# Characterizing landscape structure using landscape metrics in Melokoza Landscape, South Ethiopia

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**Abstract**

Landscape structure is a significant factor in ecological integrity, sustainable land management, and policy making. Assessing landscape structure is therefore critical for understanding its current state and providing support for its protection. Consequently, the current study was carried out in the Melokoza district, which includes a variety of land uses/covers, to investigate the spatial layout of the landscape structure at various scales using landscape metrics. Landsat photos were used to assess land use/cover types, and landscape indices were generated to characterize the landscape structure by employing the FRAGSTATS software. The study area's landscape is distinguished by a progressive increase in values of all the landscape metrics related to agriculture and settlement, including patch number (73 and 70), total area (42.877 and 33.169 ha), patch density (9023.17 and 8652.35 ha), largest patch index (4855.56 and 3566.67 ha), Shannon Diversity Index (8.6474 and 11.52), and Shannon evenness index (12.11 and 15.15). Conversely, the values among all the landscape metrics related to bare land, forest, and shrub land were declined. These declined metrics included patch number (3, 5 and 3), total area (1.62, 2.43 and 0.81 ha), patch density (370.82, 618.03 and 370.82 ha), largest patch index (177.78, 266.67 and 77.78 ha), Shannon Diversity Index (0.53, 0.88 and 0.68), and Shannon evenness index (0.76, 1.27 and 0.62). In light of these findings, significant losses in forests, shrub lands, and barren areas combined with widespread farming and populated areas have caused previously unheard-of fragmentation levels of the landscape. Given the growing population in the area, it is likely that this fragmentation tendency will continue. This requires scientific-based knowledge and the participation of the local community and stakeholders in conservation and restoration.

**Keywords:** Class level,landscape matrix,landscape metrics, landscape structure, Patch level

**1. Introduction**

Geographically varied regions with interdependent ecosystems and human activity are referred to as landscapes (Soh *et al.,* 2019; Bindajam *et al.,* 2021). Landscape structure is an indicator of the ecosystem's spatial patterns in addition to the connectivity of distinct landscape features (Zhang *et al.,* 2014). Landscape dynamics is a complicated aspect of land use that can be assessed using land use/land cover (LULC) data (Vadjunec *et al*., 2018). Changes in land use patterns brought about by human activity have become a major factor impacting the structure, configuration, and dynamics of landscapes in the last few decades of the 20th century (Singh *et al.,* 2017; Winkler *et al.,* 2021; Oertli *et al.,* 2002; Jia *et al.,* 2024). The main issue is the fragmentation of the landscape caused by different human activities, including the development of infrastructure (Spinti *et al*., 2023), mining, population growth, deforestation (Fischer *et al*., 2021), expansion of agriculture, and meeting human needs (De Matos *et al*., 2021; Cáceres *et al.,* 2023). These changes cause degradation of natural ecosystem functions (Shao *et al*., 2021), increased surface runoff resulting in flooding, changes in water quantity and quality, change landscape structure, climate variations, habitat loss, and demographic shifts within the landscape (Bindajam *et al.,* 2021; Burandt *et al*., 2023; Zhang *et al*., 2023).

Detecting changes in land use and cover is a crucial technique for understanding spatial dynamics and how they relate to human activity. Nevertheless, it frequently falls short of providing specific structural aspects of the environment, like composition and structure (Liu & Weng, 2018; Dewan *et al.,* 2012). Landscape structure and any structural alterations are necessary to comprehend landscape function and process (Matsushita *et al*., 2006). To quantify the spatial patterns of landscape function and processes, a number of landscape metrics have been created (McGarigal *et al.,* 2012).

According to research, around 32% of global landscapes have been transformed, especially from 1960 to 2019 (Winkler *et al.,* 2021; Romanillos *et al.,* 2024). Concerns about the consequences of altering land usage patterns owing to deforestation and agricultural expansion or abandonment; this has resulted in crisis over the standard of natural resources across the landscape (Ziegler *et al.,* 2004). Given that human and economic endeavors occur predominantly on the landscape level, it is seen as an ideal spatial scale for investigating human activity-induced changes to the environment over a landscape structure (De Montis *et al.,* 2017). Thus, dynamic techniques for planning land usage sustainably include analyzing past human land use, assessing landscape changes, and assessing structure (Wilson *et al.,* 2016). In this context, according to Cushman (2016), landscape metrics are methods that are used to quantify the geographical attributes of classes, patches, or mosaics throughout the whole terrestrial landscape (Cushman, 2016). According to (Akın *et al.*, 2013 & Wang *et al.*, 2014), landscape metrics provide a useful method of comparison of the landscape states of various land uses and land cover types.

Metrics that capture characteristics of landscape pattern are required to associate landscape spatial pattern with significant environmental qualities relevant to the relationship of landscape pattern to human and biological activities. Composition and configuration can be considered parts of a landscape's structure. Features pertaining to the quantity or presence of various land cover types are referred to as landscape composition that are not spatially explicit, while landscape configuration refers to the spatial distribution of cover types within the landscape and includes measurements of cover type placement relative to one another or patch shape (McGarigal & Marks, 1995). Thus, comprehending the effects of human activity on different land use/cover types which serve considerably as primary information in the analysis of spatial-temporal landscape structure is especially important for understanding changes and the interplay of landscape metrics with both human and environmental influences (Wang *et al.,* 2014).

Several studies have confirmed that anthropogenic landscape fragmentation causes habitat loss, landscape structure alteration and the loss of ecosystem services (Zhou *et al.,* 2021) provided by various habitats such as forests, shrubs, grasslands, wetlands, and water bodies (Wilson *et al*., 2016; Andersson *et al.,* 2021; Pu *et al*., 2024). Disturbance and alteration of natural habitats of any extent have an impact on the physical features of the landscape and the ecosystem, ultimately leading to ecological deterioration (Soh *et al.,* 2019).

