International Journal of Scientific Engineering and Research (IJSER)
ISSN (Online): 2347-3878
SJIF (2024): 6.623

Behavior of Landscape Metrics based on Change of Spatial Resolutions

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Abstract: ***Spatial resolution is very important in landscape analysis, whether it is a natural or man - made landscape. Changing spatial resolutions may affect or not the behavior of some landscape metrics. In this study, we attempt to analyze the behavior of landscape metrics at different scales of spatial resolution to understand on how the change of spatial resolution can affect landscape metrics behavior. To achieve the purpose of the study, supervised classification technique was applied to Landsat TM image for 1990 covering Bamako District by using Maximum Likelihood Classifier Method. A thematic map of seven classes were extracted, then resampled at 30 x 30, 60 x 60, 90 x 90, and 120 x 120m resolutions. We will focus at class level on area metrics (class area, percentage of land, largest patch index and Area), aggregation metrics (number of patches, Largest shape index, aggregation index), Shape metrics (Fractal dimension, Shape); and at landscape level on area - edge metrics (total area index, largest patch index), shape metrics (Fractal dimension, Shape index), aggregation metrics (number of patches, contagion index, largest shape index, aggregation index). The results show that aggregation metrics at both class and landscape levels are significantly affected by spatial resolution changes by decreasing index values, while metrics of area and shape indexes are not significantly affected. However, despite these changes on aggregations metrics values according to resolutions, they highlight the same information about landscape.***

Keywords: Behavior of landscape metrics, spatial resolution, Bamako district, multi - scale levels

1. Introduction

Landscapes are heterogeneous geographical areas composed of interacting ecosystems and human activity [1] whose structure and composition differ on whether we are in natural or human environment. Landscape and resources utilization by human activities has emerged serious changes in landscape structure and pattern by increasing significantly their dynamics over the last few decades of the 20th centuries [2]. The changes that have taken place through these activities causes numerous degradation of the natural ecosystem functioning, increased volume of surface runoff causes flooding, water quantity and quality [3], [1], [4], [5].

To understand changes in landscape various metrics are used analysing different types and levels of changes. There are hundreds of landscape metrics computed by FRAGSTATS software have been developed to quantify landscape status. FRAGSTATS is a stand - alone software program designed to compute a wide variety of landscape metrics to understand landscape fragmentation [6], [7]. However, not all of these metrics can be used for a particular landscape analysis because most of them are highly correlated to one another and few of them are redundant [8], [9], [10], [2], [1]. Therefore, only selected metrics is used to avoid the redundancy of landscape metrics. These metrics can quantify the area, shape, core area, nearest neighbour distances, isolation and connectedness in patch, class or landscape level [11], [12], [13], [2], [1].

In geographical terms, landscapes are defined as the combination of environmental and human phenomena, which coexist in specific locations on the earth's surface. Urban areas are the most striking example of the human landscape. These areas involve the highest levels of human activity and are often severely affected by environmental factors.

Many studies were carried out using remote sensing data sets to study changes in space–time landscape patterns [14], [15], [16], [17]. The main purpose of these studies is to analyze the LC dynamics of space–time, especially urban growth/disorder and rural land loss. Most of these studies clearly show that LC patterns and their changes are related to natural and social processes [16]. These natural and social processes, known as drivers or change factors, may be related to natural disaster events, economic growth, population growth, changes in physical conditions in the landscape environment, political management [18], etc.

Landscape pattern metric is widely used to study the spatial characteristics, change analysis, simulations to predict future urban spatial patterns and urban land use driving forces [14], [19], [20], [21], [22].

Landscape pattern analysis methods were also widely studied by many authors. A standardized approach to measure and monitor landscape pattern attributes is described to support habitat monitoring [23]. The process of monitoring uses disaggregated landscape maps, where selected habitat attributes or different categories of habitat quality are represented as different patch types, using maps generated by modeling methods [24].

Studies were focused on landscape pattern analysis using remotely sensed data and landscape metrics [18], [18] in different aspects, such as characterizing landscape patterns [25] predicting pattern changes like sprawl in the future using regression models [26], and quantifying patterns [27], [20]. Most of these studies have used different methods to achieve their purposes (such as spectral, indexes [28], regression models, cellular automata Markov chain (CA - Markov) model, multi - approach analysis, etc.).

Several studies have been done using landscape metrics to analyze human and natural environments as can be seen above. However, none of these studies focused on the impact of spatial resolution variation of landscape metrics for a considered metric. To our knowledge, this is the first study investigating the responses of changing the spatial resolution of imagery on the behavior of landscapes metrics. These changes in spatial resolution at different scales can potentially have effects on the behavior of landscape metrics; therefore we discuss the results of this study in the context of their implications for changes in results after computing landscape metrics based on each spatial resolution.

The objective of this study is an attempt to analyze the behavior of landscape metrics at different scales of spatial resolution to understand on how the change of spatial resolution can affect landscape metrics behavior.

2. Materials and Methods

2.1. Materials

For this study, Landsat image for the year 1990 was downloaded free of charge by Earth Explorer. The characteristics on this image are shown in Table 1. The remote sensing software eCognition Developer 8.7, ENVI 5.3, and the Geographical Information System software Arc GIS 10.8 were used for further data analysis.

Table 1: The characteristics of image data

Landsat	*Path*	*Row*	*Sensor*	*Spatial Resolution*	*Bands number*	*Radiometric resolution*	*Acquisition date*
Landsat 5	199	51	TM	30 m	7	8 bits	09/11/1990

TM: Thematic Mapper

2.2. Methods

2.2.1. Image pre - processing

Using ENVI 5.3 software, the radiometric calibration and atmospheric correction were performed. The atmospheric correction benefit is carried out to reduce the atmospheric effects on the electromagnetic radiation. The Fast Line - of - sight Atmospheric Analysis of Hypercubes (FLAASH) module was used as the main tool for atmospheric correction of multispectral and hyperspectral images that operate in the wavelength range from visible to infrared (above 3 µm). After this, the study area boundaries were extracted from the preprocessed images using Bamako district administrative limits shape file in ArcGIS by clipping method.

