SPATIOTEMPORAL ASSESSMENT OF LANDSCAPE TRANSFORMATION AND ECOLOGICAL RISK IN HALTI BEEL

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ABSTRACT

This study investigates the ecological risk of *Halti Beel,* one of the significant parts of the largest wetland ecosystem of Bangladesh, following the US Environmental Protection Agency (EPA) ecological risk assessment (ERA) guidelines. Physicochemical parameters of water and sediment were analyzed in reference to Environmental Conservation Rules (ECR) and EPA standards. Socio-economic data from local communities and species data from wetland authorities were integrated through questionnaire surveys. Multispectral satellite imageries were used to evaluate the ecological risks associated with LULC changes from 2000 to 2023. ENVI Thematic Change Workflow (TCW) tool was used for LULC change dynamics analysis over 2000-2010, 2010-2023, and 2000-2023. An ecological risk model was developed using Landscape Ecological Risk Indexes (LERI) in Fragstats 4.2; risk zones were mapped, and risk levels were categorized from minimal to severe. A linear regression analysis in SPSS was done to reveal significant relationships between ecological risk and different stressors. The results indicate that the collected samples' DO, turbidity and electric conductivity exceed the ECR, 1997, and EPA, 2012 standards. The socio-economic prospects of the area largely depend on fishing, farming, and wetland resources, which support local livelihoods despite growing environmental pressure. However, low education levels, poor sanitation, and unregulated land use challenge the local people's socioeconomic condition. Most of the environmental and anthropogenic factors have strong connections with ecological risk and leave the current status of species highly vulnerable. The significant LULC transformation: from 2000 to 2023, 55.63 % of deep water was converted into shallow water, 11.68 % to agricultural land, and 19.52% of agricultural land was converted to rural settlements, indicating increasing anthropogenic pressure. Between 2000 and 2010, notable changes are that 60.86 % of deep water was converted into shallow water and 18.54 % shifted to agricultural land. From 2010 to 2023, a major transformation of almost half of the deep water area was converted into shallow water and 9.09 % to agricultural land. Ecological risk fluctuated over time; in 2023 ecological risk spread all over the area and middle, highest, and higher risk areas increased synchronously. Major ecological risk areas shifted to the southwest part of the area. The overall results indicate that ecological risk is increasing evidently.

Keywords: Halti beel; LULC; ERA; Physiochemical parameters; Socio-economic condition

INTRODUCTION

Wetlands are one of the important connectors between dry land and water bodies. They play a crucial role in ecosystems to perform many vital functions, including conservation of biological diversity, flood and erosion control, water storage and purification, providing ecosystem services through aquatic resources, and supporting habitat for fisheries and wildlife resources for human populations (Keddy, 2010; Xia *et al*., 2017). Wetland in Bangladesh provides a multitude of livelihood resources. Nearly 50 % of the country's population depends on wetland resources, and almost 80 % of the rural people in Bangladesh rely on wetlands for fish and other aquatic resources (Ahmed, 2023). In Bangladesh, the total area of wetlands is about 50 % of the total land surface, which is estimated at seven to eight million hectares (Rahman & Rashid, 2016). These wetlands are integral to the blue economy due to their significance for human settlement, biodiversity, fisheries, agricultural diversity, navigation, communication, and eco-tourism (Colgan, 2018). Wetlands in Bangladesh not only provide environmental services but also hold social and economic values (Yousuf & Kibria, 2017). They also contain rich components of biodiversity for local, national, and regional aquatic species and commercially important species (Islam, 2010). Regrettably, due to natural and anthropogenic causes, these wetlands are degrading day by day.

Wetland degradation has increased alarmingly in this century due to rapid Urbanization and industrialization in both developed and developing countries (Ballut-Dajud *et al*., 2022). Apart from these, natural environmental causes, i.e., floods, droughts, and cyclones, also play a crucial role in wetland degradation (Siddiquee & Hoque, 2007). As a result of increasing population, agricultural encroachment, over-extraction of fish, pollution, biodiversity loss, siltation, and other anthropogenic activities, most of the rivers and *beels* in Bangladesh are under threat of partial decline (Rahman *et al*., 2022). For these reasons, day-by-day, wetland ecosystems face ecological risk. Identifying external disturbances or risk stressors like human activities, climatic factors, and natural environmental change can affect the ecosystem, which refers to ecological risk (Norton *et al*., 1992; Depietri, 2019). However, the ecological risk of an aquatic environment can be assessed using a variety of techniques, such as Landscape ecological risk assessment (LERA), Ecological risk assessment (ERA), and other methods (Xie *et al*., 2013; Jin *et al*., 2019). Alongside methodological assessment, ERA needs a well-established guideline or framework to understand the critical connection between various factors and components.

Several studies show how LULC Changes affect ecological changes. Zhu *et al.* (2022) constructed a landscape ecological risk assessment model using landscape ecological principles to investigate the spatial and temporal changes based on LULC changes. Ji *et al.* (2021) used ERA methods to characterize LULC change and evaluate risk aggregation patterns. Jin *et al*. (2019) used the Layered Multiple Chaining Model (LMCM) to simulate and predict the LULC pattern of Hefei, China, in 2025. Similarly, Young (2013) shows that urban expansion has led to causes of environmental risk in the São Paulo Metropolitan Area. In addition, Malekmohammadi & Blouchi (2014) also assess ecological risk assessment (ERA) to identify stress factors that affect wetlands and risk zoning maps using GIS and evaluate the potential risk.

Halti beel is famous for the natural breeding of fish, and a portion of *Halti beel* has been announced as a fishery sanctuary where waters remain throughout the years and serve as a habitat for local wildlife and migratory birds (Siddique *et al*., 2020). The average annual fish production of *Halti Beel* is 3000 MT (Latifa *et al*., 2022). However, Halti Beel is increasingly becoming an ecologically sensitive area due to the frequent occurrence of various anthropogenic activities, which exert vast pressure on its natural ecosystem. However, several studies on *Halti Beel* revealed that a variety of stressors like siltation, dredging, infrastructure development, and excessive use of agricultural pesticides are gradually disappearing wetlands degradation (Rahman *et al*., 2022). Sayeed *et al*. (2025) investigated the status of water and sediment and found that phosphate and ammonia are not in a suitable range, which may hamper the declining trend of aquatic life. Some of the fish species were locally extinct, and the most threatened community was birds, which comprised 28.12 % of critically endangered species (Mou *et al*., 2023). Furthermore, natural disasters like floods, droughts, storms, and cyclones contribute to the vulnerability of agriculture and the damage to infrastructure (Sivakumar, 2005). Despite the ecological, economic, and social importance of wetlands, most existing studies tend to focus on isolated components such as LULC change, physico-chemical characteristics of water and sediment, ecological risk indices (ERI) or aspects of biodiversity and socioeconomic conditions. To effectively manage and conserve this diverse ecosystem, a scientific assessment of ecological risk is essential, but no other studies have shown a comprehensive analysis of the ecosystem using a structured approach. So, this study followed a well-anticipated US EPA framework and provides a comprehensive analysis of wetlands, focusing on socioeconomic and physicochemical conditions of water and sediment and the potential impact on species status and population dynamics due to increasing ecological risk. It examines the spatio-temporal variations in land use and land cover from 2000 to 2023 and investigates the patterns of landscape ecological risk associated with these changes.

METHODS AND METHODOLOGY

Methodological framework

A framework was developed following the US EPA 1998 guidelines for ecological risk assessment. Both qualitative and quantitative methods were used to describe the risk areas. The following framework (Fig. 1) is developed with a combination of the risk assessment approach, field data, and GIS techniques.

