: a value greater than 0.80 represents strong agreement, a value between 0.40-0.80 represents moderate agreement, and a value below 0.40 represents poor agreement (Congalton, 1996). A preliminary accuracy assessment was performed on five post classifications, which are forest cover, shrubs, grasslands and sparsely vegetated areas, cropland, wetlands and water bodies.

2.2.3. Determination of NDVI

In this study, Landsat7 ETM+ and Landsat8 OLI images were used for spatial distribution of plant density. These images belong to 2001 and 2015 years. Landsat images were cut the part of the study area. A single-band NDVI image map was converted into using NDVI functions. The NDVI is a simple numerical indicator that can be used to analyse the remote sensing measurements, from a remote platform and assess whether the target or object being observed contains live green vegetation or not (Demirel et al., 2010).

The normalized difference vegetation index (NDVI) is one of the simplest and most frequently used indices in plant studies (Bonneau et al. 1999, Edwards et al. 1999). It is a ratio-based index featuring a linear relationship between the near-infrared and red spectral bands, and can be calculated as (Tucker 1979, Sabins 1987, Campbell 1996, Jensen 1996, Bonneau et al. 1999, Edwards et al. 1999, ERDAS 2003, USGS 2006):

$$NDVI = \frac{(Near - \inf rared - \mathrm{Re}\,d)}{(Near - \inf rared + \mathrm{Re}\,d)}$$

The NDVI produces a single band of data with values ranging from -1 to + 1, where higher values indicate more, or healthier, vegetation (Bonneau et al. 1999, Edwards et al. 1999). NDVI values can be stretched to an unsigned 8-bit image varying between 0 and 255 in ERDAS Imagine software (ERDAS, 2003). Values close to 255 indicate the highest possible density of green leaves, while values close to 0 indicate the lowest possible density of green leaves or bare areas. Obtained NDVI map classified equally spaced four-class options using ArcGIS 10.1 GIS software and has been named using BB (Braun - Blanquet 1964) (Table 3).

Tablo 3. Braun-Blanquet (BB) örtü-çokluk ölçekleri (Braun-Blanquet 1964).

BB (%)	BB	NDVI Classes	NDVI classes	NDVI Values
5<; Few individuals	1	1	very weak	46-101
5<; numerous individuals	1	1	very weak	46-101
5-25	2	1	very weak	46-101
25-50	3	2	weak	102-159
50-75	4	3	Moderate	160-215
<75-100	5	4	Intensive	216-255

2.2.4. Trends in Land Productivity Dynamic

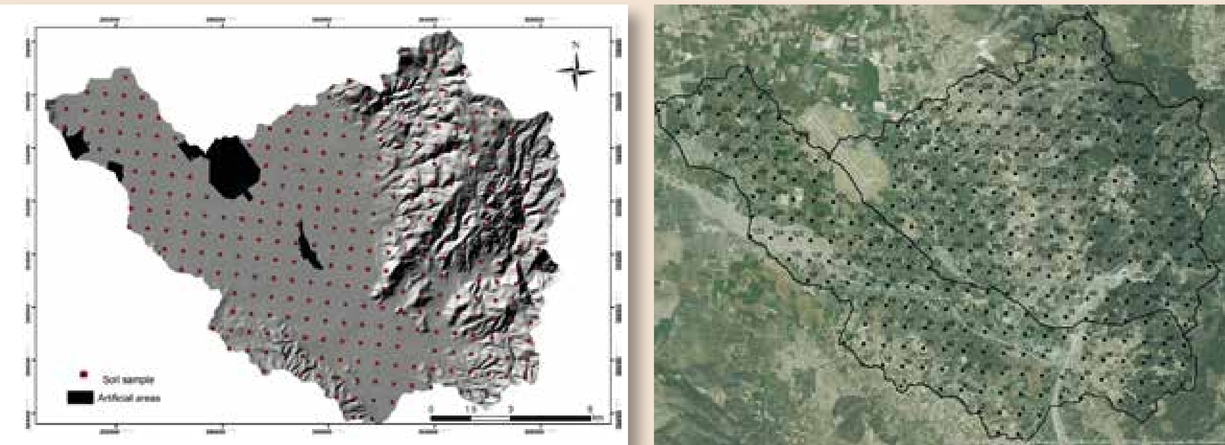
The term "dynamics of land productivity" refers to the fact that the primary productivity of a stable land system is usually highly variable between different years/vegetation growth cycles as a function of natural (semi-natural systems) or partially human induced adaptation and resilience to diverse environmental conditions and human intervention. Hence a land system's primary productivity assembles rather a dynamic equilibrium than a linear evenly evolving continuum (Retiere et al., 2014). The term land-productivity effectively captures variations in the rate, quantity and timing of standing biomass production of an ecosystem. The qualitative classes do not directly correspond to a quantitative measure (e.g. t/ha of Net Primary Productivity- NPP) of lost or gained biomass productivity, nevertheless there is an indirect relationship. The data set provides 5 qualitative classes of land productivity trends given in Table 4. The 5 classes are rather a qualitative combined measure of the intensity and persistence of negative or positive changes in over the observed period of Land Cover/Land Use and NDVI. Potentially negative trends are coded as 12, 13, 15, 23, 25, 26, 35, 36, 43. Potentially positive trends are coded as 51, 52, 53, 21, 31, 32, 61, 62, 63 (Retiere et al., 2014).

Table 4. Arazi verimliliği dinamikleri sınıfları

Value	Description
1	Declining productivity
2	Early signs of decline
3	Stable, but stressed
4	Stable, not stressed
5	Increasing productivity

2.2.5. Situation of Soil Organic Carbon Stocks

The study site was divided into 700m x 700m grid squares (Figure 5). The total of 319 grid points was obtained and while 320 soil samples were collected from surface soil (0-30 cm), 300 soil samples were taken from subsurface (30-60 cm) depths of each grid centre. Soil samples also represent for different topographic positions and land use/land cover types.



Resim 5. Harita üzerinde araştırma alanında toprak örnekleri alınan noktalar

The samples were transported to the laboratory. The soil samples were crumbled gently by hand without root material. These samples were used to determine some physico-chemical properties such as texture, bulk density, and organic matter. Selected soil properties were determined by the following methods: Bulk density (Blacke and Hartge, 1986) and organic matter was determined in air-dry samples using the Walkley-Black wet digestion method (Nelson and Sommers, 1982).

For each soil depths, SOC density was estimated with the following equation:

$$\mathrm{SOCD_D} = \frac{(1-\delta i\%)x\ \rho i\ x\ Ci\ x\ Ti}{100}$$

Where; SOCDD represents the SOC density of a soil depth D (cm); δi % represents the volumetric percentage of the fraction >2 mm (rock fragments), ρi is the bulk density (g.cm–3), Ci is the SOC content (ton.ha–1), and Ti represents the thickness (cm) of the layer i.