2.2.2. Land Cover/Land Use classification

Seven classes were defined based on the local conditions of the study area and others papers, by using supervised approached. These classes are: built – up, forest, water, farmland, grassland, bareland, and rock [18]. Classes' description is shown in Table 2. "Supervised classification is the process of identification of classes within a remote sensing data with inputs from and as directed by the user in the form of training data" [29]. The used supervised classification technique is the Maximum Likelihood Classification (MLC) approach. "This method of classification calculates the 'probability for a given pixel' to each class and then the pixel will be allocated to a 'particular class' with the highest probability. It calculates the mean and covariance matrix for the 'training samples' and assumes that the pixel values are normally distributed". "Then a probability density function is defined and the input pixels are mapped based on the likelihood that the pixel belongs to that particular class" [30].

Table 2: Classification class descriptions [18].

Class code	*Class name*	*Class description*
1	Built - up	Residential areas, settlement areas, industrial zones, commercial zones, facilities, transportation networks.
2	Forest	Natural vegetation, reserve vegetation areas
3	Water	River
4	Farmland	Cereals croplands, vegetables croplands, orchard lands
5	Grassland	Grasses, shrubs, pasture
6	Bareland	Non - vegetation and non - cultivate areas,
7	Rock	Mountain rocks, river rocks, and hill rocks

2.2.3. Landscape metrics behavior at different spatial resolutions

In this study, landscape metrics behavior at different spatial resolutions detection and analysis was mainly focused on landscape metrics variation analysis at both landscape and class levels.

To achieve the purpose of this study, satellite image for 1990 for Bamako was firstly used for supervised classification to generate a classification map or thematic map. Secondly, a number of suitable landscape metrics were selected to be computed at different retained spatial resolutions (30 x 30, 60 x 60, 90 x 30 and 120 x 120). The selected metrics are presented in table 2 and table 3. Finally, by using the produced classification or categorical landscape map, Landscape pattern analysis program software package FRAGSTATS (version 4.2) was used to calculate the selected landscape metrics, both at landscape and class level.

The methodology flowchart is presented in figure 1.

Table 3: Class metrics and descriptions [31], [32], [18].

Class Metric	*Formula*	Description
Percentage of landscape (%PLAND)	$p_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} (100)$	%LAND equals the sum of the areas (m2) of all patches of the corresponding patch type, divided by total landscape area (m2), multiplied by 100 (to convert to a percentage)
Class Area (CA)	$CA = \sum_{n=1}^{\infty} a_{ij} (\frac{1}{10000})$	CA equals the sum of the areas (m2) of all patches of the corresponding patch type, divided by 10, 000 (to convert to hectares); that is, total class area. CA approaches 0 as the patch type becomes increasing rare in the landscape.
Number of Patches (NP)	$NP = n_i$	Number of patches of corresponding patch type (class)
Largest Patch Index (LPI)	$LPI = \frac{\max(a_{ij})_{j=1}^{n}}{A} (100)$	LPI 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)
Patch Area Index (AREA)	$AREA = a_{ij} \left(\frac{1}{10,000}\right)$	AREA equals the area (m2) of the patch, divided by 10, 000 (to convert to hectares).
Shape Index (SHAPE)	$SHAPE = \frac{.25\, p_j}{\sqrt{a_{ij}}}$	SHAPE equals patch perimeter (m) divided by the square root of patch area (m2), adjusted by a constant to adjust for a square standard.
Fractal Dimension Index (FRAC)	$FRAC = \frac{2\, ln\left(.25_{p_{ij}}\right)}{ln\, a_{ij}}$	FRAC equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m2); the perimeter is adjusted to correct for the raster bias in perimeter.
Aggregation Index	$AI = \left[\frac{g_{ii}}{max \rightarrow g_{11}}\right] (100)$	AI equals the number of like adjacencies involving the corresponding class, divided by the maximum possible number of like adjacencies involving the corresponding class, which is achieved when the class is maximally clumped into a single, compact patch; multiplied by 100 (to convert to a percentage).

Table 3: Landscape Metrics and descriptions adopted from [31], [33]; [18].

Landscape Metric	*Formula*	Descriptions
Number of Patches (NP)	$NP = N$	NP equals the number of patches in the landscape. NP does not include any background patches within the landscape or patches in the landscape border.
Largest Patch Index (LPI)	$LPI = \frac{\max(a_{ij})_{j=1}^{n}}{A} (100)$	LPI 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); in other words, LPI equals the percentage of the landscape that the largest patch comprises.
Landscape Shape Index (LSI)	$LSI = \frac{0.25E'}{\sqrt{A}}$	LSI equals the sum of the landscape boundary (regardless of whether it represents true edge) and all edge segments (m) within the landscape boundary (including those bordering background), divided by the square root of the total landscape area (m2), adjusted by a constant for a circular standard (vector) or square standard (raster)
Contagion (CONTAG)	$CONTAG = \left[1 + \sum_{i=1}^{m} \sum_{j=1}^{m} \frac{p_{ij} \ln(p_{ij})}{2 \ln(m)}\right] [100]$	CONTAG equals 1 plus the sum of the proportional abundance of each patch type multiplied by number of adjacencies between cells of that patch type and all other patch types, multiplied by the logarithm of the same quantity, summed over each patch type; divided by 2 times the logarithm of the number of patch types; multiplied by 100 (to convert to a percentage).
Landscape Total Area (TA)	$TA = A \left(\frac{1}{10,000}\right)$	TA equals the total area (m2) of the landscape, divided by 10, 000 (to convert to hectares). Note, total landscape area (A) includes any internal background present.
Shape Index (SHAPE)	$SHAPE = \frac{.25\, p_j}{\sqrt{a_{ij}}}$	SHAPE equals patch perimeter (m) divided by the square root of patch area (m2), adjusted by a constant to adjust for a square standard.
Fractal Dimension Index (FRAC)	$FRAC = \frac{2\, ln\left(.25_{p_{ij}}\right)}{ln\, a_{ij}}$	FRAC equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m2); the perimeter is adjusted to correct for the raster bias in perimeter.

