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AN INTEGRATED GIS AND FUZZY LOGIC APPROACH FOR ASSESSING LAND DEGRADATION VULNERABILITY IN COASTAL ZONE OF BANGLADESH

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ABSTRACT

Land degradation in the coastal zone of Bangladesh poses a significant risk to ecological sustainability, agricultural productivity, and socio-economic resilience. The present study aims to assess the spatial vulnerability of land degradation in the coastal zone of Bangladesh by integrating Geographic Information Systems (GIS) with a fuzzy logic-based Multi-Criteria Decision Analysis (MCDA) approach. A total of eighteen factors influencing land degradation were considered, including geology, soil type, soil texture, soil pH, soil organic carbon (SOC), elevation (m), slope (%), topographic wetness index (TWI), rainfall (mm), land surface temperature (LST, °C), groundwater depth (m), distance from river (km), soil salinity (dS/m), soil erosion, normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), land use and land cover (LULC), and population density. The study was carried out within a GIS-based spatial modeling framework, where each thematic layer was standardized through fuzzy membership functions to generate continuous membership values ranging from 0 (no vulnerability) to 1 (very high vulnerability). Suitable membership function types were chosen based on the direction of each factor's influence on land degradation, while the midpoint and spread parameters were determined using expert judgment and literature review to govern the shape of the membership curves. The standardized fuzzy layers were combined using the Fuzzy Gamma operator ($\gamma=0.9$) to generate a composite Land Degradation Vulnerability (LDV) map, divided into five vulnerability levels: very low, low, moderate, high, and very high. Results showed that 59.77% of the coastal area falls under high to very high vulnerability, 19.88% under moderate vulnerability and 20.34% falls under low to very low vulnerability. Model validation using Google Earth imagery and the ROC curve method generated an AUC value of 0.84, indicating strong predictive performance. The study shows that combining remote sensing data and fuzzy logic is a viable, cost-efficient, and time-saving method for detecting regions prone to land degradation. This methodology helps policymakers, planners, and environmental managers select intervention zones and develop adaptive land management plans in coastal Bangladesh.

Keywords: *Coastal Bangladesh, Land Degradation Vulnerability, Fuzzy logic, GIS, Remote sensing.*

1. INTRODUCTION

Land is an important element of the Earth's supporting ecosystem, providing basic services on which both humans and animals depend on (Yadav et al., 2023). Land degradation is the temporary or permanent decrease in land productivity caused by the deterioration of its physical, chemical, and biological qualities (Sandeep et al., 2021b). Over the last few decades, it has been recognized as a key worldwide environmental concern, receiving considerable attention from researchers, planners, and policymakers (Han et al., 2019). Land degradation causes major threats to sustainable development, accelerates biodiversity loss and climate change, worsens the shortage of food, compromises water supplies and ecological balance, and negatively effects local people's livelihoods (Nacishali Nteranya et al., 2024). The scale and severity of land degradation are rising, with estimates showing that around 20% of croplands, 30% of forests, and 10% of grasslands globally are impacted by various types of degradation (Sandeep et al., 2021a; Malav et al., 2022). Approximately 33% of the world's land is degraded, affecting nearly 3.2 billion people (AbdelRahman, 2023; von Keyserlingk et al., 2023). In order to tackle this challenge, the United Nations General Assembly created Sustainable Development Goal 15.3 in September 2015, aiming for land degradation neutrality (LDN) by encouraging optimal management methods that reduce the loss of productive land while maintaining or improving its fertility (Wunder et al., 2017).

Land Degradation Vulnerability (LDV) is the degree to which the land is expected to undergo deterioration, showing its sensitivity and capacity to lose productivity, ecological stability, as well as sustainability over time (Nacishali Nteranya et al., 2024). LDV analysis implies assessing and quantifying the strain on land resources generated by many variables that impact the quality and resilience of the land system (Parmar et al., 2021). Prior studies have used an extensive set of land degradation influencing factors, including slope, aspect, topographic wetness index (TWI), curvature, soil type, lithology, soil texture, soil erosion, soil depth, soil pH, geology, land use/land cover (LULC), land surface temperature (LST), rainfall, temperature, distance to river, distance to drainage network, distance to road, normalized difference moisture index (NDMI), normalized difference vegetation index (NDVI), terrain ruggedness index (TRI), salinity index (SI), groundwater quantity, groundwater quality, soil organic carbon, population density, which were obtained from field surveys or various global raster datasets (Hembram & Saha, 2025; Moradi et al., 2024; Nga et al., 2024; Nacishali Nteranya et al., 2024; Swamy et al., 2024; Yadav et al., 2023; Das et al., 2023). Multiple approaches have been proposed for evaluating land degradation; however, geospatial techniques, such as Remote Sensing (RS) and Geographic Information System (GIS), have emerged as a more efficient alternative to traditional surveys, which are often time-consuming, expensive, and difficult to conduct in inaccessible areas (AbdelRahman et al., 2016). The combination of geospatial approaches with multi-criteria decision analysis (MCDA) provides a robust framework for assessing and mapping LDV. Traditional deterministic models like Boolean overlay and weighted linear combination simplify complicated procedures, but they lack flexibility in dealing with ambiguity (Romshoo et al., 2020). Conversely, the fuzzy logic technique successfully resolves unpredictability and imprecision, resulting in a more realistic assessment of various land situations (Lu et al., 2022).

