ASSESSMENT OF LAND DEGRADATION IN KHOTANG DISTRICT USING REMOTE SENSING AND GIS

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Keywords: Land degradation, Remote sensing, GIS, AHP, Khotang District, Soil Erosion, Sustainability

SUMMARY:

Land degradation is one of the burning issues in the mid-hill of Nepal contributing to the deformation of soil and turning it into infertile and unproductive land. It seems that the significant study in identifying degraded land by applying a multi-criteria approach is still lagging. Hence, this study attempts to map and quantify land degradation area and its key indicators in the Khotang district using GIS and remote sensing integrated with an Analytical Hierarchical Process (AHP). The rational for selecting the Khotang District is based on its socio-economic factors and the geographic condition of its location in the mid-hill of Nepal. Different thematic layers, including satellite imagery and secondary data, were utilized to analyze land degradation indicators such as vegetation cover, soil erosion, land cover, LST, SOC, rainfall, slope, bulk density, and soil texture. The methodology involved was data preprocessing, resampling, reclassification, and applying the Analytical Hierarchical Process (AHP) for weightage assignment. Weighted overlay analysis was performed to generate a land degradation map. The result indicates that nearly 57.49% of the total area is prone to moderate degradation risks; 40.20% is prone to low risks; and 2.25%, 0.02%, and 0.02%are prone to high, very high and very low risks, respectively. The classification of land degradation in Khotang based on each municipality illustrates that Halesi Tuwachung followed by Rupakot, Saakela, Jantedhunga, Diprung, and Khotehang were observed to be more degraded. Validation of land degradation was carried out using high-resolution Google Earth images and we claim that the study contributes to the existing knowledge and understanding of land degradation processes in the Khotang District.

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1. INTRODUCTION

Land is an essential part of the supportive ecosystem of the Earth. Humans and animals are dependent on ecosystem services, such as food, fiber, and shelter, provided by this natural resource (Tagore et al., 2012). Land degradation (LD) processes are widespread in dry lands worldwide and are accelerated by climate change. The UNCCD defines land degradation as "the reduction or loss of the biological or economic productivity and complexity of rain-fed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from a combination of pressures, including land use and management practices" (Sims et al., 2021). Land degradation is not an absolute term because the process itself depends on the land use category (ICIMOD, 2000). It is a long-term process that requires approved and standardized methods for its monitoring as well as a large amount of data.

In 2015, the UN launched the 2030 Agenda for Sustainable Development, including SDG 15, "Life on Land,". SDG 15 focuses on "Life on Land," targeting improved forest management, combating desertification, and reversing land degradation. A key indicator for this goal is SDG 15.3.1, which measures the proportion of degraded land relative to the total land area (Sims et al., 2021). Nepal is facing the challenges of land degradation as both natural and manmade activities are playing roles in land degradation(Ramesh Kumar Dahal, Pradeep Adhikari, n.d.). Both the hill and mountain regions occupy 70% of the country's total land and suffer from soil erosion, landslides, and washing away of the topsoil (Maskey et al.,2020). Land degradation is a significant global issue that adversely affects farming efficiency, environmental conditions, and food safety (Abebaw, 2019) It is driven by factors such as unsustainable land management and rising population pressures, projected to reach nearly ten billion by 2050, necessitating a 70% increase in global food production (Goal et al., 2017). Alarmingly, approximately 60% of ecosystem services have been degraded, and 25% of the world's land area is at risk (UNCCD, 2014). This degradation threatens not only food security but also social and economic stability, highlighting the urgent need for sustainable practices. Initiatives such as Sustainable Agriculture Management in Nepal's Chure region and the Sustainable Soil Management Program have shown promise in enhancing soil productivity and breaking the cycle of poverty in vulnerable communities (Dhakal & Acharya, 2016).

To address the issue of land degradation, it seems important to identify the degraded land. Hence, this study attempts to assess the degraded land in Khotang District by applying the AHP approach.

