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Habitat Quality Assessment with Changes of Landscape Pattern Using InVEST-HQ and Semivariogram Model in Durgapur Subdivision

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ABSTRACT
Habitat quality is immensely influenced by dynamic landscape patterns, especially in rapidly urbanized areas. Therefore, assessing the influence of changing landscape structure on habitat quality is inevitable. The study evaluated habitat quality using landscape metrics and land use and land cover data for 1991, 2011, and 2023. The study has used the habitat quality module of the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model to get the habitat quality pattern in the study area and the Semivariogram model to delineate the spatial changing structure in habitat quality within the study period. The study has shown that the spatial orientation of habitat quality varies with the changes in landscape patterns, and spatial heterogeneity also increased due to urbanization. The expansion of human-modified areas and shortening of the natural area have dropped the average quality from 0.22 in 1991 to 0.18 in 2023 and restricted the north and northeast parts as higher quality zones within the study period.

Key words: Habitat quality, Landscape pattern, Land cover, Semivariogram, Urbanization

INTRODUCTION

Habitat Quality (HQ) denotes the suitable environmental conditions for individuals and populations for survival, reproduction, and existence (Hall et al. 1997). Habitat Quality is usually associated with the presence or absence of vegetation (Morrison et al. 1991) and denotes the ecosystem service capacity and biodiversity (de Blust and Heremans 2020). Land use modification due to the expansion of urbanization, and interference by human beings drives the transformation of landscape patterns in city areas, directly affecting the biodiversity process (Zhou et al. 2014) and threatening the succession of natural ecosystems (Zhu et al. 2020). Landscape pattern is the combination of various attributes, including spatial composition and configuration, that influences the habitat quality (Hu et al. 2022). Several studies (Bai et al. 2019, Li et al. 2021, Hu et al. 2022) have explored that urbanization is the prime suspect in changes in habitat quality. The measurement of habitat quality has drawn attention from researchers due to the deterioration of the environment. Generally, there are two prime methods in assessing the quality of habitat: one is an analysis of various attributes such as availability of resources, competition level, and relationship with predators. Another method is observing, recording the target organism, and measuring its density in an area (Hu et al. 2022). With the proceeding of time, many quantitative models have been developed in assessing habitat quality including Maximum Entropy Model (Na et al. 2018) for determining the habitat suitability of Red-crowned cranes in the breeding period, Integrated Ecological Modeling System–IEMS (Johnston et al. 2017) to predict water quality and quantity, habitat suitability for aquatic biota, fish biomasses, population densities, productivities, and contamination by methylmercury across headwater watershed, Artificial Intelligence techniques for habitat suitability (Ghareghan et al. 2020) to delineate the spatial distribution and make the habitat suitability model for *M. persica* species using four data mining models: maximum entropy (MaxEnt), support vector machine (SVM), generalized linear model (GLM), and boosted regression trees (BRT). However, among the models, the habitat quality module in the InVEST model is quite popular among the researchers for free accessibility, higher accuracy, and less data requirement (Terrado et al. 2016, Gong et al. 2019, Admasu et al. 2023). The model's advantages are that it can calculate the habitat quality in the past and for larger fields. The study's objective is to explore the spatial changes in habitat quality with the changes in landscape patterns in an urbanized area.

STUDY AREA

Durgapur Sub Division is the part of Paschim Bardhaman District located between 23°24'-23° 44'N and 87°09'-87°32'E (Fig. 1). The Subdivision consists of four community blocks- Ondal, Pandebswar, Farridpur-Durgapur, Kanksa and one municipal corporation, i.e., Durgapur Municipal Corporation, with a total area of 1028.65 km2 (2001Census). The study area is under the tropical climate where the average temperature is 30°C in summer and 14°C in winter, and rainfall is 1400 mm. The city is known as a 'steel city' (Dutta and Kumar 2013) for having a large iron and steel industry registered as the 3rd largest urbanized city in West Bengal (Anonymous 2017-18). The total population of the subdivision is 1396960 as per the 2011 census. The subdivision is bounded by two important rivers, i.e., on the south side of the Damodar River and the north side of the Ajoy River, besides many small streams, Singaran, Tamla (Peterson 1910), flowing across the subdivision. One of the crucial features of the division is the Durgapur Forest, located in the Kanksa block. The forest range consists of 5 beats (Arrah-20, Basudha-61, Gopalpur-34, Shibpur-50 and Molandighi-34 have plant species) (Bauri et al. 2013), allowing a wide range of species for habitat.