Interpolation and statistical analysis

Geostatistical method was used to generate SOC distribution map of the study area for surface and sub surface soils for both depth, values of SOC were described with classical statistics (mean, standard deviation, maximum and minimum mean, and coefficient of variation, Skewness, Kurtosis). In addition, range, nugget and sill variance values were determined using semi-variograms. The degree of spatial dependence of a random variable Z(xi) over a certain distance can be described by the following semivariogram function:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{n} (Z_{(x_i)} - Z_{(x_i+h)})^2$$

Where γ(h) is the semivariance for the interval distance class h, N(h) is the number of pairs of the lag interval, Z(xi) is the measured sample value at point i, and Z(xi+h) is the measured sample value at position (i+h). To determine spatial variability of SOC variables, the isotropic semivariogram models as spherical and exponential were used for both depths.

The isotropic spherical model:

$$\gamma(h) = \begin{cases} C_0 + C\left[\dfrac{3h}{2a} - \dfrac{1}{2}\left(\dfrac{h}{a}\right)^3\right] & 0 \le h \le a \\ C_0 + C & h > a \end{cases}$$

The isotropic exponential model:

$$\gamma(h) = C_0 + C\left[1 - \exp\left(\frac{-h}{a}\right)\right]$$

Where; Co is the nugget variance ≥0, C is the structural variance ≥Co, (Co+C) is the sill variance, and is the range of spatial correlation.

Geostatistical software (GS+ 7.0, 2007) was used to construct semivariograms and spatial structure analysis for variables. In addition, maps of SOC variables for each depth (surface and subsurface soils) were produced by kriging technique (Isaaks and Srivastava, 1989) using ArcGIS 9.3v geography information system program.

All statistical analysis was carried out in SPSS13.0 (SPSS Inc. Chicago I11inois, USA). An analysis of variance (ANOVA) was performed to evaluate if land use and land covers have a relationship with SOC that is significant beyond that which would expected by chance.

3 RESULTS and DISUCSSIONS

3.1. Changing of Land Cover/Use

Land Cover Change would be considered especially for critical transitions from semi-natural land cover classes (Forest, shrubs, grasslands and sparsely vegetated areas) to cropland and to artificial surfaces, from cropland to artificial surfaces as well as from cropland to semi-natural land cover types.

Classified images of 2001 and 2015 years were generated (Figure 6 and Figure 7) and the amount of changing area for land use and land cover types was given in Table 5. In addition, results of accuracy analysis were given in Table 6 and Table 7 for each year. From 2001 to 2015 forest land increased about 321.8 ha (1.93%) due to afforestation whereas shrub, grassland, sparsely vegetated areas decreased about 6.35% due to mostly occupied by artificial area and croplands. It was determined also increasing area in artificial and croplands that cause negative effect on LDN. The biggest negative changing was found in shrub, grassland, sparsely vegetated area, on the other hand forest area has positive influence on it. There is no significantly change in water body.

Table 5. Image classification area and relative change in Ilıcak and Kum Çayı Micro Catchments

Land cover/use Class	2001		2015		Change between 2015-2001 %	Effect on LDN
	ha	%	ha	%		
Forest	2534.8	15.23	2856.6	17.16	1.93	+
Shrub, grassland, sparsely vegetated area	5802.8	34.86	4746.6	28.51	6.35	-
Crop lands	7128.0	42.82	7275.2	43.70	0.88	-
Wetland and water body	10.0	0.06	10.0	0.06	0.00	no change
Artificial area (settlement, road, airport etc.)	1171.4	7.04	1758.6	10.56	3.52	-
Total	16647.0	100	16647.0	100		

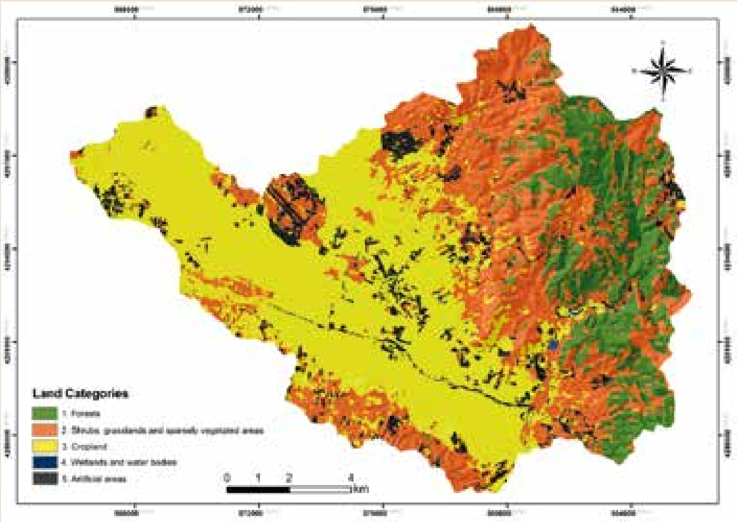


Figure 6. Map of land use and land cover types for 2001.

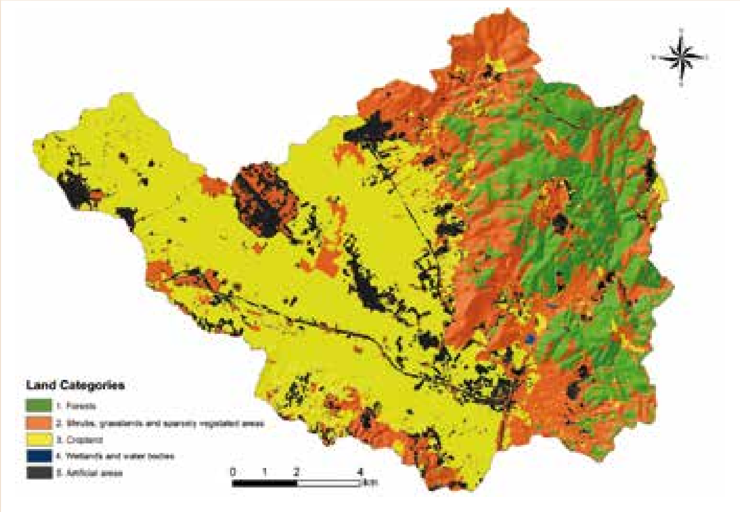


Figure 7. Map of land use and land cover types for 2015.

Accuracy assessment was critical for a map generated from any remote sensing data and final step of the classification process. The goal is to quantitatively determine how effectively pixels were groups into the correct land cover classes. The "Accuracy Assessment" tool was used to evaluate the accuracy of the classified image, based on 200 control points of satellite images of 2001 and 2015 separately in the field.

