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Research Article

Integrating Geospatial Indicators and Statistical Modelling to Assess Environmental Drivers of Faunal Diversity Responses in the Rohingya Influx of Bangladesh

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Abstract

The southeastern coastal landscape of Bangladesh particularly the Cox's Bazar district Ukhiya-Teknaf region is a globally important yet extremely fragile biodiversity zone in the Indo-Burma hotspot. Habitat conditions have changed dramatically due to rapid expansion of Rohingya settlements, forest fragmentation and climate-related environmental stresses. However, there is little understanding of the quantitative relationship between satellite-derived ecological changes and taxon-specific faunal responses. The study uses multi-source geospatial data and statistical modelling to evaluate the environmental drivers of vertebrate faunal diversity between 2015 and 2026. Vegetation, thermal, moisture and ecological indicators comprising the Normalized Difference Vegetation Index (NDVI), Transformed Difference Vegetation Index (TDVI), Enhanced Vegetation Index (EVI), Land Surface Temperature (LST), evapotranspiration (ET) and Ecological Health Index (EHI) were derived from Sentinel-2A, Landsat-8/9 and MODIS datasets. These were integrated with secondary biodiversity data standardised from Cox's Bazar South Forest Division, Teknaf Wildlife Sanctuary, Inani National Park, Nishorgo conservation databases, UNDP/UNHCR reports and published scientific research. The temporal study indicates a Substantial habitat transformation with a reduction of dense vegetation from 36,791 to 24,306 pixels (−33.9%) and an expansion of built-up by 121.2%, from 2015 to 2025. The maximum land surface temperature increased from 35.50 ℃ to 48.99 ℃, indicating increasing thermal pressure. Correlation analysis, regression modelling, and multivariate analysis indicated potential associations between vegetation condition (NDVI/TDVI/EHI), heat stress (LST), moisture variability (ET), and faunal responses; however, statistically significant evidence for these relationships was limited. The observed patterns demonstrated comparably larger connections of mammal and bird responses with vegetation degradation and habitat fragmentation, whereas reptile and amphibian responses exhibited greater correspondence with heat and moisture variability. The integrated geospatial-statistical approach identifies biodiversity sensitive zones and provides scientific basis for habitat restoration and climate resilient conservation planning in rapidly changing tropical environments.

Keywords

Geospatial Indicators, Vertebrate Diversity, Remote Sensing, Climate Stress, Ecological Health Index, Rohingya Settlement Landscape

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1. Introduction

The Indo-Burma biodiversity hotspot is worldwide recognized for its outstanding species richness and ecological importance, but is particularly vulnerable to habitat destruction, change in land-use and environmental stress due to climate change [1, 2]. The southeastern coastal region of Bangladesh, especially Ukhiya and Teknaf landscapes near Cox's Bazar has tropical semi-evergreen forests, protected areas and wildlife corridors with unique vertebrate assemblages. However, the rapid growth of settlements, deforestation, and use of resources have raised the fragmentation of the ecosystem and endangered the survival of biodiversity [3, 4].

Recent advances in remote sensing and geospatial modelling have demonstrated the usefulness of ecological indicators derived from satellite data such as NDVI, EVI, LST and evapotranspiration for monitoring habitat dynamics, vegetation health and climate-driven ecological changes [5-7]. Habitat fragmentation and climate variability can change vegetation structure, thermal conditions and ecosystem functioning, which can influence species distributions [8, 9]. Thus, the integration of biodiversity records with multi-temporal remote sensing and statistical techniques is critical to comprehend complicated species environment interactions.

Previous remote sensing based biodiversity studies have established the utility of vegetation, temperature and moisture indicators in identifying environmental change [30]. Nevertheless, methodological constraints persist. Satellite generated indicators are indirect indices of habitat state and cannot substitute standardized field-based species inventories for direct measurement of species richness [30]. Secondary biodiversity records can also vary in survey effort, geographical and temporal coverage, detection likelihood and taxonomic completeness, which may skew estimates of biodiversity change [31, 32]. Furthermore, models based on short annual time series and several correlated environmental factors may have low statistical power, unstable coefficient estimates and a greater risk of overfitting [33]. Also, the temporal dependence between consecutive annual observations may contradict the independence assumption of traditional correlation and regression models and may lead to false statistical inference [34]. Hence, for short ecological time series, cautious exploratory approaches based on descriptive trajectories, effect sizes, rank-based associations, permutation-based inference and explicit residual autocorrelation diagnostics may be more defensible than strong multivariable prediction or causal interpretation [34, 35].

The research develops an improved geospatial statistical framework to examine temporal variations of faunal diversity to landscape change and climate stressors across the 2015-2026 period. The approach combines satellite-derived ecological indicators, verified vertebrate diversity datasets and predictive modelling to detect trends of vulnerability of biodiversity. Exploratory statistical analyses suggested that vertebrate taxa may show different patterns of association with vegetation degradation, thermal pressure and moisture variability. Mammal and avian responses appeared to correspond more closely with vegetation-related changes, whereas reptile and amphibian responses showed comparatively greater correspondence with thermal and hydrological variability. However, these patterns require cautious interpretation because the short annual time series limits statistical power and the ability to establish causal relationships. Such integration provides essential scientific support for climate resilient conservation planning, ecological restoration and sustainable habitat management in the rapidly changing Rohingya settlement landscapes of south-eastern Bangladesh. Ecosystem monitoring with remote sensing is becoming popular yet there are few quantitative studies relating ecological indicators from satellites to long-term observations on fauna by taxa. A major issue for research is therefore to better understand the regulation of different vertebrate groups depending on vegetation state, heat stress and moisture fluctuation.

1.1. Objectives

The main objectives of this research are:

1) To assess spatiotemporal variation of vertebrate faunal diversity, richness trends and degradation trajectories in the south-eastern Rohingya settlement zones of Bangladesh between 2015-2026.
2) To integrate multi-source remote sensing indicators (NDVI, TDVI, EVI, LST, ET, and EHI) for characterizing habitat quality, ecological stress, and climate-induced environmental changes.
3) To quantify the links between satellite derived environmental determinants and taxon-specific faunal responses in terms of correlation, regression modelling and multivariate statistical techniques.
4) To establish an integrated geospatial-statistical system for identifying biodiversity sensitivity zones and for supporting climate resilient habitat conservation, restoration and management methods.

1.2. Research Significance and Scope

In this section, we present an integrated methodology for the analysis of temporal relationships between satellite-derived environmental variables and vertebrate faunal responses in the Rohingya settlement landscapes of southeastern Bangladesh. The study combines vegetative, thermal, moisture and ecological variables with taxon-specific biodiversity records to assist in the identification of potential patterns of ecological fragility among mammals, aves, reptiles and amphibians. However, the statistical links are viewed as exploratory ecological associations because of the low adjusted R2 values and statistically non-significant p-values resulting from the regression models. The findings may help future field based biodiversity monitoring, habitat restoration, wildlife corridor protection and climate-resilient conservation planning in the Ukhiya–Teknaf region. The study covers the 2015-2026 period and analyses environmental and faunal changes at the landscape level, rather than causal correlations at the species level.