2. MATERIAL AND METHODS

2.1 STUDY AREA

Khotang District lies in the Koshi Province of eastern Nepal with Diktel as its district headquarters, spans an area of 1,591 square kilometers, and has a population of 206,312 as of 2021. Geographically, Khotang is a hilly district of Eastern Nepal. Khotang is one of 32 of Nepal's 77 districts which have witnessed a sharp decline in population (Times, 2023).

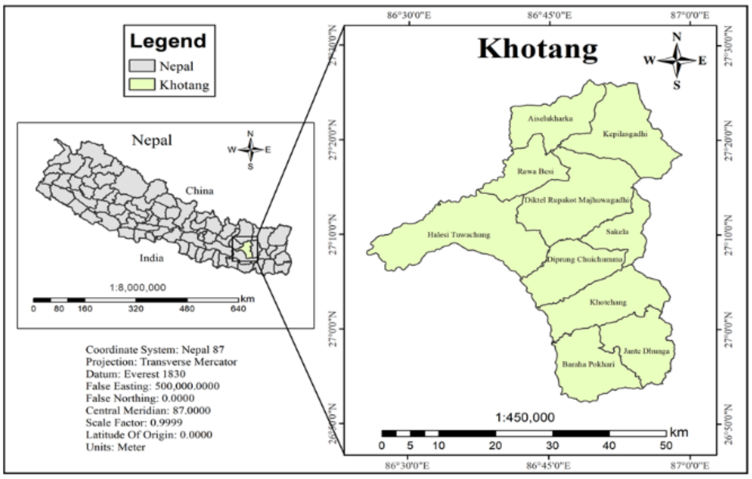

Figure 0-1 Study Area

2.2 FACTORS INFLUENCING LAND DEGRADATION

2. 2.1 LULC

According to (Nachtergaele et al., 2016), land use and land cover have a relationship with richness in biodiversity. For instance, forested areas are areas of high biodiversity while areas used for agriculture are characterized by low biodiversity.

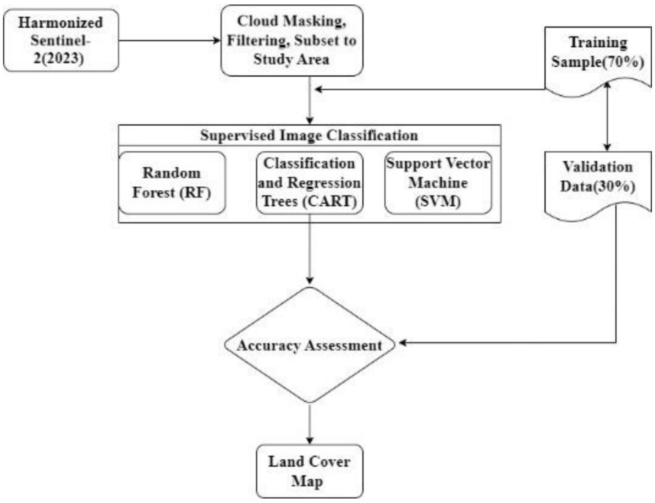

Figure 0-2 Methodological Diagram For LULC

Sentinel Harmonized Sentinel-2 MSI image collection was attained via Google Earth Engine only images with less than 30% cloud coverage were used for this study. The reference data for classification were then prepared, with 70% being used as training samples and the remainder 30% being used to validate the image classification results. The study area was divided into six categories and a total of 2603 sample pixels evenly distributed in the area were collected. The pixels were dispersed in the categories as follows: Forest (584 points), Agriculture (643), Built-up (402), Rangeland (508), Barren (324), and Water (142). The images were classified, and land cover information was extracted using Random Forest (RF), Classification and Regression Trees (CART), and Support Vector Machine (SVM) machine learning algorithms. Based on the training samples, image classification was applied to sentinel images to produce LULC maps for 2023 using all three machine-learning algorithms. Subsequently, each classification result was subjected to postprocessing, which included weighted refining with a 3 × 3 moving window to eliminate "noise" and editing of misclassified parts to create final LULC maps.