Bangladesh is experiencing serious land degradation, compromising the availability of food for its growing inhabitants. The cultivable area decreased from around 20 million hectares in 1983-84 to 17.5 million hectares in 1997, and then to 8.52 million hectares by 2011 (Khan & Shoumik, 2022). According to DoE (2005), the nation loses around 82,000 hectares per year due to land transformation, indicating a persistent loss of arable land. Bangladesh's coastal zone is especially vulnerable due to several interconnected variables, including significant population stress, vigorous agricultural and aquaculture practices, tidal and storm surge consequences, salinity intrusion, waterlogging, and vulnerability to cyclones and coastal erosion, making it critical for farming, fishing, ecological diversity, and livelihoods. In response, Bangladesh agreed to the Land Degradation Neutrality (LDN) Target Setting Programme on December 31, 2015, seeking to stop, reverse, or recover land degradation by 2030 (Khan & Shoumik, 2022). Regardless of these attempts, assessments of LDV in Bangladesh, especially in the coastal zone, utilizing GIS and remote sensing approaches are still inadequate. As a result, the objective of this project is to provide a comprehensive framework for analyzing LDV in the region using fuzzy logic, as well as to identify priority sites for landscape-scale targeted recovery. The findings are necessary to provide a scientifically sound foundation for land degradation prevention and sustainable management in the research area and other similar places.

2. METHODOLOGY

2.1 Study Area

The current research focuses on the entire coastal region of Bangladesh, extending from 20°60′N to 23°50′N latitude and 88°50′E to 92°60′E longitude (Figure 1). The coastal zone accounts for 32% of the country's geographical area (47,201 km²), with a 710 km-long coastline and a population of roughly 40 million across 19 administrative districts (Hoque et al., 2019). Nearly 80% of the people in this zone lives in rural regions, and more than 70% of them work in agriculture and associated livelihoods (BBS, 2011). The coastal region is ecologically as well as economically significant, featuring diverse natural resources such as the Sundarbans mangrove forest (6107 km^2), the world's longest uninterrupted sea beach (120 km), coral islands, hill ranges, tidal estuaries, and abundant agricultural, marine, and energy resources (Huq et al., 2015). The coastal zone is usually divided into three sub regions: eastern, central, and western coasts. The eastern coast has comparatively higher elevations and stable land formations, with significant land-use change occurring in the past few decades. The central coast is an active deltaic habitat created by the Ganges-Brahmaputra river system, with low elevation and constant erosion and sediment deposition triggered by intense tidal and fluvial processes. The western coast, in comparison, creates a mature delta with massive saline regions and vast mangrove forests, although it is getting more susceptible to human stress and resource extraction (Chowdhury & Islam, 2006; Hoque et al., 2019). Overall, Bangladesh's coastal zone is mostly low-lying, with over 62% of the entire area lying below 3 meters and approximately 86% of the entire area lying below 5 meters above mean sea level (Huq et al., 2015). Because of its unique geomorphological context, the area is very dynamic while also being susceptible to natural and human-induced changes.

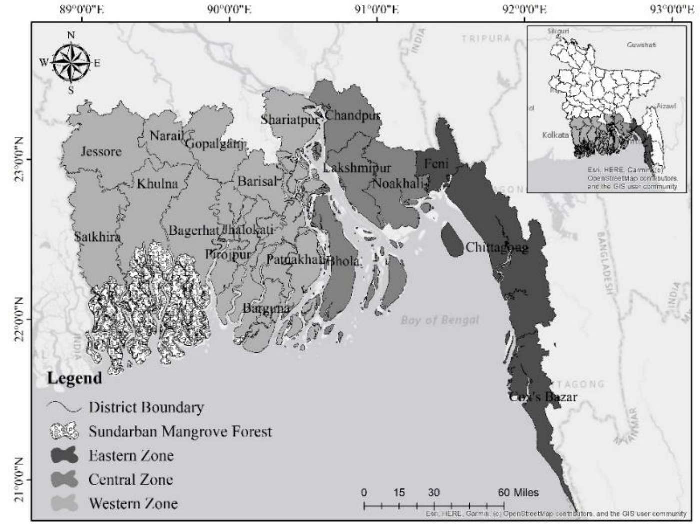


Figure 1: Study Area Map

2.2 Data Collection and Preparation of Thematic layer

Eighteen biophysical and anthropogenic factors were selected through a comprehensive literature review and obtained from reliable national and global sources to assess land degradation vulnerability (Table 1). Using Remote Sensing (RS) and Geographic Information System (GIS) techniques within the Google Earth Engine (GEE) and ArcGIS environment, data processing and thematic layer preparation were performed.

Table 1: Specifications of several datasets used in LDVI

Factor	Data Source	Time / Coverage	Spatial Resolution
Geology	Geological Survey of Bangladesh (Energy & Mineral Resources Division)	2020	-
Soil Type	Bangladesh Agricultural Research Council (BARC)	2020	-
Soil Texture	BARC	2020	-
Soil pH	BARC	2020	-
SOC (Soil Organic Carbon)	Food and Agriculture Organization (Global Soil Organic Carbon Map)	2020	1 km
Elevation (m)	USGS/SRTMGL1_003 (via USGS)	-	30 m
Slope (%)	Derived from SRTM	-	30 m
TWI (Topographic Wetness Index)	Derived from SRTM	-	30 m
Rainfall (mm)	ERA5-Land	1950-present (monthly)	9 km
LST (°C)	MOD11A1 V6.1 (MODIS)	2015-2024	1 km
Groundwater Depth (m)	Bangladesh Water Development Board (BWDB)	2018-2022	-
Distance from River (km)	Local Government Engineering Department (LGED)	2020	-
Salinity (dS/m)	BARC	2021	-
Erosion	European Soil Data Centre (ESDAC Global Soil Erosion)	2019	25 km
NDVI	COPERNICUS/S2_HARMONIZED	2022	10 m
NDMI	COPERNICUS/S2_HARMONIZED	2022	10 m
LULC	ESA_WorldCover_v100 (Esri Land Cover 10 m)	2021	10 m
Population Density	WorldPop	2020	100 m

2.3 Analytical Methods

The analytical methodology used in this study utilizes a fuzzy logic approach to handle the uncertainty and unpredictability of environmental factors impacting land degradation. Zadeh (1965) introduced fuzzy logic, which extends classical set theory by enabling spatial units to belong to numerous classes with different membership values (0-1), making it particularly suitable for modeling continuous and overlapping environmental situations.