2. Materials and Methods

2.1. Study Area

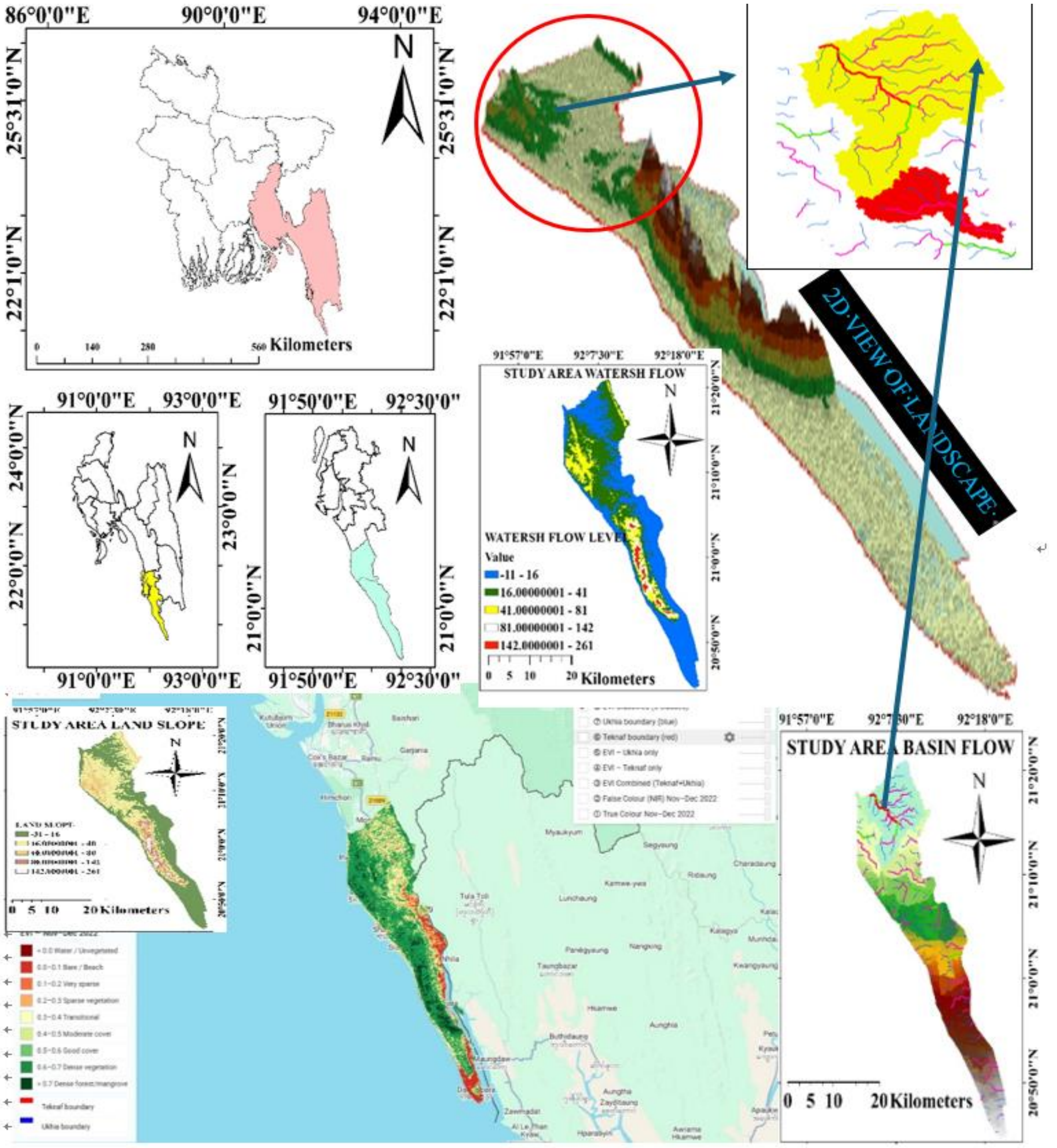

Figure 1. Geomorphological and ecological landscape characteristics of the Ukhiya-Teknaf study area in southeastern Bangladesh, illustrating forest ecosystems, protected habitats, coastal-hilltransition zones, watershed structure and ingya settlement expansion within the faunal diversity assesments framework (2015-2026).

The study was undertaken in the Ukhiya and Teknaf Upazilas of southeastern Bangladesh (Cox's Bazar), representing forest ecosystems, protected habitats, coastal landscapes, and settlement-forest transition zones that sustain diverse vertebrate groups. This is a highly dynamic socio-ecological landscape, where rapid development of Rohingya settlements, forest degradation, habitat fragmentation, and climate-related stresses have altered ecological conditions. The conversion of natural habitats into built-up regions has created significant challenges for maintaining wildlife connectivity, ecosystem functionality, and long-term ecological resilience. The region's diverse terrain, heterogeneous vegetation structure, and proximity to marine and forest ecosystems make it a critical landscape for assessing faunal responses to environmental change. The interaction between topographic variability, vegetation dynamics, and anthropogenic pressure creates a unique ecological gradient for investigating biodiversity vulnerability. The Digital Elevation Model (DEM) was integrated to characterize elevation variability, terrain influence, and settlement expansion patterns, providing additional insights into habitat susceptibility and landscape transformation.

By combining topographic information with satellite-derived ecological indicators and biodiversity datasets, this study establishes a comprehensive geospatial framework for understanding climate-sensitive habitats, identifying biodiversity risk areas, and supporting conservation strategies in rapidly changing settlement-dominated landscapes. The area therefore serves as an important natural laboratory for evaluating how environmental stressors influence vertebrate diversity and habitat resilience under increasing anthropogenic pressure.

2.2. Data Source and Acquisition

The study utilized data from a variety of satellite sources, environmental data, and biodiversity data to assess the impact of landscape change and climate stress on faunal diversity in the southeastern Rohingya population areas from 2015 to 2026. For Land Surface Temperature (LST) estimation, the Landsat-8 and Landsat-9 Collection 2 Level-1 images were downloaded from the United States Geological Survey (USGS) Earth Explorer [10]. Sentinel-2A Level-2A images downloaded from the Copernicus data platform were used to calculate vegetation and ecological indicators such as NDVI, TDVI, EVI and Ecological Health Index (EHI) [11]. MODIS eight-day composite ET products (500 m spatial resolution) were captured and processed for assessment of evapotranspiration [12].

Given the considerable cloud variability of the tropical monsoon environment, scenes with minimum cloud cover were selected for each analysis year. Digital Elevation Model (DEM) datasets were used as ancillary elevation information to describe terrain variability and settlement expansion trends. Fauna diversity data were sourced from records of protected areas in Cox's Bazar South Forest Division, Teknaf Wildlife Sanctuary, Inani National Park, Nishorgo conservation databases, UNDP and UNHCR publications and peer-reviewed biodiversity research. The merged data sets thus provided a thorough basis for testing links between environmental changes and vertebrate diversity patterns.

2.3. Methodological Framework Workflow

A complete geospatial-statistical process was developed to study the associations between environmental change, habitat modification and faunal diversity responses in the Rohingya settlement landscape in southeastern region. The framework integrates multi-source remote sensing datasets, ecological indicators, topographic information and secondary biodiversity records in sequential analytical steps. First, the satellite data were acquired and pre-processed to extract vegetation, temperature, moisture and ecological stress indicators. These environmental factors were later linked to taxon-specific faunal datasets to explore species-environment interactions. The workflow also involves spatial-temporal analysis, correlation assessment, regression modelling and multivariate statistical techniques to uncover major ecological variables driving vertebrate diversity trends. This comprehensive methodology allows identifying sensitive regions to biodiversity and provides scientific support for the management of climate-resilient habitats and the prioritization of restoration and conservation plans.

Figure 2. *Integrated geospatial framework for quantifying environmental drivers and vertebrate faunal diversity responses in the southeastern Rohingyia settlement landscape during 2015-2026.*

2.4. Remote Sensing Data Processing (NDVI, TDVI, EVI, LST, ET, EHI)

The satellite data were processed using arc GIS, involving atmospheric correction, radiometric calibration, band stacking, mosaicking, spatial alignment and clipping to the study area. Vegetation indices (NDVI, TDVI and EVI) were obtained from Sentinel-2A data. The EHI was produced by merging vegetation condition and environmental variables to determine ecosystem stability. LST was derived from the thermal bands of Landsat-8/9 by applying radiative transfer techniques with emissivity correction, and the moisture dynamics were characterized using MODIS evapotranspiration products [12]. All obtained indicators were normalized for comparison in spatio-temporal assessment and merged with validated faunal datasets. Environmental drivers in the statistical analyses were important for vegetation condition (NDVI/EHI) and for thermal stress (LST) and moisture variability (ET). Vegetation variables were more strongly correlated with mammals and birds, while thermal and moisture variables were more important for reptiles and amphibians.

2.5. Faunal Diversity Data Compilation and Sources

Faunal diversity was evaluated by comprehensive compilation of secondary biodiversity datasets from government, conservation organizations, international agencies and published scientific literature. Information on species occurrence and diversity was collected from Cox's Bazar South Forest Division [18], Teknaf Wildlife Sanctuary [19], Inani National Park [20], Nishorgo conservation database [21], UNDP [22] and UNHCR [23] environmental reports and peer-reviewed biodiversity studies with scholarly references. For consistency with temporal biodiversity evaluation the compiled datasets were grouped into key vertebrate groups namely mammals, aves, reptiles and amphibians. The datasets provided the needed information for the ecological baseline and the annual biodiversity response to evaluate faunal changes at the landscape scale from 2015-2026;

2.6. Faunal Dataset Pre-processing, Validation and Remote Sensing Integration

Pre-processing of the compiled faunal datasets included removal of duplicates, correction of discordant species records and standardisation of taxonomy to approved vertebrate categorisation systems. Mammalian nomenclature and national conservation status were checked against the IUCN Red List of Bangladesh: Volume 2-Mammals [29]. To increase dependability species observations were cross-validated between institutional databases, conservation reports and published scientific sources. Biodiversity records were matched to the study period and annual taxon-specific responses summarized to ensure temporal comparability. The dataset was employed as an indicator of the landscape-scale biodiversity response, rather than an absolute estimate of extinction, due to constraints of secondary observations such variations in survey intensity and detection frequency. The validated faunal data were merged with remote sensing derived environmental indicators (NDVI, TDVI, EHI, LST and ET) for correlation analysis, multiple regression modelling and multivariate assessment of species-environment correlations. This synergistic paradigm allowed us detection of taxon-specific sensitivity patterns and environmental drivers of biodiversity change across the landscape of the southeastern Rohingya camp.

2.7. Estimation of Taxon-specific Richness-equivalent Responses

After the data compilation, pre-processing and validation procedures outlined in Sections 2.5 and 2.6, the aggregated vertebrate dataset was split into four taxonomic groups: mammals, bird species, reptiles and amphibians. The 2015 reference dataset consisted of 334 recorded vertebrate species, including 43 mammals, 210 bird species, 54 reptiles, and 27 amphibians. These values served as the taxon-specific reference baselines for analyzing temporal change.

Benchmark estimations were based on annual values validated by adequately comparable secondary biodiversity records. The relative percentage degradation from the 2015 baseline was determined for each taxonomic category as:

$$D_{\{i,t\}} = \left(\frac{R_{\{i,0\}} - R_{\{i,t\}}^{\{obs\}}}{R_{\{i,0\}}}\right) \times 100 \quad (1)$$

where *Di,t* represents the relative degradation percentage of taxon i in benchmark year t, *Ri,0* represents the richness of taxon *i* in the 2015 reference year, and $R_{\{i,t\}}^{\{obs\}}$ represents the consolidated richness estimate obtained from the available comparable secondary records for benchmark year t.

