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QUANTIFY THE CHANGES IN LANDSCAPE PATTERNS AND THEIR IMPACT ON ECOSYSTEM SERVICES VALUES USING LAND USE LAND COVER DATA IN THE MIDDLE REACHES OF THE DAMODAR RIVER BASIN

SOUGATA MAJI[1]*, DRUHEEN CHAKRABORTTY[2]

[1]Bankura Christian College, Bankura University, West Bengal and Bidhan Chandra College, Asansol
[2]Bankura Christian College, Bankura University, West Bengal
*Email: majisougata14@gmail.com

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Abstract
Human activities continuously modify the landscape area for their purpose which forces the landscape structure to change continuously. Therefore, it is essential to examine the impact of changing landscape structure on Ecosystem services values (ESV). The study has quantified the dynamic of ESV using land use land cover data and landscape metrics. The study has applied the Costanza et al. (1997 &2014) method to estimate ESV in the Middle reaches of the Damodar River Basin area and the Getis-Ord Gi* technique to delineate the dynamic hot spot and cold spot region in ESV within the stipulated period. The study has shown that the ESV decline from 2000-2023 with the shortening of area of vegetation, agricultural land, and waterbody. The diminishing of vegetation, agricultural land, water body area and the expansion of built-up area has shifted the ESV zone from the North-West part in 2000-2012 to the wider part of North-West and North-East in 2012-2023 and 2000-2023periods and marked the North-West and North-East part as a more dynamic zone within the study period.

Keywords: Anthropogenic activities, Landscape Metrics, Ecosystem Services Values, Landscape Structure, Land uses

1. Introduction

Human beings have long been engaging in the alteration of natural landscapes to fulfil the needs of an expanding population (Verhagen et al., 2016). The landscape alteration over the time led to habitat fragmentation, environmental pollution, and defects in the ecosystem services (M.A 2005; Zhang & Gao 2016a). Landscape structure is the combination of the composition and configuration which is displayed by the arrangement of land use land cover (LULC) (Karimi et al., 2021) and is the major role player in providing ecosystem services and fostering biodiversity (Zhang & Gao 2016b;Taylor et al., 1993). The ecosystem is a complex interactive process between a biotic and abiotic environment by which human beings receive goods and services directly and indirectly (Wu et al., 2021a). Quantification of ecosystem services values in monetary form based on GDP or using the market is quite understandable and comparable with other economic indicators while in ecological form is hard to understand by common people (Wu et al.,2021b).Ecosystem services valuation is essential for urban planning (Estoque and Murayama, 2013), continuous socioeconomic development (Wu et al., 2021c), and to assessment of the capacity of the surrounding ecosystem(Su et al., 2020). Several studies have worked on the quantification of ecosystem services including changes in landscape structure on ecosystem services (Frank et al., 2012;Palomo et al., 2014;Zhang and Gao2016c; Mitchell et al.,2015; Herrero-Ja´uregui et al.,2018; Liu et al., 2020a;Maheng et al.,2021;Baude and Meyer 2023a), impact of land use land cover changes on ecosystem services (Li et al., 2010a; Song and Deng 2017;Ye et al.,2018;Liet al.,2018;Wang et al.2018;Chen et al., 2019), linking between landscape structure and ecosystem services (Zhang and Gao 2016d;Yushanjiang et al.,2018a; Muelta and Biru 2019a; Liu et al.,2020b). Some studies have worked on one or two types of ecosystem services (Nathen et al, 2008; Hadley and Betts 2012). Several methods have been applied e.g. Network analysis (Spens et al. 2007), Graph theory (Bunn et al.,2000), Process-based method and Unit value method (Costanza et al., 1997a; Xi et al., 2003a, 2008a) to quantify the ecosystem services values. Costanza was the pioneer, developed and defined 17 types of ecosystem services in 1997 (Costanza et al., 1997b; Wu et al., 2021d) using expert -based unit value transfer method. However, due to limitation in benefit transfer techniques several modifications have been made by different authors including Xi et al. (2003, 2008) modified and developed a new method to fill the gap in Costanza et al. (1997c) estimation. Xi et al. (2003b) used the weighting factors per unit to correct the value coefficient (Li et al., 2010b) and divided it into 4 major types with nine sub-types of ecosystem services (Xi et al.2008b). The method measured the relative supply of ecosystem services by using land use land cover data and assigned monitory value coefficient (Ye et al., 2018a). The value coefficient is the average value of nine ecosystem services (Ye et al., 2018b). Song and Deng (2017) measured the ESV in parts of China with the combination of Costanza et al.(1997d) and data from the Millennium Ecosystem Assessment (2003, 2005). Later Costanza et al. (2014a) introduced an updated estimation for ecosystem services based on updated unit ecosystem service values and land use changes from 1997-2011. The objective of the study is to quantify of ecosystem services values with the changes of landscape structure and demarcates the dynamic zones in ecosystem services values in the Middle reaches of Damodar river Basin area from 2000-2023 periods. The study shows the relationship between changing landscape patterns and ecosystem service values. In addition, the study delineated the dynamic zones of ESV produced by the dynamic landscape pattern, which is hardly covered by any study.