Globally, there's a rising percentage of anthropogenic landscape deterioration, particularly in African regions experiencing high population growth (Acharya *et al*., 2019; Pacheco *et al*., 2023). Furthermore, a variety of intricate socioeconomic and biophysical elements commonly cause ecosystems in the East African region to undergo reconfiguration (Tilahun *et al*., 2024). For instance, Kayitesi *et al*. (2022) found that 20 million hectares of woodlands have been changed to less woody types due to fragmentation, while the growth in croplands by 34.8% between 1998 and 2017 is indicative of fragmentation in East Africa (Bullock *et al*., 2021).

There are several approaches for gathering, storing, processing, and interpreting data about natural resources, in spite of the fact that comprehending how human activity affects the structure and functionality of natural landscapes is a difficult task (Acharya *et al.,* 2019). A viable option for quick, easy, and reasonably priced data collecting and analysis is provided by geospatial technology (Acharya *et al*., 2019; Bill *et al*., 2022). FRAGSTATS is a standalone software application that is specifically built to compute a various landscape metrics to assess landscape structure and fragmentation (McGarigal, 2006; Cushman, 2016; Amini *et al*., 2024).

Despite that many landscape measures have been created to measure fragmentation, strong correlations and duplication among them make them unsuitable for use in a given landscape analysis (McGarigal, 1995; Uuemaa *et al.,* 2009). Landscape measures at the landscape, class, and patch levels consider various elements of LULC changes, including composition, configuration, and connectivity (Kavian *et al*., 2020).

Given the variety of landscape measurements available, the most appropriate metrics ought to be selected according to the study's goals and the outcomes of the metrics' correlation analysis. In order to prevent redundancy, a careful selection of metrics is necessary. In order to examine how the landscape behaves and influences different processes, these metrics can measure a variety of factors at the patch, class, or landscape levels, including area, shape, core area, nearest neighbor distances, isolation, and connectedness (McGarigal, 2006; Liu *et al*., 2017; Wang *et al*., 2014).

An analysis of landscape structure and change is essential for sustainable resource management; effective planning for land usage and the research of ecological services, as well as processes (Kavian *et al*., 2020). Additionally, this method of quantifying landscape structure can offer technical reliability and scientific soundness. Metrics enable the examination of the connection between ecological processes and spatial patterns, and scientific support for evaluating the landscape structure is provided (Tolessa *et al*., 2016; Frazier & Kedron, 2017; Sertel *et al*., 2018; Cadavid *et al*., 2019). In Ethiopia and most of the tropical African landscape, insufficient research has been done to quantify the patterns and structure of the landscape (Asfaw *et al.,* 2021).

The purpose of this research is to characterize landscape structure in the Melokoza Landscape by utilizing a structural landscape metrics. In order to achieve this, the extent, complexity, and spatial arrangement of the landscape structure in this area are being investigated. Another important topic is the response of landscape measurements at different landscape levels. How landscape measurements react at different landscape levels is also an important consideration. To do this, the current study seeks to quantify landscape structure metrics in the Melokoza district at three distinct levels: patch, class, and landscape levels. The findings could be important tools for tracking landscape changes and making land-use management decisions.

**2. Materials and Methods**

## 2.1. Study Area

The research was carried out within the District of Melokoza, South Ethiopia in the Gofa zone. The research area was located at 6º 15' to 6º 39' North latitude and 36º 20’00 to 36º50'00 East longitude (Figure 1). The elevation varies between 700 and 3200 meters above sea level. The area receives rain for nine months, with an annual average of 1100-1300mm. The average annual temperature within the research area is 220C. The district is home to 152,502 people overall, as stated by the Agriculture Office in Melokoza. With a minimum of 750 mm and a maximum of 1500 mm, the district experiences bimodal rainfall. The lowest and highest recorded temperatures are 15.10C and 27.50C, respectively. The area has extensive crops of sesame and maize. In terms of land use pattern, the overall 168,180.93ha of land are covered, of which 31,884.093ha are covered by perennial crops, 6,885ha by annual crops, 33,687.15ha by natural forest, and 48620.78 ha by other land use. In the Melokoza district, 20.3% of farmers own more than two hectares of land, while 26.7% of farmers have a smallest land property of less than 0.5 hectares, as reported by department of agriculture.

C:\Users\Abera\Desktop\Ayele Map.tif Figure 1 Study area Map

Across agro ecologies, the district's soil types are categorized as clay (15%), loam (50%) and sandy loam (35%). In the higher altitudes, the vegetation consisted of woodland intermingled with highland bamboo and moist forest. The Sirso Natural Forest possesses the largest area coverage (3501.5ha) of any forest area in the district.

### 2.1.2 Data collection

Remote sensing and Geographic Information Systems (GIS) were used to detect changes in land cover and use in spatial and temporal dimensions.Satellite images were downloaded using earth explorer Google. By using ArcGIS the satellite images were proceed and different land classes were identified and categorized based on their patch types.The landscape mosaic of the research was grouped into five landscape matrix or classes i.e., forest, settlement, agricultural land, shrub land and barren land. Landscape metrics such as Patch, Class shape metrics, size, Area and edge metrics, Core area metrics, Aggregation metrics and Isolation metrics were identified. Within each of these groups, metrics were grouped into patch, class, and landscape metrics.

### 3.1.3 Data analysis

**Metrics selection and computation**

The landscape measure was generated, and information on the structure, composition, and configuration of patches, as well as the geographic pattern of various landscapes, were examined using the FRAGSTATS software for measuring the features of the landscape. The measurements were divided into three categories based on the feature of the landscape pattern measured: 1) area and shape metrics, 2) aggregation metrics, and 3) diversity metrics. Metrics within each of these groups were further classified as patch, class, and landscape level metrics. The metrics and equations used in their calculations are as follows:

**1. Area and shape metrics**

In this study the area of patches, total class area and the proportion of the landscape, largest patch index, core area, shape index, and fractal dimension were computed.

**A) Area metrics**

**i) Patch level metrics**

a) Area: is equivalent to dividing the patch's area (measured in m2) by 10,000 (to convert to hectares).

AREA= aij

Where aij = area (m2) of patch ij.

b) Core area (CORE): equals, divided by 10,000 (to convert to hectares), the area (m2) within the patch that is located beyond the designated depth-of-edge distance from the patch perimeter.