MATERIAL AND METHODS

The following Landsat series data, Landsat 5 TM for 1991, Landsat 7ETM+ for 2011, and Landsat 8 OLI for 2023 path and row 139/44, have been taken from the USGS Earth Explorer (https://earthexplorer.usgs.gov) for the present study. Making a land use land cover (LULC) map is the foremost step for assessing landscape patterns and habitat quality for the study. For each year, the Landsat data have been divided into six land classes, including vegetation, agricultural land, barren land, built-up area, industry and mining, and water body. The confusion matrix has been used for overall accuracy, greater than 84% in 1991, 2011, and 2023.

Landscape metrics analysis

Landscape ecology studies the configuration and composition of landscape elements and changes over time (Turner and Gardner 2001, Satir and Erdogan

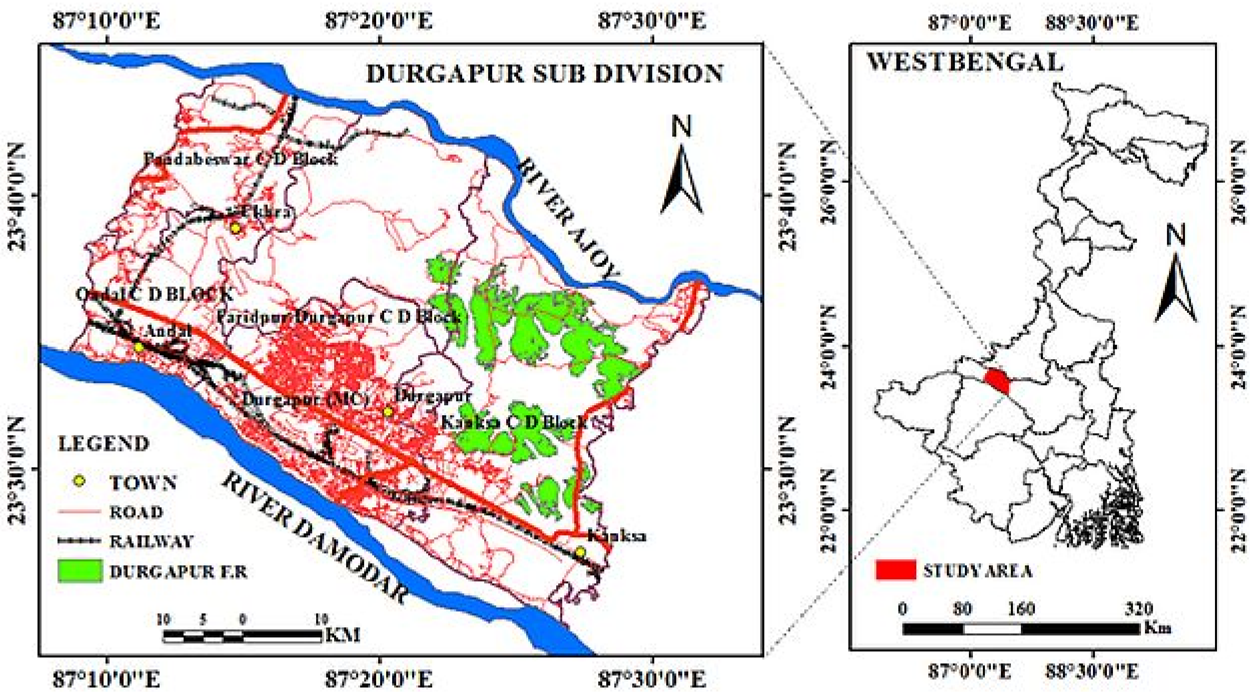

Figure 1. Location of the study area

2016). Any changes in the landscape elements are detected by analyzing landscape metrics using land use data. The five-landscape metrics (LM) have been selected, namely Edge Density (ED), Mean Shape Index (MSI), Mean Core Area (MCA), Shannon Diversity Index (SHDI), and Aggregation Index (AI), for the study (Table 1).