2. Study area

The study area is the part of the Damodar River Basin located between 23°26’N-23°50’N, 86°40’E-87°17’E (Fig.1) covering about 6.19% of the total catchment area (25820 sq.km) of the Damodar River Basin (Mondal et al., 2018). The river stretch extends from Maithon and Panchet Dam to Durgapur Barrage has been considered here, which enclose two provinces one is an industrial-based urban area i.e. Asansol City and its surrounding area of Paschim Bardhaman District and another one agricultural-based rural area i.e. part of Purulia and Bankura Districts, with a total area of around of1600.5 sq.km. The elevation of the middle reaches is decreasing from the South-West part to the South-East part where the highest and the lowest elevation are 643m and 32m respectively. The Barakar River, one of the tributaries of Damodar River is flowing southward to meet the Damodar River at Dishergarh. The study area is influenced by

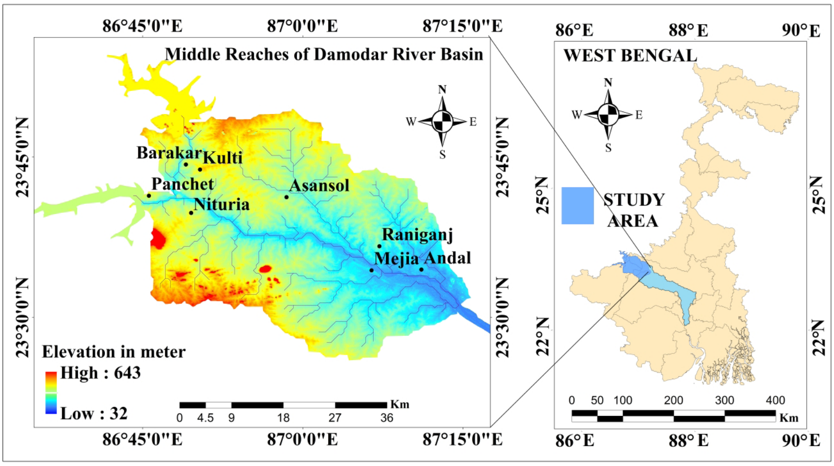

Fig. 1. Map representing the location of the study area

the tropical climate (Singh and Hasnain 1999) where average precipitation is 86.69mm and average summer temperature and average winter temperature 29.47°c and19.9°c respectively (CRU TS data). The upper section of the river stretch has two dams: one is the Maithon Dam fed by the Barakar River and another is the Panchet Dam drainage by the Damodar River and in lower section it has the Durgapur Barrage. The dams are famous for providing ecological, cultural and recreation services. However, the middle reaches is widely used for agricultural activities, industrial waste disposal, and sand mining. As a result, human activities have largely impacted the area of interest, altering the landscape pattern and ecological processes.

3. Materials and Methods-

For the study, three satellite images for different years have been acquired to analyse the changing pattern of ESV with the changing landscape structure. The first and second-year images i.e. in 2000 and 2012 of Landsat Enhanced Thematic Mapper Plus (ETM+) and the end-year image i.e. in 2023 of Operational Land Imager (OLI) have been collected from the United States Geological Survey (USGS- http://earthexplorer.usgs.gov). All the images have been acquired in the dry season to avoid cloud cover and get clear spectral signatures (Table 1). The satellite images have been pre-processed (Radiometric Correction, Layer Staking) the preparation of land use land cover map with the help of Arc Gis 10.5. The supervised

Table 1. Specification of Satellite Data

	Study Years		
Attribute Name	2000	2012	2023
Acquisition Date	29/03/2000	14/03/2012	14/04/2023
Satellite	Landsat 7	Landsat 7	Landsat 8
Sensor	ETM+	ETM+	OLI
Path/Row	139/44	139/44	139/44
Resolution	30×30m	30×30m	30×30m
Bands Consideration	1-5 & 7	1-5 & 7	2-7

classification method with a maximum likelihood algorithm has been applied to classify the land classes. In the post process, Google Earth images have been taken as referenced data to check the accuracy of different land use land cover maps to identify the true position of points between the image and real ground. The accuracy assessment has been validated by the confusion matrix of each year. The overall accuracy of the classified images is 81.51% in 2000, 82.93% in 2012, and 84.25% in2023 respectively. The percentages are good in term of accuracy.