The referenced values were recorded on the "Region of Interest" in ENVI 5.1v. These points were used as references for the accuracy assessment of satellite images of 2001 and 2015 years respectively.

Error matrix is in the most common way to present the accuracy of the classification results (Fan et al, 2007). Overall accuracy, user's and producer's accuracies, and the Kappa statistic were then derived from the error matrices for land use classes. Kappa analysis is a discrete multivariate technique used in accuracy assessments (Moller-Jensen 1997). According to Congalton (1996), our analysis results showed that producer's accuracy and user's accuracy of individual classes for 2001 and 2015 maps are greater than 0.80 (80%) representing strong agreement. Kappa coefficient for each image was given in Table 6 and Table 7.

Table 6. The results of accurate analysis in 2001.

Class	Forest	Grassland	Cropland	Wetlands	Artificial areas	Column Total	Producer Accuracy	User Accuracy
Forest cover	40	2	0	0	0	42	100	95.24
Shrubs	0	33	1	0	8	42	82.50	78.57
Cropland	0	0	35	0	2	37	87.50	94.59
Wetlands	0	0	0	40	0	40	100	100
Artificial areas	0	5	4	0	30	39	75	76.9
Total	40	40	40	40	40	200		
Overall Accuracy = **% 86.25** Kappa Coefficient = 0.8167								

Table 7. The results of accurate analysis in 2015.

Class	Forest	Grassland	Cropland	Wetlands	Artificial areas	Column Total	Producer Accuracy	User Accuracy
forest cover	38	2	1	0	0	41	90.48	95
Shrubs	2	34	1	0	4	41	85	82.93
Cropland	0	2	35	0	1	38	91.11	93.14
Wetlands	0	0	0	40	0	40	100	100
Artificial areas	0	2	3	0	35	40	87.50	83.33
Total	40	40	40	40	40	200		
Overall Accuracy = **% 88.62** Kappa Coefficient = 0.8482								

3.2. Changing of NDVI between 2001 and 2015 years

Indices developed for vegetation hold important place in remote sensing technology and they are commonly used. One of them is Normalized Difference Vegetation Index (NDVI) which is developed for vegetation and accepted in worldwide. In this study, spatial distribution of plant density of the study are in 2001 and 2015 years were mapped using Landsat7 ETM+ (Enhancement Thematic Mapper Plus) and Landsat8 OLI/TIRS (The Operational Land Imager/ Thermal Infrared Sensor) images, respectively and that maps were showed Figure 8 and Figure 9.

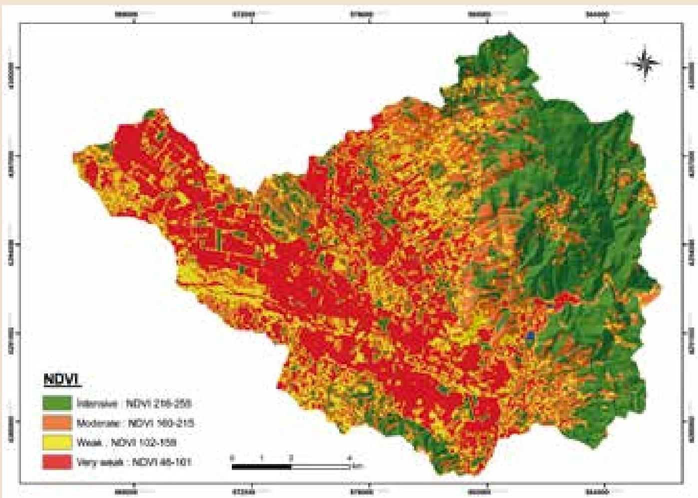


Figure 8. Map of the NDVI classes for 2001.

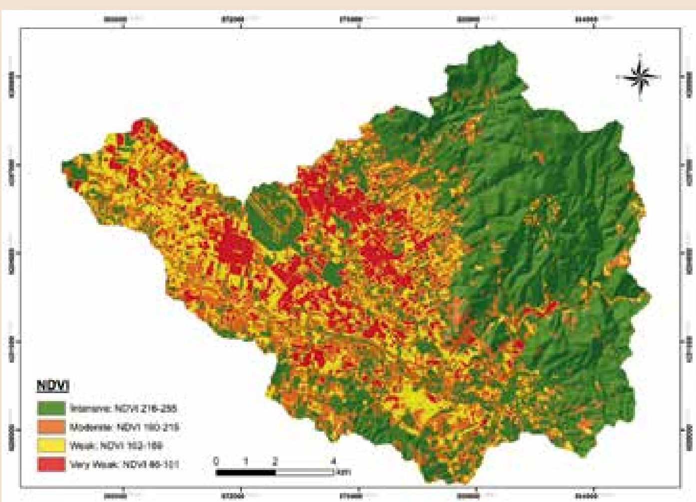


Figure 9. Map of the NDVI classes for 2015.

Obtained NDVI maps were classified as very weak, weak, moderate and intensive plant density classes for the first time by utilizing Braun Blanquet cover abundance classes (BB) and geographic information systems (GIS) and their area and ratio were given in Table 8. According to 2001 image NDVI analysis, the results of the study indicated that the majority of the study area takes place in the intensity class (32.5 %) and very weak density class. This were followed by weak (18.2 %) and moderate (17.2 %).

In addition to that, when taking into consideration of NDVI maps for 2015, the most common area has intensive class (52.5%) followed by moderate (16.8%), weak (16.7%) and very weak (14.1%). Potentially negative and positive trend were also given in this table. It can be seen that very weak, weak lands have decreased, which leads to positive trend. In addition to that intensive plant density area has increased so, it has positive trend. On the other hand, moderate density area has negative trend.

Tablo 8. Alan ve yüzde olarak NDVI sınıfları dağılımı

NDVI Class	2001		2015		Change (%)	Trend
	Area (ha)	Ratio (%)	Area (ha)	Ratio (%)		
Very weak	5353.1	32.2	2339.6	14.1	18.1	+
Weak	3024.9	18.2	2774.5	16.7	1.5	+
Moderate	2855.2	17.2	2790.5	16.8	0.04	-
Intensive	5413.9	32.5	8742.4	52.5	20.0	+

3.3. Land Productivity Dynamics in the Study Area

Complex processing of regular space-based observations provide an assessment of the land productivity dynamics that is a proxy expression of the sustained land quality status.