Fig. 1: Methodological framework of this study

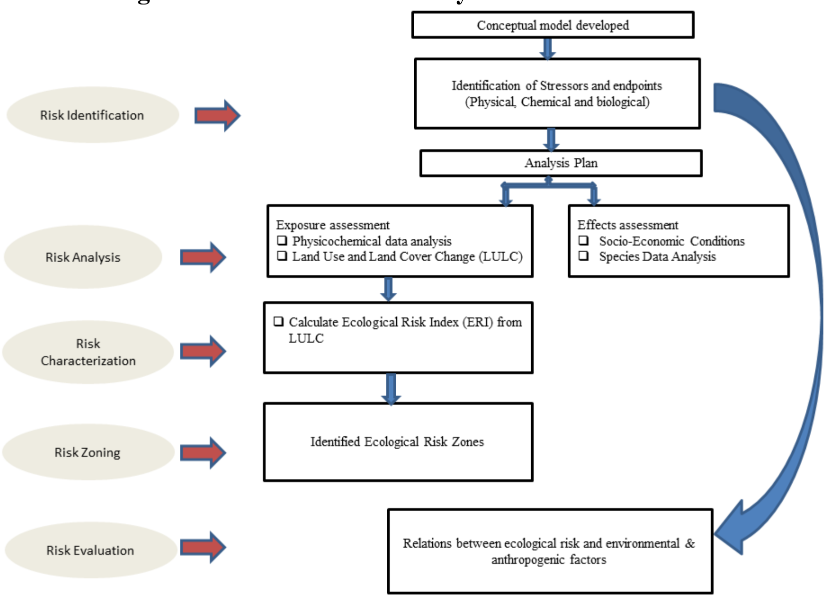
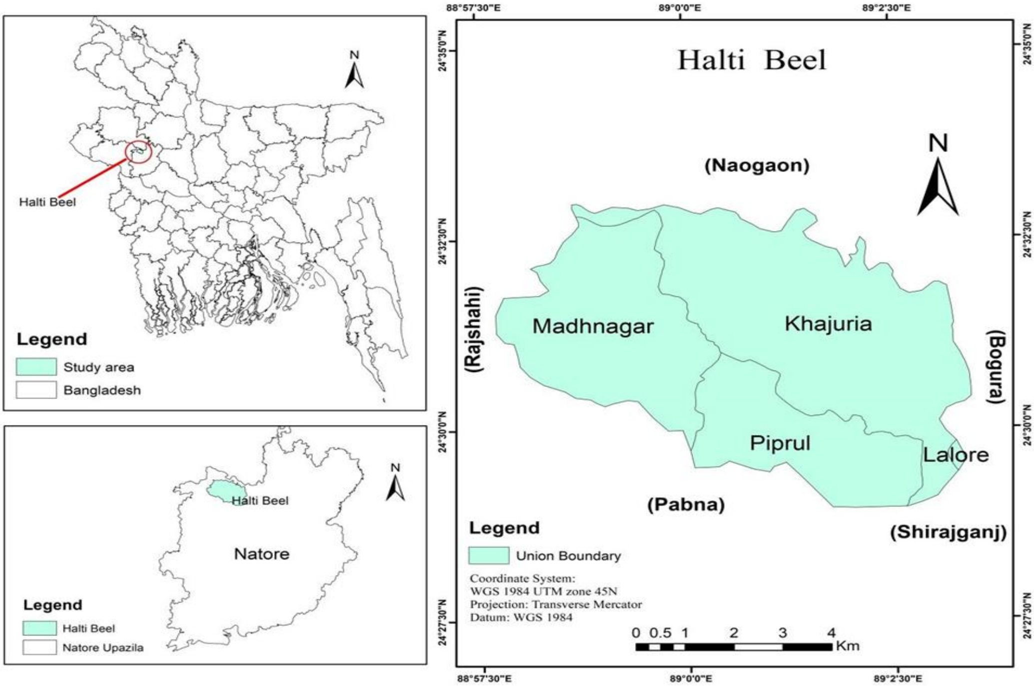


Fig. 2: Study Area Map



DATA COLLECTION

Primary data collection

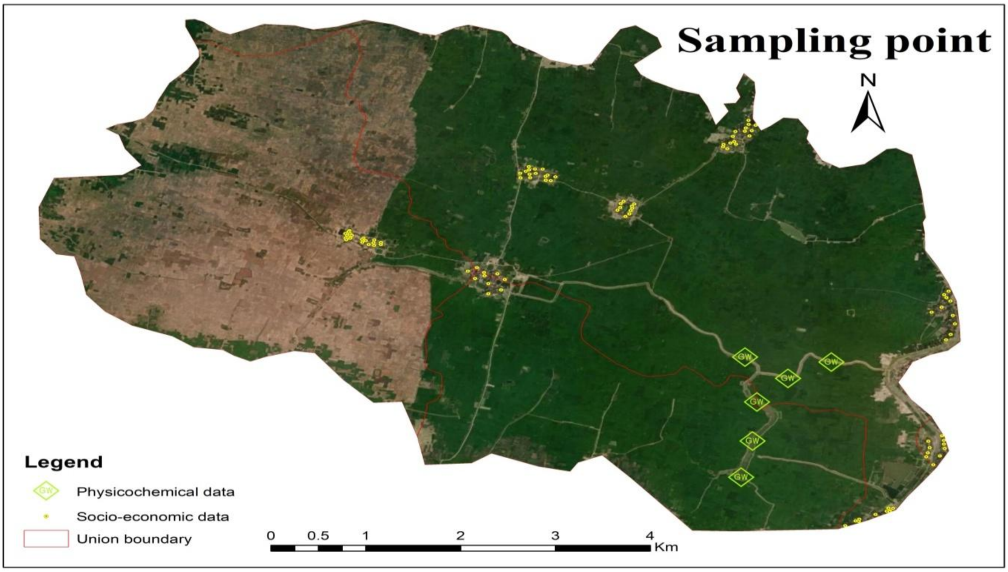
Field surveys were used to collect both environmental and socioeconomic data as part of primary data collection (Fig. 3). Environmental parameters, such as water, sediment, etc., were used for physicochemical assessment, and different socioeconomic parameters were needed to evaluate ecological status.

The core area of Halti Beel, locally called 'Halti Beel Tanky Sanctuary,' was chosen for environmental sample collection. Six water samples from 1m depth and six sediment samples from adjacent areas, maintaining a 500-meter distance threshold from each sample, were collected in standard 500-ml sample containers. Each container was previously washed with distilled water to avoid unexpected contamination. After sample collection, all bottles were sealed tightly and immediately transferred to the Environmental Analysis Laboratory, Department of Geography and Environment, Islamic University, Bangladesh, for analysis. The samples were stored in a dry, cold, and clean place. Water and sediment samples were filtered through filter papers to remove undesirable materials before starting analysis. Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Dissolved Solids (TDS), pH, Temperature, Total Suspended Solids (TSS), Turbidity, salinity, and Electrical Conductivity (EC) values of samples were measured by following methods as per Table 1.

Table 1: Data analytical techniques

Parameters	Analytical Technique	Methods	Standard Values	References
DO	Do Meter (accuracy +- .5)	Electrochemical	5 mg/l or more	ECR,1997
BOD5	Do Meter (accuracy +- .5)	Electrochemical	6 mg/l or less	
COD	Water quality detection meter	Colorimetric	20-60 mg/l	
TDS	CLEAN 30 Series Tester	Electrochemical	500-1000 mg/l	
pH	Portable pH meter (accuracy +- .1)	Colorimetric	6.5-8.5	
Temperature	CLEAN 30 Series Tester	Physical	20-30°C	
TSS	Portable TSS Meter	Optical	150-200 mg/l	
Turbidity	Turbidity Meter TUB-430	Nephelometric	10 NTU	
Salinity	Water Salinity Meter, AZ8372	Optical	5ppt or less	
EC	CLEAN 30 Series Tester	Electrochemical	150-500 µhos/cm	EPA,2012

Fig. 3: Sampling point



To collect socioeconomic data, this study focused on the purposive sampling method to ensure the selection of participants with knowledge and relevance about the research objective (Balcik & Kuzucu, 2016). A detailed questionnaire survey with 100 participants was done based on their indigenous knowledge and dependence on *Halti Beel*. Both key informative interviews (KIIs) and focus group discussions (FGDs) were conducted with local stakeholders, wetland experts, and the Upazila Statistics and Fisheries Department representatives in the *Halti Beel*.

Secondary data collection

Satellite data collection and processing

Landsat satellite images covering *Halti Beel* for 2000, 2010, and 2023 with a spatial resolution of 30 m were downloaded from the USGS (United States Geological Survey) Earth Explorer official website (https://earthexplorer.usgs.gov/) and are shown in Table 2. The downloaded images were originally in GeoTiff format with a UTM (Universal Transverse Mercator) projection. They were subsequently reprojected to the GCS (Geographic Coordinate System) WGS (World Geodetic System) 1984 UTM Zone 45 N (datum).

Table 2: Description of Landsat images used for LULC classification

Satellite	Sensor Type	Path/Row	Date of acquisition	Spatial resolution(m)	Cloud Cover (%)	Image quality
Landsat 5	TM	138/43	2000/01/26	30	0.00	7
Landsat 5	TM	138/43	2010/01/21	30	1.00	9
Landsat 8	OLI/TIRS	138/43	2023/01/09	30	0.22	9

After satellite data collection, data processing was done using the ENVI (Environment for Visualizing Images) version 5.3 image processing software. First, metadata and radiometric calibration were utilized to transform the Landsat scene's DN (Digital Number) into absolute radiance units (Wm-2sr-1). After that, the atmospheric correction was performed using the FLAASH (Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes) module (Yuan & Niu, 2008). FLAASH is a MODTRAN4 (MODerate Resolution Atmospheric Transmission) based atmospheric correction algorithm. Equation 1 calculates the geographically averaged reflectance that is calculated from the spatially averaged radiance image, which is computed using the following equation 2 (Perkins *et al.*, 2012).

$$L=\left(\frac{A\rho}{1-\rho_e S}\right)+\left(\frac{B\rho}{1-\rho_e S}\right)+L_a \quad (1)$$

$$L_e \approx \left(\frac{(A+B)\rho_e}{1-\rho_e S}\right)+L_a \quad (2)$$

Where, ρ Is the pixel surface reflectance, ρ_e It is the average surface reflectance for the surrounding region, and S is the atmosphere's spherical albedo (which captures backscattered surface-reflected photons). L_a Is the radiance backscattered by the atmosphere without reaching the surface) A and B are surface-independent coefficients that vary depending on atmospheric and geometric conditions.

Other secondary data

During the study, some other secondary data, e.g., Flora & Fauna Species and population data, were collected to understand the present status, and alongside that, also collected species and population data provide insight into biodiversity and abundance Table 3.

Table 3: Species and population data

Data type	Year of data	Data source
Flora and Fauna species	2024	Upazila fisheries department, Upazila Animal Resources Office & IUCN, 2015
Population data	2011, 2021	Bangladesh bureau of statistics (BBS) & Upazila statistics department

Risk Identification

Ecological risk identification is a process of determining how likely it is that exposure to one or more stressors may result in detrimental ecological impacts or that such effects already exist (US EPA, 1998). The ecological characteristics of a wetland are based on an examination conducted by Dugan & Jones (1993), which included three broad general groups: biological change, physical modification, and changes in the water regime. Table 4 shows the stressors and endpoints that were pre-identified by literature review, expert opinion, and on-field survey.