Selection of Landscape Metrics

Landscape Metrics is the most well-known and useful method for the analysis of landscape patterns. Landscape metrics can quantify and characterize the spatial pattern based on the patch's configuration and composition (Muleta & Biru 2019b). The raster data i.e. land use land cover map for different years has been used as input data. The Fragstats software is used to identify and describe the landscape pattern (McGarigal and Marks 1995; McGarigal et al. 2012). The Landscape Metrics have been selected

Table 2. Details of Landscape Metrics used in the study

Acronym	Metrics	Explanation	Sources
PLAND	Percentage of Landscape	Proportion of landscape occupied by specific LULC class	Muleta and Biru (2019)
NP	Number of Patches	Number of patches in a specific LULC class	Muleta and Biru (2019)
PD	Patch Density	Number of patches of a specific class per unit area	Rutledge, D. (2003)
ED	Edge Density	The length of edges of a specific class per unit area	Yushanjiang et al. (2018)
LSI	Landscape Shape Index	It is the standardized measurement of total edge or edge density. It indicates the shape complexity and spatial heterogeneity	Yushanjiang et al. (2018)
IJI	Interspersion/ juxtaposition	It indicates the aggregation based on the adjacency of patches	Rutledge, D. (2003)
COHESION	Patch Cohesion	It is proportionate to the division of the area-weighted perimeter area ratio by the area-weighted mean shape index	Rutledge, D. (2003)
DIVISION	Division Index	It is the probability that two randomly identified locations do not occur within the same patch	Rutledge, D. (2003)
SPILT	Splitting Index	The number of patches of equal size of a specific class requires dividing the landscape at the desired level	Rutledge, D. (2003)
AI	Aggregation Index	The ratio between the actual edge and the total amount of possible edges. It measures the degree of connectivity	Rutledge, D. (2003)

based on previous studies (Zhang and Gao 2016e;Yushanjiang et al., 2018b;Muleta and Biru 2019c;Liu et al., 2020c; Maheng et al., 2021) which can portray the dynamic of landscape pattern. In the study, the following landscape metrics have been used to examine the dynamic of landscape pattern at the class level (Table 2).

Ecosystem Services Values Estimation

In the study ESV for each year has been estimated with the methodology proposed by Costanza et al. (1997e) and the updated estimation of Costanza et al.(2014b). The study has considered the methods for global applicability in ecosystem services values estimation. The land classes have been identified analogues to Costanza et al. (1997f) for instance vegetation class corresponds to the forest class; water body corresponds to the Lakes and rivers. (Table 3.)

To calculate the ESV for each land use cover following equation has been used

$$ESV_i = (A_K * VC_K) \qquad (1)$$

$$ESVt = \sum (A_K * VC_K) \qquad (2)$$

Where, ESVi is the ecosystem value of the individual class, AK- is the Area in hectares, VCK- is the Value Coefficient (USD $ha^{-1}yr^{-1}$), and ESVt- is the total ecosystem value of the landscape.

Here, the ecosystem services values are calculated by multiplying the area with the value coefficient of each land use and land cover. The percentage change in the ecosystem services values over the year is determined using the below equation.

$$\text{ESV change percentage} = \frac{\text{ESVfinalyear} - \text{ESVinitial year}}{\text{ESV initial year}} \times 100 \qquad (3)$$

Dynamic Zone in Ecosystem Services values

To identify the dynamic zone in ecosystem services values through hot spot analysis spatial autocorrelation Moran's I, Spatial statistics Getis-Ord Gi* and Inverse Distance Weighted (IDW) interpolation technique have been used.

Spatial Autocorrelation Moran's I

Spatial autocorrelation is used to explore the existing spatial variation in a variable (Haining 2001). Here spatial autocorrelation local Moran's I has been used to delineate the location of high clustering, low clustering and outliers zones (Huo et al. 2012). Usually, the value lies between 1 to -1. The local Moran's I is expressed by the following formula-

$$\text{Moran I} = \frac{n(Xi - \bar{X}) \sum_{i=1}^{n} wij(xj - \bar{X})}{\sum_{i=1}^{n}(xi - \bar{X})} \qquad (4)$$

Hot Spot Delineation

A hot spot denotes a restricted place that has a higher concentration of a specific phenomenon. In the study hot spot analysis has been done by Getis-Ord Gi* method in Arc Gis 10.5. The method applied Gi*

Table 3. Ecosystem services values of land classes as per Costanza et al. (1997 & 2014)