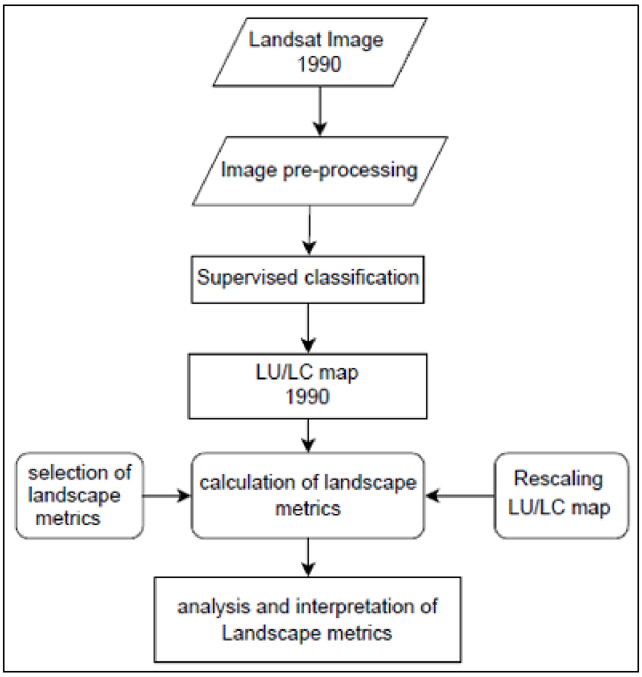

Figure 1: Methodology flowchart

3. Results and discussion

3.1 Land Cover/Land Use map

In this study, one thematic map for the year 1990 was produced by applying the supervised classification method on multitemporal Landsat images. Figure 2 illustrates the classification results. There are a total of eleven classes; however, the classification has been applied on only those classes (7) that represent area feature objects (built - up, forest, water, farmland, grassland, bareland, and rock).

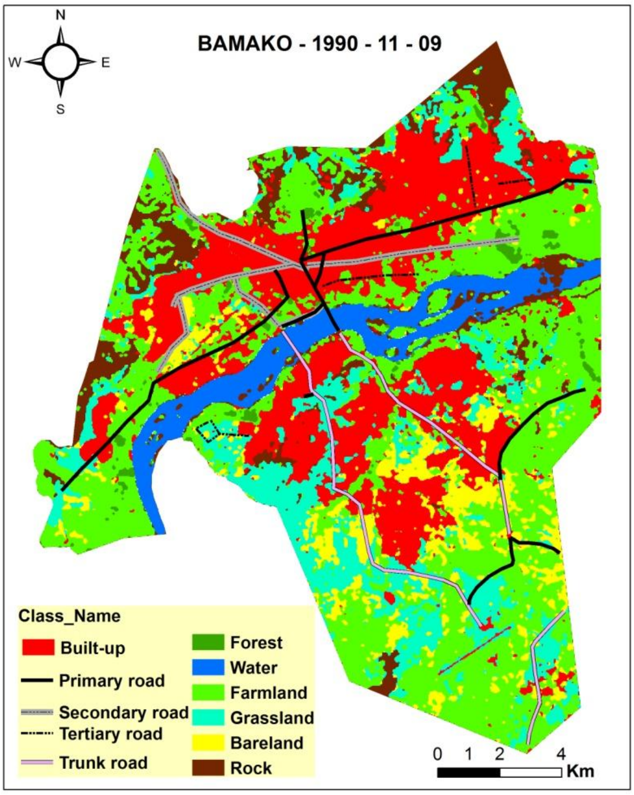

Figure 2: Land Use/Land Cover classification map in Bamako district for 1990

3.2. Landscape metrics behavior at different spatial resolution

3.2.1. Landscape metrics behavior at class level

This study presents three types of landscape metrics results at class level: area metrics (CA, PLAND, LPI, and AREA), shape metrics (FRAC and SHAPE) and aggregation metrics (NP, LSI and AI). The trends of these metrics are presented in Tables 4.