Comparable taxon-specific records were not available for every year in the study period. Thus, when an annual value was absent between two reported benchmark years, the missing value was calculated independently for each taxonomic group using linear interpolation, a well-established approach for imputing missing observations in time-series data with defined limits [36]:

$$R_{\{i,t\}}^{\{int\}} = R_{\{i,a\}}^{\{obs\}} + \left(\frac{t-a}{b-a}\right)\left(R_{\{i,b\}}^{\{obs\}} - R_{\{i,a\}}^{\{obs\}}\right) \quad (2)$$

where $R_{\{i,t\}}^{\{int\}}$ represents the interpolated richness-equivalent response of taxon *i* for missing year *t*; $R_{\{i,a\}}^{\{obs\}}$ and $R_{\{i,b\}}^{\{obs\}}$ represent the benchmark richness estimates for the nearest preceding year a and succeeding year b, respectively; and a<t<b. Linear interpolation was conducted separately for mammals, avian species, reptiles and amphibians.

The linear interpolation assumes a constant rate of change between the previous and the next benchmark measurement. It was applied solely to internal data gaps bounded by two accessible benchmark values and not utilized to extrapolate beyond the reported temporal range [36].

The relative degradation percentage for an interpolated year was subsequently calculated as:

$$D_{\{i,t\}}^{\{int\}} = \left(\frac{R_{\{i,0\}} - R_{\{i,t\}}^{\{int\}}}{R_{\{i,0\}}}\right) \times 100 \quad (3)$$

The overall vertebrate richness-equivalent series was obtained separately from the pooled overall benchmark records, rather than being computed from the rounded taxon-specific values reported in Table 3. If a total annual value was missing between two recorded total benchmark years, it was calculated using the same linear-interpolation procedure:

$$R_{T,t}^{int} = R_{T,a}^{obs} + \left(\frac{t-a}{b-a}\right)\left(R_{T,b}^{obs} - R_{T,a}^{obs}\right) \quad (4)$$

where $R_{T,t}^{int}$ represents the interpolated total richness-equivalent response for missing year t. $R_{T,a}^{obs}$ and $R_{T,b}^{obs}$ represent the consolidated total benchmark estimates for the nearest preceding year a and succeeding year b, respectively.

Overall relative degradation from the 2015 total reference baseline was calculated as:

$$D_{T,t} = \left(\frac{R_{T,0} - R_{T,t}}{R_{T,0}}\right) \times 100 \quad (5)$$

where $(D_{T,t})$ represents the overall relative degradation percentage in year (t), $(R_{T,0})$ represents the total vertebrate reference value in 2015, and $(R_{T,t})$ represents either the benchmark or interpolated total richness-equivalent response for year (t).

No equal or arbitrary weighting was applied across the four taxonomic groups. Taxon-specific response trajectories were calculated separately using their respective 2015 reference baselines, whereas the consolidated total response trajectory was derived independently from the available total benchmark estimates.

All computations were done using unrounded numbers when they were available; only the final values in the table were rounded to one decimal place. The interpolated decimal values were expressed as richness-equivalent responses rather than as actual species counts. They are not to be considered fractional species, documented local extinction, or independently field-verified annual species richness. Interpolation was only used to generate continuous descriptive trajectories between observed benchmark years and was not utilised to anticipate biodiversity conditions outside the observation period available.

2.8. Statistical Analysis and Interpretation

The whole set of annual richness-equivalent response trajectories for 2015–2026, including the benchmark and internally interpolated values reported in Section 2.7, were used for descriptive temporal evaluation and exploratory statistical analysis. Summary statistics and graphical trajectories were first used to describe temporal changes in environmental variables and taxon-specific richness-equivalent responses.

Exploratory multiple linear regression models were used to explore possible correlations between the selected satellite-derived environmental variables and the richness-equivalent responses of mammals, bird species, reptiles and amphibians. Regression outputs, including model coefficients, (R^2), adjusted (R^2) and (p)-values were kept to offer a transparent explanation of the direction and relative size of the observed correlations.

The analysis had only ~ 11-12 yearly observations and several environmental factors, hence the ratio of data to predictors was insufficient for robust confirmatory modelling. Fitting models to short datasets might result in unstable coefficients, low statistical power and a higher risk of overfitting [33]. Also, some environmental indicators are representative of correlated ecological processes and may hold redundant information. So, the regression models were viewed as exploratory association models rather than robust predictive or causal models.

For the richness-equivalent response trajectories, values were obtained by interpolation between the available benchmark observations, as stated in Section 2.7 [36]. Such interpolated values are important for generating continuous descriptive trajectories, but they are not independent field observations. Therefore, classical (p)-values were preserved for transparency and interpreted judiciously, not as the only confirming evidence for environmental causality [37].

Because the observations were made once a year, the time dependence between succeeding years was also considered when the data were interpreted. In brief time series, there is little power to reliably estimate temporal autocorrelation, and the usual assumption of independence may not be fully met [34]. As such, the regression results were examined primarily for direction of association, effect size, fit of the model, and consistency with the descriptive ecological trajectories. The regression results were not interpreted as evidence of a causal relationship.

Statistical analyses were used to detect potential taxon-specific response patterns and associations with the environment. Environmental indicators with positive or negative regression coefficients were considered as possible related variables, not statistically established predictors. The data did not statistically significantly support strong environmental prediction, as overall model findings were non-significant ($p>0.42$) and adjusted (R^2) values were low (~0.04–0.06). The findings should therefore be considered exploratory and hypothesis-generating and require verification using larger time series data sets and systematic field-based biodiversity monitoring. Formal autocorrelation estimates were not treated as definitive because of the short annual series and the inclusion of interpolated observations. Potential temporal dependence was therefore retained as a limitation, and the regression results were restricted to exploratory interpretation.

2.9. Software and Computational Tools

Satellite-image pre-processing, atmospheric correction, cloud masking, band extraction, raster stacking, spatial alignment, clipping, spectral-index calculation, raster classification and map preparation were performed using ArcGIS Desktop 10.8.2 (Esri, Redlands, California, USA). Land use and land cover change analysis and associated geospatial modelling were performed using TerrSet 2020 (Clark Labs, Clark University, Worcester, Massachusetts, USA).

Secondary biodiversity records were assembled, collated and validated using Microsoft Excel 2021 (Microsoft Corporation, Redmond, Washington, USA). Taxon-specific reference baselines, relative degradation percentages, linear interpolation of missing internal observations, taxon-specific and total richness-equivalent responses, and accompanying data tables were also calculated and prepared in Microsoft Excel 2021. Calculations were performed using the available unrounded values wherever possible, and only the final values reported in the manuscript were rounded to one decimal place.

Exploratory correlation and multiple linear regression analyses were performed using R version 4.6.1 (R Foundation for Statistical Computing, Vienna, Austria). The statistical outputs comprised regression coefficients, R^2, adjusted R^2, and p-values. The statistical visualizations were also prepared with R version 4.6.1. The regression models were understood as exploratory models of association, rather than as confirmatory models of prediction or causation (Section 2.8).

3. Statistical Analysis and Ecological Modelling

3.1. Spatial Distribution of NDVI Classes in the Study Area From 2015 to 2026

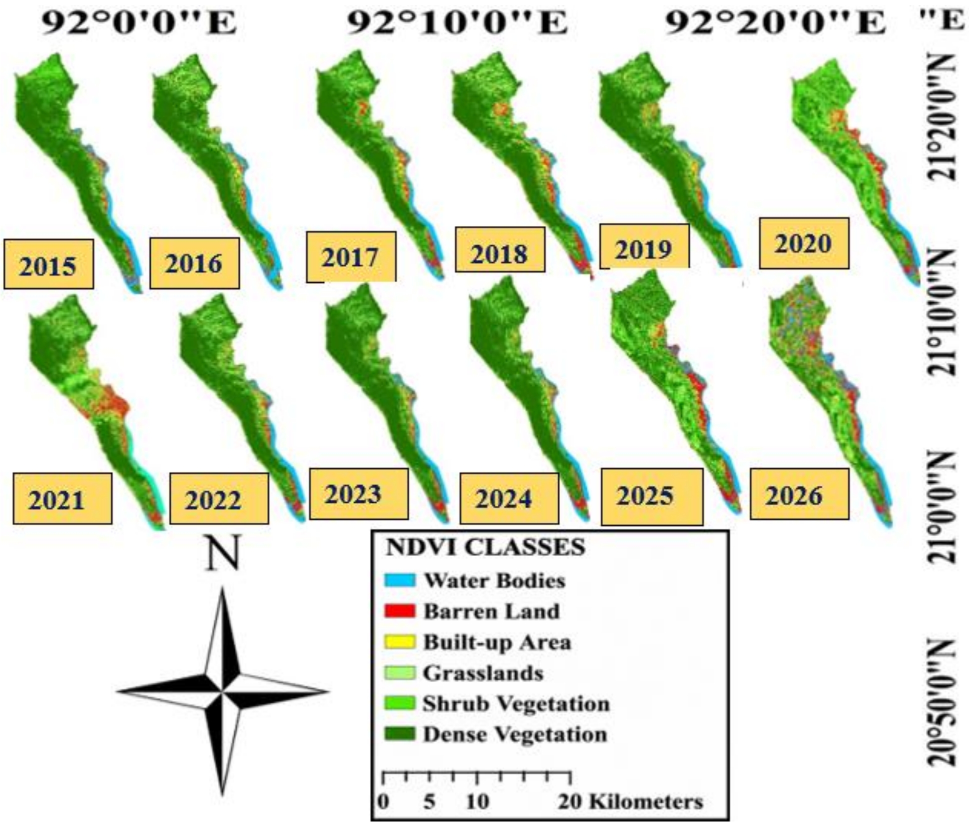

Figure 3. *Spatiotemporal dynamics of NDVI classes in the study area during 2015–2026.*

The NDVI classification obtained from Sentinel-2A (Figure 3) shows the time change of vegetation conditions in the Ukhiya - Teknaf landscape between 2015 and 2026. The Sentinel-2A images were obtained from the ESA Copernicus platform (MSI sensor, Tile ID: 46QDJ, 10 m spatial resolution) Level-2A surface reflectance products and processed in ArcGIS by applying atmospheric correction, cloud masking, band extraction, raster stacking, spatial alignment and clipping to the study area. The red (Band 4: 665 nm) and near-infrared (Band 8: 842 nm) spectral bands were used to determine the vegetation condition:

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} = \frac{(band\ 8-band\ 4)}{(band\ 8+band\ 4)} \quad (6)$$

Sentinel-2A Band

$$NDVInorm = \frac{NDVI-NDVImin}{NDVImax-NDVImin} \quad (7)$$

where B8 represents near-infrared reflectance and B4 represents red reflectance.