The fuzzy logic analysis was performed using the Spatial Analyst toolbox in ArcGIS 10.8, which includes two key elements: the Fuzzy Membership functions and the Fuzzy Overlay tool. The Fuzzy Membership functions were used to allocate continuous membership values between 0 and 1 to the attribute data within each thematic layer, while the Fuzzy Overlay tool was used to combine the individual fuzzy membership layers into a single composite vulnerability index map.

In this study, two of the fuzzy membership functions, namely Fuzzy Large and Fuzzy Small, were used to perform the fuzzification of the selected thematic layers. The Fuzzy Large function was used to allocate higher membership values to larger observed data, whereas the Fuzzy Small function was used to allocate higher membership values to smaller observed data.

Both the functions are defined by two parameters, midpoint (f_1) and spread (f_2), which are specified by the user. The mathematical expressions for these functions are:

$$\mu_1(x) = \frac{1}{1+\left(\frac{x}{f_1}\right)^{-f_2}} \tag{1}$$

$$\mu_2(x) = \frac{1}{1+\left(\frac{x}{f_1}\right)^{f_2}} \tag{2}$$

Here, x represents the input raster values of the different factors, whereas μ_1 (x) and μ_2 (x) represents the Fuzzy-Large and Fuzzy-Small membership functions, respectively.

The midpoint is the observed value of a factor with a fuzzy membership value of 0.5, which indicates moderate vulnerability. The spread parameter controls the pace at which membership values fluctuate around the midpoint. A large spread causes a gradual change with more intersections, whereas a small spread produces an abrupt and distinct separation. The midpoint and spread parameters for each membership function were determined based on the statistical distribution of the input data, expert judgment, and insights from the literature review (Table 2).

Table 2: Fuzzy membership parameters of factors used in LDVI

Factor	Fuzzy Membership Type	Midpoint (f_1)	Spread (f_2)
Geology	Large	3.5	1.5
Soil Type	Large	3.8	1.2
Soil Texture	Large	3.6	1.3
Soil pH	Large (on deviation)	6.8	1.5
SOC	Small	150	1.5
Slope (%)	Large	5	2.0
Elevation (m)	Small	50	2.0
TWI	Large	10	2.0
Rainfall (mm)	Small	2500	1.5
LST (°C)	Large	27.0	1.5
Groundwater Depth (m)	Small	4.0	1.5
Distance from River (km)	Small	0.35	1.2
Soil Salinity (dS/m)	Large	2.5	1.5
Soil Erosion	Large	5.0	2.0
NDVI	Small	0.25	1.5
NDMI	Small	0.30	1.5
LULC	Large	3.0	1.5
Population Density	Large	300	1.3

The fuzzy overlay approach assesses the chance that a phenomena belongs to many classes, as well as the connections between these classes' membership values in a multi-criteria overlay analysis. Different fuzzy operators, such as fuzzy AND, fuzzy OR, fuzzy SUM, fuzzy PRODUCT, and fuzzy GAMMA, are used to represent different aspects of each cell's membership across multiple input factors. Among them, a suitable overlay method should be chosen based on the desired outcome of the final map. Fuzzy Gamma serves as a bridge between two fuzzy operators, balancing the increasing effect of the Fuzzy Sum with the diminishing effect of the Fuzzy Product. It is expressed using the following equation:

$$\mu_\gamma = \left(\prod_{i=1}^{n} \mu_i\right)^{1-\gamma} \; \left(1 - \prod_{i=1}^{n}(1-\mu_i)\right)^{\gamma} \tag{3}$$

Here, n denotes the number of membership functions to be combined, μ_i represents the i-th membership function, and γ is a parameter chosen within the range of 0 to 1. When $\gamma = 1$, the Fuzzy Gamma combination is equal to the Fuzzy Sum, whereas when $\gamma = 0$, it equals the Fuzzy Product. Thus, selecting an appropriate gamma value helps to optimize the combination of membership value. The Fuzzy Gamma operator was applied in this study to combine the fuzzy membership layers for preparing the final LDV map. This fuzzy operator creates a compromise between the pessimistic Fuzzy Product and the optimistic Fuzzy Sum. The gamma parameter (γ) controls the level of influence between the two, enabling flexible combination of the input factors. A gamma value of 0.9 was chosen because it provides a realistic balance and effectively portrays the relationship of various biophysical and human-induced factors, resulting in a more precise and continuous geographical pattern of land degradation vulnerability. Finally the LDV map of the coastal zone of Bangladesh was divided into five classes-very low, low, moderate, high, and very high using natural breaks (Jenks) in ArcGIS.

The performance of the Fuzzy Logic model for preparing the Land Degradation Vulnerability (LDV) map was validated using Receiver Operating Characteristic (ROC) curve where 100 random points were selected across the coastal zone of Bangladesh. Reference classes were selected by visually interpreting Google Earth photos to indicate degraded and non-degraded regions. Predicted vulnerability values from the fuzzy logic model were compared with these reference data to construct the ROC curve which represents the relationship between sensitivity and specificity across different thresholds. The Area under the Curve (AUC) measures model performance, with values closer to one indicating greater reliability. This validation offered an impartial assessment of the fuzzy-based LDV model's efficacy in identifying degradation-prone locations in coastal Bangladesh.