Table 4: Landscape metrics at class level

		Area metrics				*Shape metrics*		*Aggregation metrics*		
Class name	*Scale*	*CA*	*PLAND*	*LPI*	*AREA*	*FRAC*	*SHAPE*	*NP*	*LSI*	*AI*
Rock	30	1837.71	7.50	1.26	3.82	1.04	1.26	481	23.16	84.37
	60	1809.72	7.36	1.14	5.85	1.03	1.22	309	19.38	73.66
	90	1820.88	7.43	1.11	7.78	1.03	1.24	234	18.16	62.94
	120	1748.16	7.11	1.12	11.65	1.03	1.24	150	14.87	58.82
Farmland	30	8809.02	35.96	14.13	22.70	1.05	1.38	388	25.54	92.12
	60	8891.64	36.19	14.24	29.05	1.04	1.33	306	22.84	85.97
	90	8810.37	35.97	14.19	34.14	1.03	1.34	258	21.98	79.64
	120	8929.44	36.34	14.38	48.00	1.03	1.35	186	19.51	76.11
Grassland	30	3325.86	13.57	4.93	8.59	1.05	1.34	387	23.38	88.27
	60	3296.88	13.41	4.94	11.29	1.03	1.25	292	20.09	79.77
	90	3322.62	13.56	5.85	13.34	1.03	1.24	249	19.65	70.19
	120	3293.28	13.40	5.75	18.19	1.03	1.26	181	16.84	66.03
Bareland	30	1988.73	8.11	1.66	4.39	1.05	1.27	452	24.67	83.92
	60	1999.44	8.13	1.08	4.99	1.03	1.18	400	22.02	71.22
	90	1978.83	8.07	1.09	7.09	1.03	1.22	279	20.44	59.78
	120	1990.08	8.10	1.10	8.96	1.02	1.19	222	17.93	52.77
Built - up	30	6658.56	27.18	13.70	21.41	1.04	1.27	311	16.55	94.26
	60	6695.28	27.25	13.75	29.36	1.03	1.23	228	14.71	89.86
	90	6683.31	27.28	14.11	34.80	1.02	1.21	192	13.96	85.54
	120	6707.52	27.30	14.83	55.43	1.02	1.21	121	12.14	83.36
Forest	30	296.55	1.21	0.18	2.24	1.05	1.21	132	12.10	80.27
	60	287.64	1.17	0.18	2.66	1.02	1.10	108	10.52	64.76
	90	296.46	1.21	0.18	3.57	1.02	1.12	83	9.58	51.65

	120	285.12	1.16	0.17	4.19	1.01	1.08	68	8.41	41.41
Water	30	1577.88	6.44	6.42	315.57	1.07	2.21	5	6.27	95.98
	60	1587.96	6.46	6.13	396.99	1.09	2.48	4	6.03	92.28
	90	1578.69	6.44	6.11	394.67	1.09	2.50	4	5.91	88.52
	120	1612.8	6.56	6.55	806.4	1.10	3.27	2	5.58	85.87

For Area metrics, statistics of CA, PLAND and LPI for the seven classes are correlating significantly with the trends of used scales (30, 60, 90 and 120). There is no significant and regular increasing change basing on scales trends as shown in table 4 and figure. Inversely, AREA statistics trend are regularly increasing following the increasing of scales for all classes. For Rock class the metrics trend are 3.82, 5.85, 7.78 and 11.65, respectively for scales 30x30, 60x60, 90x90, 120x120; and that is valid for all the other classes as it can be seen in table 4 and figure 3.

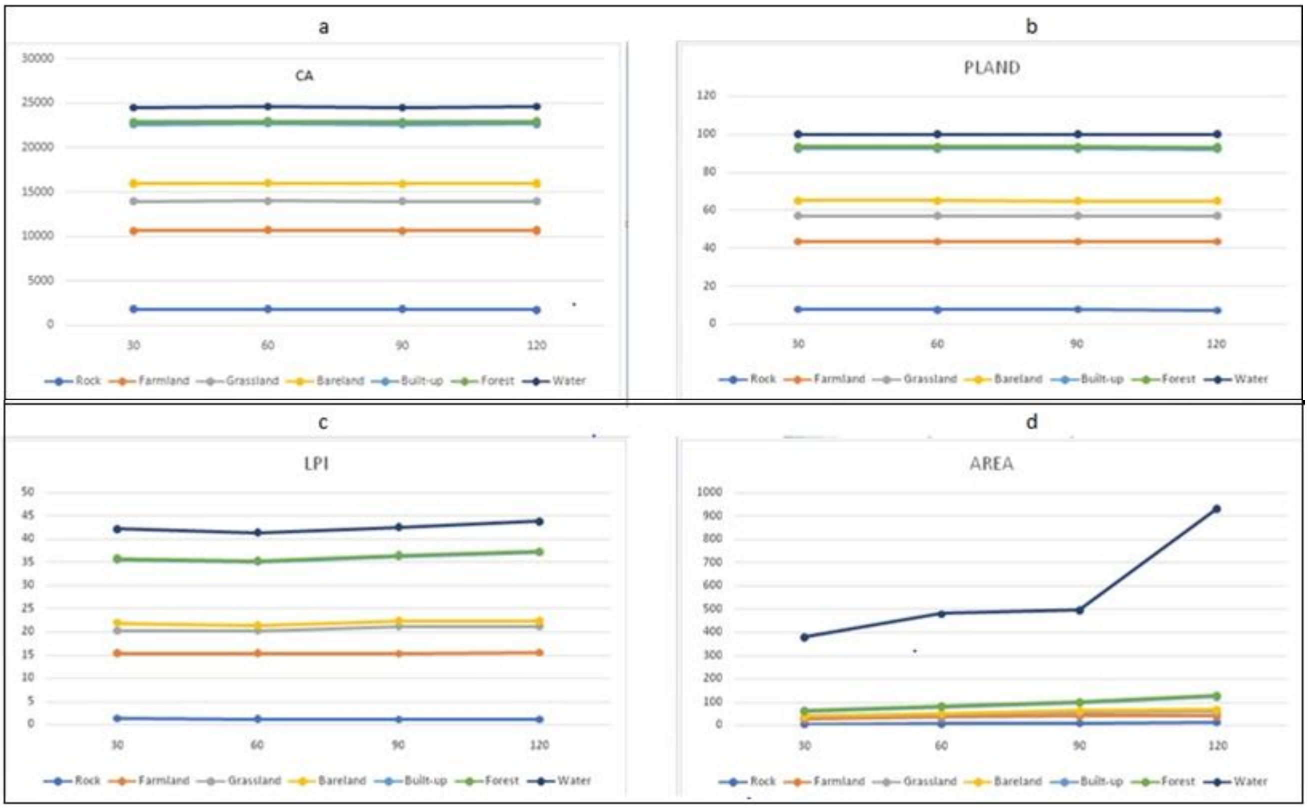

Figure 3: Curve trends for area metrics at class level in spatial resolution for 30, 60, 90 and 120 meters.
NB: a: class area; b: Percentage of Land; c: Largest Patch Index; d: Area.