The dynamics of the Earth's covering biomass, or standing biomass, is a good expression of the general level of the potential to supply, or keep on supplying, ecosystem services. Assessing vegetative cover dynamics approximates a measure for general productivity levels of the land or human-environment system. Land users exploit this land-productivity for biological products of economic value (Lal et al., 2012). A decrease in overall land-productivity could be expected to indicate a decline or degradation of the land quality (e.g. vegetation, soil and water quality and/or quantity and also e.g. crop production levels). Whether this is related to land degradation or e.g. land use changes needs then to be further explored.

Table 9 shows the land-productivity dynamics for the study area as calculated from satellite images based on LUC and NDVI analysis. In other words, Table 9 shows also not only land cover/use but also vegetation density has important role on biomass that reflects land-productivity dynamic. Although it was determined the same land cover (no change area) between 2001 and 2015, LPD class was determined in various NDVI class including different plant density.

1930.82 ha of forest which remained in 2015 shows no change while, it was classified as increasing productivity and coded as 5 due to intensive vegetation density in this location. On the other hand, 2.09 ha of forest which remained in 2015 shows that potentially trend is again no change but its land-productivity dynamics was classified as "stable, not stressed". if these two classes were compared, it can be seen that there is no change land cover/use (forest) but vegetation density of second area classified as moderate in NDVI class decreased. It was determined that 436.06 ha forest land in 2000 changed in to grassland (shrubs, grasslands, and sparsely vegetated area) in 2015 and this area was classified as "stable, not stressed" This case can be explained that although these area has intensive plant-vegetation density class in NDVI, class level was decreased or fall in to this category due to loss of biomass change from forest to grassland. On the other hand, although these areas have been detected as grassland in satellite images, most of these areas have been used under reforestation applications and forest managements. Majority of these areas have been covered by young trees

All artificial area was classified as "decline productivity" for each NDVI class. 4.54 ha of forest changed into cropland in 2015 which shows negative trend and due to agricultural activity it was classified as "stable, but stressed" even if it locates in intensive NDVI class. In intensive NDVI class, 296.76 ha cropland changed into grassland which leads to positive trend due to removing of negative pressure (intensive cultivation activities) so, this area was classified as "increasing productivity". Moreover, from grassland, cropland and artificial lands to forest area show positive trend and classified as "increasing productivity".

As for moderate NDVI class, 6.61 ha of forest land changed into cropland in 2015 which shows potentially negative trend and was classified as "early signs of decline" because of agricultural activity and decreasing of vegetation density (reducing biomass). On the other hand, the same variations which are 3.67 and 0.57 ha in 2015 in weak and very weak class of NDVI were classified as declining productivity because of agricultural activity and much more decreasing of vegetation density.

Table 9. Potentially trend and chancing of land cover and NDVI between 2001 and 2015 for LDP.

Land Cover Class (LC-2001)	Land Cover Class (LC-2015)	Change Area		Potentially Trend	NDVI Class 2015	Land Productivity Dynamic (LPD 2001-2015)	
		ha	%	- and +		Value	Description
Forest	Forest	1930.82	11.61	no change	intensive	5	increasing productivity
Forest	Grassland	436.06	2.62	-	intensive	4	stable, not stressed
Forest	Artificial area	19.95	0.12	-	intensive	1	declining productivity
Forest	Cropland	4.54	0.03	-	intensive	3	stable, but stressed
Grassland	Forest	921.87	5.54	+	intensive	5	increasing productivity
Grassland	Grassland	3009.10	18.09	no change	intensive	4	stable, not stressed
Grassland	Artificial area	328.88	1.98	-	intensive	1	declining productivity
Grassland	Cropland	191.52	1.15	-	intensive	3	stable, but stressed
Artificial area	Forest	2.27	0.01	+	intensive	5	increasing productivity
Artificial area	Grassland	225.05	1.35	+	intensive	5	increasing productivity
Artificial area	Artificial area	286.21	1.72	no change	intensive	1	declining productivity
Artificial area	Cropland	76.52	0.46	+	intensive	3	stable but stressed
Cropland	Forest	0.94	0.01	+	intensive	5	increasing productivity
Cropland	Grassland	296.76	1.78	+	intensive	5	increasing productivity

Land Cover Class (LC-2001)	Land Cover Class (LC-2015)	Change Area		Potentially Trend	NDVI Class 2015	Land Productivity Dynamic (LPD 2001-2015)	
		ha	%	- and +		Value	Description
Cropland	Artificial area	351.14	2.11	-	intensive	1	declining productivity
Cropland	Cropland	636.51	3.83	no change	intensive	3	stable, but stressed
Forest	Forest	2.09	0.01	no change	moderate	4	stable, not stressed
Forest	Grassland	61.56	0.37	-	moderate	3	stable but stressed
Forest	Artificial area	8.63	0.05	-	moderate	1	declining productivity
Forest	Cropland	6.61	0.04	-	moderate	2	early signs of decline
Grassland	Forest	2.80	0.02	+	moderate	5	increasing productivity
Grassland	Grassland	293.70	1.77	no change	moderate	3	stable, but stressed
Grassland	Artificial area	122.42	0.74	-	moderate	1	declining productivity
Grassland	Cropland	349.88	2.10	-	moderate	2	early signs of decline
Artificial area	Grassland	40.13	0.24	+	moderate	5	increasing productivity
Artificial area	Artificial area	129.16	0.78	no change	moderate	1	declining productivity
Artificial area	Cropland	139.20	0.84	+	moderate	3	stable, but stressed
Cropland	Forest	0.01	0.00	+	moderate	5	increasing productivity

Land Cover Class (LC-2001)	Land Cover Class (LC-2015)	Change Area		Potentially Trend	NDVI Class 2015	Land Productivity Dynamic (LPD 2001-2015)	
		ha	%	- and +		Value	Description
Cropland	Grassland	190.85	1.15	+	moderate	4	stable, not stressed
Cropland	Artificial area	185.85	1.12	-	moderate	1	declining productivity
Cropland	Cropland	1272.31	7.65	no change	moderate	2	early signs of decline
Forest	Forest	0.01	0.00	no change	weak	3	stable, but stressed
Forest	Grassland	16.38	0.10	-	weak	2	early signs of decline
Forest	Artificial area	4.73	0.03	-	weak	1	declining productivity
Forest	Cropland	3.67	0.02	-	weak	1	declining productivity
Grassland	Forest	0.07	0.32	+	weak	4	stable, not stressed
Grassland	Grassland	52.59	0.32	no change	weak	2	early signs of decline
Grassland	Artificial area	47.10	0.28	-	weak	1	declining productivity
Grassland	Cropland	205.8	1.24	-	weak	2	early signs of decline
Artificial area	Grassland	19.26	0.12	+	weak	3	stable, but stressed
Artificial area	Artificial area	66.67	0.40	no change	weak	1	declining productivity
Artificial area	Cropland	105.51	0.63	+	weak	3	stable, but stressed
Cropland	Grassland	52.09	0.31	+	weak	3	stable, but stressed