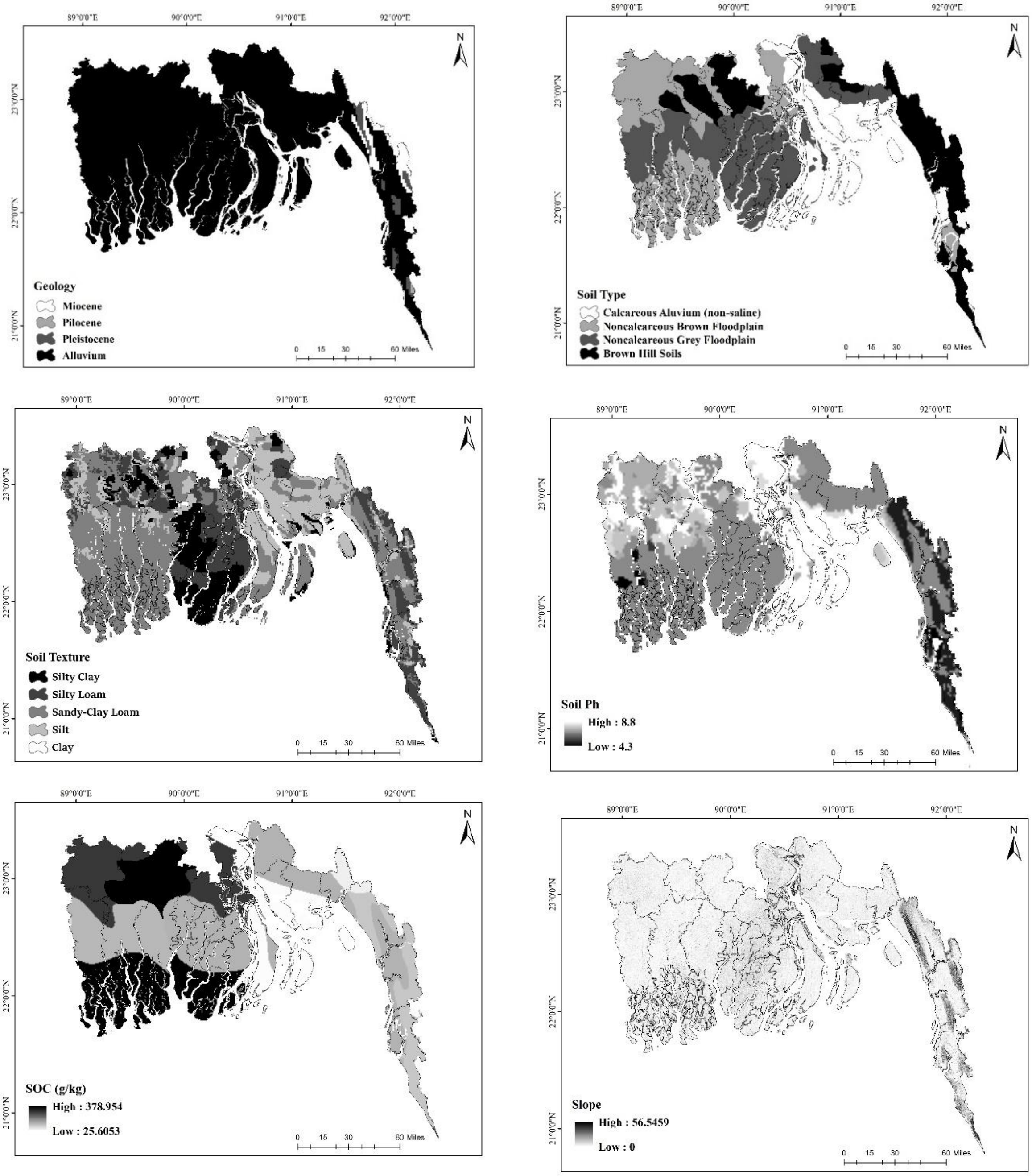
3. RESULTS AND DISCUSSION

3.1 Input Thematic Layers and Their Variability

The geology of coastal region in Bangladesh is predominantly alluvium, with Pleistocene and Miocene formations are present in the eastern hills. The fuzzy large membership function indicates that unconsolidated alluvium shows higher land degradation vulnerability, while consolidated Miocene rocks indicate lower susceptibility, highlighting that the geology of coastal zone are fragile and easily erodible in nature. The coastal soil type distribution shows that Calcareous Alluvium is mainly concentrated in the central and eastern floodplains, while Noncalcareous Brown and Grey Floodplains occupy the western and central regions, respectively. Brown Hill Soils are predominantly found in the hilly areas of the Chittagong Hill Tracts and Sylhet region. The fuzzy large membership function represents that brown hill soils are highly prone to degradation because of their shallow depth, slope-induced erosion, and limited fertility. Moreover, non-calcareous soils are more vulnerable to degradation compared to fertile calcareous alluvial soils. The coastal zone of Bangladesh contains five major texture classes- silty clay, silty loam, sandy-clay loam, silt, and clay. A Large membership function is used, representing increasing degradation vulnerability from silty clay to clay. Silty clay soils show the lowest degradation potential due to their fine texture, cohesive structure, and high moisture-retention capacity. Silty loam and sandy-clay loam exhibit moderate vulnerability, as their moderate cohesion and permeability make them partially susceptible to erosion and nutrient leaching. In contrast, silt and clay soils show the highest vulnerability, silt due to its weak structure and erodibility, and clay because of poor drainage, cracking, and salinity accumulation common in the coastal environment. Soil pH in Bangladesh's coastal zone ranges from 4.3 to 8.8, with acidic soils in the southeast, alkaline soils in the western and central floodplains, and neutral soils along riverine areas. Using a large on deviation fuzzy function (midpoint 6.8), highly acidic or alkaline soils show greater degradation vulnerability, while neutral soils exhibit lower susceptibility. SOC in Bangladesh's coastal zone ranges from 25.61 to 378.95 g/kg, with higher values in the southern coastal and western deltaic zones, and lower values in central and eastern floodplains and the hilly southeast. Fuzzy membership indicates that low SOC, common in intensively cultivated, fallow, and saline areas, corresponds to higher degradation vulnerability, while high SOC reflects greater fertility and lower susceptibility (Figure 2).