CORE=aij c

Where aij

c = core area (m2) of patch ij based on specified edge depths (m).

c) Core Area Index (CAI): equals the patch core area (m2) divided by total patch area (m2), multiplied by 100 (to convert to a percentage); in other words, CAI equals the percentage of a patch that is core area.

CAI= (100)

Where

c = core area (m) of patch ij based on specified edge depths (m)

aij = area (m2) of patch ij.

**ii) Class level metrics**

a) Total class area (CA): was a measure of how much of the landscape is comprised by a particular LULC type.

CA=

Where aij = area (m2) of patch ij.

b) Mean patch area (AREA\_MN): at a class level, it depends on how many patches are present in the LULC class and the total LULC class area.

AREA\_MN=

c) Percentage of landscape (PLAND): is the total area (m2) of all patches belonging to the same patch type divided by the total area (m2) of the landscape and multiplied by 100 (to translate to a percentage).

PLAND=Pi= \* 100

Where Pi = proportion of the landscape occupied by patch type (class) i.

aij = area (m2) of patch ij.

A = total landscape area (m2).

d) Largest Patch Index (LPI (%)): is equals the area (m2) of the largest patch of the corresponding patch type divided by total landscape area (m2), multiplied by 100 (to convert to a percentage). As such, it is a simple measure of dominance.

Where aij = area (m2) of patch ij. A = total landscape area (m2).

**iii) Landscape level metrics**

1. Mean patch area (AREA\_MN): was computed as follows;

AREA\_MN=

Where N = total number of patches.

b) Largest Patch Index (LPI): is equals the area (m2) of the largest patch in the landscape divided by total landscape area (m2), multiplied by 100 (to convert to a percentage).

LPI= 100

Where aij = area (m2) of patch ij

A = total landscape area (m2)

**B) Shape metrics**

**i) Patch level metrics**

a) Shape index (SHAPE): equals patch perimeter (m) divided by the square root of patch area (m2), adjusted by a constant to adjust for a square standard.

SHAPE=

Where pij = perimeter (m) of patch ij

aij = area (m2) of patch ij

b) Fractal dimension index (FRAC): equals twice the logarithm of patch perimeter (m) divided by the logarithm of patch area (m2); the perimeter is modified to account for raster bias.

FRAC=

Where pij = perimeter (m) of patch ij.

aij = area (m2) of patch ij.

c) Total Landscape Area

Units: Hectares

**ii) Class level metrics**

a) Mean patch shape index (SHAPE\_MN): is equal to the total of the relevant patch metric values across all patches of the same kind, divided by the total number of patches of the same type.

SHAPE\_MN=

**iii) Landscape level metrics**

a) Mean patch shape index (SHAPE\_MN): is equal to the total number of patches divided by the sum of the matching patch metric values across all patches in the landscape.

SHAPE\_MN=

Where N = total number of patches.

**2. Aggregation metrics**

In this study, aggregation index was evaluated by the number of patches; mean Euclidean nearest-neighbor distance, interspersion and juxtaposition index and proximity index.

**i) Class level metrics**

a) The number of patches (NP): was computed as;

NP = ni

Where ni = The number of patches in the landscape of patch types (class) i.

b) Mean Euclidean Nearest-Neighbor Distance (ENN\_MN): is a measure of patch dispersion or isolation. It measures the distance to the nearest neighboring patch of the same type, based on shortest straight-line distance will be computed from cell centers.

ENN\_MN=

Where Xij*=* the distance (m) between patch ij and the nearest neighboring patch of the same LULC class.

c) Interspersion and Juxtaposition Index (IJI): expresses observed interspersion over the maximum possible interspersion for the given number of patch types.

IJI= (100)

Where eik = the overall length (m) of the edge in the landscape between patch types (classes i and k.

m = number of patch types (classes) in the landscape, if any, including the presence of the landscape boundary.

**ii) Landscape level metrics**

a) Number of Patches (NP): is the number of the matching patch type (class) patches.

NP =N

Where N = the total number of patches on the landscape.

b) Mean Euclidean Nearest-Neighbor Distance (ENN\_MN)

ENN\_MN=

Where X*ij =* the distance (m) between patch ij and the nearest neighboring patch of the same LULC class.

c) Patch Density

Number per 100 hectares

**c) Interspersion and Juxtaposition Index**

**IJI= (100)**

Where eik = total length (m) of edge in landscape between patch types (classes) i and k.

E = total length (m) of edge in landscape, excluding background.

m = the number of patch kinds (classes) existing in the landscape, including any landscape borders.

**d) Edge Density**

ED**=**

All metrics were analyzed using Raster version of FRAGSTATS spatial pattern analysis software (ver.4.1) developed by McGarigal *et al.* (2012, 2015). Every statistic and index in the software documentation included a calculation and an explanation. Metrics that best fit the data type and are often used in literature to evaluate heterogeneity were chosen from this library (Garrigues *et al.,* 2006; Huang *et al.,* 2006; Plexida *et al.,* 2014; Tuanmu & Jetz, 2015). In this study, the percentage between the different variables components of the study region landscape metrics was examined.

**Principal Component Analysis (PCA)**

The link between the various landscape measures' characteristics in the Melokoza district was interpreted using the PCA. The various variables' quantitative data sets were subjected to this methodology. The multifactorial data analysis method was employed with the aim of providing a summary of the data set.

**3. Results and Discussion**

**3.1. Patch-Level Metrics**

The FRAGSTATS results for quantifying the landscape parameters of the Melokoza district were obtained at the patch level. The patch-level metrics were calculated individually for every mosaic patch. The geographical configuration of patch-level metrics in Melokoza district was checked by employing the tool for spatial analysis after integrating FRAGSTATS with ArcGIS. The patch-level results for nine metrics, including AREA, PID, PERIM, SHAPE, NCORE, FRAC, CORE, ENN, and CAI, were described. The NCORE measure for the Melokoza district landscape ranged from zero to 41. Agricultural land had the highest NCORE value at the level of patches, followed by settlement, while shrub and bare land had the lowest NCORE value at the level of patches, indicating that the varied values are connected to the patch size, number of patches and the level of fragmentation. Agricultural land and settlement had the greatest values for PERIM, SHAPE, FRAC, CORE, NCORE, and CAI metrics. Furthermore, the NCORE, CORE, and CAI metric analysis yielded the lowest value of zero was shrub land (Table 1).