Land Class	Equivalent Biome (Costanza et al. 1997)	Ecosystem Service coefficient (USD $ha^{-1}yr^{-1}$)	
		(Costanza et al. 1997)	(Costanza et al. 2014)
Vegetation	Forest	969	3800
Agricultural Land	Crop Land	92	5568
Built-up Area	Urban	0	6661
Water Body	Lakes and Rivers	8498	12512

statistics–Z-score to identify the clustering of phenomena. The significant positive changes and negative changes are symbolized as hot spot (Convexity) and cold spot (Detraction) of a region respectively (Bera et al., 2022b). For this 1000 sample points have been randomly chosen to delineate the dynamic hotspot zone. The inverse distance weighted (IDW-The nearest value is more related than further value) interpolation technique has been applied for highlighting the hot spot and cold spot region based on GiZ value (Bera et al.,2022c). The following formula of Gi* statistics is used (Getis and Ord 1992).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \dot{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \quad (5)$$

xj signifies the attribute value of j, w i,j represent the spatial weight between the feature i,j and n is the total number of feature

To compute values $\bar{X}$ and S following formulas are used

$$\bar{\dot{X}} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (6)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{\dot{X}})^2} \quad (7)$$

4. Results and Discussion

LULC Characteristics

The study prepared LULC maps shown in (Fig-2) and calculated the areas (Table-4) in 2000, 2012 and 2023 with the help of satellite images. The abundance of arable land in the study area and collective involvement of 7.39% of people as agricultural labourers to the total workers of the districts (2011 Census) supporting the agricultural activities extensively. These are the reasons that agricultural land is dominating land cover covering 39.80%, 38.83%, and 38.91% in 2000, 2012, and 2023 respectively. However, the agricultural land is declining i.e. 39.80% in 2000 to 38.91% in 2023 because the farmers are getting less interest in agriculture and the migration from rural areas to urban areas in search of jobs. The vegetation is significantly decreasing i.e. 38.95% in 2000 to 31.41% in 2023 while built up area is increasing from 11.44% in 2000 to 21.80% in 2023. The enhancement of trade, industrialization and mining activities in Asansol and its surrounding places, and progress in the tourism sector of the Purulia district are the obvious reasons for expansion in urbanization and diminished vegetation cover. There is an ample amount of water bodies because of agricultural activities but it is also in a declining trend that is 7.52% in

Table 4. Distribution of LULC in hectares in different years

Land Class	2000	2012	2023
Vegetation	63983.26 (38.95)	55362.12 (33.70)	51602.80 (31.41)
Agricultural Land	65375.83 (39.80)	63778.53 (38.83)	63918.57 (38.91)
Barren Land	3731.24 (2.27)	6928.20 (4.21)	6065.18 (3.69)
Built-up Area	18797.43 (11.44)	27984.90 (17.03)	35812.00 (21.80)
Water Body	12356.40 (7.52)	10190.75 (6.20)	6844.65 (4.16)

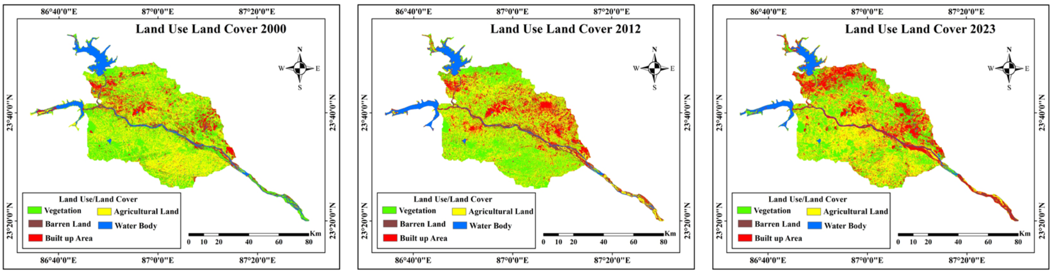

Fig. 2. Distribution of Land covers in 2000, 2012 and 2023

2000, 6.20% in 2012 and 4.16% in 2023 due to intense modification by anthropogenic activities. The barren land has covered a minimum area over the period in comparison to other land classes of the study region.