Table 4: Stressors and their ecological endpoints (Field observation, 2024)

Stressor type	Examples	Ecological endpoints
Physical	Soil erosion, Soil fertility decline, Vegetation decline, Gully formation, Water Pollution, Water Stress, Resource Overexploitation, and Infrastructure development.	Shifts in water levels, vegetation loss, and land degradation
Chemical	Agricultural Pollution (pesticides, fertilizer etc.)	Decreased aquatic and semi-aquatic species diversity and reduced water quality
Biological	Vegetation decline, over grazing and strain. Biodiversity Loss	Degradation of vegetative structure and loss of biodiversity.

Risk analysis

The analysis phase consists of the technical evaluation of data on the potential exposure and effects of the stressors (US EPA, 1998). The analysis step is based on a conceptual model that was developed in the problem identification phase. In this study, physiochemical data analysis shows the present status of the physiochemical condition of the study area, which may affect the species and population of the wetland. On the other hand, the LULC of the area is also analyzed in these phases to identify physical features and pressure on the wetland over the periods. Some of the stressors' relationships with ecological risk analysis in the risk evaluation phase are given a constructive result between different stressors and environmental risk. Effects assessment of the risk analysis phase focuses on the socio-economic conditions of the area and the present status of the flora and fauna species.

Exposure assessment

Physicochemical data analysis

To assess the potential risk, field studies may best represent the reality of multiple stressors and exposure to complex ecosystem relationships (US EPA, 1998). The measured values were compared against established thresholds, such as the Environmental Conservation Rules (1997). The results of the parameters exceeding the standard limits were identified as potential risk factors. The risk characterization was expressed in terms of the adverse effects of the current physicochemical condition of the area and the impact on species and landscape pattern changes in the area. In this study physicochemical status of water and sediment samples of the area was tested to understand the present risk scenario of the wetland. Physicochemical analysis was conducted by well-established methods mentioned in Table 1.

LULC Classification

In this study, the most popular classification technique in remote sensing, maximum likelihood classification (MLC) was applied to determine the land-use/cover categories of a chosen study area. According to Ghayour *et al*. (2021) the equation (3) for maximum likelihood (ML) is as follows:

$$\mathrm{D} = \ln(\mathrm{ac}) - [0.5\ \ln(|\mathrm{Covc}|)] - [0.5\ (\mathrm{X} - \mathrm{Mc})\ \mathrm{T}\ (\mathrm{Covc} - 1)\ (\mathrm{X} - \mathrm{Mc})] \qquad (3)$$

Where *D* (weighted distance) indicates the likelihood, c represents the specified class, X is the measurement vector of the desired pixel, M*c* is the mean vector of the class c, and COV*c* represents the covariance matrix of the pixels of the class c. Nearly 100 training data points were found for LULC classes from the preprocessed images for each study year. Using the ENVI (version 5.3) program, training examples were manually chosen from the pre-processed satellite images. For this study, five types of LULC classes were classified and shown below Table 5:

Table 5: LULC Classes used in the study

Class	Description
Deep Water	Stream channels and ponds contain water throughout the year.
Shallow Water	Water bodies are made up of aquatic vegetation such as water hyacinths, Muddy flats and shallow water channels.
Agricultural Land	Land that is used for crop production, including annual crops, agricultural fallow land, and land that goes underwater during the rainy season but is used as cropland in the dry season.
Rural Settlement	Rural settlements usually have tin shade, often covered by household-planted trees, rural paved roads, and institutions.
Vegetation	The area developed within grass, shrubs, and lighter green vegetation.

Accuracy assessment

A total of 100 (twenty for each class) random stratified points were generated using an accuracy assessment tool and validated with a reference map. The results of the accuracy assessment of LULC (land use land cover) with the assistance of Google Earth were more than 75 % acceptable (Abineh & Zubairul, 2015). The following formulas were used to calculate the user's accuracy, producer's accuracy, overall accuracy, and Kappa statistics (Islami *et al.*, 2022).

$$\text{User accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Reference Pixels in that Category (The Row Total)}} \times 100 \qquad (4)$$

$$\text{Producer accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Reference Pixels in that Category (The Column Total)}} \times 100 \qquad (5)$$

$$\text{Total (overall) accuracy} = \frac{\text{Total Number of Correctly Classified Pixels (Diagonal)}}{\text{Total Number of Reference Pixels}} \times 100 \qquad (6)$$

$$\text{Kappa Coefficient (T)} = \frac{(\text{TSxTCS}) - \sum(\text{Column Total x Row Total})}{\text{TS}\times\text{TS} - \sum(\text{Column Total} - \text{Row Total})} \qquad (7)$$

Where TS = Total Sample and TCS = Total Corrected Sample

Change detection procedure

The Thematic Change Workflow (TCW) tool on ENVI 5.3 was utilized to assess the change detection of LULC maps in the study area. The TCW method uses two registered images of the same boundary at different times to identify their alterations. The thematic change analysis group's untouched classes have no change and show in a new area that highlighted only the regions that have changed. The categories of images show class transitions (e.g., shallow to deep water). The rate of change was calculated to represent the magnitude of the change between periods using the following formula (Elias *et al.*, 2019):

$$\text{Rate of change}\left(\frac{km^2}{year}\right) = \frac{A2 - A1}{Z} \qquad (8)$$

Where, A2 = area of LULC (km^2) in time 2, A1= area of LULC (km^2) in time 1, and Z= difference of time between A2 and A1.

Effects assessments

Socio-economic Conditions

Data collected during the study period were verified to eliminate all possible inconsistences and error then coded and organized for systematic and fruitful analysis on SPSS (Statistical Packages for Social Sciences, version-25) Rahman *et al*. (2021). According to Siddique *et al*. (2020) the analysis of the data set was mainly based on tabular techniques. This technique was applied for the analysis of data by using simple statistical tools like percentage, average and graphical representation with the help of SPSS and Microsoft Excel and Google colab.

Species data

The categorization was done based on the survey data of the different types of crop patterns and wetland species. A total of 28 crop patterns, 16 wetlands Serbs, 9 aquatic plants, 59 fish species, 27 bird species, and 25 other species (mammals, amphibians, and reptiles) were found on the survey of the *Halti Beel*, and 4 categories were set to identify their current status. Then, respondents were asked to rate those cropping patterns and species on a scale of 1, 2, 3, and 4, where these numbers are represented as follows in table no 6:

Table 6: Species status assessment table

Categories	Recognizing scale	(%) Cover
Available	1	Above 75
Threatened/Vulnerable	2	50-75
Nearly extinct	3	25-49
Extinct/Vanished	4	Less than 25

Risk characterization

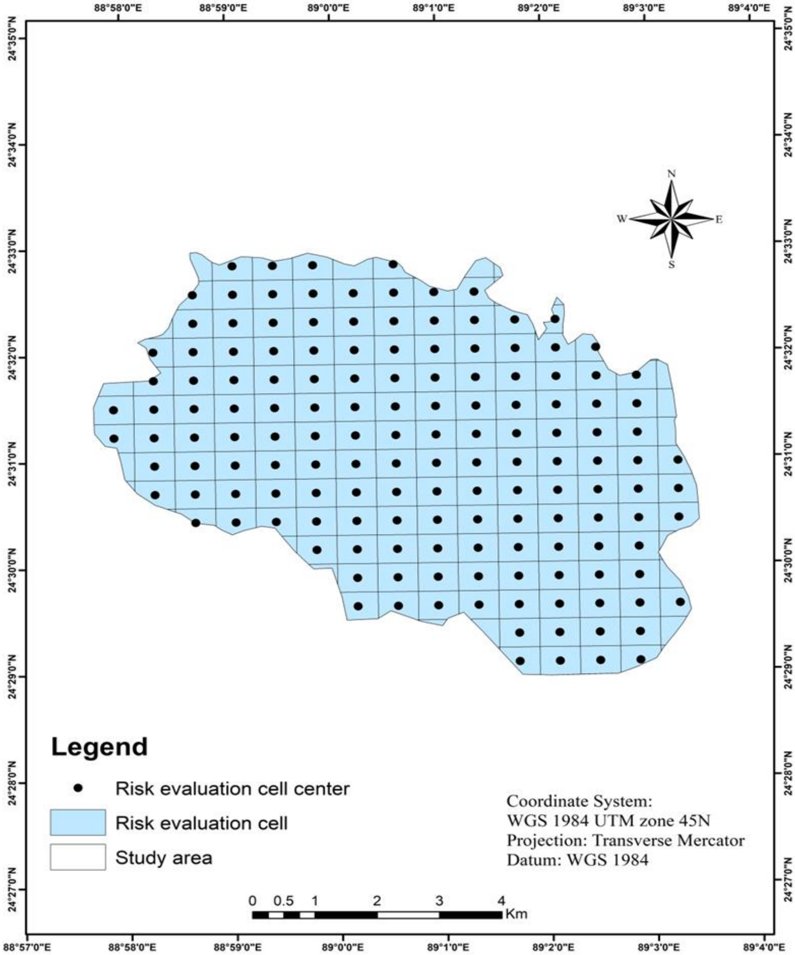
Risk characterization involves assessing the possibility of adverse effects occurring because of exposure to a stressor being evaluated (Pascoe, 1998; US EPA, 1998). There exist several methods for characterizing risks, and they frequently rely on the type of effects and quality of exposure data. The US EPA (1998) describes potentially useful techniques for characterizing risks in wetlands using a GIS-based framework. Thus, to connect effects to impact, the outcomes of several evaluations are superimposed on a map of the area of interest. In these study risk characterized was done from LULC classification.