Table 1 Metrics of landscape structure for selected indices at the level of patches

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Class | AREA | PID | PERIM | SHAPE | NCORE | FRAC | CORE | ENN | CAI |
| Agriculture | 41.79 | 83 | 21766.9 | 69.616 | 41 | 68.00 | 3.685 | 169.60 | 462.89 |
| Bare land | 3.33 | 26 | 2578.45 | 13.25 | 1 | 13.16 | 0.089 | 423.62 | 11.11 |
| Forest | 2.88 | 13 | 1918.85 | 7.583 | 2 | 7.18 | 0.179 | 0 | 23.61 |
| Settlement | 31.37 | 86 | 18408.95 | 64.7 | 25 | 61.45 | 2.248 | 359.78 | 288.29 |
| Shrub land | 1.53 | 13 | 1319.21 | 7.25 | 0 | 7.09 | 0 | 134.08 | 0 |
| Grand Total | **80.90** | **221** | **45992.388** | **162.4** | **69** | **156.88** | **6.2031** | **1087.0868** | **785.912** |

Agricultural lands and settlement areas (mosaic) made up of most of the research area’s patches. These two types of landscape structure are the most fractured and irregular when compared to the other types. The class area index (CAI) indicator demonstrated significant diversity in the agriculture and settlement area type structure. In the research region, the three measures were established differently in the five landscape types (class). The Class area indicator (Table 1) shows that agricultural land (462.8964 ha) occupied the biggest share of the research area, followed by settlement (288.2934 ha), while shrub land, bare land, and forest had the smallest core area index (0, 11, and 23.6 ha, respectively). A significant percentage of the patches index (PID) consist of agricultural land and settlement (83 and 86 ha), and smaller percentages consist of patches in bare land, forest and shrub land (26, 13 and 13 ha), respectively (Table 1).

**3.2. Spatial landscape metrics at the class and landscape level**

The spatial landscape metrics shown in Tables 2 and 3 were calculated at the class and landscape levels using 2023 LULC maps. The number of patches was determined at both the class and landscape levels (Tables 2 and 3). At the class level, agriculture and settlement had the highest values of the metrics within the research area, while the forest, shrub land, and bare land had the lowest values of the metrics such as CA, NP, PLAND, LPI, PD, TE, CORE\_MN, ED, AREA\_MN, SHAPE\_MN, TCA, CPLAND, IJI, CAI\_MN, and ENN\_MN (Table 2).

Table 2 Metrics of landscape structure for selected indices at the class level

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Metrics | Agriculture | Bare land | Forest | Settlement | Shrub land | Grand Total |
| CA | 41.79 | 3.32 | 2.87 | 31.3718 | 1.5282 | 80.90 |
| NP | 67 | 13 | 7 | 60 | 7 | 154 |
| PLAND | 5166.66 | 411.11 | 355.55 | 3877.77 | 188.88 | 9999.99 |
| LPI | 5155.55 | 377.77 | 355.55 | 3822.22 | 177.77 | 9888.89 |
| PD | 8281.54 | 1606.86 | 865.23 | 7416.30 | 865.23 | 19035.18 |
| TE | 3268.03 | 1049.37 | 659.60 | 4377.37 | 659.60 | 10013.99 |
| CORE\_MN | 3.68 | 0.08 | 0.17 | 2.24 | 0 | 6.2031 |
| ED | 4039.46 | 1297.07 | 815.30 | 5410.65 | 815.30 | 12377.79 |
| AREA\_MN | 41.71 | 2.92 | 2.87 | 30.78 | 1.43 | 79.73 |
| SHAPE\_MN | 68.61 | 10.12 | 7.58 | 61.57 | 6.25 | 154.15 |
| TCA | 3.68 | 0.08 | 0.17 | 2.24 | 0 | 6.2031 |
| CPLAND | 455.55 | 11.11 | 22.22 | 277.77 | 0 | 766.66 |
| IJI | 283.65 | 191.82 | 0 | 474.01 | 91.82 | 1041.33 |
| CAI\_MN | 462.89 | 11.11 | 23.61 | 288.29 | 0 | 785.91 |
| ENN\_MN | 84.80 | 211.80 | 0 | 179.89 | 67.04 | 543.54 |

Regarding the landscape, the quantity of patches were increasing and decreasing for some land cover class compared with the number of patches at the class level, for example the number of patches of agriculture and settlement were increased from 67 to 73 and 60 to 70, whereas, number of patches of bare land, forest and shrub land were decreased from 13 to 3, 7 to 5 and 7 to 3 at landscape level due to conversion of these patches to the other land use, also it is related with the detectable size differences of patches of land landscape level and level of fragmentation (Table 3).

Table 3 shows the sixteen (16) representative measures of the broader landscape metrics categories. This summary provides a broad overview of the quantitative results of landscape metrics at the landscape level, in addition the overall landscape-level study. The number of patches of landscape level analysis was 154 among which agricultural land and settlement accounts the highest position 73 and 70, whereas forest and shrub land exhibits the smallest number of patches. In general by the all landscape metrics such as; NP, TA, AREA\_MN, PD, LPI, TE, SHAPE\_MN, PR, CORE\_MN, CAI\_MN, ENN\_MN, IJI,PRD, SHDI and SHEI the agriculture and settlement showed the maximum values compared with the other land cover class.

The percentage of landscape (PLAND) was an alternative to express the total class area (CA), which facilitates the comparison of proportions of each LULC class. In general, the most abundant LULC classes in the research region were agriculture and settlement and bare land, shrub land, forest were the less abundant in the research region landscape. AREA\_MN is a function of the area and number of patches. AREA\_MN was evaluated at the class level (Table 2) and at the landscape level (Table 3). The LULC classes that exhibited the largest mean patch sizes were agricultural land and settlement. Whereas, the LULC classes with the smaller mean patch sizes were forest, shrub land and bare land at class and landscape level.