For shape metrics, there were no significant changes in FRAC and SHAPE for the different scales. However, it can be found that the two metrics used have their highest value for scale 30x30 for all classes except water class where the highest value is for scale 120x120 and the lowest value is for scale 30x30. The values of shape metrics are presented in table 4 and curves trends in figure 4.

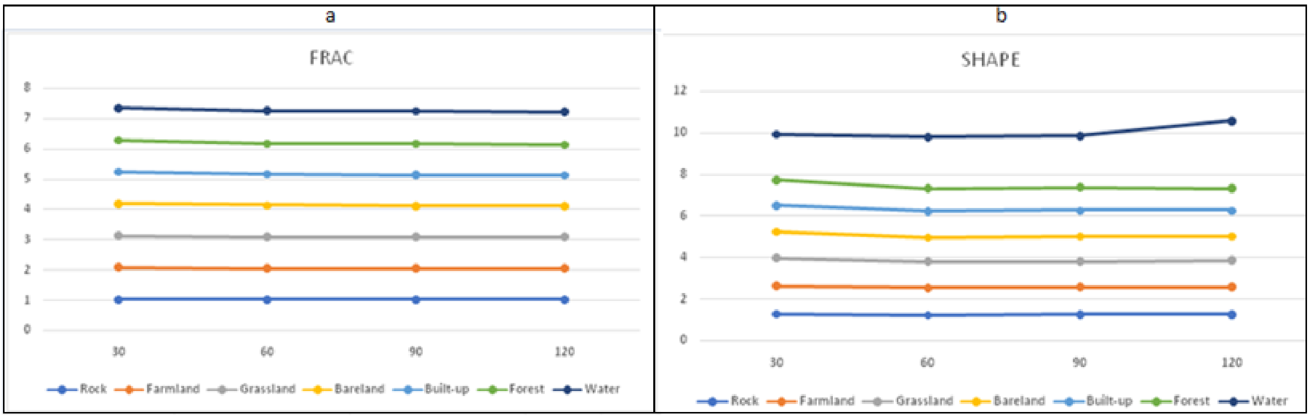

Figure 4: Curve trends for shape metrics at class level in spatial resolution for 30, 60, 90 and 120 meters.
NB: a: Fractal Dimension Index; b: Shape Index

For aggregation metrics, it can be see significant changes in statistics for all classes based on scale changes. In addition, it is important to note that this variation in metrics results is inversely decreasing as the scale grows. For farmland class, NP values were decreasing from 338, 306, 258 to 186; respectively for scales 30, 60, 90 and 120. That is valid for all the classes. Trends NP, LSI and AI values are presented in table 4 and curves trends figure 5.