Landscape Metrics characteristics

The conversion of land use land cover in the study period (2000-2023) carries different values of landscape metrics (Table5). The PLAND indicates the class dominance percentage in the area of interest. Here, the vegetation class is 39.16% in 2000, 33.73%in 2012 and31.51% in 2023 followed by agricultural class 39.34%in 2000, 38.72% in 2012 and 38.58% in 2023 occupying the study area within the study period. But the vegetation and agricultural area are consequently decreasing over the period where the built-up area is increasing from 11.58% in 2000 to 22.00% in 2023 which is the reason for the diminished of natural coverage. The NP, PD, ED, LSI values indicate fragmentation which is higher in vegetation and agricultural class over the period in the study area. As usual, the IJI value is higher in built-up areas i.e. 85.88 in 2000, 72.81in 2012 and 75.55 in 2023. The SPILT and DIVISION values are good in unused land, built-up areas and water bodies but comparatively lower in vegetation and agricultural land which indicates low biodiversity. COHESION

Table 5. Landscape Metrics of different land classes

2000					
Landscape Metrics	Vegetation	Agricultural Land	Barren Land	Built up Area	Water Body
PLAND	39.16	39.34	2.37	11.58	7.52
NP	28364	17800	10341	22757	4078
PD	17.26	10.83	6.29	13.85	2.48
ED	148.15	141.01	16.50	58.10	11.95
LSI	241.86	229.32	109.27	173.90	45.47
IJI	50.97	43.14	86.85	85.88	92.07
COHESION	98.74	99.73	81.64	94.79	98.84
DIVISION	0.99	0.95	1.00	0.99	0.99
SPILT	178.96	23.97	445073.54	5478.11	619.93
AI	71.46	73.02	47.59	62.31	87.95

2012

Landscape Metrics	Vegetation	Agricultural Land	Barren Land	Built up Area	Water Body
PLAND	33.73	38.72	4.26	17.07	6.19
NP	29434	25431	6007	22632	1305
PD	17.91	15.48	3.65	13.77	0.79
ED	150.58	187.70	17.39	77.64	5.65
LSI	264.49	306.91	86.05	191.72	24.84
IJI	31.13	53.88	79.98	72.81	52.79
COHESION	99.58	99.62	94.59	96.66	98.64
DIVISION	0.97	0.97	1.00	0.99	0.99
SPILT	38.56	43.57	23336.50	1798.57	840.18
AI	66.35	63.56	69.35	65.761	92.88

2023

Landscape Metrics	Vegetation	Agricultural Land	Barren Land	Built-up Area	Water Body
PLAND	31.51	38.58	3.70	22.00	4.18
NP	19157	15965	1722	20508	1955
PD	11.66	9.71	1.04	12.48	1.19
ED	102.64	125.42	6.39	77.98	7.01
LSI	187.08	206.08	45.08	170.10	30.73
IJI	42.52	50.11	26.17	75.55	44.17
COHESION	98.28	99.74	92.23	98.43	98.55
DIVISION	0.99	0.95	1.00	0.99	0.99
SPILT	523.65	22.17	139115.79	428.02	1028.00
AI	75.43	75.52	77.42	73.26	90.79

is higher in vegetation and water bodies. The multifunctional landscape has different types of composition and configuration providing different levels of ecosystem services (Verhagen et al., 2016). The alteration in the landscape because of anthropogenic activities has significant impacts on ecosystem services.

Ecosystem Services Values Distribution in the Study Area

The result has shown (table 6) that the net decline in ESV from 173019099 USD ha-1yr-1 in 2000 to 114049505.6 USD ha-1yr-1in 2023 according to Costanza et al.(1997f) estimation.The concerning fact is that the declination in ESV in vegetation has dropped 11996671.04 USD ha-1yr-1between 2000 to 2023, and 46838864.3 USD ha-1yr-1 for water bodies in the same period according to Costanza et al. (1997g) which are higher ESV provider according to the said method. On the other hand, with the computation of Costanza et al. (2014d) estimation vegetation, agricultural land, and water body all have decreasing ecosystem services values from 2000 to 2023 as the land area are shortening within the study period. But the enhancement

Table 6. Ecosystem Services values of different land classes

Land Class	Ecosystem Service coefficient (USD $ha^{-1}yr^{-1}$)					
	Costanza et al. (1997)			Costanza et al. (2014)		
	2000	2012	2023	2000	2012	2023
Vegetation	61999787.8	53645896.35	50003116.76	24136423	210376064.1	196090654
Agricultural Land	6014576.48	5867624.85	5880518.10	364012628	355118860.7	355899182.6
Built-Up Area	0	0	0	125209681	186407437.8	238728478.4
Water Body	105004735	86600981.87	58165870.71	154603347	127506646.9	85640312.35

of built-up area in the said period it has contributed massively i.e.125209681 USD $ha^{-1}yr^{-1}$ in 2000, 186407437.8 USD $ha^{-1}yr^{-1}$ in 2012 and 238728478.4USD $ha^{-1}yr^{-1}$ in 2023. The reduction in area of higher ESV providers slightly decreased the net ESV i.e. 886962079.5 USD $ha^{-1}yr^{-1}$ from 2000 to 876358627.3 USD $ha^{-1}yr^{-1}$ in 2023 as per the updated estimation Costanza et al. (2014e). The spatial distribution of ESV has been shown in below Fig. 3.