Agriculture and settlement presented as the dominant class of the research region because their proportion of total area were the largest (Table 3). This combination result suggested dominance of the Agriculture class in the study area, which was supported by the largest mean patch area (AREA\_MN) 35.87 ha. The values of mean shape index (SHAPE\_MN) of the agriculture and settlement class were also the largest (54.3083 and 43.2946 ha), exposing that the average agriculture and settlement patch shape had significant difference in shape index values than the other land cover class in the research region landscape. These indexes evidenced the expanding of the studied area's agricultural and settlement areas.

The Mean Euclidean nearest neighbor distance (ENN\_MN) metric is a measure of the patch dispersion in the landscape and it measures the distance to the nearest neighboring patch of the same type. At the class level (Table 2), the class with the larger values for (ENN\_MN) index were the bare land and settlement class with 423.6154 and 359.784 m of distance between patches, and the class with the smaller value for ENN\_MN were the agriculture and shrub land class with an average of 169.6038 and 134.0836 m between patches of the same land cover class at class level.

The large distances among patches of bare land indicated the low abundance (low number of patches) and small mean patch size of this LULC class. The few patches of this class were not close to each other. On the contrary, the low ENN\_MN between patches of agriculture class at class level (Table 2) was most likely due to this LULC class being very abundant in the study area and with the higher number of patches and in general, closer to each other.

In the broader context of the landscape level, the highest ENN\_MN value was exhibited by agricultural land and settlement, whereas the smallest value of ENN\_MN exhibited by bare land, forest and shrub land (Table 3). The different value of ENN\_MN among land cover class at landscape level is clearly the indicator of the NP, TA, AREA\_MN, PD, LPI, TE, SHAPE\_MN, PR, TCA, CORE\_MN, CAI\_MN, PRD and SHDI differences. As shown in the table below, the land cover class with higher values of NP, TA, AREA\_MN, PD, LPI, TE, SHAPE\_MN, PR, TCA, CORE\_MN, CAI\_MN, PRD and SHDI had the highest value of ENN\_MN. Conversely, the land cover class such as bare land, forest and shrub land comprised the lower values of NP, TA, AREA\_MN, PD, LPI, TE, SHAPE\_MN, PR, TCA, CORE\_MN, CAI\_MN, PRD and SHDI had the lowest value of ENN\_MN at landscape level (Table 3).

Table 3 Illustrative measures of the wider landscape metrics at the landscape level

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Metrics | Agriculture | Bare land | Forest | Settlement | Shrub land | Grand Total |
| NP | 73 | 3 | 5 | 70 | 3 | 154 |
| TA | 42.87 | 1.61 | 2.42 | 33.16 | 0.80 | 80.9 |
| AREA\_MN | 35.86 | 1.21 | 1.62 | 23.59 | 0.26 | 62.56 |
| PD | 9023.17 | 370.81 | 618.02 | 8652.35 | 370.81 | 19035.18 |
| LPI | 4855.55 | 177.77 | 266.66 | 3566.66 | 77.77 | 8944.44 |
| TE | 1888.86 | 89.94 | 209.87 | 2698.38 | 119.92 | 5006.99 |
| SHAPE\_MN | 54.30 | 2 | 3.16 | 43.29 | 1 | 103.76 |
| PR | 70 | 3 | 5 | 65 | 3 | 146 |
| TCA | 3.68 | 0.08 | 0.17 | 2.24 | 0 | 6.20 |
| CORE\_MN | 3.49 | 0.08 | 0.13 | 1.99 | 0 | 5.70 |
| CAI\_MN | 434.62 | 11.11 | 17.36 | 250.49 | 0 | 713.59 |
| ENN\_MN | 179.89 | 0 | 0 | 363.65 | 0 | 543.54 |
| IJI | 94.63 | 0 | 0 | 214.73 | 94.63 | 404.01 |
| PRD | 8652.35 | 370.81 | 618.02 | 8034.32 | 370.81 | 18046.34 |
| SHDI | 8.64 | 0.52 | 0.87 | 11.52 | 0.68 | 22.26 |
| SHEI | 12.11 | 0.76 | 1.26 | 15.14 | 0.62 | 29.91 |

Note: PR: Patch Richness, NP: Number of Patches, CA: Class Area, PLAND: Percent of Landscape, TE: Total Edge, TA: Total Landscape Area, SHDI: Shannon Diversity Index, LPI: Largest Patch Index, LP: Largest Patch

**Principal components analysis**

Table 4 shows the eigenvalues and variance explained by each component.

Table 4 Eigenvalues and cumulative variability in various PC for landscape metrics

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | F1 | F2 | F3 | F4 |
| Eigenvalue | 14.8257 | 1.0542 | 0.1193 | 0.0008 |
| Variability (%) | 92.6606 | 6.5890 | 0.7454 | 0.0050 |
| Cumulative % | 92.6606 | 99.2496 | 99.9950 | 100.0000 |

Figure 2 depicts a biplot (axes F1 and F2) that clearly demonstrates the relationships between land use class and landscape measures. These two land cover types such as settlement and agriculture had a positive associationbecause as settlement increases, so does agriculture which is related with the increment of human population needs both settlement and agriculture.In contrast, these three land cover types, shrub land, forest, and bare land, had a negative association because, in general, as settlement and agriculture increased, shrub land, forest, and bare land decreased because the demand for settlement and agriculture outweighed the cost of shrub land, forest, and bare land. Landscape measures were also found to be positively connected with the Melokoza district's landscape. The biplot of the major component of landscape metrics demonstrated that closely positioned on the figure were viewed as alike when graded on provided attributes (Figure 2). According to the biplot results, most of the landscape metrics in the current inquiry were located close to each other on the figure, indicating a narrow distance. This could be as a result of the land use/land cover conditions in the area.

According to the PCA analysis, the first two components account for the collection of landscape pattern measurements produced by FRAGSTATS. Land cover types like agriculture and settlement are on the opposite sides of the first factor axis, while bare land, shrub land, and forest are on the opposite sides of the second factor axis, according to a biplot of the first two factors for cases in the analysis of principal component (Figure 2).