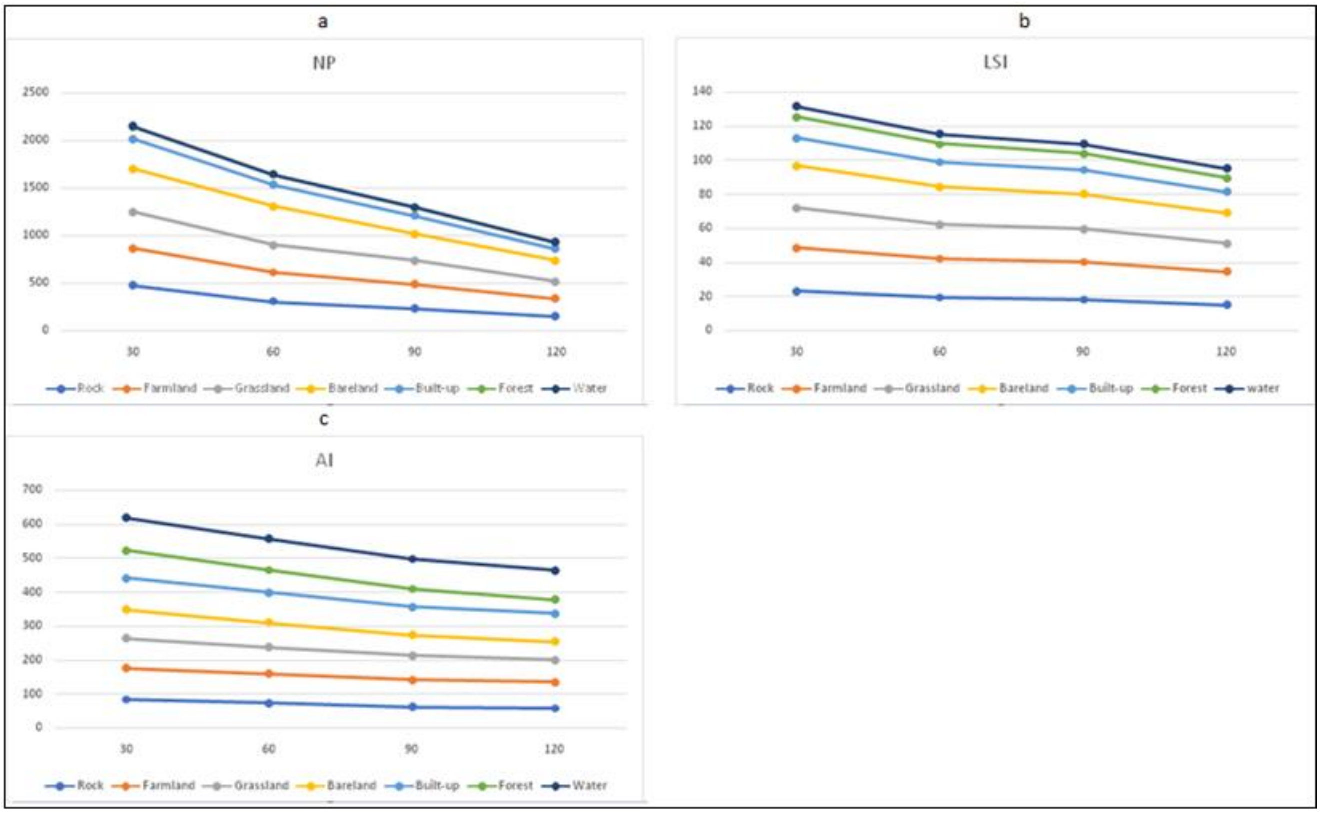

Figure 5: Curve trends for aggregation metrics at class level in spatial resolution for 30, 60, 90 and 120 meters.
NB: a: Number of patch; b: Largest Patch Index; c: Aggregation Index

3.2.2. Landscape metrics behavior at landscape level

Like the landscape metrics at class level, it has also been the same types of landscape metrics to analyze at landscape level metric changes according to the differences in scales. The used types of metrics are: area (TA, LPI), shape metrics (FRAC and SHAPE) and aggregation metrics (NP, CONTAG, LSI and AI). The trends of these metrics are presented in Tables 5.

Based on the statistics in table 5, like for landscape metrics at class level, it can be remarked no significant changes in area and shape metrics at landscape level as also shown in figure 6. This is valid for TA and LPI for area metrics; FRAC and SHAPE for shape metrics.

All aggregation metrics shows significant changes based on in spatial resolution. However, this change is decreasing in opposition to the growth order of spatial resolution scales. For NP, values are 2156, 1647, 1299 and 930; respectively for 30, 60, 90, 120 of spatial resolution; and inversely as shown in table 5 and figure 7.

Table 5: Landscape indexes at landscape level

	Area		*Shape metrics*		*Aggregation metrics*		
Scale	TA	LPI	FRAC	SHAPE	NP	CONTAG	LSI
30	24494.31	14.1344	1.0522	1.3055	2156	47.7392	25.8132
60	24568.56	14.2499	1.036	1.2379	1647	41.9108	22.3614
90	24491.16	14.1917	1.0333	1.251	1299	37.108	21.5675
120	24566.4	14.8359	1.0306	1.2483	930	34.8894	18.6832

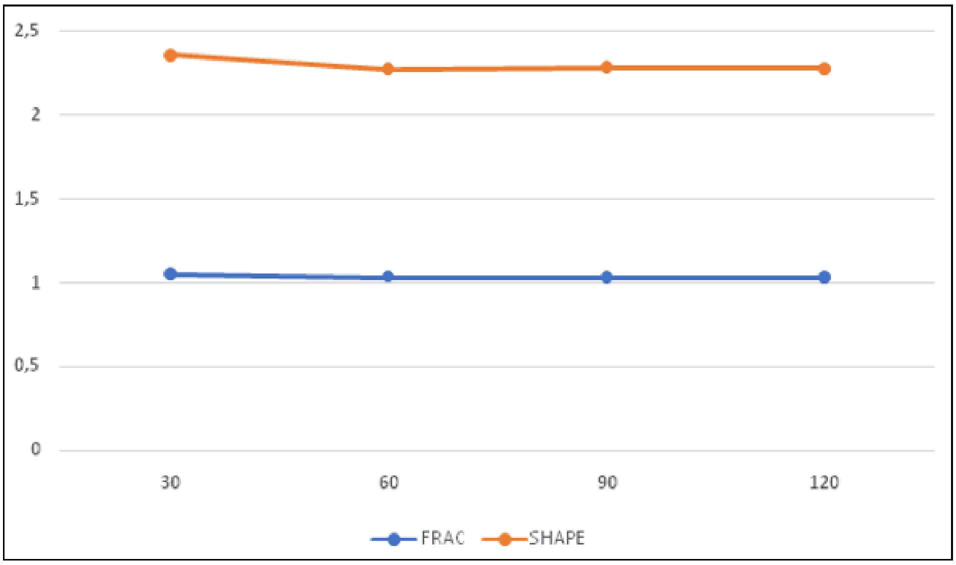

Figure 6: Curve trends for FRAC and SHAPE landscape level in spatial resolution for 30, 60, 90 and 120 meters.

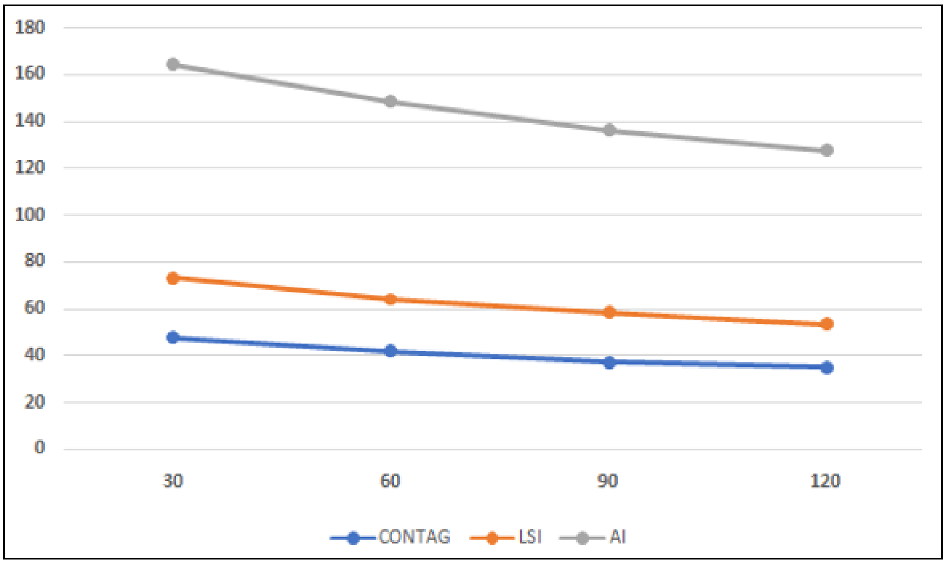

Figure 7: Curve trends for CONTAG, LSI and AI in landscape level in spatial resolution for 30, 60, 90 and 120 meters