Landscape ecological risk assessment

Determination of the risk evaluation cell

For a precise representation of landscape pattern, the suggested grid size of patch cells should be 2-5 times the average patch area (Sun & Song, 2012). The average grid size in the study area was 0.3134 km^2. According to the landscape pattern of the study area, we divided it into (1.78 km ×1.78 km) risk evaluation cells, which resulted in a total of 150 risk evaluation cells (Fig. 4). The fishnet tool in ArcGIS 10.8 was used to create these cells, and Fragstats 4.2 and Microsoft Excel were used to calculate the ERI for each assessment cell (Huang *et al.*, 2023).

Fig. 4: The ecological risk evaluation cells center



Landscape loss degree index calculation

Ri indicates the degree to which various landscape types represent ecosystems that have lost their natural properties due to both natural and human-caused disturbances (Zhu *et al.*, 2022).

The formula for R_i calculation is:

$$R_i = E_i \times F_i \tag{9}$$

Where E_i is the landscape disturbance index for each *LULC type,* and F_i is the landscape vulnerability index.

Landscape disturbance index calculation

The landscape disturbance index is designed to assess the resistance to disturbance caused by external factors, especially human activities (Ji *et al*., 2021).

The formula for E_i calculation is:

$$E_i = aC_i + bN_i + cD_i \quad (10)$$

Where C_i is the landscape fragmentation of the landscape i^{th}; N_i is the landscape segmentation of the landscape i^{th}; D_i is the landscape dominance of landscape ith; a+b+c=1, as a,b, and c are the weights of the three landscape indices. Based on previous studies (Liu *et al*., 2020; Ji *et al*., 2021), the assigned values of the parameters are 0.5, 0.3, and 0.2. The above-mentioned indexes can be seen in Table 7.

Table 7: Calculation of the landscape disturbance index (E_i)

Index	Formula	Meaning of parameters
Landscape fragmentation index (C_i)	$C_i = \frac{n_i}{A_i}$ (11)	Where n_i is the number of patches of landscape *with LULC types, Ai represents the total area of the landscape, and* A is the total area of all landscape types.
Landscape segmentation index (N_i)	$N_i = \frac{A}{2A_i}\sqrt{\frac{n_i}{A}}$ (12)	
Landscape Dominance Index (D_i)	$D_i = \frac{Q_i+M_i+L_i}{3}$ (13)	Where Q_i is the ratio of cells of i^{th} LULC type to the total cells, M_i is the ratio of the number of patches of i^{th} LULC type to the total number of patches, and L_i is the ratio of the area of i^{th} LULC type to the total area of the study area.

Landscape vulnerability index calculation

The landscape vulnerability index shows how sensitive different types of landscapes are to outside disturbance, and the degree of sensitivity is correlated with the stage of landscape ecosystem succession (Zhang *et al*., 2020). According to some previous studies, in addition to the features of the study area, the Delphi method was adopted by Ji *et al*. (2021) which suggests classifying the landscape vulnerability into 5 levels: 5 for deep water, 4 for shallow water, 3 for agricultural land, 2 for vegetation, and 1 for rural settlement (Jin *et al*., 2019). Additionally, upon normalization, the landscape vulnerability index was determined.

Ecological risk indexing

The ecological risk index reflects the connection between landscape patterns and environmental risk and the composition of the various land-use types in each evaluation unit, forming the ERI (Xie *et al.*, 2013). The landscape disturbance index (E_i) and the landscape vulnerability index (F_i) were selected in this study to build an extensive Ecological Risk Index (*ERI*) model for the ecological study of *Halti Beel*.

The formula for ERI_i calculation is:

$$ERI_i = \sum_{i=1}^{N} \frac{A_{ki}}{A_k} \times R_i \tag{14}$$

Where ERI_i is the ecological risk index of the i^{th} risk unit, n is the number of landscape types, A_{ki} is the area of *the i^{th} landscape type in the kth sample area, A_k is the total area of the k^{th} sample area, and R_i is the ecological landscape loss degree of the* i^{th} landscape type.

Risk zoning

Risk zoning is the management technique used to identify high-risk locations (Malekmohammadi & Blouchi, 2014). Risk zoning using landscape metrics involves categorizing and identifying areas based on their vulnerability to specific hazards by analyzing quantifiable landscape metrics like patch density and fragmentation to assess and map ecological risk (Syrbe & Walz, 2012). GIS evaluates the potential ecological risk by human activities or natural disasters, which are the main factors that contribute to changes in wetland ecological indexes. Using GIS tools, the zone of risk is developed. The acquired value of the ERI was allocated to the center point of the evaluation cell (Zhang *et al.*, 2018). Then, at that point, the Kriging interpolation tool in ArcGIS was utilized to get a spatial distribution map of ecological risk in the *Halti Beel*.

Risk Evaluation

Risk evaluation is the process of comparing the factors of the risk analysis with the risk evaluation criteria, defining the relationship between risk factors and their potential impact that are acceptable (Refsdal *et al.*, 2015).

Statistical Analysis

This step of the study encompasses the statistical assessment of primary data. Descriptive and inferential statistical techniques were used to analyze risk factors from various environmental and anthropogenic parameters. The statistical analysis of environmental parameters was done according to Hossain *et al.* (2019). Chi-square statistic and binary logistic regression analysis were used to evaluate the risk factors from the anthropogenic parameter dataset.

Chi-square test

A chi-square test is used to determine if there is a significant relationship between categorical values or if the observed frequencies vary from expected frequencies (Franke *et al.*, 2012). Similarly, in this study, we have used the chi-square test to determine the relationship between the observed and expected values from the socioeconomic parameters as per equation 15.

$$X^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{15}$$

Where,
X^2 is Chi-square, O_i is observed value and E_i Is the expected value
2.8.1.2 Binary linear regression model
The study also uses the binary logistic model to evaluate the possible factors of LULC changes concerning land degradation. Binary logistic regression model connects a binary dependent variable to a collection of independent factors (Tranmer & Elliot, 2008). The standard equation of the binary logistic regression model is presented in equation 16.

$$\text{Logit (Y)} = b_0 + b_1x_1 + b_2x_2 + b_3b_3 + \ldots\ldots\ldots b_ix_n \qquad (16)$$

Where, Y is the dependent variable, b_0Is the constant, X is the independent variable, and b_i= coefficient of the independent variable to, I for 1.2.3…n

A binary logistic regression model was fitted to quantify the relationship between ecological risk (dependent variable) and multiple environmental and anthropogenic factors (independent variables). These factors were identified from field survey data and environmental indices, while population data over several years were incorporated to account for human pressure on the ecosystem. The model, implemented in SPSS software, identifies the relationship between stressors and ecological risk. A model validation summary for the linear regression model is presented in Table 8.

Table 8: Model validation summary for the linear regression

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	22.709	10	.012
	Block	22.709	10	.012
	Model	22.709	10	.012
Hosmer and Lemeshow Test				
Step	Chi-square	df	Sig.	Step
1	2.374	7	.936	1

RESULTS AND DISCUSSION

Current status of physicochemical parameters of the water and sediments

Water quality parameters are crucial for aquatic ecosystems and are represented by physical and chemical parameters that maintain aquatic life within suitable ranges. Significant changes in these parameters may result in fish degradation, and any changes to the parameters can harm the development and growth of aquatic life (Talwar, 1991). The DO value of the collected water and sediment samples from Halti Beel was, on average, 3.79 mg/l (Fig. 5). According to ECR (1997), the recommended DO range for inland water sources is 5 or more. All the samples are below the acceptable range, indicating poor water quality and potentially harming fish and aquatic organisms. BOD, COD, TDS, PH, Temperature, TSS, and salinity values of all the collected samples were with an average value of 1.50 mg/l, 7.79 mg/l, 223.75 mg/l, 6.6, 24.29, 138.76 mg/l, and 0.67 ppt (Fig.5), which according to ECR (1997) recommended ranges of that's parameters shows the results of the data are in a suitable range.

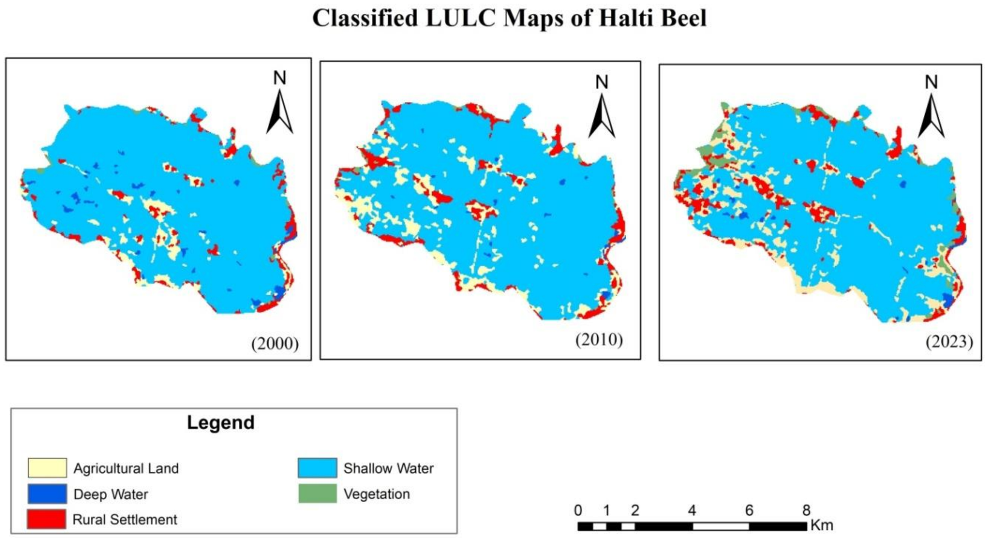
Fig. 5: Physicochemical constituent of water and sediments samples (WS= Water samples, SS= Sediment samples)

The turbidity values of the samples were with an average value of 21.77 NTU (Fig. 5). According to ECR (1997), the recommended turbidity value is 10 NTU, which indicates that the sample is not in a favorable range. The high turbidity level affects fish gills' ability to absorb and dissolve oxygen (Stevenson *et al*., 1980). The collected samples' average electric conductivity (EC) values were 505 µhos/cm (Table 9). According to the EPA (2012), the standard ranges of EC are 150-500 µhos/cm, which indicates that the ranges of EC are higher than the standard value. A study conducted by Sayeed *et al*. (2015) also mentioned that the range of EC is 25-500 µhos/cm, which is suitable for *Beel's* water. Higher ranges of EC sign high ion concentrations have adverse effects on the quality of water that often indicate pollution (Pomelo, 2022). The physicochemical analysis of water and sediment samples revealed deteriorating water quality, especially in areas of high human activity, with increasing DO, turbidity, and electric conductivity exceeding ECR, 1997, and EPA, 2012, standards. This is consistent with research on the health of wetlands, where excessive nutrient loading from agricultural runoff and household waste exacerbates ecological stress (Sarker *et al*., 2022).