Land Cover Class (LC-2001)	Land Cover Class (LC-2015)	Change Area		Potentially Trend	NDVI Class 2015	Land Productivity Dynamic (LPD 2001-2015)	
		ha	%	- and +		Value	Description
Cropland	Artificial area	128.07	0.77	-	weak	1	declining productivity
Cropland	Cropland	207.04	12.50	no change	weak	2	early signs of decline
Forest	Grassland	0.01	0.00	-	very weak	1	declining productivity
Forest	Artificial area	0.12	0.00	-	very weak	1	declining productivity
Forest	Cropland	0.57	0.00	-	very weak	1	declining productivity
Grassland	Grassland	20.81	0.13	no change	very weak	2	early signs of decline
Grassland	Artificial area	13.31	0.08	-	very weak	1	declining productivity
Grassland	Cropland	108.20	0.65	-	very weak	1	declining productivity
Artificial area	Grassland	7.92	0.05	+	very weak	2	early signs of decline
Artificial area	Artificial area	26.41	0.16	no change	very weak	1	declining productivity
Artificial area	Cropland	66.10	0.04	+	very weak	2	early signs of decline
Cropland	Grassland	24.10	0.14	+	very weak	2	early signs of decline
Cropland	Artificial area	39.90	0.24	-	very weak	1	declining productivity
Cropland	Cropland	2025.38	12.17	no change	very weak	1	declining productivity
Water body	Water body	10.00	0.06	no change	-	-	-

Percentage and hectare distributions of land-productivity dynamics show a comparable pattern within all land cover classes in Table 10 and its map was given in Figure 10. 21.86% of the territory shows stable, not stressed land-productivity dynamics. Over these areas the productivity can fluctuate according to land cover and land use variations. Appropriate levels of management and economic sustainability are assumed. Some 20.56% of the study area showed an observable increase in land-productivity for the 2001-2015 period in forest and grassland area. However, it is important to remember that this land productivity dynamics assessment focuses on mapping on-going processes. Thus land degraded or in very poor condition prior to the 2001s may well appear as stable or even improving – the 20.56% improvement (in area) also includes locations effectively starting from a very low productive standing biomass level. Therefore, this does not necessarily indicate neutrality in terms of land degradation for these areas. On the other hand, most of the declining productivity and early signs of decline classes were determined in cropland and artificial lands and found 23.42% and 24.65%, respectively. These areas have markedly different ecosystem characteristics and different actual land use and diverse land use potential and options. ***All of these areas might raise reasons for concern and were estimated impact in terms of land degradation.*** Further analysis will need to identify and, eventually, qualify the stress factors. Therefore it is necessary to take some neutrality measurement for land degradation. Moreover, Figure … shows that areas in flat slope where intensive agriculture traditionally has been a major land use have relatively more territory (57.6%) under stress, declining productivity or with early signs of decline than most of the areas in mountain and hilly areas in where land-productivity is under stable not stressed or increasing productivity.

Table 10. Distribution of LPD'class in Ilıcak and Kum Çayı Micro Catchments

Land Cover Class (LC-2015 ha)	LPD'class									
	1		2		3		4		5	
	Declining productivity		Early signs of decline		Stable, but stressed		Stable, not stressed		Increasing productivity	
	ha	%	ha	%	ha	%	ha	%	ha	%
Forest	-	-	-	-	0,01	-	2,16	0.01	2858.8	17,18
Grassland	0.10	-	121.80	0.73	425,6	2.56	3156.6	21.85	561.9	3.38
Cropland	2137.8	12.85	3979.8	23.92	1153,8	6.94	-	-	-	
Artificial area	1758.6	10.57	-	-	-		-	-	-	
Total/Ratio (%)	3896.5	23.42	4101.6	24.65	1580.4	9.50	3638.2	21.86	3407.8	20,56

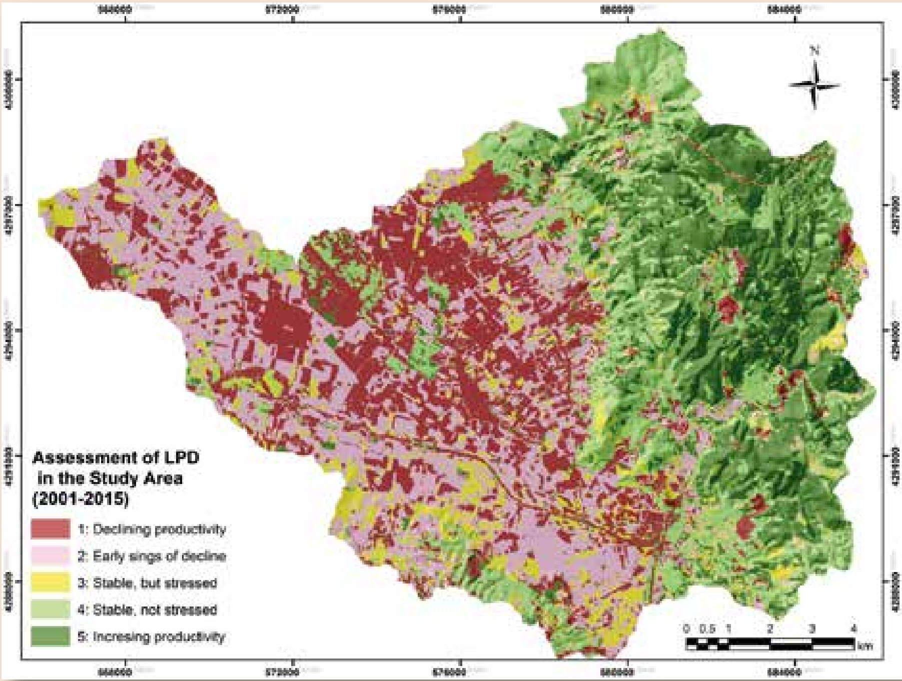
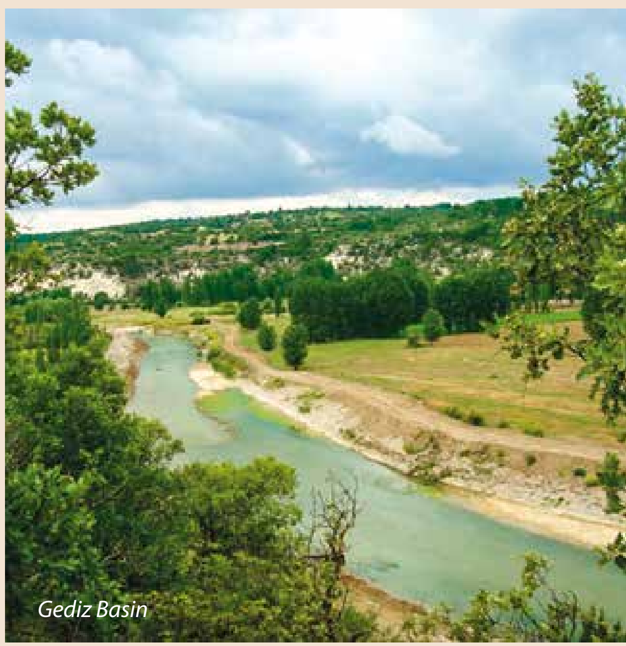