Habitat quality methods

The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST-HQ) model has been used to assess habitat quality and produce maps based on land use and land cover data, threat factors, and habitat suitability. The area's high quality leads to high species richness (Yang 2021). The HQ module follows three parameters: 1) the various threat factors that can destroy the habitat quality and the intensity of threat factors that change with distance. The weight and maximum impact distance have been assigned based on previous studies (Yang 2021, Hu et al. 2022) and the District Statistical Handbook of Burdwan (Table 2). In the study, agricultural land, built-up areas, railways, roads, industry & mining have been considered threat sources that degrade habitat quality. 2) The sensitivity of each land cover to each threat factor has been determined based on the basic principles of ecology and biodiversity conservation (Yang 2021). 3) The suitability of each land cover types for habitat (Table 3). Vegetation and water bodies have been considered high-quality habitat areas, whereas agricultural land and barren land are less suitable for habitat. Built-up areas and industry & mining are not ideal for habitat. The InVEST-HQ model produces a habitat quality map in a value range of 0-1. The distance from the value 1 denotes the degradation of the quality of the habitat.

The spatial distribution of habitat quality has been divided into three zones according to the method of natural break (Jenks), i.e., High quality, Moderate Quality, and Low Quality for each year. Habitat quality is quantified by the following formulas:

$$D_{xj} = \sum_{r=1}^{R}\sum_{y=1}^{y_r}\left(\frac{\omega_r}{\sum_{r=1}^{R} w_r}\right) i_y i_{rxy} \beta_x S_{jr} \quad ..1$$

D_{xj} represents the degree of habitat degradation in grid x for habitat type j. R is the total number of threat sources, with ωr indicating the weight of threat source r and Yr being the grid number of the threat source. The ry value represents the stress level of grid y, while i_{rxy} signifies the influence of threat source r on grid y in the habitat of grid x. It's important to note that the degree of threat decreases as the distance between the grid and the threat source increases. Additionally, âx denotes that the grid unit is close to the level of legal, institutional, social, and physical protection.

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\,max}}\right) \text{ if linear} \quad .....2$$

$$i_{rxy} = \exp\left(-\left(\frac{2.99}{d_{r\,max}}\right) d_{xy}\right) \text{ if expotential} \quad ..3$$

i_{rxy} represents the decay function of threat distance and intensity, d_{xy} denotes the linear distance between raster x and y, and drmax indicates the maximum action distance of the threat r.

$$Q_{xj} = H_j\left[1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right] \quad ....4$$

Table 1. Details of landscape metrics used in this study

Mertic	Purpose	Source
ED	It reflects the integrity of landscape. Higher ED values tend to pieced landscape.	Satir and Erdogan (2016)
MSI	It indicates the regularity of landscape. Human made landscape is more regular compared to natural landscape.	Satir and Erdogan (2016)
MCA	Core area is the indicator of sensitivety to the outside effects	Satir and Erdogan (2016)
SHDI	It indicates the richness or diversity of population	Bai et al. (2019), Satir and Erdogan (2016)
AI	It indicates the randomness of patches in landscape	Bai et al. (2019)

Table 2. Weight and maximum impact distance of threat factors

Threat factors	Maximum distance	Weight	Decay type
Agricultural land	3	0.50	Linear
Built-up area	7	1.00	Exponential
Railway	10	0.60	Linear
Road	3	0.60	Linear
Industry and Mining	3	1.00	Exponential