Spatiotemporal analysis of LULC

The spatial distribution of LULC change from 2000 to 2023 is shown in Fig. 6, and the area with the proportion of each LULC type is shown in Table 9. From 2000 to 2023, shallow water areas decreased significantly, about 40.78 square kilometers in 2000, 37.63 square kilometers in 2010, and 35.39 square kilometers in 2023. Additionally, agricultural land constantly rose from 2.76 km² (5.87 %) in 2000 to 6.23 km² (13.26 %) in 2023. Deep Water areas decreased sharply from 0.87 km² (1.85 %) in 2000 to 0.32 km² (0.69 %) in 2010 but then slightly increased to 0.48 km² (1.03 %) by 2023. This suggests fluctuations in deep water bodies, possibly due to environmental or human factors. Water bodies are under extreme human pressure from rapidly urbanizing areas, and lakes and water reservoirs may be threatened by contaminants discharged due to sedimentation (Prasad *et al*., 2009; Bedryj *et al*., 2018). Vegetation showed a slight decrease from 0.32 km² (0.68 %) in 2000 to 0.25 km² (0.54 %) in 2010 but then increased significantly to 1.62 km² (3.46 %) by 2023.

Fig. 6: LULC maps of Chalan Beel from 2000 to 2023



This suggests a recent effort to restore or expand vegetation. Rural Settlement areas have steadily increased, from 2.28 km² (4.85 %) in 2000 to 3.26 km² (6.95 %) in 2023. This reflects ongoing urbanization or expansion of rural communities. Overall trends indicate significant changes in land use, noticeable reductions in water bodies, and increases in agricultural land and vegetation. Human activities and environmental factors presumably influence these changes (Nurullah, 2024; Byomkesh *et al.*, 2009).

Table 9: LULC type area and proportion in 2000, 2010, and 2023

Year	Area	Shallow Water	Vegetation	Rural Settlement	Agricultural Land	Deep Water
2000	Area (km^2)	40.78	0.32	2.28	2.76	0.87
	Area (%)	86.72	0.68	4.85	5.87	1.85
2010	Area (km^2)	37.63	0.25	3.23	5.57	0.32
	Area (%)	80.02	0.54	6.87	11.85	0.69
2023	Area (km^2)	35.39	1.62	3.26	6.23	0.48
	Area (%)	75.27	3.46	6.95	13.26	1.03

Accuracy Assessment Results

The classification accuracy assessment results of the LULC images for the years 2000, 2010, and 2023 are shown in Table 10. The overall accuracy ranges in this study are 78 % to 86 %, and the kappa coefficient ranges are 0.76 to 0.81 from 2000 to 2023. The kappa coefficient result was acceptable, as a kappa value of less than 0.40 indicates poor classification accuracy, while a kappa value of greater than 0.75 indicates excellent accuracy (Parvin *et al.*, 2023).

LULC Change Dynamics

A change detection matrix and a thematic matrix were used to analyze the transformation of LULC from 2000 to 2023 for the following period: from 2000 to 2010, 2010 to 2023, and 2000 to 2023. The area changes and percentage change for the change detection statistics from 2000 to 2023 are shown in Tables 10 and 11. For the years 2000 to 2010, significant changes were observed from Deepwater to shallow water and agricultural land. 60.86 % of deep water was converted into shallow water and 18.54 % to agricultural land. Whereas 9.24 % of shallow water was transformed into agricultural land, and only 3.06 % was converted into rural settlement. The conversion of agricultural land to rural settlement is 20.98 %, which contains an area of 0.59 km^2. From 2010 to 2023, land cover change shows a comparative transformation pattern from deep water to shallow water and agricultural land. 50.68 % of deep water was converted into shallow water and 9.09 % to agricultural land. On the other hand, 9.19 % of shallow water is converted into agricultural land. From 2010 to 2023, a noticeable conversion occurred from agricultural land to rural settlement, which is 1.03 km^2, and in proportion, accounts for 18.20 %.

Table 10: Change Detection Statistics (CDS) of Areal Change between 2000 and 2023

	Area (Initial State 2000) in km^2							
Area (Final State (2023) in km^2	Class Names	Deep water	Shallow water	Agriculture land	Rural settlement	Vegetation	Row total	Row class
	Deep water	0.26	0.21	0.01	0.01	0.00	0.49	0.49
	Shallow water	0.49	33.62	0.86	0.49	0.01	35.47	35.47
	Agriculture land	0.10	4.36	1.28	0.57	0.01	6.31	6.31
	Rural settlement	0.03	1.70	0.55	1.04	0.05	3.36	3.36
	Vegetation	0.00	1.01	0.13	0.32	0.35	1.81	1.81
	Class total	0.88	40.90	2.83	2.44	0.41	0	0
	Class changes	0.62	7.28	1.55	1.40	0.06	0	0
	Image difference	-0.39	-5.43	3.49	0.93	1.40	0	0

Major conversion of LULC occurs during the period 2000 to 2023. Significant changes were observed in this period from deep water to shallow water and agricultural land, and shallow water to agricultural land. 55.63 % deep water converted into shallow water and 11.68 % to agricultural land. Similarly, 10.65 % of shallow water is converted into agricultural land. Agriculture indicates that deep water plays a significant role in catchment runoff under agriculture, suggesting that LULC may have a considerable impact on weathering rates and patterns, and shallow water is substantial for agricultural production and ecological sustainability (Robinet *et al*., 2018; Ren *et al*., 2018). The conversion of agricultural land to rural settlement is 19.52 % consists of an area of 0.55 km^2. This shift aligns with the previous research indicating that land-use-induced wetland degradation (Islam, 2015). There is also a significant conversion from rural settlement to vegetation, which is 13.15 %, and no significant conversion from vegetation to other LULC classes was found.

Table 11: Change Detection Statistics in percentage between 2000 and 2023

	Area (Initial State 2000) in percentage							
Area (Final State (2023) in percentage	Class Names	Deep water	Shallow water	Agriculture land	Rural settlement	Vegetation	Row total	Row class
	Deep water	29.406	0.524	0.255	0.443	0.000	100	100
	Shallow water	55.635	82.202	30.382	20.244	2.845	100	100
	Agriculture land	11.680	10.655	45.127	23.458	1.751	100	100
	Rural settlement	2.971	4.150	19.522	42.704	11.160	100	100
	Vegetation	0.307	2.469	4.713	13.151	84.245	100	100
	Class total	100	100	100	100	100	0	0
	Class changes	70.594	17.798	54.873	57.296	15.755	0	0
	Image difference	-44.160	-12.269	123.439	37.976	340.700	0	0

The major shift in LULC between 2000 and 2023 is shown in Table 12. According to the results, almost four-fifths of the land remains the same as in 2000 because 79.14 % has no change. Major conversion found that shallow water to agricultural land reaches a total area of 4.14 km^2, a proportion of 8.80 %. It is clear that the shallow water land decreased, and the agriculture land increased due to fulfilling the growing population demand for food (Hemathilake *et al*., 2022). Also, the conversion of shallow water to rural settlements is 3.43 %, which stipulates an extreme population pressure threat to water bodies (Prasad *et al*., 2009). Unplanned urbanization can exacerbate pollution and disrupt natural water flow, leading to wetland desiccation (Dewan *et al*., 2012) The conversion from deep water areas to shallow water and shallow water to deep water is 0.90 % and 0.38 %. On the other hand 1.96 % of shallow water areas were converted into vegetation, and 1.52 % of agricultural land into shallow water. As a result of various natural events and human activity, some types of LULC endure significant conversion. The various development projects around wetlands are obstructing the natural flow of the water body, leading to frequent waterlogging in its neighboring areas (Hollis, 1990). Fig. 7 shows the spatiotemporal pattern of LULC transformation from 2000 to 2023.