Figure 10. Distribution map of the LPD'class in Ilıcak and Kum Çayı Micro Catchments

3.4. Organic Carbon Stock

The descriptive statistics, as minimum, maximum, mean, Standard Deviation and coefficients of variation of soil organic carbon of surface and sub surface soil samples, are presented in Table 11. In surface soil, the values of SOC for soil samples, which ranged widely between 3.63 and 129.5, and mean value of SOC was found 49.78. As for subsurface soil, the values of SOC for soil samples, which ranged widely between 0.40 and 121.48, and mean value of SOC was found 22.71.



Gediz Basin

Table 11. Descriptive statistics of the soil organic carbon for both depths

Depth cm	Mean	S.D.	Variance	C.V %	Minimum	Maximum	Skew-ness	Kurtosis	n
SOC (0-30)	49.78	25.32	641.40	50.89	3.63	129.49	0.86	0.28	319
SOC (30-60)	22.71	19.04	362.59	83.83	0.40	121.48	0.90	1.73	319

S.D.: Standart Sapma; C.V.: Değişken Katsayısı; SOC: Toprağın Organik Karbonu;

The experiment semi-variogram depicts the variance of the sample values at various separation distances (Hani et al 2010). The ratio of nugget to sill (nugget/sill) can be used to express the extent of spatial autocorrelations of environmental factors. If the ratio is low (< 25%), the variable has strong spatial autocorrelations at a regional scale. A high ratio of the nugget effect (> 75%) indicates spatial heterogeneity of soil properties (Cambardella et al 1994). In this study, for SOC in surface soil, the isotropic spherical model provided the best fit value for the computed semi-variance points. On the other hand, the nugget value was 44 and the low ratio of nugget to sill (less than 25%) for surface SOC indicated the existence of a strong spatial auto-correlation (Table 12) and, it was found high cross validation value. In addition the distribution map of surface SOC of the surface soil is shown in Figure 11. Moreover, as for SOC in subsurface soil the isotropic exponential model provided the best fit value for the computed semi-variance points. In this model it was also found a strong spatial auto-correlation and distribution map of surface SOC of the subsurface soil is shown in Figure 12.

Table 12. Parameters of isotropic models for best fitted semi-variogram models of SOC for two depths

SOC Depth (cm)	Variogram model	Nugget (C_0)	Sill (C_0+C)	Range (m)	RSS	R^2	Cross Validation r^2	C_0/(C_0+C)	
0-30	Spherical	44	1098.9	22210	1.271	0.986	0.88	0.04	Strong
30-60	Exponential	1.526	0.735	5603	1.045	0.395	0.09	2.07	Strong

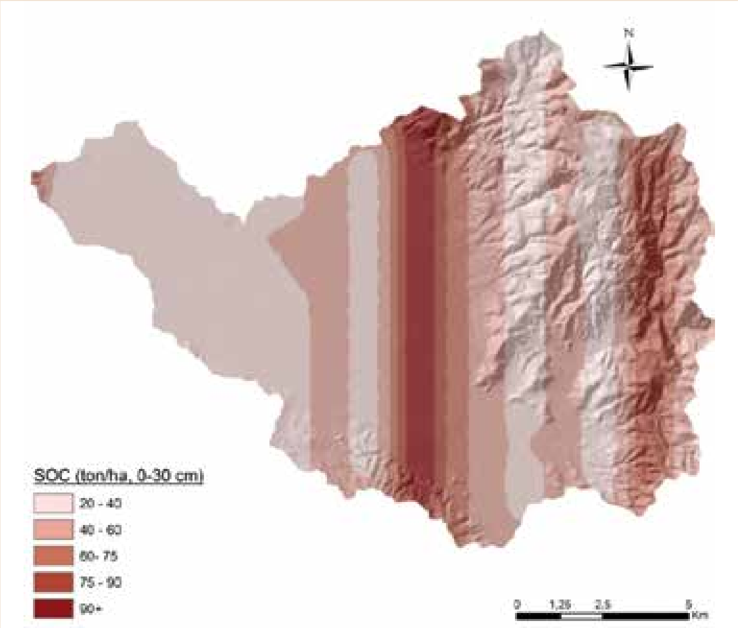


Figure 11. Spatial distribution map of SOC in surface soil (0-30 cm)

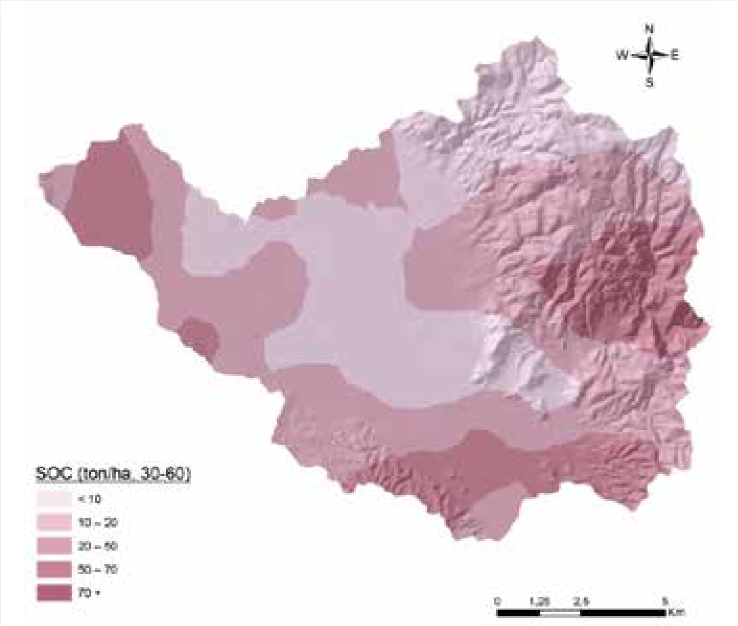


Figure 12. Spatial distribution map of SOC in subsurface soil (30-60 cm)

Correlation relationship between SOC values of surface soil and land cover/use was given in Table 13 and Table 14. In the surface soil, the highest mean value of SOC was determined in forest land whereas, the lowest value belongs to cropland in which has been used under intensive agricultural activities particularly under soil tillage applications leading to decomposition and mineralization of organic matter. On the other hand, SOC accumulation was observed in surface soil of some part of forest land which has been covered by high intensive vegetation.