Table 3. Sensitivity of each land covers to each threat factor

Name	Habitat	Agriculture	Built-up area	Railway	Road	Industry & mining
Vegetation	1	0.5	1	0.8	0.8	1
Agriculture	0.5	0.3	0.9	0.7	0.7	0.9
Barren land	0.1	0.1	0.1	0.2	0.2	0.1
Built-up area	0	0.5	0	0	0	0
Industry and mining	0	0.3	0	0	0	0
Water body	1	0.6	0.7	0.7	0.5	0.5

The habitat quality index of the grid x in habitat type j is represented as Q_{xj}. Habitat suitability H_j refers to the suitability of different habitat types as habitats. The habitat degradation degree of the grid x in habitat type j is represented as D_{xj}. The semi-saturation constant, half of the maximum degree of degradation is defined as k, and z is a parameter.

Semivariogram

Semivariogram ϒ(h) is half the variance in the difference of variables of interest between two given sites. It measures the discrepancy between pairs in distance and orientation of the line between those two sampling sites (Olea 2006). It helps analyze the spatial variance in pattern and structure (Bai et al. 2019). The study used the model to effectively analyze the spatial structure of habitat quality. The value of ϒ(h) is used to show the difference in distance between pairs. Any changes in ϒ(h) values bring changes in the distance of separation h (Gandhi 2008). The closely located pairs have subtle variances compared to the distance apart. The variation is more effective until the separation distance meets a threshold. It is called range, and the variation is no longer effective beyond the range. The maximum variance is reflected at the sill. Therefore, the sill of a model can be used to show the variability (Gandhi 2008). The nugget values become zero when the separation distance (h) is zero.

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) + Z(x_i + h)]^2 \quad \text{.....5}$$

The function ϒ(h) represents the variation, where h is the spacing distance of the sampling space. N(h) represents the total number of sample pairs when the sampling space is h, and Z(xi) and Z(xi + h) represent the measured values of Z(x) at spatial positions xi and xi + h, respectively.

RESULTS AND DISCUSSION

Land use pattern changes

Figure 2 shows the distribution of land cover for each year. Durgapur subdivision is a fertile land area because of the prevailing alluvial soil, and 17.56% of agricultural labourers among the total workers of the subdivision (2011 Census) were engaged in crop production. The subdivision has registered the agricultural land as the foremost land area each year, i.e., 28.69, 31.52, and 34.76% in 1991, 2011 and 2023, respectively. The vegetated area is mainly concentrated in the southern portion of the research area. Over the study period, the vegetation cover has shown a declining trend, i.e., 24.17% in 1991, 18.49% in 2011, and 13.19% in 2023. This is the