There are six established classes: Water Bodies (<0.018015), Barren Land (0.018015-0.140), Built-up Areas (0.140-0.270), Grasslands (0.270-0.360), Shrub Vegetation (0.360-0.720), and Dense Vegetation (≥0.720). The NDVI analysis demonstrated gradual change of vegetation associated with changes in terrain and increase of settlement. The normalized NDVI data revealed the occurrence of temporal variations with relatively steady vegetative conditions during 2015-2018, severe decline during 2019-2020 and partial recovery after 2021. However, the state of vegetation was still low compared to the previous levels suggesting the continuous ecological pressure. The spatial NDVI classes showed a loss of dense vegetation and an increase of disturbed land-cover classes, indicating habitat fragmentation and declining ecosystem quality. These vegetation dynamics were later combined with TDVI, EVI, EHI, LST, ET and faunal diversity indices to assess habitat degradation and biodiversity risk.

3.2. Environmental Indicators and Habitat Condition Assessment (2015-2026)

Vegetation dynamics from Sentinel-2A NDVI categorization are important for understanding habitat alteration in Ukhiya-Teknaf area. However, the state of vegetation alone cannot adequately explain the vulnerability of the ecosystem and responses of fauna. Other environmental indicators gathered from satellites, including TDVI, EHI, land surface temperature (LST) and evapotranspiration (ET) were evaluated to describe the broader ecological conditions affecting habitat suitability in 2015-2026. Previous research have measured these environmental changes using multi-index remote sensing techniques [3, 4]. Settlement development has been associated with increased vegetation stress, temperature variability, moisture imbalance and ecosystem degradation in previous studies. These variables were included in the current analysis as environmental drivers rather than replicating the prior landscape-level assessment, to analyses their correlations with taxon-specific faunal diversity responses.

Table 1. *Summary of satellite-derived environmental indicators and their ecological significance during 2015-2026.*

Environmental indicator	Data source	Ecological representation	Relevance to faunal diversity assessment
NDVI	Sentinel-2A MSI (Band 4 & Band 8)	Vegetation density and habitat condition	Determines habitat availability and vegetation-dependent species support
TDVI	Sentinel-2A MSI	Vegetation structure and moisture-related stress	Indicates habitat complexity and microhabitat alteration
EHI	Integrated ecological index	Ecosystem stability and environmental stress	Represents overall habitat quality deterioration
LST	Landsat-8/9 thermal bands	Surface thermal condition and climate pressure	Indicates thermal stress affecting climate-sensitive taxa
ET	MODIS evapotranspiration product	Moisture availability and ecosystem water balance	Represents hydrological suitability, especially for amphibians and reptiles

The combined environmental indicators show that the habitat conditions in the research area are under increasing ecological stress during the study period. Vegetation related indices (NDVI and TDVI) are indicative of changes in habitat structure whereas LST and ET are indicative of growing impact of thermal and moisture associated restrictions. The trend of ecological state reflected by EHI reveals the cumulative effects of landscape disturbance, vegetation deterioration, and climate pressure. These environmental changes offer the ecological backdrop in which to assess faunal diversity responses, with different taxonomic groupings likely to show varied degrees of sensitivity, based on habitat dependency and physiological characteristics.

Previous remote sensing studies have successfully detected landscape and environmental changes, but their ecological impact on diverse vertebrate taxa is poorly documented. Here, we integrate these environmental metrics with secondary biodiversity data to evaluate the effects of habitat modification and climate stresses on mammals, aves, reptiles and amphibians across the Rohingya settlement landscape.

Table 2. *Annual values of normalized vegetation indices, evapotranspiration, ecological health index, and temperature during 2015-2026.*

NDVI_ Normalized	TDV_Normalized	ET_ High (mm/d)	ET_ Low(mm/d)	EHI	Temp_High
0.2407	0.8059	52.8000	10.7000	0.3389	35.50
0.2247	0.7823	53.0000	10.2000	0.3143	35.68
0.2665	0.8274	52.8000	11.5000	0.4147	32.17
0.2603	0.8138	51.9000	6.3200	0.4068	36.60
0.2316	0.7856	53.0000	13.5000	0.3106	37.65
-0.1615	0.8095	53.2000	16.3000	0.2063	36.60
0.1482	0.6482	51.4000	13.7000	0.2437	36.52

NDVI_ Normalized	TDV_Normalized	ET_ High (mm/d)	ET_ Low(mm/d)	EHI	Temp_High
0.2493	0.8091	50.3300	18.7000	0.3631	40.67
0.2661	0.8188	53.8000	9.9000	0.3900	37.23
0.2463	0.7968	58.6000	14.5000	0.3706	32.67
0.2376	0.8171	56.2000	14.4000	0.3868	48.99
0.24195	0.80695	57.5	14.6	0.395	37.23

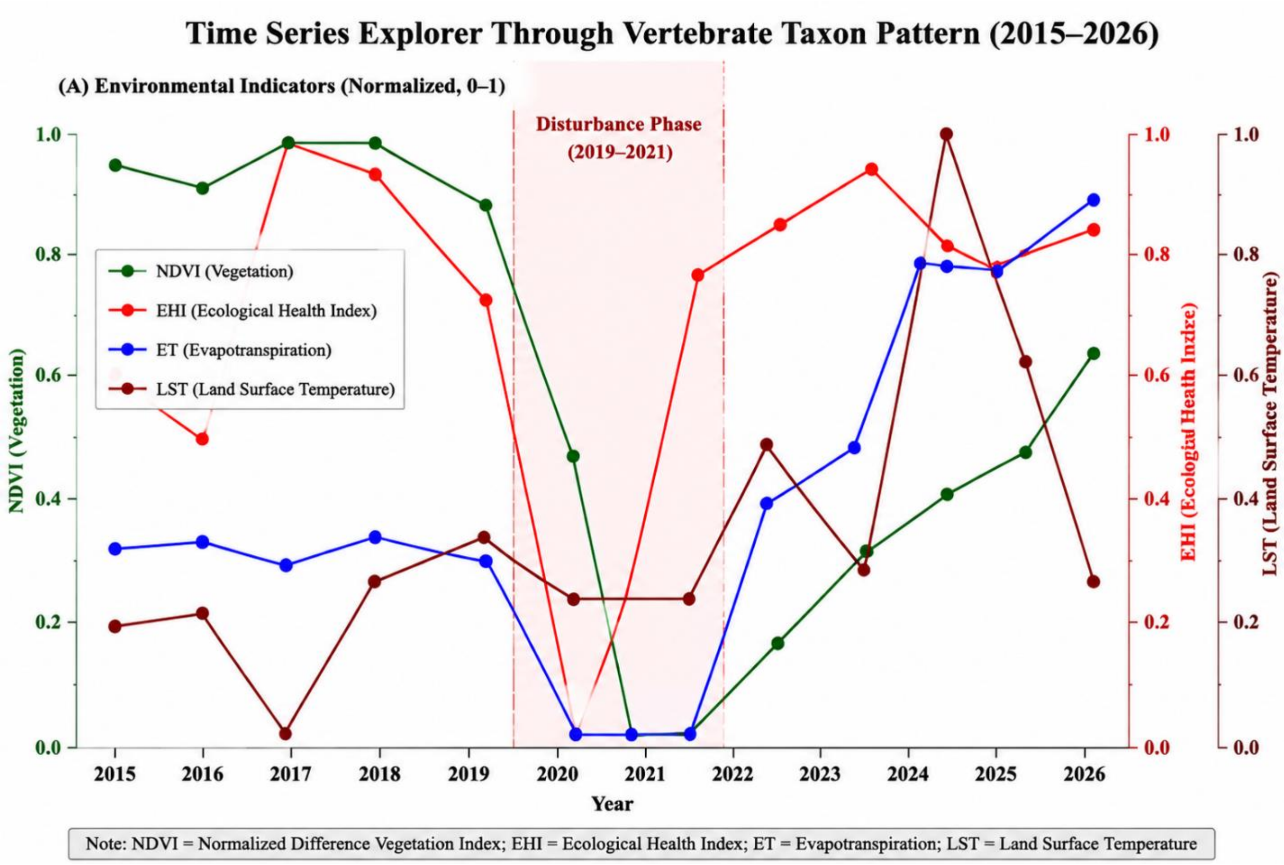

Figure 4. *Temporal dynamics of integrated environmental indicators (NDVI, EHI, ET, and LST) representing habitat condition and ecological stress patterns in the southeastern Rohingya settlement landscape of Bangladesh during 2015–2026.*

Table 2 & Figure 4 presents the integrated temporal response of vegetation condition, ecological health, thermal stress and moisture dynamics of the Ukhiya-Teknaf landscape during the period 2015-2026. The NDVI showed a rather constant trend over 2015-2019 but decreased sharply in 2020, which indicates that rapid population expansion caused severe impact on habitat and vegetation deterioration. Vegetation state was below the prior baseline indicating insufficient ecological restoration, however partial recovery was evident by 2021. The pattern of EHI was similar with ecological stability being higher in 2017-2018 and a rapid fall during the disturbance period, indicating the combined effects of habitat alteration and environmental stress. In contrast, the increasing LST values, reaching 48.99 ℃ in 2025, suggest greater heat stress due to plant loss and changes in land surface. Some ETs have increased recently indicating local recovery, but not full ecosystem recovery, and different ETs have displayed different vegetation-moisture relationships. These joint environmental reactions provide a basis for explaining faunal diversity changes. Mammals and birds are more affected by vegetation loss and fragmentation, while reptiles and amphibians are affected by heat and moisture fluctuation. Similar landscape level alterations were also documented by Hamid and Rahman [3, 4] supporting the role of combining geospatial indicators in assessment of biodiversity vulnerability.