Landscape metrics both at class and landscape levels are all sensitive to changing of spatial resolution but differently. However, these changes are more or less significant according to the types of landscape metrics. Based on the trends of metrics statistics at class level in table 4 and landscape level in table 5, it can be concluded that landscape metrics are affected but not significantly by changing in spatial resolution of image for area and shape metrics. The other important note is that aggregation metrics are all very sensitive to changing of spatial resolution at both class and landscape level as it is shown in table 4 and table 5. However, whether for class and landscape level, the effects of change of spatial resolution are identical for all aggregation metrics. They decrease continuously as the spatial resolution increases.

Scaling relations for landscape pattern when it is measured over a range of scales (grain size and extent) were explored [34], and the findings showed that the responses of landscape metrics to changing scale fell first into two categories when computed at the class level (i. e., for individual land cover types): simple scaling functions and unpredictable behaviour; and then similarly three categories were found at the landscape level. While the need for multiscale analysis is highlighted by that study in order to adequately characterize and monitor landscape heterogeneity, and provides insights into the scaling of landscape patterns; a review on the behavior of indices commonly used for quantifying landscape structure was done [35]. That review concluded that simple and easily interpretable indices with predictable reactions to changes in scale, e. g., the number of patches (NP), patch density (PD), edge density (ED), patch richness (PR), and mean patch size (MPS) of the landscape, are the most suitable indices to use for the assessment of landscape structure.

Preview studies assessed effects of changes in the spatial and thematic scales on the values of landscape indices and suggested directions for further researcher the behavior of landscape metrics. The current paper highlights the behavior of metrics to changes in spatial resolution (grain size) of image based area, shape and aggregation indices which was not the case for previous studies. We found that area and shape indices are not significantly affected by the effects of changes in spatial resolution but aggregation indices are greatly affected by changes in spatial resolution; but inversely proportional to the spatial resolutions sizes.

Although we clearly found that aggregation metrics are more affected by changes in spatial resolutions that area and shape metrics, our study has not been looking at the scientific reasons of these metrics behavior. Therefore, future and in - depth researches on the scientific reasons of these metrics behavior will be timely for a better understanding of the effects changes in spatial resolution in the analysis of landscape metrics at both landscape and class level.

References

[1] Kumar M., Denis D. M., Singh S. K., Szabó S., Suryavanshi S., 2018, *Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed*, Remote Sensing Applications: Society and Environment 10 (2018) 224–233

[2] Singh, S. K., Srivastava, P. K., Szilard, S., Petropoulos, G. P., Gupta, M., Islam, M., 2016. Landscape transform and spatial metrics for mapping spatiotemporal land cover dynamics using Earth Observation data - sets. Geocarto Int.1–15. http: //dx. doi. org/ 10.1080/10106049.2015.1130084.

[3] Campbell, D. J., Gichohi, H., Mwangi, A., Chege, L., 2000. Land use conflicts in S. E. KajiadoDistrict, Kenya. Land Use Policy 17, 338–348.

[4] Kumar, N., Singh, S. K., Singh, V. G., Dzwairo, B., 2016. Investigation of impacts of land use/land cover change on water availability of Tons River Basin, Madhya Pradesh, India. Model. Earth Syst. Environ.4, 295–310. http: //dx. doi. org/10.1007/s40808 - 018 - 0425 - 1.

[5] Kumar, N., Singh, S. K., Srivastava, P. K., Narsimlu, B., 2017. SWAT Model calibration and uncertainty analysis for streamflow prediction of the Tons River Basin, India, using Sequential Uncertainty Fitting (SUFI - 2) algorithm. Model Earth Syst Environ.3 (30). http: //dx. doi. org/10.1007/s40808 - 017 - 0306 - z.

[6] McGarigal, K., Cushman, S. A., Neel, M. C., Ene, E., 2002. FRAGSTATS: spatial pattern analysis program for categorical maps. Amherst: Computer software program produced by the authors at the University of Massachusetts. Available from ⟨http: //www.umass. edu/landeco/research/fragstats/fragstats. html⟩.

[7] Lamine, S., Petropoulos, G. P., Singh, S. K., Szabó, S., Bachari, NEI, Srivastava, P. K., Suman, S., 2017. Quantifying land use/land cover spatio - temporal landscape pattern dynamics from Hyperion using SVMs classifier and FRAGSTATS ®. Geocarto Int.6049, 1–17. http: //dx. doi. org/10.1080/10106049.2017.1307460.

[8] McGarigal, K., Marks, B. J., 1995. Spatial pattern analysis program for quantifying landscape structure. General Technical Report PNW - GTR - 351. US Department of Agriculture, Forest Service. Pacific Northwest Research Station.

[9] Turner, M. G., Gardner, R. H., O´Neill, R. V., 2001. Landscape Ecology in Theory and Practice. Springer - Verlag, New York, pp.401. http: //dx. doi. org/10.1007/978 - 1 - 4939 - 2794 - 4.