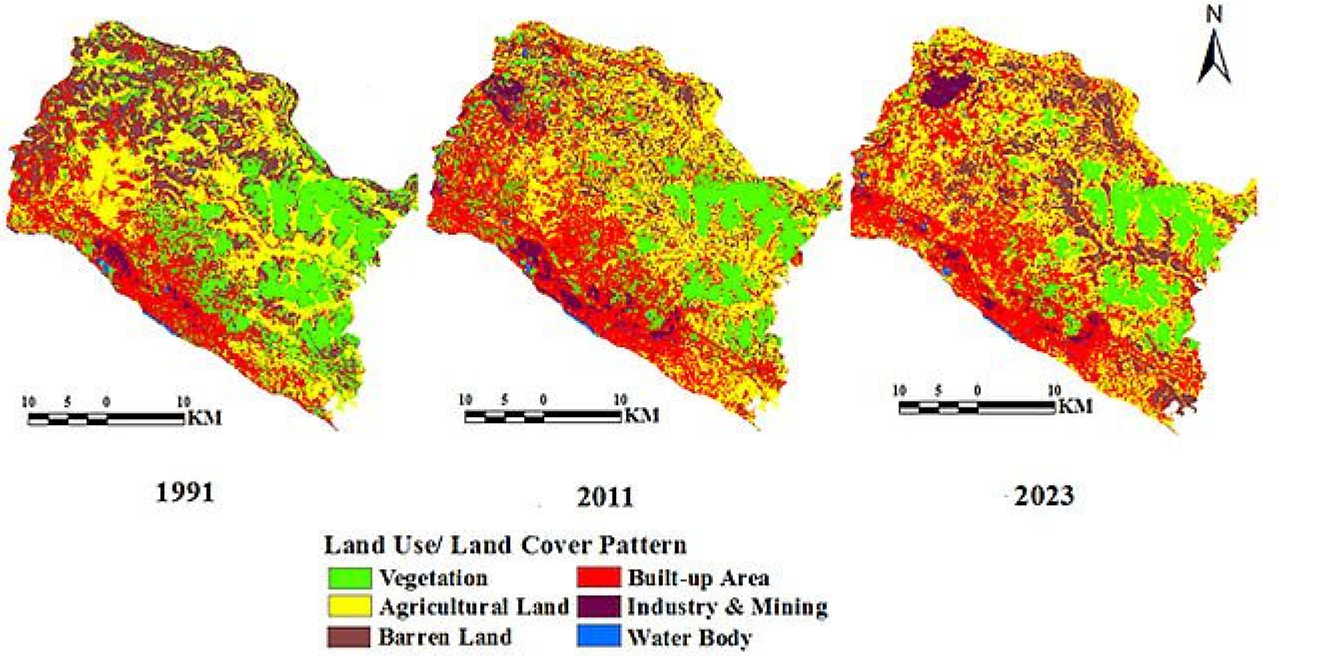

Figure 2. Changes in land use patterns

most rapidly declined land cover, i.e.10.98% from 1991 to 2023. At the same time, the built-up area expanded rapidly, i.e. 21.02% in 1991, 34.55 % in 2011, and 35.48 % in 2023. It is one of the driving forces behind the reduction of vegetation cover. The growth of population, the expansion of industrialization, and mining has helped in the development and extension of built-up areas. Another significant land cover was water bodies, covering 0.78% in 1991, 0.60% in 2011, and 0.79% in 2023.

Spatial transformation of land covers (1991-2023)
In this study, land use transformation has shown to understand the changes in land cover orientation during the study period 1991-2023 (Fig. 3). Vegetated land mainly converted to agricultural land (7.5%), followed by settlement (5.1%). During the same period, 7.93% of agricultural and 6.97% of barren land was replaced by built-up area. A significant area (10.96%) was also altered into agricultural land from barren land. The major land use changes were seen in settlement areas, which increased by 35.49% followed by agricultural land by 34.76%.

Landscape pattern changes
The landscape level matrix has shown the landscape pattern changes in the study area from 1991 to 2023 (Fig. 4). ED denotes the integrity of a landscape; the higher the values, the more the landscape tends to be pieced (Satir and Erdogan 2016). ED value remains low (146.65) at the end of the year, while it was high in 2011 (161.72). Less integrity of the landscape leads to less complexity. The shape index reflects that the landscape in 2023 was the most regular (1.21) compared to 1991 and 2011. This means that human beings will have the most intervention in 2023. It shows the naturalness of the landscape (Satir and Erdogan 2016). The large core area can resist the outside effects, especially the human pressure (Satir and Erdogan 2016), which is suitable for the habitat quality. Besides, large core areas can regenerate the landscape. MCA decreased from 1.3727 in 1991 to 0.9286 in 2023.

SHDI reflects the diversity of the population. SHDI has a positive relationship with complexity, and complexity generates biodiversity (Concepcion et al. 2008). SHDI level declined from 1991 (1.4858) to 2023 (1.4148), indicating the low biodiversity level in 2023. AI has a strong connection with topography. The plain area with higher construction has low patch density and richness (Bai et al. 2019) and less negative correlation with habitat quality (Hu et al. 2022). AI level was high in 2023 (77.98) compared to the 1991 and 2011 landscape because of the high built-up area (35.48%).