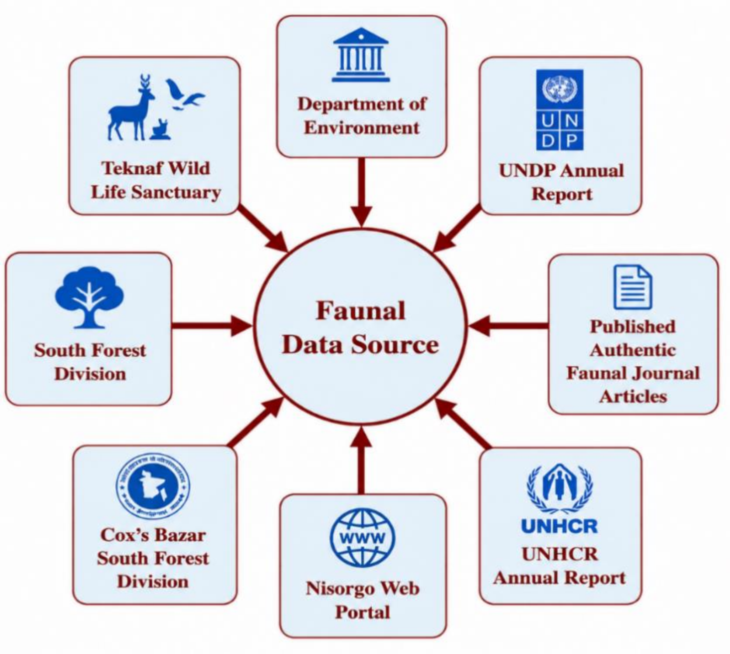

Figure 5. *Multi-source compilation framework of secondary faunal diversity datasets used for vertebrate diversity assessment.*

Table 3. *Temporal dynamics of vertebrate faunal richness and degradation responses (2015-2026) derived from multi-source biodiversity datasets in the southeastern Rohingya settlement landscape of Bangladesh.*

2015	43	0	210	0	54	0	27	0	334	0
2016	43	0	210	0	54	0	27	0	334	0
2017	35.3	18	178.7	14.9	45.7	15.3	24.2	10.2	283.9	15
2018	24.4	43.3	135	35.7	34.2	36.7	20.4	24.4	213.2	35.9
2019	16.7	61.3	103.8	50.6	26	51.9	17.6	34.6	165	50.9
2020	12	72.09	85	59.52	21	61.11	16	40.74	134	59.88
2021	12	72.09	85	59.52	21	61.11	16	40.74	134	59.88
2022	11.4	73.5	84	60.1	20.3	62.5	15.9	41.2	131.2	60.7
2023	10.8	74.9	81	61.4	19.5	63.9	15.5	42.5	126.8	61.9
2024	10.2	76.2	78.2	62.8	18.9	65	15.4	43.1	122.5	63.4
2025	9.5	78	75.5	64.1	18.2	66.2	14.9	44.8	116.6	65.1
2026	8	81.4	70.6	66.3	17.2	68.1	14.6	45.9	109.8	67.2

Note: Benchmark values were derived from consolidated and comparable secondary biodiversity records. Values for years without directly comparable records were estimated by linear interpolation between the nearest preceding and succeeding benchmark years. Decimal values represent richness-equivalent responses rather than direct species counts. No extrapolation was performed beyond the available benchmark period. Identical values for 2015–2016 and 2020–2021 indicate benchmark intervals for which the consolidated secondary records did not support an independently distinguishable annual change.

3.3. Temporal Trend and Statistical Analysis of Modelled Vertebrate Richness Responses (2015-2026)

Analysis of secondary biodiversity statistics (Figure 5) showed a gradual reduction of predicted vertebrate richness in the Ukhiya-Teknaf region from 2015 to 2026. The collected data set provided a pre-influx baseline of about 334 known species of vertebrates, including 43 mammals, 210 birds, 54 reptiles and 27 amphibians. The biodiversity trajectory trend changed from a relatively stable baseline era (2015-2016) to the increasing ecological stress after rapid growth of settlements, as reflected in the degradation intensity gradient in Figure 6 and the annual contraction matrix in Table 3. The first significant decline was recorded in 2017 in parallel with the onset of habitat modification related to settlement. The simulated richness reduced from 334 to around 283.9 modelled richness units, a reduction of over 15%. Taxon-specific responses showed that mammals (18%) were the most sensitive group in the early stages, followed by reptiles (15.3%), birds (14.9%) and amphibians (10.2%). This pattern suggests a comparatively rapid response of habitat-dependent taxa to increasing fragmentation and disturbance. Analogous patterns have been found in tropical ecosystems, where land-use change and habitat isolation are disproportionately affecting specialist vertebrate taxa [13, 14].

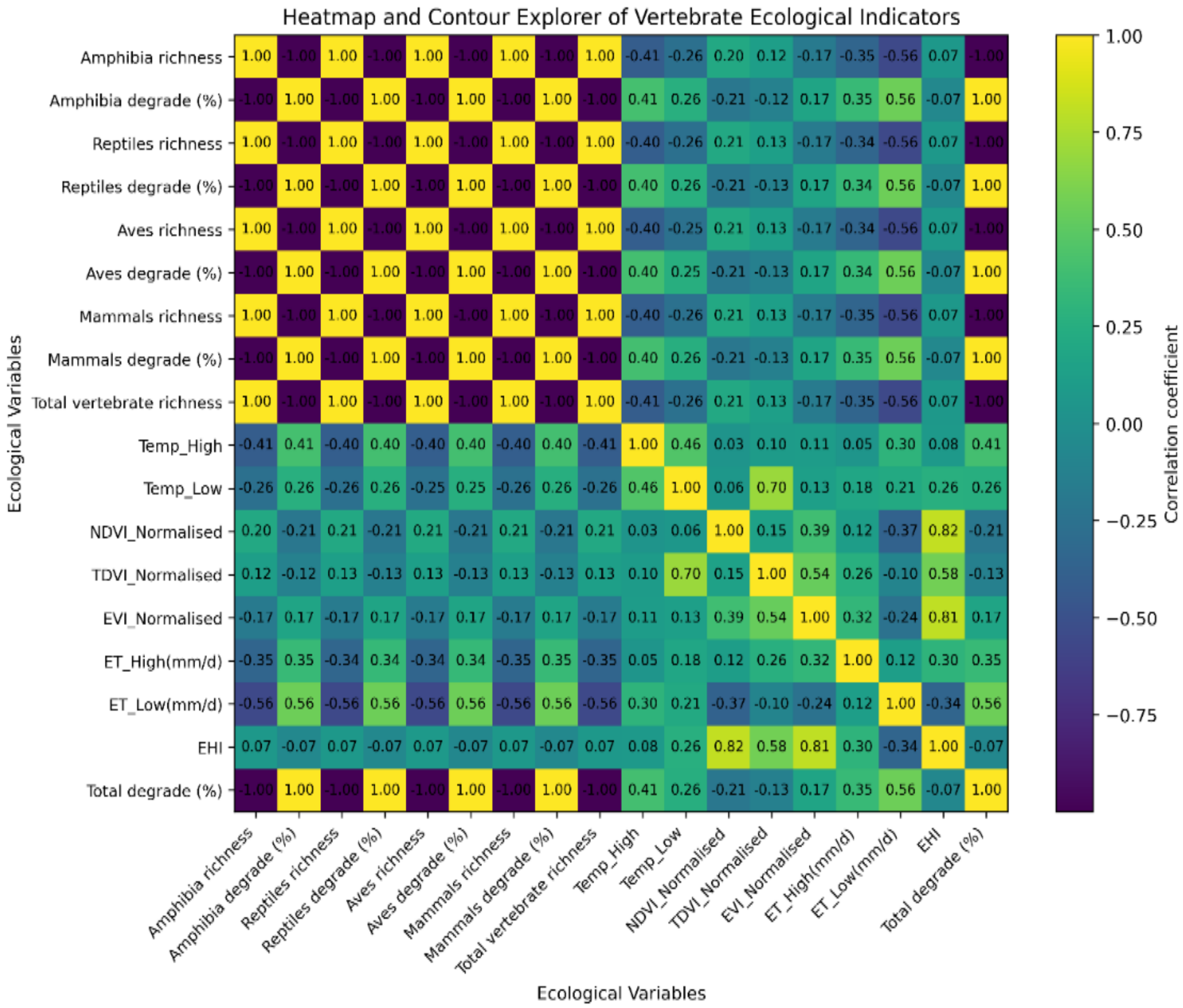

Figure 6. *Heatmap representation of temporal variation in vertebrate taxonomic richness decline and degradation intensity across the south-eastern Rohingya settlement landscape (2015–2026).*

The most notable ecological shift happened between 2018 and 2020 when the heatmap showed substantial deterioration intensity across all vertebrate taxa. The estimated richness trajectory By 2020, the modelled vertebrate richness response indicated a reduction equivalent to approximately 134 species, a decrease of 59.88% compared to the baseline condition. Taxon-specific responses differed significantly, with the greatest contraction shown by mammals (72.09%), followed by reptiles (61.11%), birds (59.52%) and amphibians (40.74%) (Table 3). This period is a critical phase of the ecological change in the settlement area with a large-scale vegetation loss, habitat fragmentation and landscape reorganization. Mammals' strong response indicates their reliance on broad, contiguous ecosystems and transportation routes. Large-bodied species, notably elephants, are very susceptible to habitat isolation as disturbance of corridors hinders movement, lowers connectivity and increases risks of human-wildlife conflicts [15]. Similar effects of fragmentation have been reported worldwide, with larger mammals being more sensitive to landscape isolation than disturbance-tolerant species [16, 28].