Impact of Landscape Metrics on Ecosystem Services

There is a significant association between ES and Landscape metrics. The percentage of land-PLAND is the first level of information about the level of change in certain land uses (Muleta and Biru 2019d). In our study area reduction in vegetation, agricultural and water bodies and the increase in built-up area provided information about the intense modification by human beings and the smaller the natural coverage area over the period. The result is similar to another study (Moreno-Sanchez et al.2011).

The increase of patch number of a specific land cover which consequently increases the patch density leads to fragmentation, and affects structural connectivity (Muelta and Biru 2019e; Yushanjiang et al., 2018c), ecological process reduces the supply of

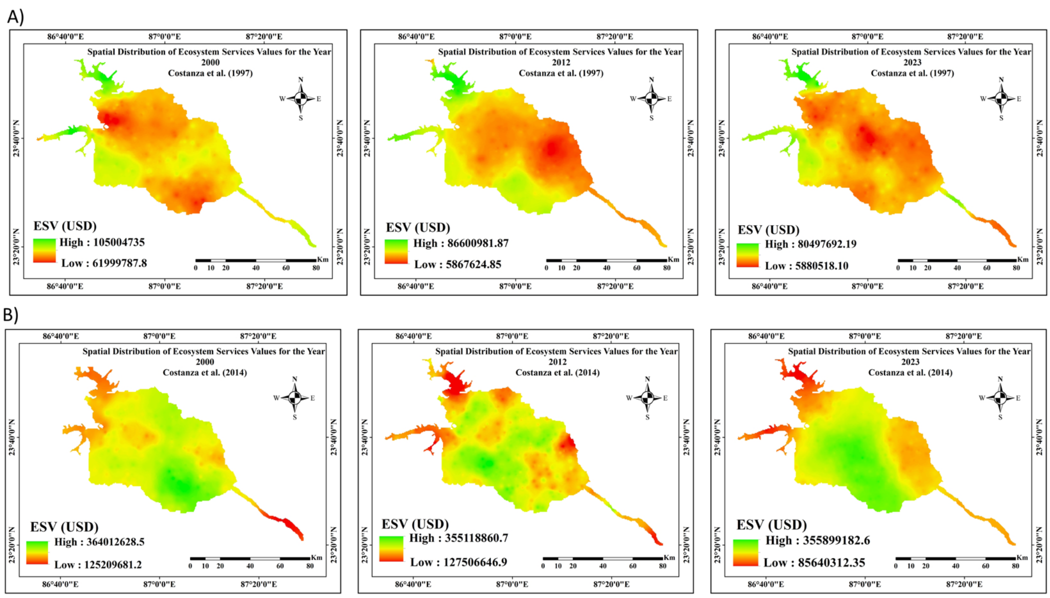

Fig. 3. Spatial Distribution of ecosystem services values A) as per Costanza et al. 1997 B) as per Costanza et al. 2014

ecosystem services (Liu et al., 2020d). In our study vegetation, agricultural land and built-up areas have a higher level of patch density and number of patches.

A higher level of edge density maintains habitat structures and high biodiversity (Baude & Meyer 2023a) and the high biodiversity signifies stable ecosystem services (Liu et al., 2020e). The result has shown that the vegetation and agricultural land have registered high edge density whereas the water body has a low level of edge density.

LSI is the indicator of complexity and spatial heterogeneity in the landscape (Yushanjiang et al., 2018d). An increase in LSI signifies to the irregularity of the landscape pattern which helps to increase the supply of ESV (Chen et al.,2021). The agricultural land has a higher level of LSI compared to other classes where the water body is the most regular and simple landscape.

IJI is the adjacency of patches. The ecosystem services capacity is decreasing with the lengthening of the edges between the patches (Liu et al.,2020f). The built-up area has the highest level of edge length in comparison to other land classes within the study periods.

The DIVISION and SPILT symbolize fragmentation and splitting which have a positive correlation with biodiversity (Baude and Meyer 2023b) and biodiversity has a positive correlation with ecosystem stability (Liu et al., 2020g). In the study, the agricultural land has a low SPILT index whereas the built-up area followed by the water body has a high SPILT index within the study periods.

COHESION indicates connectivity, well connectivity leads to high capacity of ecosystem services (Liu et al., 2020h). The result has shown that the COHESION index of all classes is good within the study periods.

AI is the aggregation index, it signifies the connectedness of patches. If the AI value is high the class would be less fragmentation (Zhao et al., 2020) and have a high capacity for ecosystem services. The patches of the water body are well connected within the study period. The AI value of built-up area consequently increased over the period i.e.62.31 from 2000 to 73.26 in 2023whereas the vegetation and agricultural class fluctuated. In 2012 the AI value of vegetation and agricultural class are less connected because of increasing patch number that leads to fragmentation.