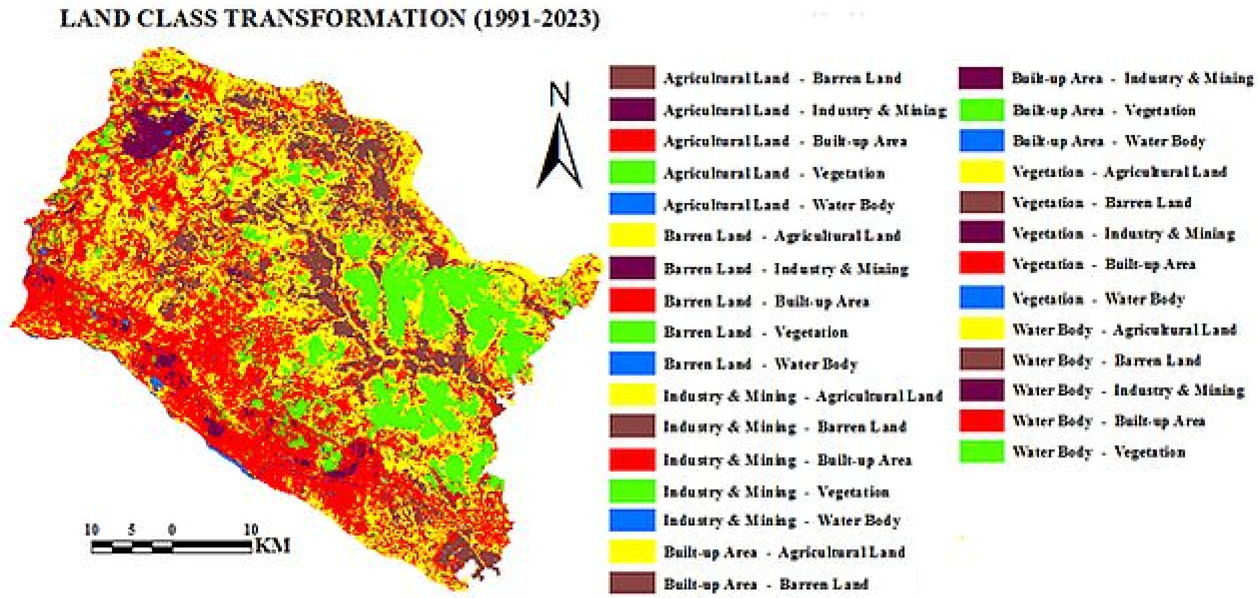

Figure 3. Spatial transformation of land covers (1991-2023)