The slope of the coastal region of Bangladesh ranges from 0° to 56.54°, indicating predominantly flat terrain. The majority of places have mild slopes (0-5°), which is generally found in deltaic plains, although steep slopes exist in the southern hilly zones. The fuzzy large membership function for slope indicates that places with steeper slopes are more vulnerable due to increased runoff and erosion potential, whereas flatter areas are less vulnerable. The elevation of coastal Bangladesh ranges from 0 to 305 m. Higher elevations exist in the eastern coastal region particularly around the Chittagong Hill Tracts, whereas lower elevation exists in most of the coastal areas which are low-lying deltaic plains near sea level. The small fuzzy membership function classifies low elevated areas as highly vulnerable as these areas are frequently exposed to tidal flooding, storm surges, and saline water intrusion. On the other hand, higher elevation zones shows less vulnerability due to better drainage and reduced exposure. TWI values in the coastal zone of Bangladesh range from 3.19 to 27.36, with higher values concentrated in low-lying floodplains and river basins, indicating greater soil moisture accumulation and higher degradation vulnerability. Conversely, lower TWI values occur in elevated, well-drained areas, reflecting low vulnerability due to limited water retention and reduced saturation risk (Figure 2).

The annual average rainfall varies from 1608.13 mm in the west to 4157.4 mm in the east, with an increasing tendency towards the southeastern coast. The small fuzzy membership function demonstrates that regions with less rainfall were more vulnerable, whereas greater rainfall zones were less vulnerable, indicating their capacity to retain soil moisture and plant cover. Land Surface Temperature (LST) ranged from 23.83°C to 30.81°C, with higher temperatures predominantly observed in the southeastern and northwestern regions. In contrast, relatively lower temperatures occurred across the southwestern riverine delta, particularly near the Sundarbans, as well as in the central coastal zones. A fuzzy large function with midpoint 27°C identifies zones with elevated surface temperatures as highly degraded. These areas correspond to bare, built-up, or sparsely vegetated surfaces. Lower LST regions shows lower vulnerability, typically under vegetation cover or water bodies (Figure 3).



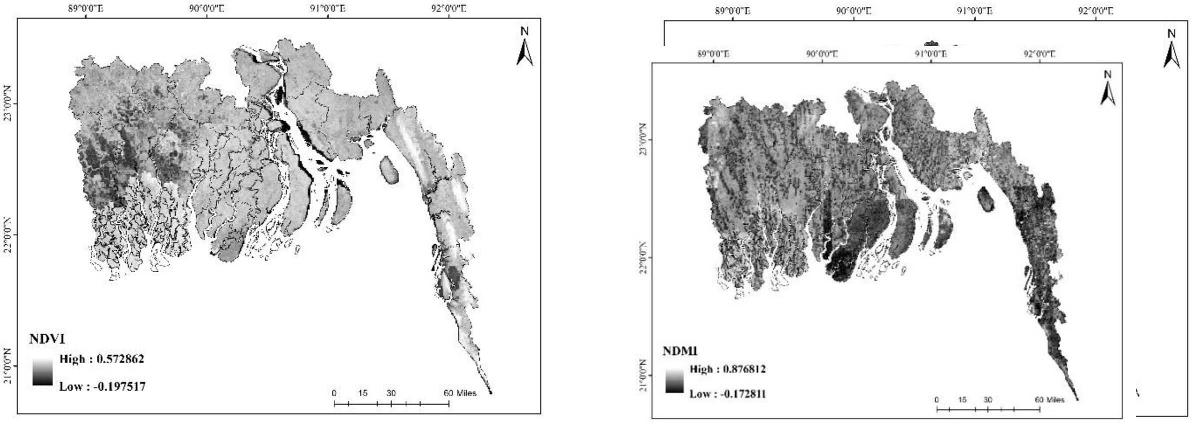


Figure 2: Spatial variations of geology, soil type, soil texture, soil pH, SOC, slope, elevation and TWI of the study area