Agriculture was negatively correlated with PR, TA, SHAPE\_MN, LPI, AREA\_MN, TCA, CAI\_MN, and CORE\_MN and positively correlated with Component 1 and some landscape metrics like IJI, ENN\_MN, TE, SHDI, and SHEI. These correlations between the land use/land cover class centers and the Components 1 and 2 clearly demonstrate the high degree of fragmentation of landscape structure in the area. Additionally, settlement showed a negative correlation with PR, TA, SHAPE\_MN, LPI, AREA\_MN, TCA, CAI\_MN, and CORE\_MN and a positive correlation with Component 1 and a few landscape metrics, including IJI, ENN\_MN, TE, SHDI, and SHEI. These results suggest that the same landscape metrics were responsible for both kinds of land covers. On the other hand, the organizations of centers of land use/land cover classes in relation to the Components 1 and 2 indicate that shrub cover was positively correlated to Component 2 as opposed to agriculture and negatively correlated as opposed to settlement. However, forest and bare land were positively correlated to Component 2 as opposed to agriculture and negatively correlated as opposed to settlement (Figure 2).

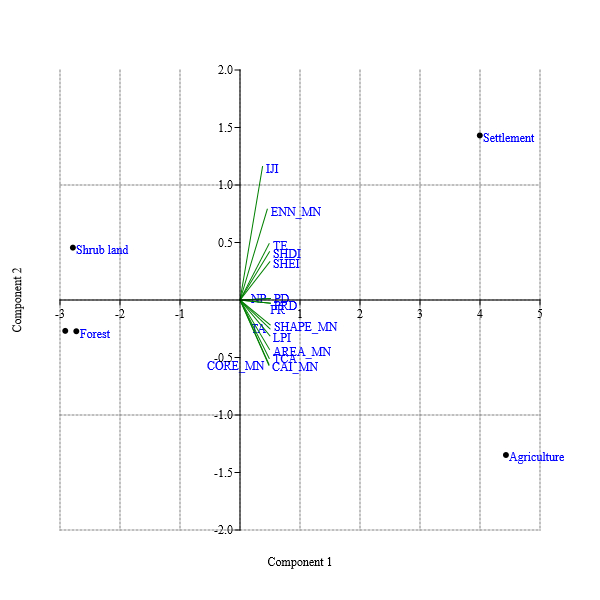


Figure 2 Biplot (axes F1 and F2)

The second and third sample sites for agriculture and settlement were located separately farther away and were clustered around the coordinate point (4.4318 and 3.996), while the land cover class was clustered at three sites (shrub land, bare land, and forest) around the coordinate point -2.7864, -2.9128, and -2.7286) for PC1 based on the correspondence ordination diagram (Table 5).

The site of the land cover coordinate point is influenced by the percentage of each type of land cover at the sample site and the number of sample sites that have a particular land cover, as the coordinate point distances among sample sites indicate differences based on the land cover percentage in a given landscape. The ordination figure demonstrates that, for three sample sites agriculture and settlement the variance in land cover % was comparatively similar among land cover categories of the landscape metrics. However, for two sample sites, it was different (agriculture and settlement). The degree of connectedness between different land cover types can be deduced from the value.

Table 5 Factor scores loading matrix

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Land cover | PC 1 | PC 2 | PC 3 | PC 4 |
| Agriculture | 4.4318 | -1.3474 | 0.13518 | 9.74E-05 |
| Bare land | -2.9128 | -0.26812 | -0.24432 | 0.04044 |
| Forest | -2.7286 | -0.27137 | -0.28794 | -0.03918 |
| Settlement | 3.996 | 1.4312 | -0.14597 | 0.000984 |
| Shrub land | -2.7864 | 0.45561 | 0.54305 | -0.00234 |

Figure 3 shows the values for the observation axes F1 and F2. An examination of ax F1 and F2 values reveals that there are significant disparities between line -2.9128, line -2.7864, line 4.4318, and line 3.996 land cover classes at the landscape scale (Table 5). The composition of lines 4.95 and 4.46 in the land cover class (agricultural and settlement) was superior. Line -2.9128, -2.7286, and -2.7864 land cover classes (bare land, forest, and shrub land) had lower coverage levels.

The observation plot in Figure 3 was split up into five groups: shrub land type (group 1), bare land type (group 2), forest type (group 3), settlement type (group 4), and agriculture type (group 5). While group four settlement type and group five agricultural type lines were expanding, group one shrub land type, group two bare land types, and group three forest type lines were all together declining. This suggests that, generally speaking, the main causes of the decline in the lines representing shrub land, forest, and bare land group types were raising agricultural group types and settlement group types (Figure 3).

Figure 3 Observation axes F1 and F2 value

Table 6 shows the extent of association between the component factors and each landscape measure based on the association between variables and factor analysis results. Regarding the landscape-level analysis, while the first-factor component was substantially connected with all landscape measures, the second component factor correlated with IJI, ENN\_MN, TE, SHDI and SHEI. The third component factor likewise was connected with TA, AREA\_MN, LPI, SHAPE\_MN, TCA, CORE\_MN, CAI\_MN and IJI and the fourth factor was correlated with TA, AREA\_MN, LPI, SHAPE\_MN, CORE\_MN, CAI\_MN and ENN\_MN (Table 6).