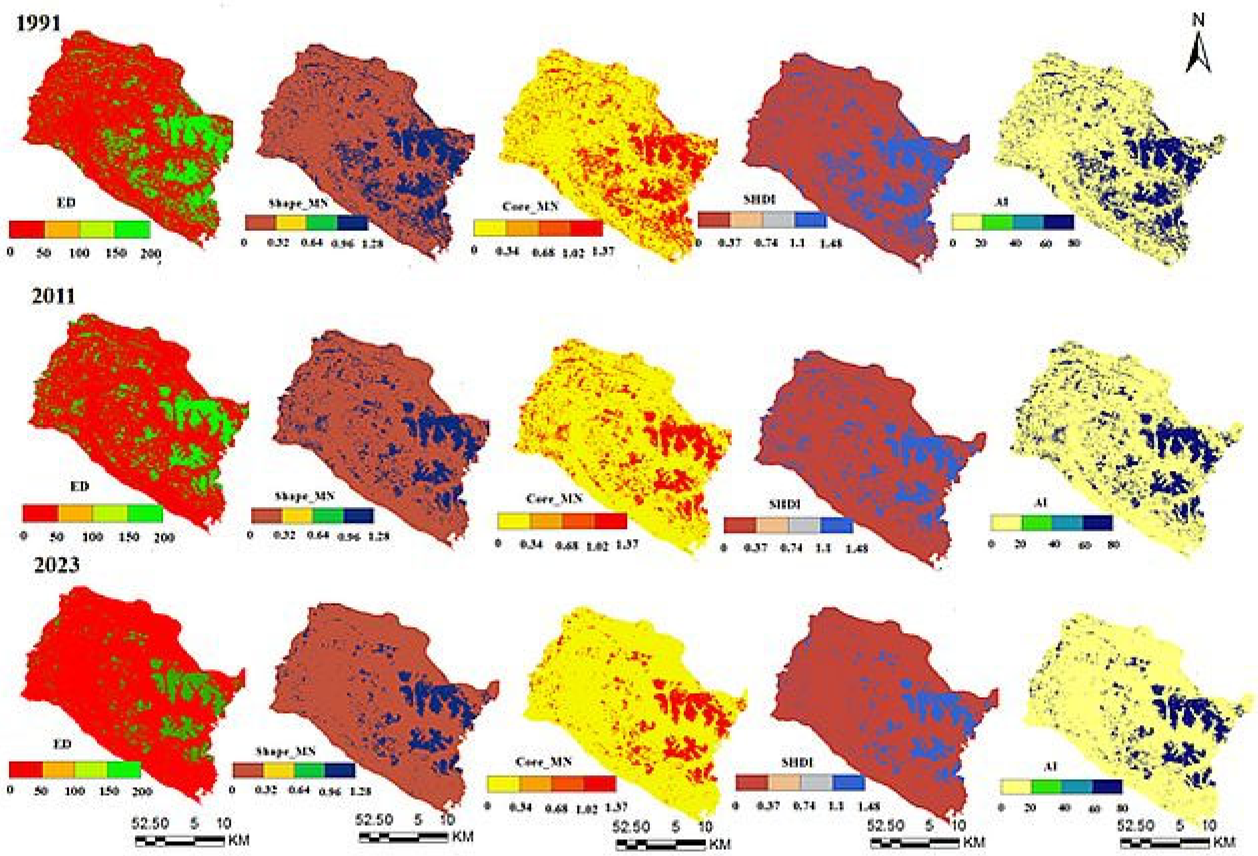

Figure 4. Spatial distribution of landscape metrics in 1991, 2011, and 2023

Habitat quality pattern

The average habitat quality was 0.22 in 1991, 0.17 in 2011, and 0.18 in 2023, showing a declining trend. However, the overall habitat quality in the area of interest is low as the lower area dominates each year, i.e., 47.02% in 1991, 49.47% in 2011, and 51.40% in 2023. The lower quality area enhanced (4.38%) from 1991 to 2023. In 2023, the low-quality area occupied a higher proportion than in the previous two years. In 1991, the high-quality area had a markedly higher proportion (16.43%), and the moderate quality was high in 2011 (37.54%). The higher quality area has dropped 5.41% from 1991 to 2023. Generally, the modification of land uses and the increasing number of threat sources are the barriers to habitat quality and biodiversity (Fig. 5).

Spatial pattern of habitat quality

The spatial orientation of habitat quality changes per land cover pattern (Fig. 5). The quality area is concentrated in the north and northeast parts of the Kanksa block, where forest areas have prevailed over the years. The forest coverage allows species diversity and acts as a lifeline for the region. The middle part, the north and east part of Farridpur-Durgapur and Kanksa block for 2011 and 2023, and the west part of Pandebswar block in 1991, were suitable for moderate quality habitat because of agricultural land. The low-quality area was more in the western part, the southern part of the Ondal block, and the Durgapur Municipal Corporation, because of settlements, industries, and mining activities. There is remarkable growth in the lower-quality area in the last year compared to the initial year as also reported by Han et al. (2019).

Changes in the spatial structure of habitat quality

The study has shown the spatial structure of habitat quality in the focused area. The goal is to select a model to lessen the deviations from the points. The comparison has shown that the spherical model perfectly fits the data. The characteristic of the spherical model is that first it rises, then it levels off with the increasing distance (Anonymous nd). The semivariogram parameters Sill (Co+c), Nugget (Co), and Range (A) have been calculated for two-time phases (Table 4). They increased from 0.0261 in 1991 to 0.0322 in 2023. Sill is measured to show the fluctuation level in habitat quality. The increasing sill value indicated spatial heterogeneity in habitat quality distribution increased (Bai et al. 2019). The other parameter range extended from 3184.6652 in 1991 to 3273.323 in 2023 and reflected a long-distance range that had influenced habitat quality because of urban expansion (Bai et al. 2019). Nugget explains the measurement error which arises through sampling, measurement methodology, and other sources (Verma et al. 2018). Nugget to Sill ratio