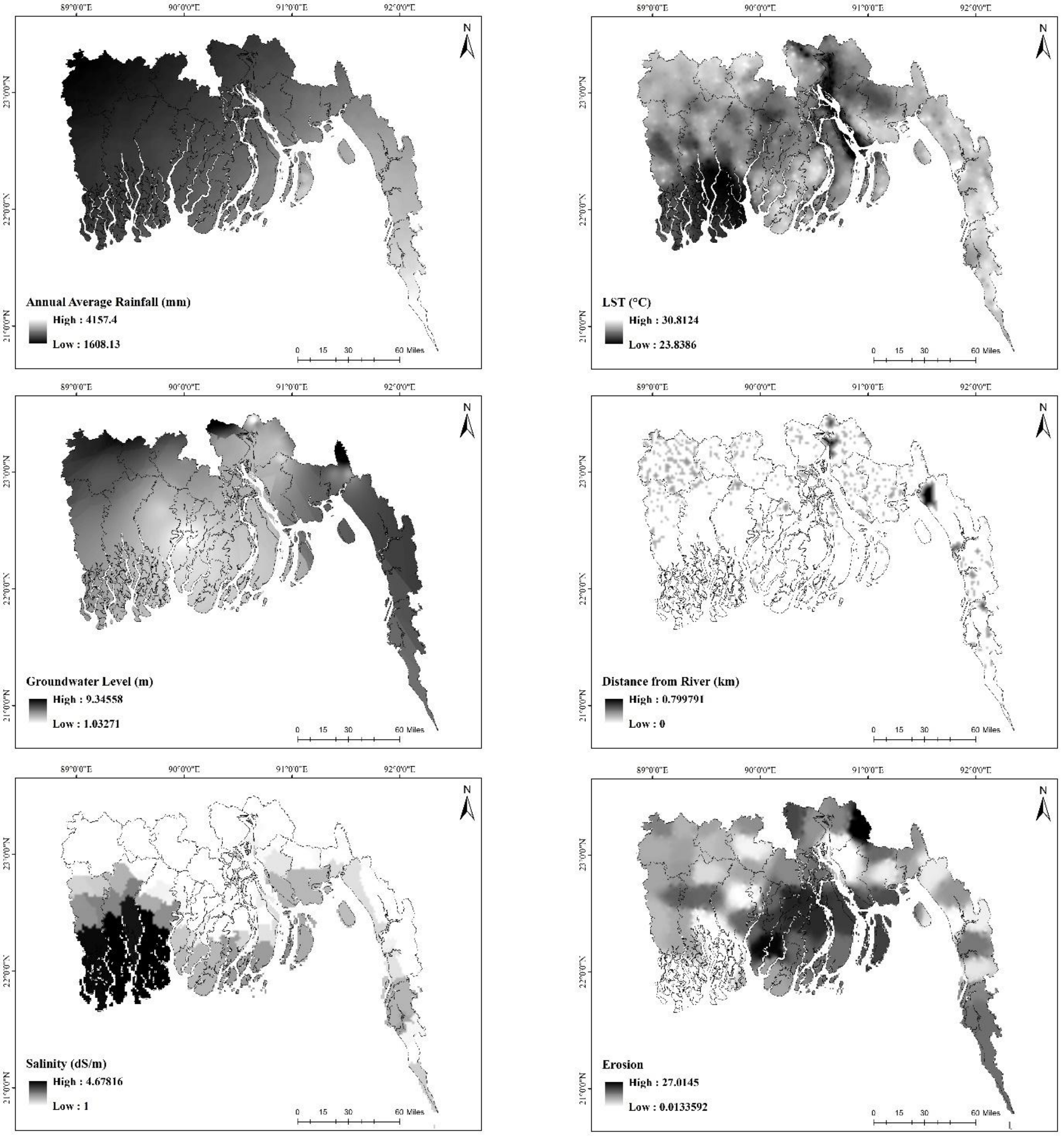
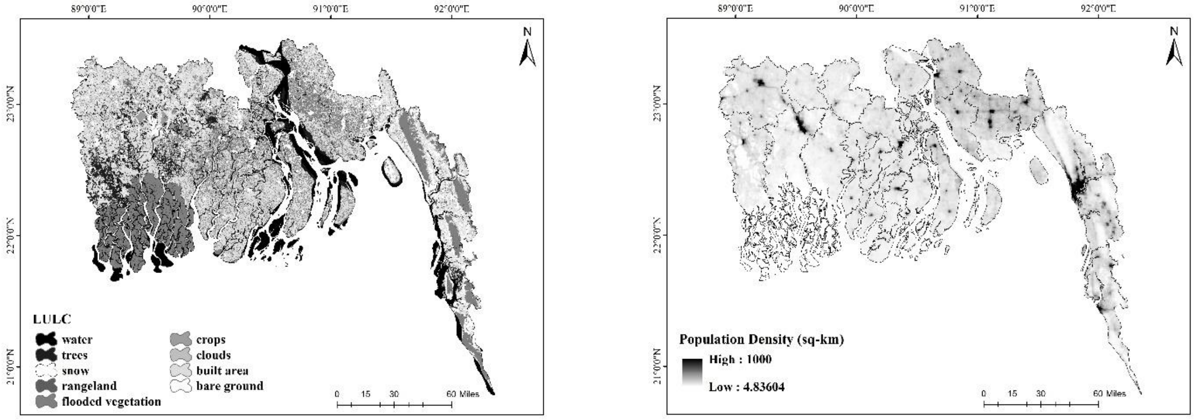


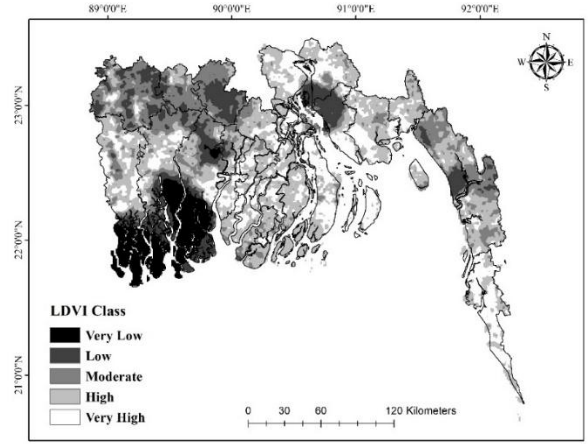
Figure 3: Spatial variations of rainfall, LST, groundwater level, distance from river, salinity, erosion, NDVI, and NDMI of the study area

Figure 4: Spatial variations of LULC and population density

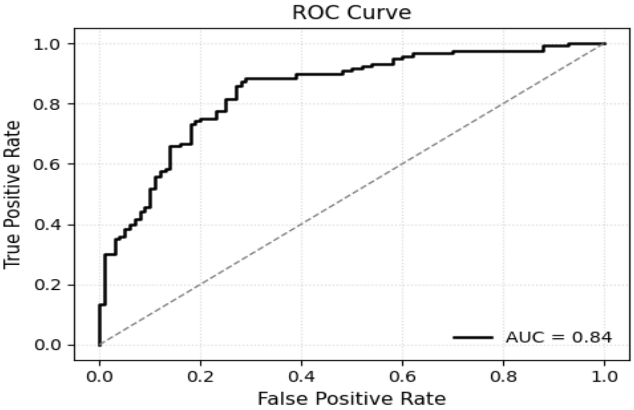
Groundwater depth ranges from 1.03 to 9.35 m, with shallower levels in the central and southwestern coast. The fuzzy small membership shows high vulnerability in shallow zones due to saline water rise and waterlogging, while deeper areas exhibit lower vulnerability. Distance from rivers ranges from 0 to 0.799 km across the coastal zone. The fuzzy small membership shows that areas within 350 m of major rivers are highly vulnerable due to erosion, salinity intrusion, and flooding, with vulnerability decreasing farther away (Figure 3).

Soil salinity in the coastal region ranges from 1.0 to 4.68 dS/m, with the highest levels around the Sundarbans due to tidal flooding, seawater intrusion, and shrimp farming. The fuzzy large membership function indicates that high salinity (>2.5 dS/m) reduces soil fertility leading to increased land degradation. Soil erosion in the coastal region varies from 0.013 to 27.01. River dynamics, tidal action, and storm surges are the reasons for this significant spatial variation. The fuzzy large membership indicates that high erosion in central and southwestern coasts indicates high vulnerability which results in topsoil loss, decreased fertility, and poor crop production (Figure 3).