Table 6 Results of the factor analysis for the first four factors

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Factor number | | | |
|  | 1 | 2 | 3 | 4 |
| Eigenvalue | 14.8257 | 1.05423 | 0.119272 | 0.000794234 |
| % variance | 92.661 | 6.589 | 0.74545 | 0.004964 |
|  | **Factor loadings** | | | |
| Metrics | PC 1 | PC 2 | PC 3 | PC 4 |
| NP | 0.25967 | 0.0066049 | -0.05036 | -0.04775 |
| TA | 0.2574 | -0.12913 | 0.031034 | 0.081628 |
| AREA\_MN | 0.25278 | -0.22087 | 0.10127 | 0.22675 |
| PD | 0.25967 | 0.0066049 | -0.05036 | -0.04775 |
| LPI | 0.25615 | -0.1598 | 0.053616 | 0.075298 |
| TE | 0.24968 | 0.25197 | -0.2689 | -0.52555 |
| SHAPE\_MN | 0.25801 | -0.11118 | 0.013296 | 0.028446 |
| PR | 0.25967 | -0.014077 | -0.03405 | -0.09754 |
| TCA | 0.24998 | -0.26082 | 0.12203 | -0.15947 |
| CORE\_MN | 0.24736 | -0.2917 | 0.16216 | 0.13243 |
| CAI\_MN | 0.24776 | -0.28727 | 0.15656 | 0.09394 |
| ENN\_MN | 0.23365 | 0.40604 | -0.37123 | 0.72719 |
| IJI | 0.19301 | 0.59691 | 0.77719 | -0.00377 |
| PRD | 0.25967 | -0.014077 | -0.03405 | -0.09754 |
| SHDI | 0.25255 | 0.21593 | -0.20962 | -0.14533 |
| SHEI | 0.25482 | 0.17098 | -0.23357 | -0.18415 |

To determine how many principle components should be preserved, the results of a principal components analysis are commonly summarized using a scree plot. Scree graphs help you visualize how the variability of the data is accounted for by each component. The most noticeable decrease in slope in the scree plot is at component 4. As a result, based on the scree plot, one could argue that the top two components should be kept. These main components (PCs) accounted for 92.2% of the overall variability seen in landscape measurements across land cover classifications.

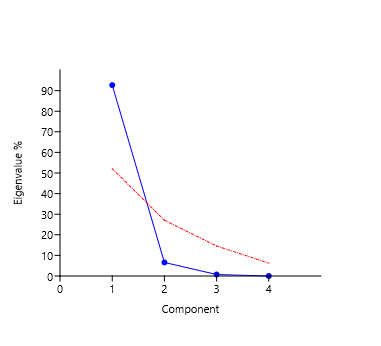


Figure 4 Scree Plot

F1 generated the largest Eigenvalue, 14.82, followed by F2 (6.59), F3 (0.12), and F4 (0.0008) (Table 4).

**Discussion**

In the research area with regard to all the metrics of the patches, agriculture and settlement depicts the largest compared with that of the other patches at patch level metrics. In general, the landscape in the study area manifested larger size of agricultural land and settlement than the others. Kennedy (2021) asserts that the growing distribution of land among various farmers makes the agricultural patch area appear larger, which is also in line with the outcomes of the current study. The primary causes of the fragmentation of natural vegetation may be linked to the high demand for construction activities in addition to the rise in the need for suitable agriculture lands. Patches of shrub land, barren ground, and woodland were therefore also divided due to the rising demand for food to feed the expanding population. There are indications of a comparable circumstance in other highland regions of Ethiopia (Gashaw *et al*., 2017; Yesuph and Dagnew, 2019). Our findings for the patch level metrics indicator likewise line up with those of De Cola (1989) and O'Neill *et al*. (1988). The study area's agricultural and settlement areas had the greatest FRAC values; these tendencies demonstrate the dynamic relationship between land cover, landscape structure and landscape fragmentation. Mcgarigal (2015), states that high FRAC values are indicative of high degrees of form and size fragmentation, making people more susceptible to environmental problems that may have an effect on ecosystem functioning and landscape structure. Thus, comprehension of these processes is necessary for land management plans that effectively maintain the richness and integrity of the ecosystem in the Melokoza district.

As presented in Table 2,the largest patch index were shown by agricultural and settlement (5155.56 and 3822.22 ha), respectively in the class level metrics. LPI variations with size extent are found to be significant for many landscape pattern characteristics, although the overall sensitivity of this metric is not very great. LPI tends to increase when map extent decreases if class abundance is not high, because a patch of a given size occupies a bigger percentage of the entire area in a map of smaller spatial extent. The percentage of landscape (PLAND) was used to express the total class area (CA), allowing for easier comparisons of proportions within each LULC class. Agriculture and settlement were the most prevalent land use/cover types in the research area, whereas forest, shrub land, and bare land were the least common. Conversely, when class abundance is great, the largest patch tends to grow throughout the landscape, regardless of its extent similar to the spanning cluster that emerges in basic random maps, the results are consistent with (Gardner *et al.,* 1987; With & Crist, 1995).

A land cover class's core region is an area that is farther away from a specified edge distance (McGarigal, 2012). When compared to other land cover types in this study, the core areas of agricultural and settlement had the highest concentrations. According to McGarrigal (2012), the core area (CA) of forest and shrub land had the lowest values, which amply illustrates the edge effects: the larger the core area, the less the edge effect. The increased agriculture and settlements in the research region were associated with these reductions in the core area of forest and shrub land.

Compared to other land cover types, the study area's agricultural and settlement patch areas appear to be bigger. The outcomes of a sizable patch area of agriculture and settlement align with Kennedy's (2021) research findings in the Mara basin. Consequently, there were less shrublands and forest patches. The tendency of forest and shrub land fragmentation also resulted in a higher variety of the perimeter and shape of forest fragments and shrublands, as already found in earlier research (Forman, 1995; Moreira *et al.,* 2001). Because more trees and shrubs were removed at the cost of more agricultural land and settlement, the ED of the Melokoza landscape displays a growing trend for agriculture and settlement. According to authors (e.g., Hepcan & Hepcan, 2015; Fischer *et al*., 2021), edge density refers to the overall number of edges in the overall landscape area, and the larger the number of edges, the greater the level of landscape structural fragmentation; this also applies to the study area. While a declining tendency was noted for forests, shrub land, and bare land, the mean patch size (AREA\_MN) for farming and settlement likewise displayed a comparable pattern to the LPI. It serves as a useful indicator to help comprehend patch fragmentation. Patch size increases over time and gradual clustering of the patches can both lead to increase (AREA\_MN) (Hepcan, 2015, Fischer *et al*., 2021). AREA\_MN was also highlighted by Lausch and Herzog (2002) as a crucial component of forest patches that affects habitat functioning, especially when paired with neighborhood and core area indices. The shape metrics that defined the patch fractal dimension and the complexity of the landscape shape were discovered in the present study.