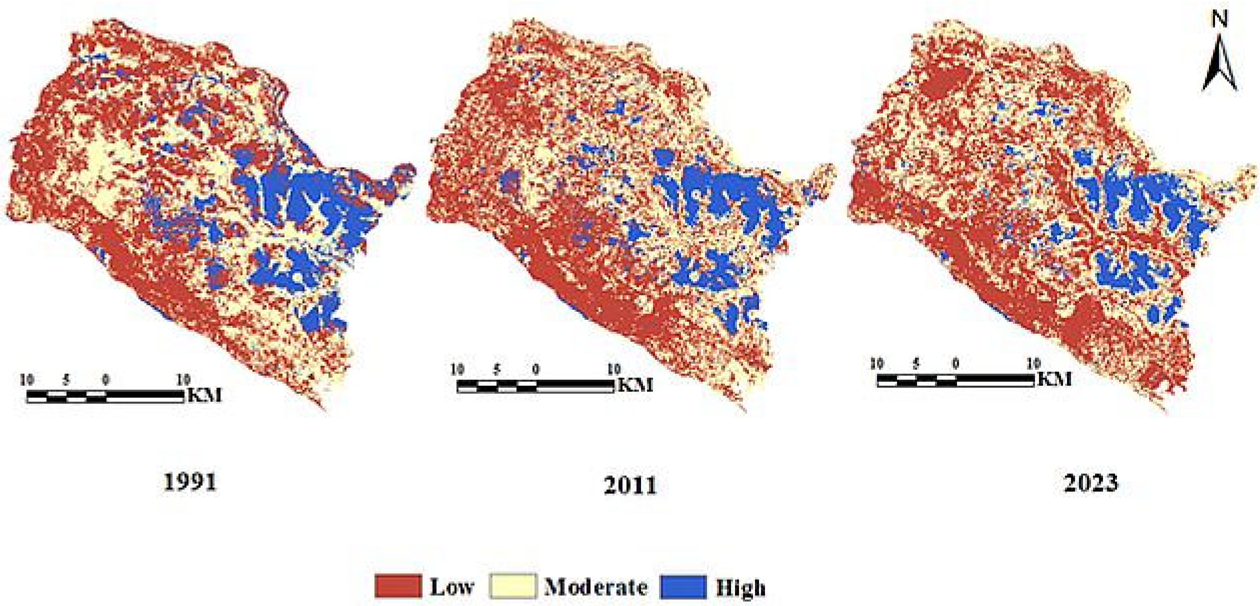

Figure 5. Spatial pattern of habitat quality

Table 4. The parameters of semivariogram model

Year	Range (A)	Sill (Co+C)	Nugget (CO)	Proportion (Co/(Co + C))	Model
1991	3184.665	0.0261	0.0154	0.5908	Spherical
2023	3273.323	0.0322	0.0126	0.3922	Spherical

reflects the location interrelation (Verma et al. 2018). The proportion in 1991 and 2023 has shown that habitat quality in the study area in space is positively correlated. Human beings' social and economic activities have greatly influenced the landscape pattern, which has brought changes in the structure of habitat quality in the research area as also recorded by Zhang et al. (2022).

CONCLUSIONS

The study of spatiotemporal changes of HQ is relevant for biodiversity conservation. The study has explored the changes in landscape pattern and their influence on habitat quality. The result showed that agricultural land and vegetation land declined while the built-up area expanded during the study period. Landscape patterns are changing regularly due to human intervention over time, and subsequently, biodiversity is declining. The habitat quality in the study area has deteriorated from the initial year to the end year. The overall habitat quality is low, and higher quality areas are restricted only to the north and north-east sides. The study has suggested terrestrial spatial planning is required for biodiversity conservation in urbanized areas.

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