After 2021, the degrading path of the heatmap was relatively slower but steady. The projected dataset indicated a modelled richness response equivalent to approximately 109.8 species by 2026 under the observed environmental degradation trajectory, representing a 67.2% reduction from the baseline richness condition. The highest anticipated sensitivity was for mammals (81.4%), followed by reptiles (68.1%), birds (66.3%) and amphibians (45.9%) (Table 3). The figures are predictions of biodiversity response to observable trends in environmental deterioration, not direct evidence of proven species loss. The ongoing contraction indicates that recovery of the habitat was still constrained by prolonged fragmentation, diminished ecological connectedness and changed environmental circumstances in spite of lower immediate disturbance intensity after implementation of measures for stabilization of the settlement.

The temporal pattern also shows divergent reactions between disturbance tolerant and habitat specialist organisms. Generalist species that can use modified settings may be able to persist under transformed landscape conditions, while specialists that depend on forest, e.g. hornbills, primates and forest-associated amphibians, are more sensitive to reductions in habitat complexity and microclimatic instability. Ecological filtering mechanisms have been reported in fragmented tropical ecosystems, where disturbance benefits adaptable species and decreases the number of specialists in biological communities [17]. Overall, the temporal assessment provides a descriptive trajectory consistent with progressive biodiversity reduction and landscape modification associated with settlement expansion.

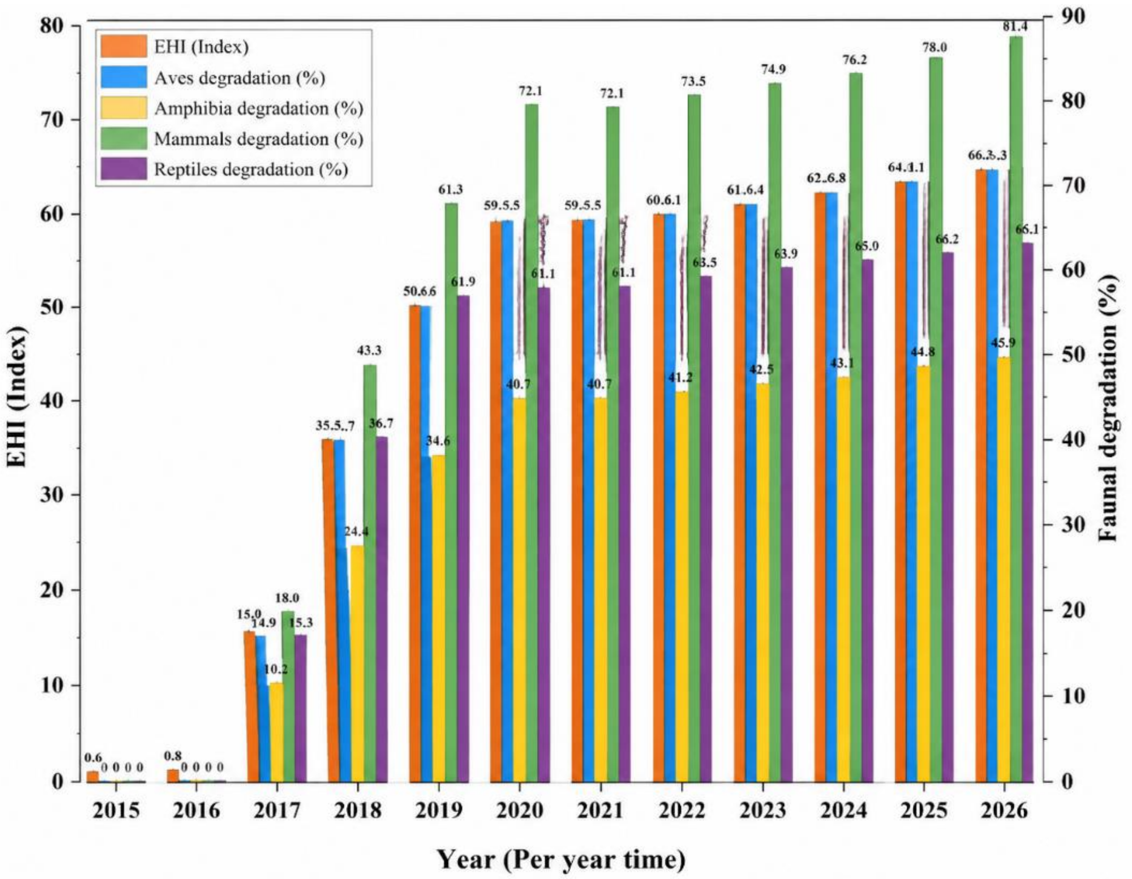

Figure 7. *Temporal trajectory of ecological health deterioration and taxon-specific vertebrate degradation patterns in the southeastern Rohingya settlement landscape of Bangladesh (2015–2026).*

Combined secondary faunal observations and geospatial indicators suggested potential associations of vertebrate responses with vegetation degradation, thermal stress and habitat fragmentation. These findings provided the ecological basis for the subsequent exploratory correlation, regression and multivariate analyses of environmental factors potentially associated with faunal diversity patterns.

3.4. Integrated Statistical Assessment of Environmental Predictor Associations With Vertebrate Diversity Responses

We conducted integrated statistical analyses to assess relationships between environmental indicators and taxon-specific vertebrate responses along the temporal biodiversity patterns estimated from the secondary faunal dataset (Figure 5), heatmap intensity analysis (Figure 6), and annual richness contraction matrix (Table 3). The integrated assessment of vegetation condition (NDVI, TDVI), ecological stability (EHI), thermal stress (LST) and moisture dynamics (ET) provided an ecological framework to understand how environmental changes corresponded with modelled biodiversity responses across the southeastern Rohingya settlement landscape.

The time trajectories given in Figures 7 and 8 suggest a change from a reasonably stable ecological state in 2015-2016 to an increased environmental stress throughout 2017-2020, in the midst of substantial habitat modification, vegetation decline and landscape fragmentation. The strongest simulated response to the expected deterioration scenario in 2026 was for mammals (81.4%), followed by reptiles (68.1%), birds (66.3%) and amphibians (45.9%). Mammals depend on broad habitats, corridors of migration and landscape connectivity, which respond more robustly. Large-bodied mammals are sensitive to fragmentation in tropical environments, where habitat isolation diminishes ecological connectedness and increases susceptibility (Fahrig, 2003; Haddad et al., 2015).

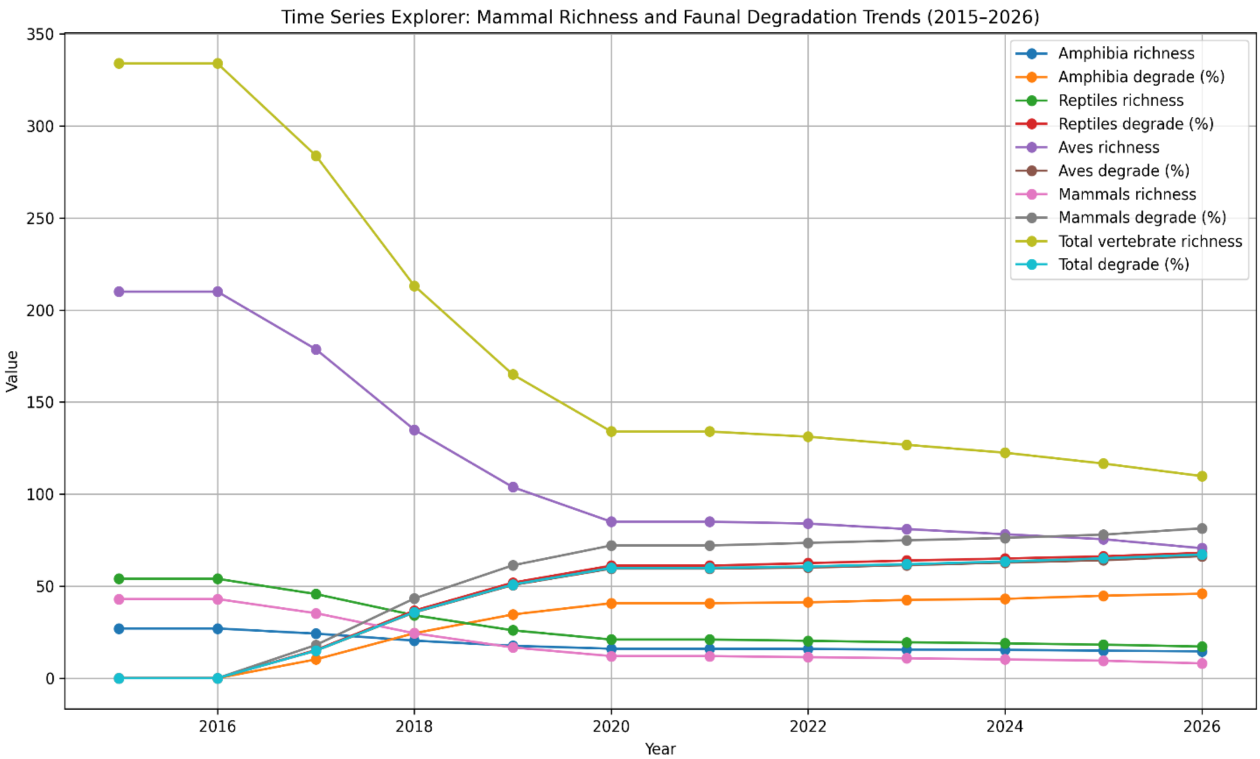

Figure 8. *Temporal trajectory of vertebrate richness decline and taxon-specific degradation responses in the southeastern Rohingya settlement landscape of Bangladesh (2015–2026).*