[10] Uuemaa, E., Antrop, M., Roosaare, J., Marja, R., Mander, U., 2009. Landscape metrics and indices: an overview of their use in landscape research. Living Rev. Landsc. Res.3, 1–28. (URL). ⟨http: //www.livingreviews. org/lrlr - 2009 - 1/⟩.

[11] Li, X., Lu, L., Cheng, G., Xiao, H., 2000. Quantifying landscape structure of the Heihe River Basin, north - west China using FRAGSTAT. J. Arid Environ.48, 521–535.

[12] Olsen, L. M., Dale, V. H., Foster, T., 2006. Landscape patterns as indicators of ecological change at Fort Benning, Georgia, USA. Landsc. Urban Plan.79, 137–149.

[13] Kamusoko, C., Aniya, M., 2007. Land use/cover change and landscape fragmentation analysis in the Bindura District, Zimbabwe. Land Degrad. Dev.2, 221–233.

[14] Keita M., 2022 Urban sprawl pattern change and driving factors analysis in Bamako district, Mali. Ph. D. Thesis, University of Hohai, Nanjing, 2022

[15] Dewan, A. M.; Yamaguchi, Y. *Using remote sensing and GIS to detect and monitor land use and land cover change in Dhaka Metropolitan of Bangladesh during 1960–2005*. Environ. Monit. Assess.2009, 150, 237–249.

[16] Fichera, C. R.; Modica, G.; Pollino, M. *GIS and Remote Sensing to Study Urban - Rural Transformation During a Fifty - Year Period*. In Computational Science and Its Applications - ICCSA; Springer: Berlin, Germany, 2011; pp.237–252.

[17] Yuan, F.; Sawaya, K. E.; Loeffelholz, B. C.; Bauer, M. E. *Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing*. Remote. Sens. Environ.2005, 98, 317–328.

[18] Keïta M. A, Ruan R., Ru A., 2021, *Spatiotemporal Change of Urban Sprawl Patterns in Bamako District in Mali Based on Time Series Analysis*, Urban Sci.2021, 5, 4. https: //doi. org/10.3390/urbansci5010004

[19] Feng, Y. J.; Liu, Y. Fractal dimension as an indicator for quantifying the effects of changing spatial scales on landscape metrics. Ecol. Indic.2015, 53, 18–27.

[20] Peng, Y.; Mi, K.; Qing, F. T.; Xue, D. Y. Identification of the main factors determining landscape metrics in semi - arid agro - pastoral ecotone. J. Arid Environ.2016, 124, 249–256.

[21] Jia, Y.; Tang, L.; Xu, M.; Yang, X. Landscape pattern indices for evaluating urban spatial morphology–A case study of Chinese cities. Ecol. Indic.2019, 99, 27–37.

[22] Kaza, N. The changing urban landscape of the continental United States. Landsc. Urban Plan.2013, 110, 74–86.

[23] Liu, L. Analysis of Urbanization in China by Remotely - Sensed Data. Ph. D. Thesis, University of Hong Kong, Hong Kong, 2014.

[24] Cushman, S. A.; Compton, B. W.; McGarigal, K. Chapter 20. Habitat fragmentation effects depend on complex interactions between population size and dispersal ability: Modeling influences of roads, agriculture and residential development across a range of life - history characteristics. In Spatial Complexity,

Informatics, and Wildlife Conservation; Cushman, S. A., Huettmann, F., Eds.; Springer: Tokyo, Japan, 2010; p.18.

[25] Hai, N. N.; Ahn, N. T.; Khuong, T. N. L.; Dung, B. Q.; Nguyen, M. K. Research on urban sprawl trends and landscape change in Pleiku city, Gia Lai Province. Vietnam J. Hydrometeorol.2019, 2, 37–47.

[26] Karl, R.; Reddy, G. O.; Kumar, N.; Singh, S. K. Monitoring spatio - temporal dynamics of urban and peri - urban landscape usingremote sensing and GIS—A case study from Central India. Egypt. J. Remote Sens. Space Sci.2018, 21, 401–411.

[27] Rimal, B.; Zhang, L.; Keshtkar, H.; Sun, X.; Rijal, S. Quantifying the Spatiotemporal Pattern of Urban Expansion and Hazard and Risk Area Identification in the Kaski District of Nep. Land 2018, 7, 37.

[28] Shahfahad; Mourya, M.; Kumari, B.; Tayyab, M.; Paarcha, A.; Asif; Rahman, A. Indices based assessment of built - up density and urban expansion of fast - growing Surat city using multi - temporal Landsat data sets. GeoJournal 2020.

[29] Anand A, 2017. '*Unit 13 Image classification'*. http://egyankosh. ac. in//handle/123456789/39543 (accessed 30 April 2020)

[30] Minu Nair S and Bindhu J S. *'Supervised Techniques and Approaches for Satellite Image Classification'*, International Journal of Computer Applications 2016, Volume 134 - No.16.

[31] McGarigal K and Marks B J. *FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure, Gen. Tech. Rep*. PNW - GTR - 351. USDA - Forest Service, Portland, Oregon, USA, 1995

[32] Sertel E; Topaloglu R H; Sali B; Algan I Y; and Aksu G A. *'Comparison of Landscape Metrics for Three Different Level Land Cover/Land Use Maps*', ISPRS International Journal of Geo - Information, 2018, 7, 408; doi: 10.3390/ijgi7100408

[33] Wu J; Shen W; Sun W; and Tueller P. T. '*Empirical patterns of the effects of changing scale on landscape metrics'*, Landscape Ecology 2002, 17: 761–782

[34] Wu J., *Effects of changing scale on landscape pattern analysis: scaling relations,* Landscape Ecology, 2004, 19: 125 – 138

[35] Simova P. and Gudlova K, *Landscape indices behavior: A review of scale effects*, Applied Geoagraphy 34 (2012), 385 - 394