Fig. 7: LULC transformation from 2000-2010, 2010-2023, and 2000-2023

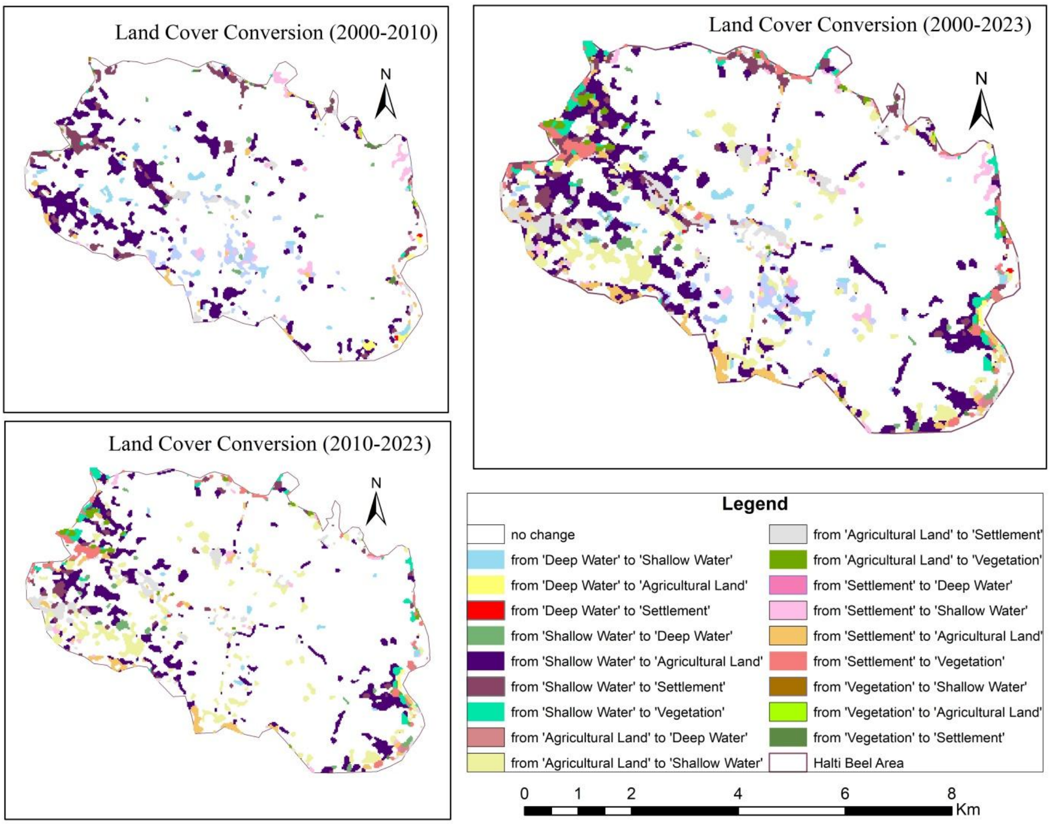


Table 12: Major shift in LULC between 2000 and 2023

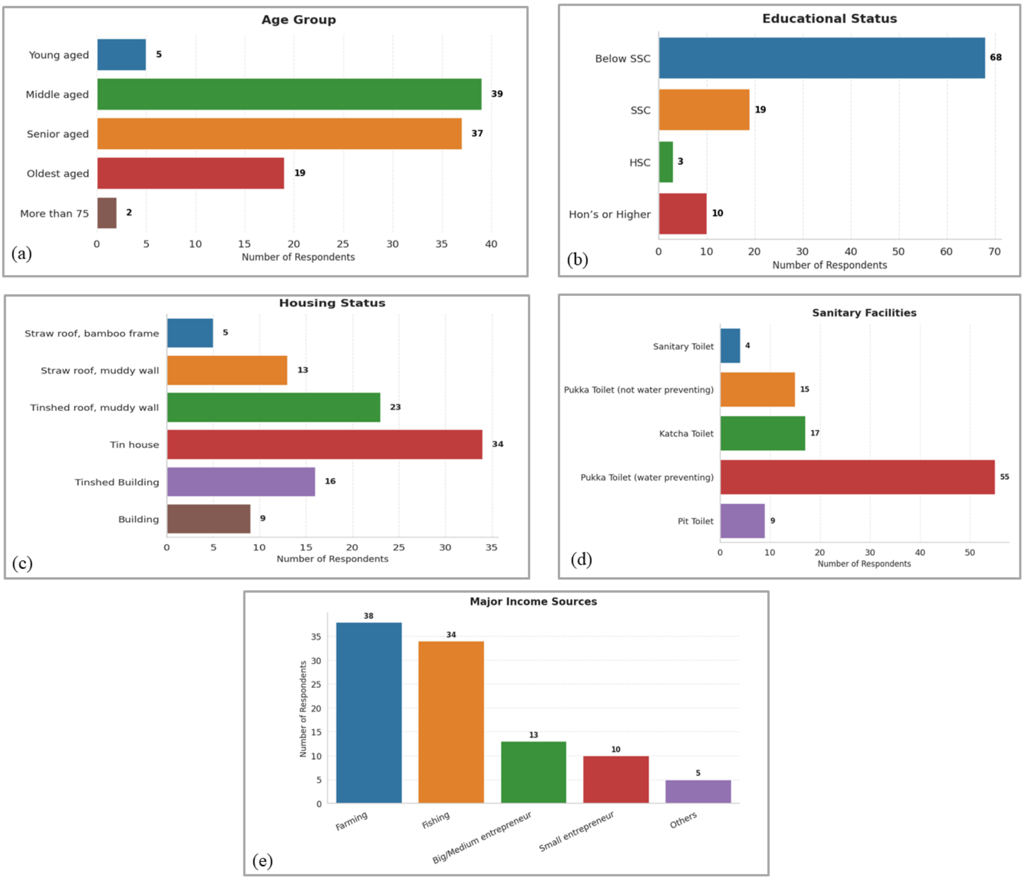
From	2000	To	2023	Area km^2	Area (%)
From	No change	To	No change	37.22	79.14
	Deep Water		Shallow Water	0.42	0.90
	Deep Water		Agriculture Land	0.08	0.17
	Deep Water		Rural settlement	0.01	0.02
	Shallow water		Deep Water	0.18	0.38
	Shallow water		Agriculture Land	4.14	8.80
	Shallow water		Rural settlement	1.61	3.43
	Shallow water		Vegetation	0.92	1.96
	Agriculture Land		Shallow water	0.72	1.52
	Agriculture Land		Rural settlement	0.46	0.97
	Agriculture Land		Vegetation	0.11	0.24
	Rural settlement		Shallow water	0.40	0.85
	Rural settlement		Agriculture land	0.48	1.01
	Rural settlement		Vegetation	0.25	0.53
	Vegetation		Settlement	0.02	0.05

Socio-economic condition of the study area

The study was conducted to identify the socio-economic status of the respondents of the study area. The variables considered in the study are age group, educational status, housing Status, sanitary facility and Major income sources in Fig. 8.

The respondents were divided into the following four groups: young, aged 20–35 years; middle-aged, aged 35–50 years; senior, aged 50–65 years; and oldest, aged above 65 years. The percentages of the four groups shown are 5 %, 39 %, 37 %, and 19 %, respectively. The lowest and highest respondents in Halti Beel were young and middle-aged. Halim *et al.* (2017) found that in the fisherman communities of the Kafrikhal Beel, 5 % were 18 to 24 years old, 65.5 % were 25 to 34 years old, and 29.5 % were 35 to 55 years old. Education is a crucial factor in determining a society's status and lifestyle. This study divided the study group into four categories: secondary school certificate, secondary school certificate (SSC), Higher Secondary Certificate (HSC), and Hon’s or higher study. About 68 % of respondents were below the SSC level, 19 % had completed SSC, and 3 % had a bachelor’s or higher degree. The study reveals that a significant portion of the population has education below the SSC level, since low literary rates are frequently linked to increased resource exploitation and detained sustainable wetland management practices (Dugan, 1988). The housing conditions of the study area are derived from six types of houses found in the study; 5 % of the respondents' houses are straw-roofed, bamboo-framed. 13 % of the houses of respondents have straw roofs or muddy wall roofs. 23 % of houses' conditions were tin shed roofs and muddy walls. 34 % of houses were tin houses. 16 % of respondents' houses were finished buildings, and 9 % were building houses (Fig. 8). Rahman *et al.* (2021) reported that 5 % of fishermen's houses were kacha houses (made of wood, tree leaves, and bamboo), 70 % of houses were tin sheds, 18 % of houses were half buildings (made of brick and tin), and the rest of the 7 % of houses were found buildings (proper, good quality, made of bricks) in the chalan beel area of Faridpur upazila, Pabna district. Sanitary facilities in the area have different variations. The most common type is the pukka toilet (water preventing) with 55 %, followed by the katcha toilet at 17 % and the pukka toilet (not water preventing) at 15 %. Pit toilets and sanitary toilets are 9 % and 4 %. Housing data shows that most of the houses are tin shed structure and more than 40 % lack improved sanitation, relying on kacha toilets that allow direct contamination of wetland water sources, increasing bacterial pollution and nutrient loads (Wear *et al*., 2021). Fishing and farming are the main occupations of the Halti Beel respondents. In this study, we found that 38 % of respondents were involved in fishing, 34 % were dependent on farming, 13 % and 10 % were big and small entrepreneurs, and 5 % earned their income from other professions. Additionally, most of the population depends on fishing and farming, which leads to habitat damage, overfishing, and water pollution from fertilizer and pesticides (Adeyemo, 2003).