The temporal richness trajectory in Figure 8 also supports that a structural transformation of vertebrate groups occurred, rather than a short-term fluctuation in population. The total vertebrate richness dropped from a pre-disturbance baseline of 334 species to about 134 species in 2020 and a forecast 109.8 species in 2026. The biggest drop was recorded in the disturbance phase of 2017-2020 marked by fast forest conversion and settlement growth. This pattern aligns with worldwide biodiversity studies that link species reduction in tropical environments to land-use change and habitat isolation [13, 24].

Table 4. *Ecological interpretation of environmental predictor associations with vertebrate diversity responses (2015-2026).*

Taxon	Environmental variables showing stronger ecological associations	β coefficient direction	R^2	Adjusted R^2	Model p-value
Mammals degradation	NDVI, EHI, LST	NDVI (−), EHI (−), LST (+)	0.479	0.045	0.4458

Taxon	Environmental variables showing stronger ecological associations	β coefficient direction	R^2	Adjusted R^2	Model p-value
Aves degradation	NDVI, EHI, TDVI	NDVI (−), EHI (−), TDVI (−)	0.48	0.046	0.4447
Reptiles degradation	LST, TDVI, ET	LST (+), TDVI (−), ET (−)	0.475	0.038	0.4524
Amphibians degradation	LST, ET, EHI	LST (+), ET (−), EHI (−)	0.489	0.062	0.4289

The associations involving LST, ET and EHI were consistent with the physiological dependence of amphibians on stable microclimatic conditions. Previous studies have shown that amphibians are particularly sensitive to variations in temperature and moisture because of their permeable skin and dependence on suitable terrestrial and aquatic microhabitats [25, 26].

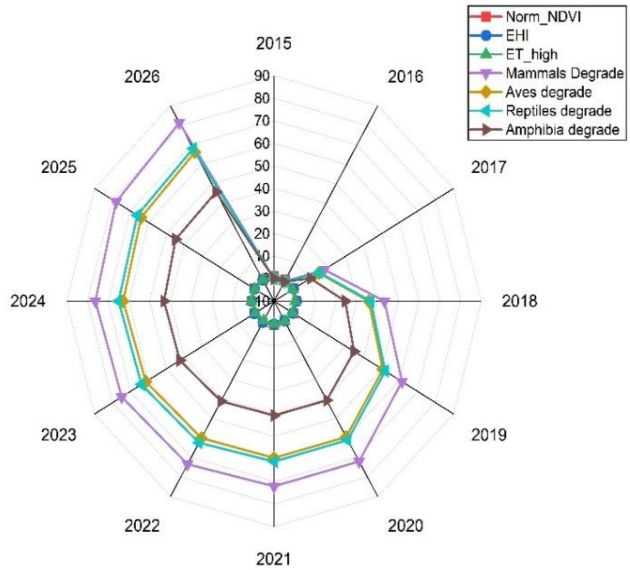

Figure 9. *Radar-based visualization of integrated ecological stress responses and vertebrate taxonomic degradation patterns during 2015–2026.*

Further support for taxon-specific ecological responses was provided by the multivariate visualizations. The degradation-based radar assessment (Figure 9) suggested an increasing divergence between environmental stress indicators and patterns of faunal response. The multivariate visualisations suggested comparatively stronger associations of mammal and avian responses with vegetation-related indicators, whereas reptile and amphibian responses showed comparatively stronger associations with thermal and moisture-related indicators. These descriptive patterns are consistent with the ecological sensitivity of habitat-specialist taxa to landscape transformation [17].

The corresponding richness-based multivariate visualization is presented in Figure 10.

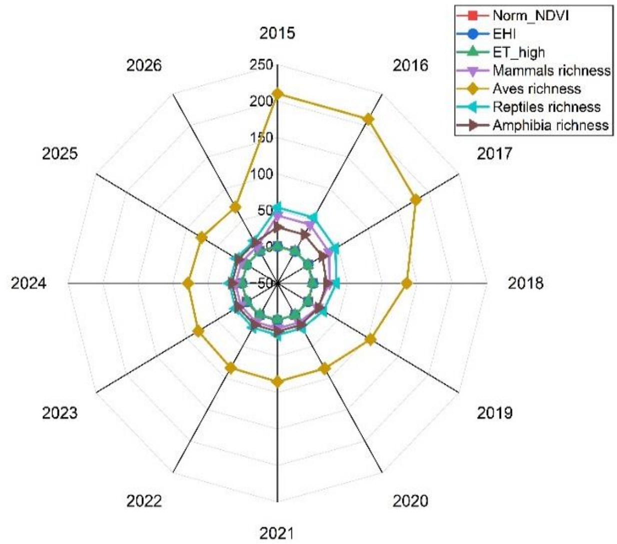

Figure 10. *Radar-based visualization of vertebrate richness dynamics and taxonomic responses under changing environmental conditions during 2015–2026.*

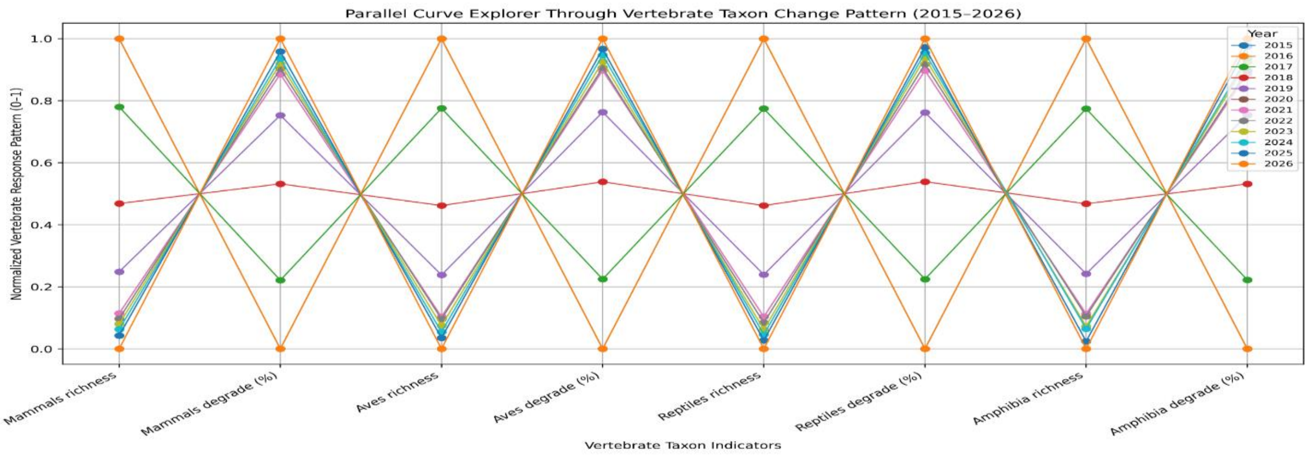

Figure 11. *Parallel coordinate visualization of temporal shifts in vertebrate taxon-specific richness and degradation responses across the southeastern Rohingya settlement landscape (2015–2026).*

Table 5. *Multiple regression analysis of vertebrate richness response to environmental changes*.

Taxon richness	Main controlling variables	Relationship	R^2	Adjusted R^2	Significance
Mammals richness	NDVI, EHI, LST	Vegetation loss & thermal stress reduced richness	0.479	0.045	p=0.4457
Aves richness	NDVI, TDVI, EHI	Habitat degradation reduced richness	0.48	0.047	p=0.4441
Reptiles richness	LST, ET, TDVI	Thermal/moisture instability effect	0.477	0.041	p=0.4497
Amphibians richness	ET, LST, EHI	Moisture stress sensitivity	0.488	0.06	p=0.4308

Multiple regression analysis was undertaken to further evaluate the associations between environmental indicators and taxon-specific responses (Table 5). The direction and relative magnitude of the estimated coefficients suggested possible taxon-specific ecological relationships. Mammalian responses showed descriptive associations with NDVI, EHI and LST, whereas avian responses showed descriptive associations with NDVI, TDVI and EHI. Reptile responses were descriptively associated with LST, ET and TDVI, while amphibian responses showed descriptive associations with ET, LST and EHI. These patterns were treated as exploratory ecological associations rather than evidence of statistically significant predictive relationships.