It can be said that the landscape pattern can influence ecosystem services in different ways which is shown by above studies (Estoque and Murayama, 2013; Zhang and Gao 2016; Baude and Meyer 2023). The result revealed the patch number and the patch density are decreasing from 2000-2023 i.e. 83340-59307 and 50.63-36.08 respectively. The landscape of the study area is moving from fragmentation to continuous and spatial heterogeneity is getting weaker simultaneously the shape complexity is also reducing and becoming regular and simple that is 799.82 in 2000 to 639.07 in 2023. Similarly, the connectivity among patches is getting strengthened from 342.33in 2000 to 392.42 in 2023.

Correlation between ESV and Landscape Metrics

Costanza et al. (1997h) have estimated 17 types of ecosystem services, which include water regulation, waste treatment, food production, and recreation. For this study, we have considered the same services provided by the selected land classes which are equivalent to Costanza et al. (1997i) and correlated them with landscape metrics. The correlations have been computed for each year i.e. 2000, 2012, 2023. The result has revealed that NP, PD, ED, LSI have highly negative correlation (-1.00) with Ecosystem Services including water regulation, waste treatment and recreation services in 2000, 2012, 2023 whereas IJI, COHESION, DIVISION, SPILT, AI have highly positive correlation (+1.00) with water regulation, waste treatment and recreation services in the mentioned years. The correlations in both cases are significant at 0.01 levels. The correlation between food

Table 7. ESV change in percentage in different periods

	Costanza et al. (1997)			Costanza et al. (2014)		
Land Class	2000-2012	2012-2023	2000-2023	2000-2012	2012-2023	2000-2023
Vegetation	-13.47	-6.79	-19.35	-13.47	-6.79	-19.35
Agricultural	-2.44	0.22	-2.23	-2.44	0.22	-2.23
Built-up Area	0.00	0.00	0.00	48.88	28.07	90.66
Water Body	-17.53	-32.83	-44.60	-17.53	-32.83	-44.60

services and landscape metrics including NP (+0.217), PD (+0.216), ED (+0.581), LSI (+0.572) have moderate positive correlation but with COHESION has highly positive correlation (+ 0.972). On contrary the remaining metrics- Division (-0.990), SPILT (-0.796), AI (-0.549) are negatively correlated in 2000. Similarly, in 2012 the metrics including NP (+0.510), PD (+0.510), ED (+0.759), LSI (+0.722), IJI (+0.410), COHESION (+0.647) are positively correlated but DIVISION (-0.619), SPILT (-0.614), AI (-0.684) are negatively correlated with food services. In 2023 IJI (+0.939), COHESION (+0.950) have strong positive correlation but DIVISION (-0.990), SPILT (-0.928) and AI (-0.615) have negative correlation with food services. The correlations with food services are not significant at 0.01 levels in 2000, 2012, 2023.

ESV Change in the Basin Area- The result has shown (Table 7) us that all the essential ESV providers have negative growth except agricultural in 2012-2023 in the aforesaid study periods as per the 1997 value coefficient. The highest negative growth has been seen in water bodies which is -44.60% followed by vegetation i.e. -19.35% from 2000-2023 time period. The ESV change estimations as per Costanza et al. (2014g) has shown a similar growth to previous estimations. But one noticeable change has been seen in the built-up area. The land class has registered remarkable positive growth that is 90.66% from 2000-2023 as the addition of value coefficient to the built-up area. The overall net change in total ESV varies -33.44 - -66.18% based on Costanza et al. (1997j) whereas -4.54-24.48 is based on Costanza et al. (2014h). The changing percentage of ESV seems to vary greatly.

HOTSPOT Analysis

Spatial Autocorrelation evaluates the attribute pattern expressed by clustered, dispersed, and random. The associated Z-score and P-value indicate the statistical significance of the pattern. In the study the Global Moran's I have been applied to check the spatial pattern of ESV dynamic in three different periods i.e. (2000-2012), (2012-2023) and (2000-2023). The result has shown that the spatial pattern of ESV in three periods is highly clustered with a high positive Z-score value (Fig.4). The Getis-Ord GI* statistics has shown the spatial distribution of hotspot and cold spot in three different periods (Fig.5) and the associated GiZ score and GiP value. The range of GiZ score and GiP value is in 2000-2012 -3.2923-5.7146, 0.0000-0.0009in 2012-2023 -0.9620-0.2667, 0.3360-0.7896 and -3.3825-5.9637,0.0000-0.0007 in 2000-2023 respectively. In the 2000-2012 time period, the hot spot region has concentrated in the middle of the North-West part whereas the cold spot found on top of the North-West part of the study area with a dynamic value is 48.88. But from 2012 to 2023 the hot spot has occupied extensively two areas that are North-West part and the North-East part and the cold spot region focused on the South-West part of the study area with the dynamic value of 28.07. Similarly, in the 2000-2023 time period, the hot spot region has concentrated on North-West and North-East parts and the cold spot region focused on the Southern part of the study area respectively. The dynamic change value is 90.66 in the period. Therefore, it can be concluded that the North-West and North-East part is most dynamic in comparison to other part of the study area. The IDW interpolation technique has delineated the changeability in ESV in the said periods. The hotspot of ESV mainly focused on where built-up area, vegetation and agricultural land are collectively concentrated within the study area. This is because Costanza et al. (2014i) updated estimation has added the value coefficient to the built-up area.