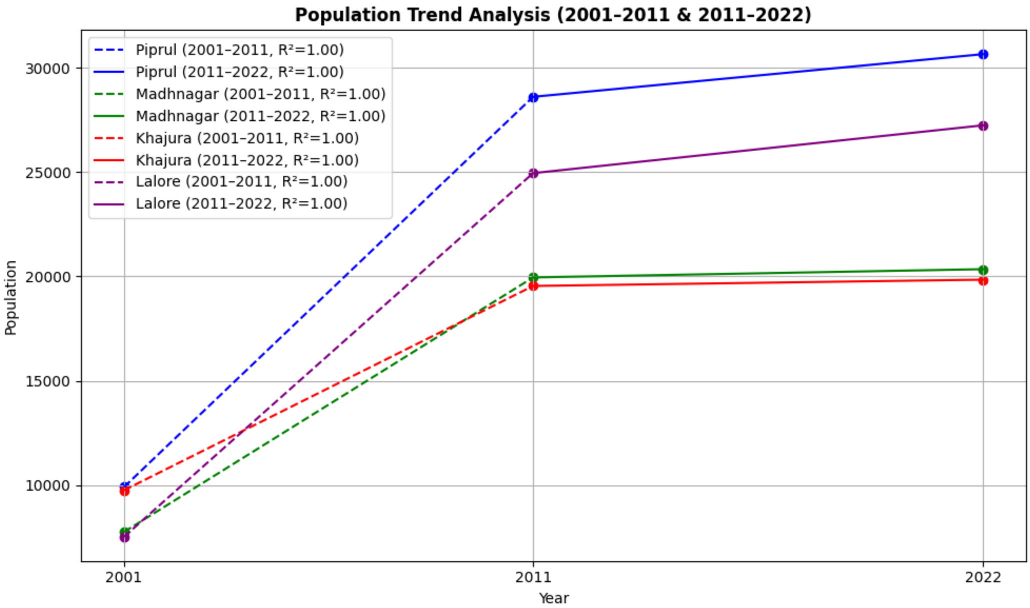
Fig. 8: Age Group(a); Educational status(b); Housing condition(c); Sanitary facilities(d); Major income sources(e). (Field observation, 2024)



Population trends and species status

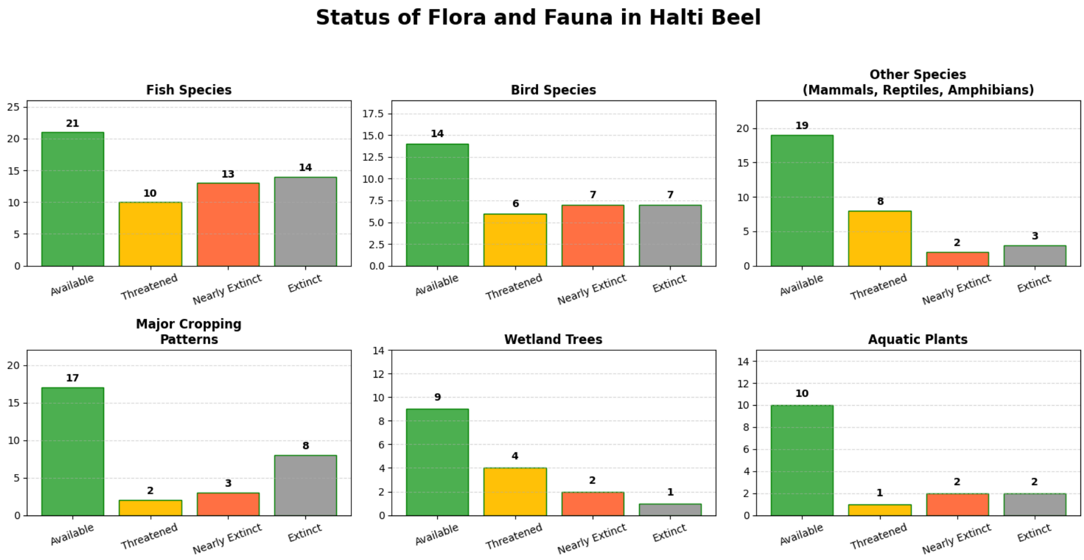
Fig. 9 shows the population growth in four unions from 2001 to 2022. All unions experienced population increases, whereas Piprul, Khajura, Madhnagar and Lalore showed the most significant absolute increase in 2001-2011, 9905 to 28614, 9751 to 19545, 7752 to 19954 and 7518 to 24955, annual growth rate of these period are 11.16 %, 9.85 %, 7.10 %,12.77 % which may indicate urbanization, socioeconomic causes driving the rise, and proximate better living standards (Rong, 2003). Similarly, 2011-2022, all Unions are showing steady demographic growth, annual growth rates for this period are 0.63 %, 0.18 %, 0.14 % and 0.80 %. The overall trend of the population data is showing a quadratic increase. This means the population increases at a changing rate over time, showing an upward curve.

Fig. 9: Population trends of the study area (Source: BBS & Statistics Department of Naldanga Upazila, 2024)



In this study, 57 fish species were identified based on local knowledge. Among them, 21 were available, 10 were threatened, 13 were nearly extinct, and 14 were found extinct. Rahman *et al*. (2022) found that at least 19 fish species that were formerly considered to be a threat may go extinct locally. On the other hand, 34 bird species were found, where 14 were available, 6 were threatened, 7 were nearly extinct, and 7 were found extinct. According to the field survey and the IUCN, 2015 report, many native fish and bird species have shown significant declines, attributed to climate change, water pollution, and anthropogenic activities (Aziz, 2021). Among the rest of the faunal species (mammals, reptiles, and amphibians) 19 were available; 8 were threatened, 2 were nearly extinct, and 3 were found extinct. According to Şekercioğlu *et al*., (2004) found 6.5 % bird species are functionally extinct and 21 % are extinction prone. The Daily Sun, (2024), reported that many birds and other species are threatened with extinction due to pesticide use in agriculture. Apart from these, major cropping patterns changed over time. 8 indigenous cropping practices were diminished over time, and 3 types were nearly extinct; here, 2 were found threatened and 17 cropping practices were found available. Most of the wetland trees and aquatic plants are available. Four wetland trees were threatened, and 1 aquatic plant was threatened, but the same number of trees and plants were found nearly extinct, and a tiny number of species were found extinct (Fig. 10).

Fig. 10: Present status of fauna and flora species



Spatiotemporal Changes in Landscape Ecological Risk

This study used the Jenks natural break point classification method to classify the landscape ecological risk of the study area (Li *et al*., 2018). The landscape ecological risk was divided into five classifications, as shown in Table 13.

Table 13: Ecological Risk Level

Risk Level	Lowest Risk	Lower Risk	Middle Risk	Higher Risk	Highest Risk
ERI	<12.82	12.82-14.03	14.03-15.23	15.23-16.41	16.41-18.25

Ecological risk of human activities and natural disasters evaluated by GIS & RS to identify risk by zoning map from risk characterization data. Similarly, a study conducted by Wang & Cheng (2011) using GIS and RS technology applied ERA in the zoning of the Baiyang-dian basin in China. The landscape ecological risk of the study area is shown in Fig. 11. In 2000, the higher and highest-risk zones were mainly found in the northwest, northeast, and southmost areas, including Union, Madhnagar, Khajura, and Piprul. Some of the middle-risk areas were also seen in these unions. Lower-risk areas of the southeast region in 2000 converted into a higher and highest-risk region in 2010, and the higher-risk area of Khajura Union converted into the highest-risk areas. In 2010, significantly higher and highest-risk areas from 2000 were converted into lower and lowest-risk areas, which included Madhnagar and Piprul Union. The western part had a higher and highest risk areas in 2000 and 2023 but became the lowest and lower risk area in 2010. In 2023, the southern part of the area was identified as the higher and highest risk zone, but in 2000 and 2010, it was the lower and lowest risk area. The Northeast part was a lower and middle-risk area in 2000 and 2010 but under the middle-risk and higher-risk area in 2023. The risk areas were spared subsequently in the maximum parts of the study area in 2023.

In 2000, the areas with the lowest ecological risk were 25.42 % of the total area and 39.29 % in 2010. After 10 years, it almost increased to 13.87 % from 2000. The main LULC types in these lowest-risk areas were shallow water, deep water, and vegetation land. However, the area decreased in the next 13 years; the proportion count was 18.29 % in 2023. The lowest ecological risk has fluctuated over the years. According to Battisti *et al*. (2016), environmental disturbance and risk are affected by the impact of human activities. The lower and middle risk areas of 2000 were 38.77 % and 17.79 %, which also decreased in 2010.