The comparison of land classification methods shows that the Random Forest (RF) algorithm performs best overall, consistently delivering the highest accuracy across most land use categories over SVM and CART as shown in Table 2-1. Likewise, Table 3-1 shows the reclassification of LULC classes.

Table 0-1 Overall Accuracy and Kappa Coefficient of 3 Algorithms

Algorithms	Overall Accuracy (%)	Kappa Coefficient
Random Forest (RF)	85.67	0.82
Classification and regression (CART)	73.86	0.68
Support Vector Machine (SVM)	66.59	0.57

2. 2.2 NDVI

The mean annual NDVI for each year from 2013 to 2023, derived from LANDSAT 8 satellite imagery provided by the United States Geological Survey (USGS), was used to calculate the 10-year average long-term NDVI. The NDVI, a dimensionless index ranging from -1 to +1, is a reliable indicator of vegetative greenness, where higher values denote healthy vegetation, and lower values indicate stressed vegetation. The resulting NDVI layer for the study area was categorized into five subclasses (Table 3-1) using the natural break method, following the approach described by Yadav et al. (2023).

2. 2.3 Rainfall

Annual rainfall data was obtained from DHM (Department of Hydrology and Meteorology) Nepal from 2010 to 2023.IDW method was used which yielded the best results and was consistent with the conclusion of cross-validation (Chen et al., 2017). The downloaded rainfall data were resampled to a 30m cell size by using the bilinear interpolation method (Tolche et al., 2022). The thematic layer of rainfall was categorized into five subclasses (Table 3-1) using the natural break method which was used for various hazard mapping applications by (Yadav et al., 2023).

2. 2.4 LST

Increased LST often accompanies land degradation, as the loss of vegetation cover reduces transpiration and exposes bare soil to direct sunlight. In this study, data from LANDSAT 8 were used, from 2013 to 2023 using GEE. The mean annual LST was calculated for each year and then averaged to determine the 10-year long-term mean LST. Using Equation (Fejl*! Ingen tekst med den anførte typografi i dokumentet.**1***), data were converted to degrees Celsius (◦C):

$$LST = 0.02 \times DN - 273.15 \qquad \text{Fejl! Ingen tekst med den anførte typografi i dokumentet.}\mathbf{1}$$

2. 2.5 Soil Erosion

Soil erosion, driven by natural forces like water and soil, is a critical contributor to land degradation, posing substantial threats to ecosystem sustainability and agricultural productivity

(Montgomery, 2007). Using the Revised Universal Soil Loss Equation (RUSLE) in GIS enables the assessment of soil erosion and calculation of soil loss, aiding in effective soil conservation and sustainable land management. ((Montgomery, 2007);(Renard et al., 1997);(Lai, 2001)). The formula of RUSLE is given below:

$$A = R*K*LS*C*P \quad \textbf{2.2}$$

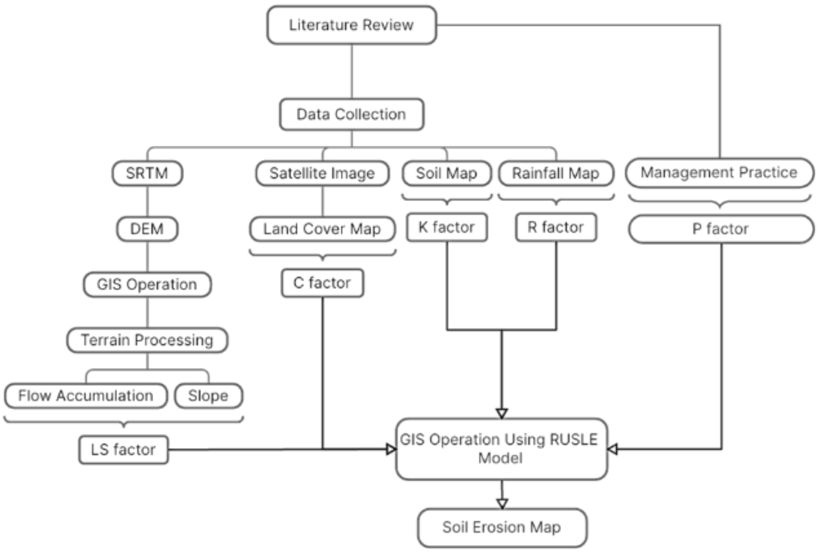

Figure 0-3 Methodological Diagram for Soil Erosion

Where,
A = Annual Soil Loss, R = Rainfall Erosivity Factor, K = Soil Erodibility Factor, LS = Slope Length and Steepness Factor, C = Cover and Management Factor, P = Support Practice Factor, A = Annual Soil Loss, R = Rainfall Erosivity Factor, K = Soil Erodibility Factor, LS = Slope Length and Steepness Factor, C = Cover and Management Factor and P = Support Practice Factor. The above flowchart in Figure shows detailed procedures that were followed.

2. 2.6 Soil Organic Carbon

SOC stocks are central to soil health, fertility, quality, and productivity. When there is an increase in SOC stock it can improve soil health, reduce soil erosion, give energy to soil biota, improve the soil's ability to store things, help filter and break down nutrients and pollution, and increase carbon dioxide sequestration ((Lorenz et al., 2019); (Hengl et al., 2017)). The SOC data was sourced from ISRIC-World Soil Information and the Obtained SOC map layer was clipped to the study area and reclassified into five classes as shown in Table 3-1.

2. 2.7 Bulk Density

FAO (1980) suggested that the increase in soil bulk density from year to year is one way to measure the physical degradation of soil. The main physical properties of soil erosion are an increase in bulk density and a decrease in the rate at which water can pass through the soil. Infertile soils are characterized by higher bulk density, lower porosity, and lower soil moisture ((Aminu & Jaiyeoba, 2015); Al Shammary et al., 2021). The map layer was sourced from ISRIC-World Soil Information, then clipped to the study area and reclassified into five categories as shown in Table 3-1.

2. 2.8 Slope

The percentage of cultivated land on a steep slope is an important indicator of pressures that lead to land degradation. Cultivating sloping land aggravates soil erosion, particularly in areas with less management or protection and results in the gradual degradation of resources (FAO UNESCO, 1995). The downloaded SRTM DEM from ALOS PALSAR was then reclassified to five classes as shown in Table 3-1.

2. 2.9 Soil Texture

Soil texture impacts water retention and fertility and soil erosion is directly controlled by the size and distribution of soil particles.(Ewunetu et al., 2021) .The soil texture data was collected from ISRIC-World Soil Information. The study area consists of soil classes such as loam, clay loam, sandy clay loam, and sandy loam which is reclassified as shown in Table 3-1.

3. STUDY METHOD

The land degradation assessment process starts with collecting biophysical (vegetation, climate, terrain) and chemical (soil) indicators. Data is resampled to a 30-meter resolution and reclassified into thematic layers. The Analytic Hierarchy Process (AHP) was used to assign weightage to all of the indicators. The weighted layers were overlayed to obtain a land degradation map, which was then validated using high-resolution images to ensure accuracy.