The regression models produced R^2 values ranging from 0.475 to 0.489; however, the adjusted R^2 values were low (0.041–0.060), and all overall model p-values exceeded 0.42. Given the small number of annual observations and the number of environmental variables included, the coefficient estimates may be unstable and susceptible to overfitting. Thus, the results provide limited statistical evidence of associations between the environmental indicators and taxon-specific responses. The indicators should not be interpreted as statistically significant predictors or causal drivers. The observed patterns require validation using longer time series and additional field-based biodiversity data.

Table 6. *Integrated assessment of geospatial environmental indicators and their ecological contributions to vertebrate faunal diversity responses in the southeastern Rohingya settlement landscape (2015-2026).*

Environmental indicator	Effect on biodiversity	Sensitive taxa	Statistical evidence
NDVI decline	Habitat loss and fragmentation	Mammals, Aves	Regression evaluated
EHI decline	Ecological instability	All taxa	Regression evaluated
LST increase	Thermal stress	Amphibians, Reptiles	Regression evaluated

Environmental indicator	Effect on biodiversity	Sensitive taxa	Statistical evidence
ET variation	Moisture imbalance	Amphibians, Reptiles	Regression evaluated
TDVI change	Vegetation structure change	Reptiles, Aves	Regression evaluated

Taken together, the results indicate a set of biodiversity-risk patterns that should be examined further using field-based monitoring and longer temporal datasets. In this study, the remote-sensing indicators were used as ecological surrogates of habitat condition rather than as direct measurements of faunal change. Their combined use nevertheless provided useful information on changes in vegetation condition, thermal stress and moisture availability, consistent with their established application in biodiversity and habitat assessment [5, 27].

Table 7. *Summary and ecological interpretation of environmental indicators associated with vertebrate diversity responses across the Rohingya settlement landscape (2015–2026).*

Predictor	Effect direction	Ecological interpretation	Most sensitive taxon
NDVI	Negative relationship with degradation	Vegetation decline increases habitat loss	Mammals & Aves
EHI	Negative relationship with degradation	Ecological instability reduces habitat quality	All vertebrates
LST	Positive relationship with degradation	Thermal stress increases biodiversity vulnerability	Amphibians & Reptiles
ET	Negative relationship with richness loss	Moisture regulation controls habitat suitability	Amphibians
TDVI	Negative relationship with degradation	Vegetation structure decline affects habitat complexity	Reptiles & Aves

The synthesis presented in Tables 4-7 suggests that the observed biodiversity responses were associated with a combination of changes in vegetation condition, ecological stability, temperature, moisture availability and habitat structure rather than with a single environmental factor. Declining NDVI and TDVI values reflected deterioration in vegetation condition and habitat structure, while the decline in EHI suggested increasing ecological stress. The increase in LST indicated greater thermal pressure, and variation in ET reflected changes in moisture conditions that may influence habitat suitability. Given the limited statistical support from the regression models, these results are interpreted as descriptive ecological associations rather than evidence of predictive or causal relationships.

The broadly similar patterns observed in the temporal assessment (Figures 7-8), multivariate visualizations (Figures 9-11) and exploratory regression analyses (Tables 4-7) provide a consistent, although preliminary, picture of taxon-specific vulnerability. Mammalian and avian responses showed comparatively stronger descriptive associations with vegetation-related indicators, whereas reptile and amphibian responses showed comparatively stronger associations with thermal and moisture-related indicators. These findings require confirmation through longer time series and standardized field observations, but they offer a useful basis for guiding habitat restoration, forest-corridor protection and climate-resilient biodiversity management in the Ukhiya–Teknaf ecosystem.

4. Conclusion

An integrated geospatial-statistical approach was created to study environmental change and vertebrate faunal responses over the southeastern Rohingya settlement landscape of Bangladesh during 2015–2026. Multi-source remote-sensing indices such as NDVI, TDVI, EHI, ET and LST were analyzed together with consolidated secondary biodiversity information. This incorporation provides us with a descriptive framework to investigate the relationship between changes in vegetation condition, temperature stress, moisture availability and habitat structure and taxon-specific faunal response patterns.

During the research period, a significant change in the landscape was noted, including a 33.9% reduction in thick vegetation, 121.2% growth in built-up areas and an increase in maximum land surface temperature from 35.50 ℃ to 48.99 ℃. The predicted overall vertebrate richness-equivalent response declined from 334 reported species in the 2015 reference baseline to around 109.8 richness-equivalent units by 2026. This decimal figure is a simulated reaction and should not be construed as a direct species count or evidence of confirmed local extinction. The most substantial shift was found during 2017–2020, which coincided with rapid development of settlements, habitat modification and growing fragmentation.

The four vertebrate groups showed different sensitivities to ecological impacts. By 2026, the highest predicted degradation response was seen for mammals (81.4%), followed by reptiles (68.1%), birds species (66.3%) and amphibians (45.9%). Mammalian and avian responses were comparatively more strongly described by vegetation related variables such as NDVI, TDVI and EHI. In comparison, the reactions of reptiles and amphibians exhibited significantly stronger descriptive relationships with the thermal and moisture-related markers, especially LST and ET. However, the low adjusted R^2 values, overall model p-values >0.42, and small number of annual observations suggest that these correlations were not statistically significant. Hence, their status as preliminary ecological connections rather than established predictive or causal impacts should be acknowledged.

The historical, ecological and statistical studies together offered a tentative description of overall biodiversity vulnerability in the Ukhiya–Teknaf area. Although the results need validation with larger time series and systematic field-based biodiversity monitoring, the potential utility of combining remote-sensing indicators with secondary faunal records for conservation evaluation was revealed. The trends discovered can promote habitat restoration, protection of forest corridors, climate-resilient ecosystem management and long-term biodiversity monitoring in rapidly changing tropical environments.

5. Recommendation

1) Geospatial-based biodiversity monitoring and early warning framework

A continuous biodiversity-monitoring framework should be established by combining NDVI, TDVI, EHI, ET, LST and land-use indicators with standardized field observations. Such a framework could be used to monitor potential ecological stress, detect emerging patterns of habitat degradation and support timely conservation responses. Remote-sensing indicators should be treated as ecological surrogates and periodically validated against field-based biodiversity records.

2) Habitat restoration and ecological connectivity improvement

Priority should be given to improving habitat quality and maintaining landscape connectivity, particularly for large mammals and forest-dependent species. Degraded forest areas should be restored using native vegetation, and fragmented ecological corridors should be re-established where feasible. Restoration priorities should be informed by field assessments, habitat suitability and the spatial patterns identified through geospatial analysis.

3) Wildlife corridor protection and taxon-specific conservation

Key wildlife corridors should be protected, and taxon-specific conservation measures should be developed for threatened mammals, forest birds and herpetofauna, including reptiles and amphibians. Particular attention should be given to areas where habitat fragmentation, thermal stress and changing moisture conditions may increase ecological vulnerability.

4) Climate-resilient ecosystem management

Nature-based adaptation measures should be applied in areas experiencing increasing temperature and moisture stress. These measures may include forest rehabilitation, wetland protection and the conservation of climate-sensitive microhabitats that support ectothermic organisms. Their effectiveness should be evaluated through regular ecological and microclimatic monitoring.

5) Long-term biodiversity database development and predictive modelling

A long-term biodiversity information system should be developed by integrating standardized field surveys, secondary biodiversity records, remote-sensing data and relevant environmental observations. Future statistical and species-distribution models should be developed and validated using longer time series, larger sample sizes and independent field observations before being applied for prediction or conservation decision-making.

6) Integrated conservation governance and stakeholder collaboration

Geospatial evidence should be incorporated into coordinated conservation planning involving government agencies, researchers, conservation organisations and local communities. Participatory monitoring and data-sharing arrangements should be encouraged to support sustainable landscape management. These actions would contribute to SDG 13 (Climate Action), SDG 15 (Life on Land) and SDG 17 (Partnerships for the Goals).

Abbreviations

AI	Artificial Intelligence
DAAC	Distributed Active Archive Center
DEM	Digital Elevation Model
EHI	Ecological Health Index
EOSDIS	Earth Observing System Data and Information System
ESA	European Space Agency
ET	Evapotranspiration
EVI	Enhanced Vegetation Index
GIS	Geographic Information System
ID	Identification
IUCN	International Union for Conservation of Nature
LP	Land Processes
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Instrument
NASA	National Aeronautics and Space

	Administration
NDVI	Normalized Difference Vegetation Index
NIR	Near-infrared
SDG	Sustainable Development Goal
TDVI	Transformed Difference Vegetation Index
UN	United Nations
UNDP	United Nations Development Programme
UNHCR	United Nations High Commissioner for Refugees
USGS	United States Geological Survey
CODE OR SYMBOL	Elaboration
B4	Band 4
B8	Band 8
L3	Level 3
MOD11A2	Modis/Terra Land Surface Temperature/Emissivity 8-day Level 3 Global 1-km Sinusoidal Grid Product
$NDVI_{max}$	Maximum Normalized Difference Vegetation Index
$NDVI_{min}$	Minimum Normalized Difference Vegetation Index
$NDVI_{norm}$	Normalized Difference Vegetation Index
R^2	Coefficient of Determination
SIN	Sinusoidal Grid Projection

Author Contributions

Nurul Hamid: Conceptualization, Formal Analysis, Investigation, Project administration, Resources, Software, Visualization, Writing – original draft

Md. Redwanur Rahman: Conceptualization, Data curation, Methodology, Supervision, Validation, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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Biography

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