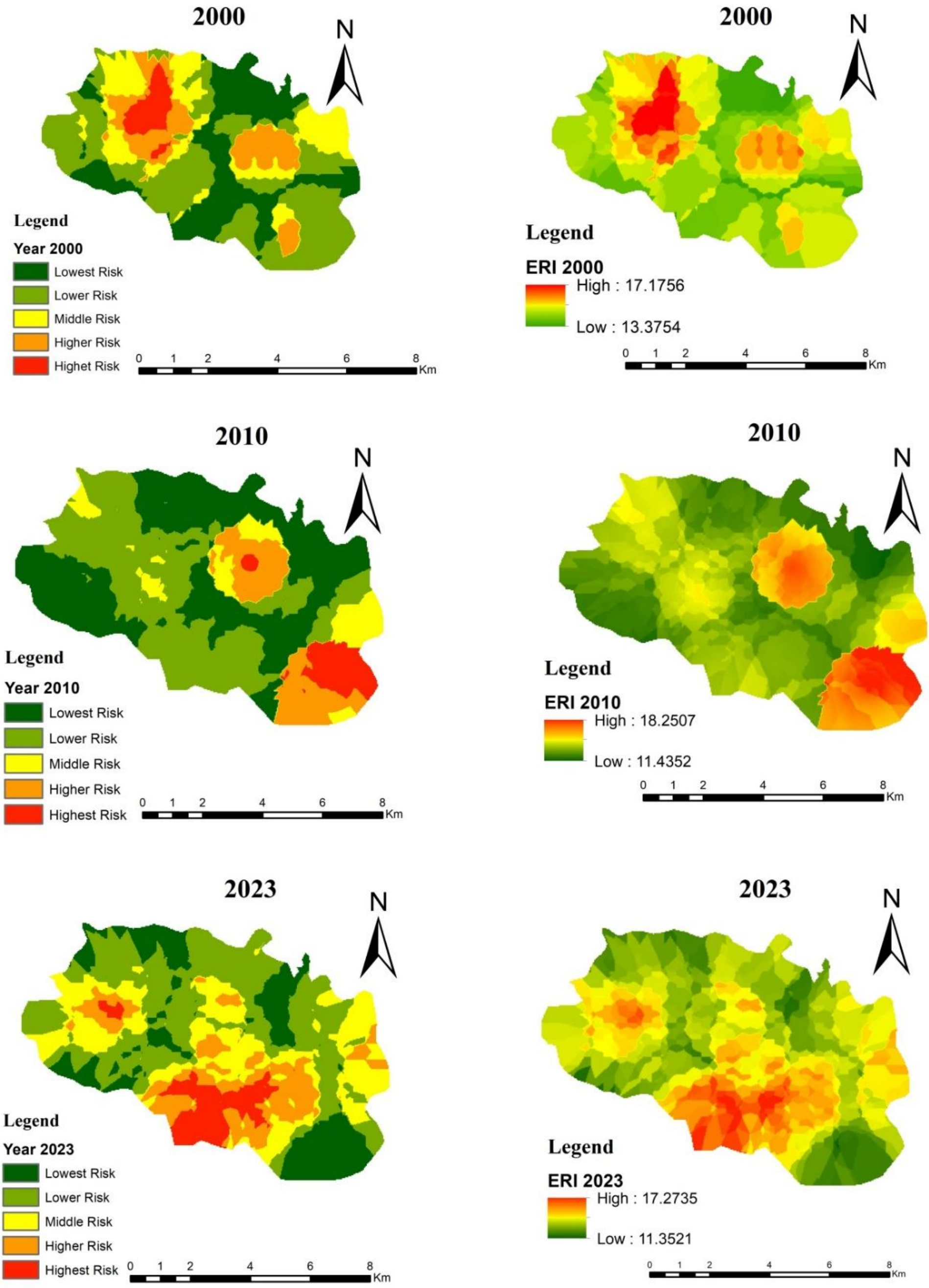
In 2010, the higher-risk areas decreased by 2.61 % from 2000, but in 2023, the highest and higher-risk areas almost doubled from 2000. The results show that in this area, development activities were more stable than in the next 13 years as the highest risk zone increased. Anthropogenic activities affect regional landscape patterns and their rise, resulting in remarkable changes in ecological risk intensities (Ai *et al*., 2022; Wang *et al*., 2021).

In 2023, the highest ecological risk zone spared all of the union from 2000 to 2010. *Halti Beel* has become a significant tourist attraction for thousands of tourists in the country. The increase in tourism in Halti Beel can adversely affect ecosystems and the environment, placing immense pressure on an area and increasing risk (Voronkova *et al*., 2021). Considering the middle risk, it decreased from 2000 to 2010, but it increased in 2023. The proportion of the middle-risk areas was 17.79 %, 8.29 %, and 23.80 %. The middle-risk area consists of LULC types of agricultural land, vegetation, rural settlements, and deep water bodies (Table 14). The lowest and lower risks decreased in 2023, but the middle, higher, and highest risks increased simultaneously (Fig. 11). This study is related to previous research conducted by Jin *et al*. (2019). In landscape ecological risk assessment, the landscape factors mainly focus on quantification and analysis of landscape patterns, and the findings are utilized to either directly or indirectly characterize the landscape ecological risk.

Table 14: Ecological risk area and proportion in 2000, 2010, and 2023

Year		Lowest Risk	Lower Risk	Middle Risk	Higher Risk	Highest Risk
2000	Area Sq. Km	11.95	18.23	8.36	6.34	2.12
	Percentage (%)	25.42	38.77	17.79	13.48	4.52
2010	Area Sq. Km	18.47	17.08	3.90	5.11	2.44
	Percentage (%)	39.29	36.34	8.29	10.87	5.19
2023	Area Sq. Km	8.60	17.10	11.18	6.64	3.47
	Percentage (%)	18.29	36.38	23.80	14.12	7.39

Fig. 11: *Halti Beel* Ecological Risk Classification (left) and Ecological Risk Index (right) in 2000, 2010, and 2023



Relationships between Ecological risk and stressors

The study's use of binary logistic regression revealed several important variables of ecological risk in Table 15. Of specific importance are soil erosion (β = 1.852, p = 0.034), resource overexploitation (β = 3.241, p = 0.007), agricultural contamination (β = 2.632, p = 0.019), biodiversity loss (β = 2.520, p = 0.027), and infrastructure development (β = 3.854, p = 0.036), all of which show solid positive relationships with expanded environmental risk. These factors eminently raise the probability of natural corruption, with infrastructure development and resource overexploitation showing exceptionally articulated impacts. Brinson & Malvárez (2002) also mentioned major factors that are responsible for losses and degradation of ecology include eutrophication, agricultural pollution and contamination, grazing, harvests of plants and animals, invasions of exotics, and the practices of filling, diking, and draining.

Table 15: Binary logistic regression to evaluate the predictor of ecological risk

Variables in the Equation		β	S.E.	Wald	df.	Sig.	Exp.(β)	95 % C.I for Exp.(β)	
								Lower	Upper
Step 1[a]	Soil erosion	1.852	1.941	.910	1	.034	6.374	−1.948	5.652
	Soil fertility decline	-1.796	1.115	2.593	1	.107	.166	-3.981	0.389
	Vegetation decline	.344	1.021	.113	1	.736	1.410	-1.657	2.345
	Gully formation	-1.474	.852	2.994	1	.044	.229	-3.143	0.195
	Water Pollution	-.817	1.770	.213	1	.644	.442	-4.286	2.652
	Water Stress	.635	.868	.535	1	.465	1.887	-1.066	2.336
	Resource Overexploitation	3.241	1.191	7.404	1	.007	25.554	0.907	5.576
	Agricultural Pollution	2.632	1.126	5.470	1	.019	13.905	0.426	4.838
	Biodiversity Loss	2.520	1.139	4.897	1	.027	12.431	0.289	4.751
	Infrastructure Development	3.854	1.834	4.414	1	.036	47.188	0.260	7.448
	Constant	-14.485	4.555	10.111	1	.001	.000		

β= regression coefficients, which stand for the odds ratio of the probability of success to the probability of failure. **S.E.=** standard error of the estimate, **Wald statistics**= [β/S.E.]2, **df**=degrees of freedom, **sig**= significance level, Ex (B)= e^{β} where e=2.718

Gully formation (β = -1.474, p = 0.044) shows a negative connection with risk, recommending a likely balancing out influence. In addition, soil fertility decline, vegetation decline, water pollution, and water stress did not accomplish factual importance in the study area. This study identifies the relationship between stressors and wetland risks that are part of the risk assessments. Galatowitsch (2018) also discussed six major drivers: infrastructure development, pollution, overharvesting, overexploitation, water withdrawal, and invasive species that threaten the loss of wetland ecology. A key future challenge is to develop a sustainable strategy for wetland conservation amid growing pressure from climate change, population growth, and the drivers that have historically threatened wetlands

CONCLUSION

The overall results summarize a significant increase in population over the study period, accompanied by major changes in LULC types that have led to heightened ecological risk in the area. These shifts have profoundly impacted the local ecosystem, leaving the current status of species highly vulnerable. The current state of physicochemical properties of DO, turbidity and electric conductivity was above the permissible limits, leading to harm for wetland species. The major LULC change is characterized by a declining trend in deep and shallow water, as well as an inclining trend in agricultural land and settlements. The conversion matrix found that almost 8.80 % of shallow water bodies converted to agricultural land and 0.90 % of deep water bodies converted to shallow water bodies. Indicating anthropogenic activities influence the natural environment. As the area stays inundated for almost 3 to 4 months of the year, the expansion of agricultural land and rural settlement shows a significant increase trend. The ecological risk analysis revealed that the risk of the area in 2023 spread all over the union, and the lowest and lower risks of the area decreased in 2023, but the middle, higher, and highest risks increased synchronously. The critical ecological shift summarizes the expansion of the highest & highest-risk zones to the southern part of the area over 23 years, including Khajura and Piprul Union, and the lowest & lower-risk areas, including Lalore Union. The impacts are evident in the alarming decline of various species, including flora and fauna. Many of them are now classified as vulnerable or have faced local extinctions. This study also founds Environmental and anthropogenic parameters "soil erosion, resource overexploitation, agricultural contamination, infrastructure development, and biodiversity loss" have strong relationship with ecological risk. This study identifies the ecologically critical areas of *Halti Beel* based on LULC dynamics and investigates present conditions of socio-economic and physicochemical parameters of water & sediments and species status, which is important for analyzing, understanding, and protecting the ecological flow and ecological condition of the area to maintain ecological services.

This study assessed the ecological risk of *Halti Beel* without analyzing the risk assessment and with an insufficient understanding of the impacts of anthropogenic activities and natural disasters on its biodiversity and environment. Future research should focus on continuous monitoring of physicochemical data and include a risk zoning map of all parameters of resource exploitation trough including mitigation & management strategy and sampling to account for seasonal variations of the risk.

CONFLICT OF INTEREST

The authors declared that there is no conflict of interest to disclose.

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