The downward trend suggests that the patches are becoming more fragmented. The results obviously point to the dominance of agricultural and settlement lands in the Melokoza district, where agricultural activities served as the primary socioeconomic and livelihood system for the local populations. High LPI and (AREA\_MN) values are markers of landscape homogeneity. This finding is consistent with the findings of Tolessa *et al*. (2016), who noted that in the Jibat forest in western highland Ethiopia, the cultivated category develops sizable, detached areas. This observation was also supported by (Muleta & Biru, 2019), who reported comparable data and hypothesized that rising food and housing costs are the main causes of the growth of agricultural land and settlement. Redistributing land for young couples and the illegal land holding system were two major factors contributing to the expansion of the settlement patch (Yesuph & Dagnew, 2019). Different human activities lead to the transformation incorporating multi-functional landscapes into increasingly homogeneous human-dominated landscapes, as de Groot (2006) explained. As a general rule, continuous structural changes to the landscape may have detrimental effects on ecological processes, which may cause a reduction in ecosystem services (Pazurova *et al.,* 2018). If effective methods are not created, the negative effects of this structural shift in the landscape could intensify in the future.

Our findings also revealed that, several landscape variables correlated similarly with certain forms of land cover. In this case, total edge, patch density, IJI, SHDI, and SHDE were all positively connected with agriculture and settlement, indicating that the landscape in the area was complex and mosaic-like. A complex patch indicated a high land surface structure complexity (Zhou *et al.,* 2019). As highlighted by McGarigal (2006), the positive correlation of TE for all land cover categories in the area indicates a significant change and reduction in the spatial changeability of the landscape. This was true for the research area's land cover types over the landscape structure. Similarly, the greater TE value given by forests indicates that the ecosystem has no or little central tendency due to invasions and disturbances across numerous landscapes (Daye & Healey, 2015).

There were noticeable disparities in size across various land cover categories, settlement, and agriculture. This illustrates that the studied region is primarily composed of extremely fragmented patches. This conclusion was also corroborated by Yu & Ng (2006); Fang *et al.* (2021) & Lewis *et al.* (2023), who reported comparable findings and indicated that increasing cultivated land and settlement development predominantly results in increased patch fragmentation.

Similar to research conducted in other ecosystems, its overall variance is defined by the first four determinants of variation (Schindler *et al*., 2008). The principal component method's factor analysis results revealed that the first factor alone accounted for 92.66% of the difference in16 landscape measures, while the first two factors contributed 6.59% of the variation (Table 6). As a general guideline, factors should be retained if the corresponding eigenvalue is larger than one (Riitters *et al*., 1995). This condition was satisfied by the first two parameters, the first of which seemed to have a substantial correlation with the landscape metrics. Altogether the landscape measures have a substantial positive correlation with the first axis. The second axis has a negative correlation with TA, AREA\_MN, LPI, SHAPE\_MN, PR, TCA, CORE\_MN, CAI\_MN, and PRD and a positive correlation with NP, PD, TE, ENN\_MN, IJI, SHDI, and SHEI. In most research, one of the determinants has been metrics that assess the patches' shape (Lausch & Herzog, 2002; Cushman *et al.,* 2008; Schindler *et al.,* 2008). Furthermore, because humans prefer to create regular-shaped patches and buildings also lower the value of this metrics, SHAPE\_MN is an excellent predictor of human effect on landscapes because its value is much lower for places with strong human influence. Because they quantify the size of areas in the landscape and whether certain classes predominate there, these two axes were given the name "dominance." According to Cushman *et al.* (2008) and Riitters *et al.* (1995), there is a strong correlation between one of the axes and the big patch dominance measure. The IJI measurements and the second axis had a reasonably good correlation.

Scree plot F1 is ranked higher than F2, F3, and F4, as seen in (Figure 4), which is consistent with the Scree plot figure published by Lim & Jahng (2019). The outcomes of the parallel analysis, which point to dependable components, are displayed by the dashed red line. The eigenvalues of the factors or components are displayed in a scree plot in the order of biggest to smallest (Figure 4). Lines representing selection criteria for the amount of factors/components to keep can be added to scree plots, as in the case of the parallel analysis mentioned by (Lim & Jahng, 2019; Revelle, 2022).

Top of all, present study clearly depicts increased agricultural and settlement development has contributed to a reduction in forest and shrub land areas, leading to fragmentation of the landscape. This has been supported by many previous studies conducted in the different region of Ethiopia by several authors such as, (Reid *et al.,* 2000; Tsegaye *et al.,* 2010; Meshesha *et al.,* 2014; Wondrade *et al.,* 2014; Fetene *et al.,* 2016) and also from many tropical countries by (Lira *et al.,* 2012; Nahuelhual *et al.,* 2014; Putz *et al.,* 2014).

**4. Conclusion**

To analyze the degree and geographical dynamics of landscape structure, three levels of patch, class, and landscape metrics were widely applied independently. In the current study, every landscape indicator across all three layers is thoroughly and in-depth studied. The Melokoza district, which was discovered to be extremely fragmented, has significant modifications in land cover structure and spatial landscape structure. Significant alterations in important landscape measures served as indicators of this fragmentation. The study found that, at the class, patch, and landscape levels, there has been a steady growth in the area under agriculture and settlement. The documented negative consequences of agriculture and settlement, combined with a loss in forest and shrub land patches, are mostly caused by population growth. To address these difficulties, comprehensive and long-term environmental restoration and management strategies must be developed, taking into account the changing landscape structure. Regulatory frameworks that encourage sustainable land-use practices are critical to achieving ecological and socioeconomic well-being in the research region. The study findings provide vital insights for policymakers, allowing them to make informed decisions about how to maintain a healthy ecosystem across the landscape. Future research should focus on creating spatial frameworks for landscape restoration and evaluating the effects of landscape structural alterations on ecosystem services. To better comprehend the human components that influence landscape dynamics, interdisciplinary views, such as social sciences and economics, must be included.

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The authors declare that they have no conflict of interests.

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**Data availability statement**

The data that support the findings of this study are included in the paper and available from the corresponding author, upon reasonable request.[..\RAW Data e&e.docx](../RAW%20Data%20e&e.docx)

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