Table 13. correlation relationship between SOC values of surface soil and land cover/use

Land Cover/Use	Descriptive statistics of the soil organic carbon for surface soil					
	Mean (Ton/ha)	Min. (Ton/ha)	Max. (Ton/ha)	S.D	CV (%)	Sample (n)
1-Forest	79.94**a**	34.09	129.49	19.88	24.87	73
2-Grassland	61.74**b**	23.19	124.06	21.24	34.40	59
3-Cropland	34.24**c**	3.63	91.26	12.56	36.68	187

Means which was defined with different letters in the same column were different each other at $p<0.05$ levels

As for SOC of subsurface soil, when compared with SOC values of surface soil the same order result was found in terms of organic matter accumulation and presented in Table 14. In other words, the highest mean value of SOC was determined in forest land whereas, the lowest value belongs to cropland.

Table 14. Correlation relationship between SOC values of subsurface soil and land cover/use

Land Cover/Use	Descriptive statistics of the soil organic carbon for subsurface soil					
	Mean (Ton/ha)	Min. (Ton/ha)	Max. (Ton/ha)	S.D	CV (%)	Sample (n)
1-Forest	25.64**a**	0.97	121.48	23.41	0.91	73
2-Grassland	23.52**b**	0.40	8217	20.93	0.88	59
3-Cropland	21.32**c**	0.96	54.23	16.32	0.76	187

Means which was defined with different letters in the same column were different each other at $p<0.05$ levels

4 CONCLUSIONS

Land degradation is a complex phenomenon caused by interacting biophysical and societal factors. There are no agreed scientific based assessment and measurement protocols or complementing indicators today. However, long-term satellite-based observations offer considerable potential as a source of information on land-productivity dynamics, which offers potential as a baseline on which to further integrate contextual information in view of land degradation assessment. This is still subject to further verification and research to understand the complex social, economic and biophysical processes that drive the local both positive and negative changes in land-productivity dynamics (Cherlet et al., 2013).

Figure 10 shows that areas in western parts of the study area where intensive agriculture traditionally has been a major land use have relatively more territory under stress or with early signs of decline than most of the areas in eastern part of the study area. In addition according to Table 14, it was also detected that there is only small area (0.01 ha) which was classified as stable but stressed. The highest declining, early stage of declining and stable but stressed classes were found in croplands. Moreover, the second biggest declining class was found in artificial area. Only very small land of the study area is coincident with stable but stressed category in forest land.

West part of the farmland areas which were categorized as declining and early signs of decline are low productive soil and located on coarse soil texture and dune area. These areas include also the lowest organic carbon accumulation due to natural (coarse soil texture including big size pore leads to fast mineralization) and human effects such as removing of organic matter with intensive agricultural application. Therefore, it should be remain plant residues on soil. On the other hand, for the arable land of the east part of the study area located on most productive soil has fine soil texture and organic carbon accumulation more than west part's soil. In addition, it should be developed land management system such as crop rotation, green manure, low tillage system to prevent soil compaction, sealing/crusting, disturbing soil structure.

Most of the grassland area located on high slope land and shallow soil depth are coincident with declining, early signs of declining and stable but stressed due to covering with weak and very weak vegetation density. Main threats are overgrazing that causes particularly for soil erosion.

Soil loss can results in lower land-productivity. Soil loss by degrading processes, such as loosing soil structure and chemical characteristics, or by erosion (i.e. the physical loss of topsoil including most of the soil's organic matter), should be prevent with biophysical measurements such as terracing, fertilizing, low grazing and so on.

Table 15. Presentation of national basic data using the LDN indicators framework

Land-Use Category	Land area (2001)	Land area (2015)	Net change in area (2001-2015)	**Net land productivity change** (sq km, 2001-2015)					Soil organic carbon (2015 (0-30 cm)
	sq km	sq km	sq km	**1** sq km	**2** sq km	**3** sq km	**4** sq km	**5** sq km	ton/ha
Forest land	25.35	28.57	3.22	-	-	0.0001	0.02	28.58	79.94
Shrubs, grasslands and sparsely vegetated areas	58.03	27.27	30.76	0.01	1.22	4.26	31.56	5.62	61.74
Cropland	71.28	72.75	1.47	21.39	39.80	11.54	-	-	34.24
Wetlands and water bodies	0.10	0.10	0,00	-	-	-	-	-	-
Artificial areas	11.71	17.59	5.87	17.58	0.11	-	-	-	-
Bare land and other areas	-	-	-	-	-	-	-	-	-
Total	166.47	166.47		21.38	41.12	15.79			

1: Declining**, 2:** Early signs of declining**, 3:** Stable but stressed**, 4:** Stable not stressed, **5:** Increasing

In the course of field study, it was observed that some forest areas have been used under some forest management such as protected with bio-physical measures such as tracing, nursery plantation etc. after cutting. For that reason, these area was detected as grassland which is 514.01 ha in forest area (in Figure 13). In reality, total forest area's size was not changed on the other hand, biomass has changed in there. Therefore, LPD class decreased or fall into lower level category in terms of density of vegetation coverage on surface.

Figure 13. Reforestation lands in the study area

In addition to above mentions, analysis of long-term changes and current efficiency levels of vegetative or standing biomass combined into land-productivity dynamics is only a first step. The results need to be further integrated with more detailed additional information reflecting climatic and/or societal information such as local land use processes, changes in land use practices and/or yield outputs, population movements, etc.

LPD map of EC-JRC' study result about Turkey was given Figure 14. According to EC-JRC map in which was used Modis satellite image that has 5 km x 5 km cell (25 km^2-2500 ha), almost all land of the study area was found in two categories that are stable not stressed and increasing productivity. On the other hand when we compare with Landsat image's result, almost half of the study catchment was determine decline and early sing of decline classes. Therefore, ***Modis resolution cannot capture individual field, small scale or plot level or categories including detailed processes, such as erosion, organic matter decline etc.*** In order to provide the detail information for studying localized situations, it should be work with satellite image that has moderate or high resolution such as Landsat satellite image (30m x 30m cell size) to make exhaustive analysis for coming to a final conclusion on LPD.