NDVI values in the coastal zone range from -0.19 to 0.57. The fuzzy membership function reveals that places with low NDVI, such as bare soils, urban areas, and exposed croplands, have a high degradation potential, whereas vegetated and mangrove forest areas are less vulnerable. The NDMI values in the coastal zone range from -0.17 to 0.87. The fuzzy membership indicates that dry, sparsely vegetated areas are highly vulnerable, whereas places with NDMI > 0.4 are less vulnerable due to sufficient canopy moisture (Figure 3).There is a wide variation in LULC pattern in the coastal region of Bangladesh. The fuzzy membership suggests that bare ground and built-up regions (classes 5-4) are highly vulnerable, croplands (class 3) are moderately vulnerable, and trees and flooded vegetation/rangelands (classes 1-2) are the least vulnerable. Population density across the coastal region varies from 4.83 to 1,000 persons per square kilometer. The fuzzy membership function shows that densely populated areas are more vulnerable to land degradation due to intense resource pressure, whereas sparsely populated areas experience lower anthropogenic stress (Figure 4).



3.2 Land Degradation Vulnerability

The final LDVI map of the coastal zone of Bangladesh (Figure 5) shows a significant regional variation in land degradation vulnerability. Approximately 35.42% of the area falls under high vulnerability and 24.35% under very high vulnerability, which comprises 59.77% of the coastal region. These highly vulnerable zones are mostly found in the south-central and southeastern districts. Areas with moderate vulnerability cover about 19.88% of the coastal zone, representing transitional zones characterized by mixed levels of stability. Conversely, the low (12.82%) and very low (7.52%) vulnerability classes, which together constitute 20.34% of the coastal zone, are mainly found in the southwestern coastal area, particularly within the Sundarbans region, where dense vegetation cover and sturdy soils lead to greater ecological resilience (Table 3). Overall, the LDVI study shows that a significant area of the coastal region is very vulnerable to land degradation, highlighting the critical need for sustainable land management practices and ecosystem-based interventions to prevent future environmental hazards.

Figure 5: Land degradation vulnerability map of the study area

Table 3: Area covered under different LDVI classes

LDVI Class	Area (sq. km)	Area (%)
Very High	9527.08	24.35
High	13857.82	35.42
Moderate	7778.73	19.88
Low	5016.26	12.82
Very Low	2943.31	7.52
Grand Total	39123.20	100.00

3.3 Validation of Land Degradation Vulnerability Zones

For testing the model's performance, the ROC curve approach was used, with validation done by Area under the Curve (AUC). It is generally a well acknowledged technique in probability-based mapping that successfully determines prediction precision. The AUC value of 0.84 shows great accuracy, demonstrating that the model's predictions are substantially consistent with the observed data (Figure 6).

Figure 6: ROC curve of the LDVI map using fuzzy logic model

4. CONCLUSIONS

In this study land degradation vulnerability was analyzed in the coastal zone of Bangladesh using geospatial Multi-Criteria Decision Analysis (MCDA) and fuzzy logic. Eighteen thematic layers, including geology, soil type, soil texture, soil pH, SOC, elevation, slope, TWI, rainfall, LST, groundwater depth, distance from river, soil salinity, soil erosion, NDVI, NDMI, LULC, and Population Density were utilized to generate a comprehensive Land Degradation Vulnerability Index (LDVI) map. The analysis indicated that 59.77% of the area falls under high to very high vulnerability, 19.88% of the area falls under moderate vulnerability and 20.34% of the area falls under low to very low vulnerability. The validation of the land degradation vulnerability zones were conducted using Google Earth imagery and the ROC curve method, which yielded an AUC value of 0.84. It shows that integrating GIS with fuzzy logic efficiently detects locations prone to land degradation in the study area while being cost and time effective. The study shows that fuzzy logic reflects the continual character of land degradation processes and is an effective decision making tool. However, it is restricted by its dependence on secondary data as there is a lack of substantial field-based ground truth data. Moreover, adding more socioeconomic and environmental variables might enhance the assessment. Despite these limitations, the findings might help policymakers and stakeholders prioritize initiatives to reduce land degradation and increase coastal resilience.

Declaration of Use of AI

AI tools were used solely for language editing, improving the clarity and readability of the manuscript. No AI tools were used in the research design, methodology, data collection, analysis, or interpretation of results. The authors take full responsibility for the content, accuracy, and conclusions presented in this paper.

REFERENCES

AbdelRahman, M. A. E. (2023). An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications. *Rendiconti Lincei. Scienze Fisiche e Naturali*, *34*(3), 767–808.

AbdelRahman, M. A. E., Natarajan, A., Srinivasamurthy, C. A., & Hegde, R. (2016). Estimating soil fertility status in physically degraded land using GIS and remote sensing techniques in Chamarajanagar district, Karnataka, India. *The Egyptian Journal of Remote Sensing and Space Science*, *19*(1), 95–108.

BBS. (2011). *Yearbook of Agricultural Statistics of Bangladesh*. Bangladesh Bureau of Statistics (BBS), Ministry of Planning.

Chowdhury, A. M., & Islam, S. (2006). Banglapedia: National Encyclopedia of Bangladesh. *Bengali and English Combined CD Edition Copyright by Asiatic Society of Bangladesh. Dhaka: Asiatic Society of Bangladesh*.

Das, B., Desai, S., Daripa, A., Anand, G. C., Kumar, U., Khalkho, D., Thangavel, V., Kumar, N., Obi Reddy, G. P., & Kumar, P. (2023). Land degradation vulnerability mapping in a west coast river basin of India using analytical hierarchy process combined machine learning models. *Environmental Science and Pollution Research*, *30*(35), 83975–83990. https://doi.org/10.1007/s11356-023-28276-4

DoE. (2005). *Bangladesh National Action Programme (NAP) for Combating Desertification in Bangladesh* (Issue August).