5. Conclusion

The study has quantified landscape composition and configuration and delineated the dynamic zones of ESV in the study area. It has been observed that patch's configuration has effects on the stability of ESV. Our results has shown that a net decline in ecosystem services values from 2000 to

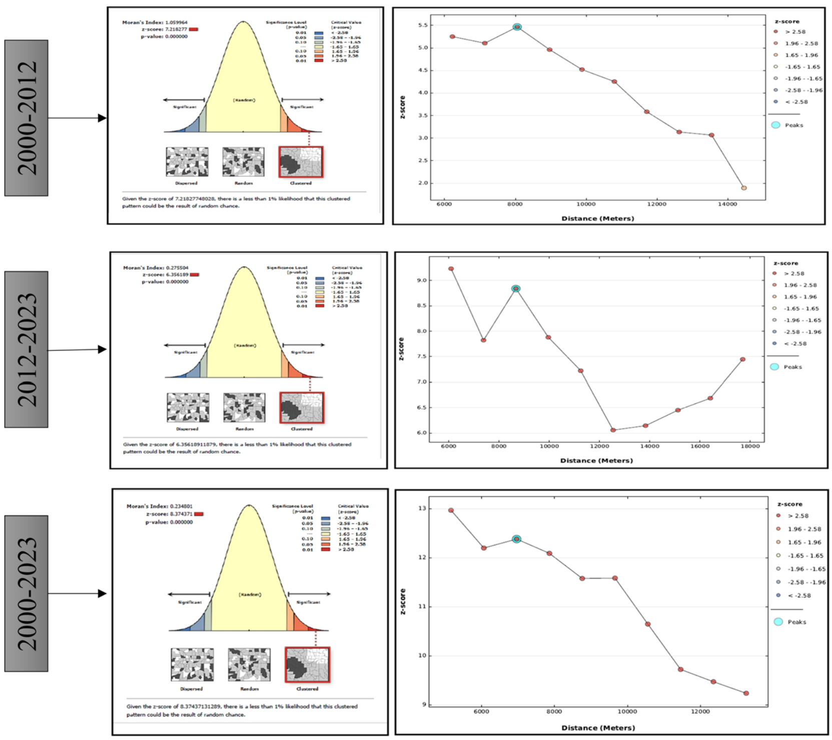

Fig. 4. Depiction of a significant pattern of Moran's I and the Distance band with the peak value in the three study periods

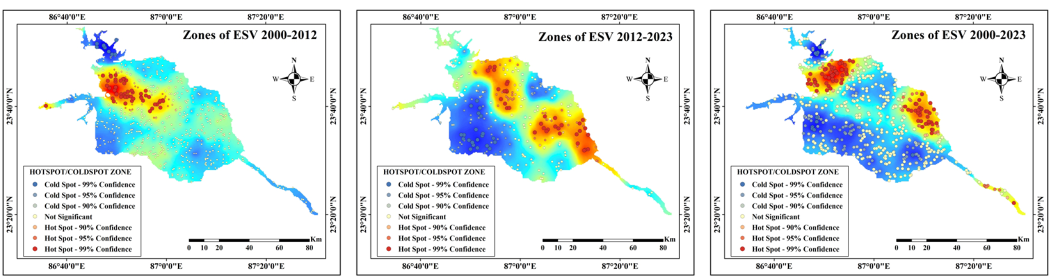

Fig. 5. The concentration zone of Hot spot and Cold Spot in ecosystem services values

2023 according to Costanza et al. (1997k &2014j) estimations. The ESV of Built-up class has marked positive growth while vegetation, water body, and agriculture land classes shown downfall in the stipulated period which marked the North-West and the North-East part as dynamic zone. The study is significant for planning purposes considering the dynamic landscape pattern. Future research needs to focus on the accurate calculation of the value coefficient on regional basis and land classifications to make the right planning.

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