For example, according to JRC analysis used MODIS image total negative trend land; declining, early stage of declining and stable but stressed of LPD classes in forest land of Turkey was determined 1,127,980 ha. However, 4,473,890 ha forest areas of Turkey have been taken measure against land degradation between 2000-2014 with bio-physical applications such as erosion control, afforestation, rehabilitation etc. For that reason, Turkey has achieved LDN targets in terms of forests. On the other hand, our cultivated areas are under significantly risk in terms of biomass productivity trend. Therefore, these areas should be investigated in detail with high resolution images.

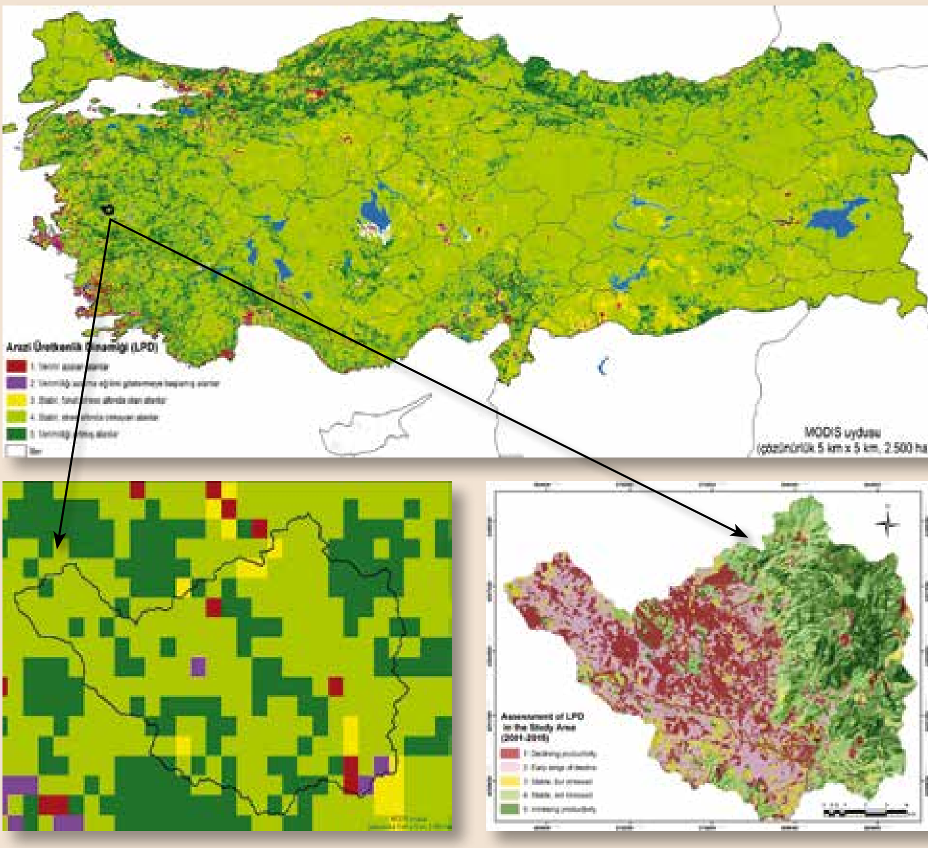


Figure 14. Comparison between satellite images in terms of LPD

Finally, This methodological process should be also associated further integrating thematic and/or area specific information, including some soil properties, climate and socio-economic aspects, will ultimately in order to determine land degradation neutrality's targets for a land degradation assessment .

5 REFERENCES

Bonneau, L.R., Shıelds, K.S. and Civco, D.L., 1999. Using satellite images to classify and analyze the health of hemlock forests infested by the hemlock woolly adelgid. Biological Invasions, 1, pp. 255–267.

Braun-Blanquet J., 1964. Plant Sociology: The Study of Plant Communities, 3rd Edn. Springer-Verlag, Berlin-Wien-New York.

Congalton, R.G. and Oderwal, R.G.1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical technique. Photogrammetric Engineering and Remote Sensing 49 (2), 1671-1678.

Congalton, R.G. 1996. Accuracy assessment: A critical component of land cover mapping. In: Scott, J.m., Tear T.H. and Davis, F. (Eds.), a land scape approach to biodiversity planning (pp.119-131). Charlotte, North Carolina: American Society of Photogrammetric and Remote Sensing.

Cherlet, M., Ivits, E., Sommer, S., Toyh, G., Jones, A., Montanaraella, L., Belward, A. 2013. Land-Productivity Dynamics in Europe. Towards Valuation of Land Degradation in the EU. JRC Scientific and policy Reports, p-61.

Demirel, H., Ozcinar, C., Anbarjafari, G., 2010. Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition. IEEE Geosciences and remote sensing letters 7 (2), 333-337.

Dabelko, G., Lonergan, S., Matthew, R. 2002. State of the Art Review on Environment, Security and Development Co-operation. The World conservation Union for the Working Party on Development Co-operation and Environmet. OECD Development Assistance Committee.110p.

Edwards, M.C., Wellens, J. and Al-Eısawı, D., 1999. Monitoring the grazing resources of the Badia region, Jordan, using remote sensing. Applied Geography, 19, pp. 385–398.

Erdas, 2003. Erdas Field Guide, 7th Edn. Leica Geosystems, GIS and Mapping LLC: Atlanta, Georgia.

Fan, F., Weng, Q., Wang, Y. 2007. Land use land cover change in Guangzhou, China, from 1998 to 2003, based on Landsat TM/ETM+ imagery. Sensors, 7, 1323-1342.

Giuseppe, E., Zucca, C., Colombo, V.V.F., Musinu, S. 2008. Traditional Approach and Remote Sensing Technologies in the Development and Implmentation of Desertification Indictors. Combating Desertification Assessment, Adaptation and Mitigation Strategies. In: Gabriels, D., Cornelis, W., Eyletters, M. and Holleboch, P. (Eds.) UNESCO Chair of Eremology, Ghent University.

Lal R., Safriel U. and Boer b., Zero Net Land Degradation, A New Sustainable Development Goal for RIO+20; a report prepared for the Secretariat of the UNCCD, May 2012.

Moller-Jensen, L. 1997. Classification of Urban land cover based on expert systems, object models and texture. Computers. Environment and Urban Systems, 21(3/4), 291–302.

Retiere, A., Sommer, S., Minelli, S., Byron-Cox, R., Candelori, M. 2015. Land degredation neutrality from concept to practice. Using the UNCCD indicator framework to set LDN national voluntary targets and moitor their achievement. Methodological note, Joint Research Center, Italy. p, 13.

Sommer, S., Zucca, C., Grainger, A., Cherlet, M., Zougmore, R., Sokona, Y., Hill J., Della. R., Peruta, Roehrig, J., Wang, G. 2011: Application of indicator systems for monitoring and assessment of desertification from national to global scales. Land Degrad. Develop. 22: 184–197 (2011). Published online in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/ldr.1084.

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