Hembram, T. K., & Saha, S. (2025). Spatial land degradation vulnerability assessment in a plateau fringe river basin of Jharkhand, India. *Environmental Monitoring and Assessment*, *197*(2). https://doi.org/10.1007/s10661-024-13529-7

Hoque, M. Z., Cui, S., Xu, L., Islam, I., Tang, J., & Ding, S. (2019). Assessing agricultural livelihood vulnerability to climate change in coastal Bangladesh. *International Journal of Environmental Research and Public Health*, *16*(22). https://doi.org/10.3390/ijerph16224552

Huq, N., Hugé, J., Boon, E., & Gain, A. K. (2015). Climate change impacts in agricultural communities in rural areas of coastal Bangladesh: A tale of many stories. *Sustainability*, *7*(7), 8437–8460.

Khan, M. Z., & Shoumik, B. A. Al. (2022). Land degradation neutrality concerns in Bangladesh. *Soil*

Security, *9*(August), 100075. https://doi.org/10.1016/j.soisec.2022.100075

Lu, A., Tian, P., Mu, X., Zhao, G., Feng, Q., Guo, J., & Xu, W. (2022). Fuzzy Logic Modeling of Land Degradation in a Loess Plateau Watershed, China. *Remote Sensing*, *14*(19). https://doi.org/10.3390/rs14194779

Malav, L. C., Yadav, B., Tailor, B. L., Pattanayak, S., Singh, S. V., Kumar, N., Reddy, G. P. O., Mina, B. L., Dwivedi, B. S., & Jha, P. K. (2022). Mapping of Land Degradation Vulnerability in the Semi-Arid Watershed of Rajasthan, India. *Sustainability (Switzerland)*, *14*(16), 1–16. https://doi.org/10.3390/su141610198

Moradi, E., Khosravi, H., Rahimabadi, P. D., Choubin, B., & Muchová, Z. (2024). Integrated approach to land degradation risk assessment in arid and semi-arid Ecosystems: Applying SVM and eDPSIR/ANP methods. *Ecological Indicators*, *169*(November). https://doi.org/10.1016/j.ecolind.2024.112947

Nacishali Nteranya, J., Kiplagat, A., Ucakuwun, E. K., & Kabonyi Nzabandora, C. (2024). Land degradation vulnerability modelling for landscape restoration planning in Eastern DR Congo using the analytical hierarchy process (AHP) and geospatial techniques. *Geomatics, Natural Hazards and Risk*, *15*(1). https://doi.org/10.1080/19475705.2024.2426682

Nga, N. T. T., Phuong, P. M., Khanh, N. Q., Hanh, T. T., Quoc, P. B., Lahori, A. H., Yeremenko, S., Tyshchenko, V., & Murasov, R. (2024). Risk of Land Degradation: A Case Study of Phu Yen Province, Vietnam. *Ecological Questions*, *35*(2), 95–106. https://doi.org/10.12775/EQ.2024.019

Parmar, M., Bhawsar, Z., Kotecha, M., Shukla, A., & Rajawat, A. S. (2021). Assessment of land degradation vulnerability using geospatial technique: A case study of Kachchh District of Gujarat, India. *Journal of the Indian Society of Remote Sensing*, *49*(7), 1661–1675.

Romshoo, S. A., Amin, M., Sastry, K. L. N., & Parmar, M. (2020). Integration of social, economic and environmental factors in GIS for land degradation vulnerability assessment in the Pir Panjal Himalaya, Kashmir, India. *Applied Geography*, *125*, 102307.

Sandeep, P., Reddy, G. P. O., Jegankumar, R., & Arun Kumar, K. C. (2021a). Modeling and assessment of land degradation vulnerability in semi-arid ecosystem of Southern India using temporal satellite data, AHP and GIS. *Environmental Modeling & Assessment*, *26*(2), 143–154.

Sandeep, P., Reddy, G. P. O., Jegankumar, R., & Arun Kumar, K. C. (2021b). Modeling and Assessment of Land Degradation Vulnerability in Semi-arid Ecosystem of Southern India Using Temporal Satellite Data, AHP and GIS. *Environmental Modeling and Assessment*, *26*(2), 143–154. https://doi.org/10.1007/s10666-020-09739-1

Swamy, S. L., Mishra, A., Mukherjee, P., Sahoo, G. R., & Thakur, T. K. (2024). Modeling land-degradation vulnerability in coal-mined environs through geospatial and AHP techniques: potential strategies for eco-restoration. *Environmental Science and Pollution Research*, *0123456789*. https://doi.org/10.1007/s11356-024-35721-5

Tolche, A. D., Gurara, M. A., Pham, Q. B., & Anh, D. T. (2022). Modelling and accessing land degradation vulnerability using remote sensing techniques and the analytical hierarchy process approach. *Geocarto International*, *37*(24), 7122–7142. https://doi.org/10.1080/10106049.2021.1959656

von Keyserlingk, J., Thieken, A. H., & Paton, E. N. (2023). Approaches to assess land degradation risk: a synthesis. *Ecology and Society*, *28*(1).

Wunder, S., Kaphengst, T., & Frelih-Larsen, A. (2017). Implementing land degradation neutrality (SDG 15.3) at national level: general approach, indicator selection and experiences from Germany. In *International yearbook of soil law and policy 2017* (pp. 191–219). Springer.

Yadav, B., Malav, L. C., Jiménez-Ballesta, R., Kumawat, C., Patra, A., Patel, A., Jangir, A., Nogiya, M., Meena, R. L., Moharana, P. C., Kumar, N., Sharma, R. P., Yadav, L. R., Obi Reddy, G. P., & Mina, B. L. (2023). Modeling and Assessment of Land Degradation Vulnerability in Arid Ecosystem of Rajasthan Using Analytical Hierarchy Process and Geospatial Techniques. *Land*, *12*(1). https://doi.org/10.3390/land12010106

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353. https://doi.org/https://doi.org/10.1016/S0019-9958(65)90241-X