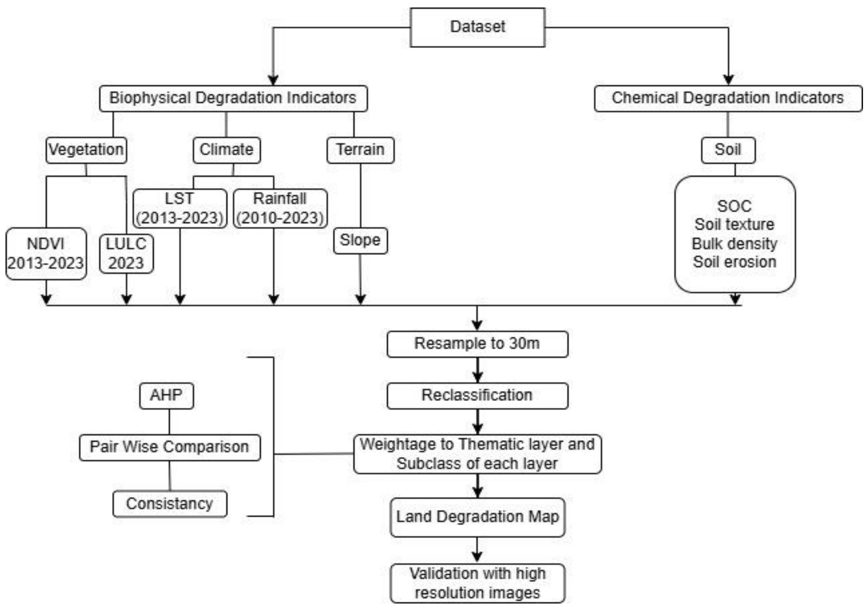

Figure 3-2.Methodological Flowchart

3.1 Ranking and Development of Pairwise Comparison Matrix

The Analytic Hierarchy Process (AHP) is a method for organizing and analyzing complex decisions, using math and psychology. It was developed by Thomas L. Saaty in the 1970s. It provides a mathematical approach used to determine the consistency of pairwise comparisons, hence consistency index (CI) and a consistency ratio (CR) need to be computed(Taherdoost, 2017)

To assess land degradation, we assigned scores to each contributing factor based on its impact using a pairwise comparison matrix with Saaty's nine-point scale. This method helps compare factors by their importance in driving degradation. A score of 1 means the two factors are equally important. Higher scores, closer to 9, indicate that the row factor is more significant than the column factor. Conversely, scores near 1/9 suggest the column factor is more crucial than the row factor. This approach helps allocate weights to different criteria, making it easier to evaluate land degradation and guide effective conservation efforts.

— Ranking of the Land Degradation

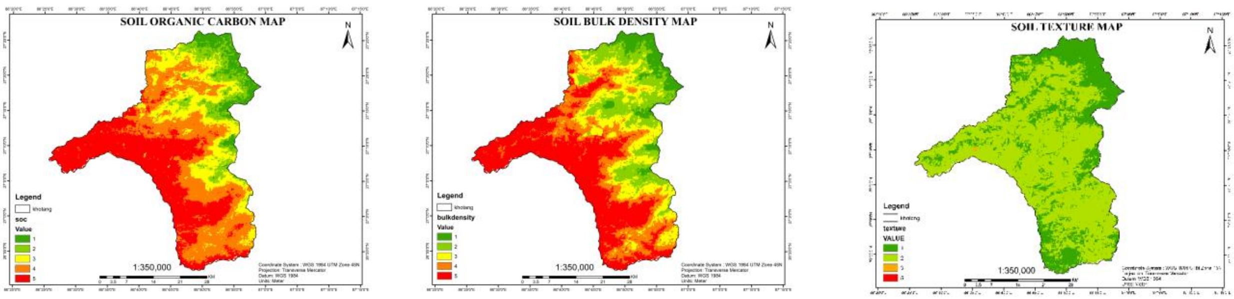

Figure 3-3 Rating Maps of Land Degradation Indicators

Table 3-1 Ranking Table

Criteria	Sub-criteria	Value	Criteria	Sub-criteria	Value
Soil Erosion	0-5	1		1152.92-1307.38	1

(Mg $h^{-1}yr^{-1}$)	5-10	2	Precipitation (mm/yr)	1307.38-1434.70	2
	10-20	3		1434.70-1561.25	3
	20-40	4		960.68-1152.92	4
	>40	5		787-960.68	5
NDVI	0.41-0.55	1	LST (°C)	5-15	1
	0.35-0.41	2		15-20	2
	0.30-0.35	3		20-25	3
	0.21-0.30	4		25-30	4
	-0.12-0.21	5		>30	5
LULC	BuiltUp/Water	1	Soil Texture	Loam	1
	Forest	2		Clay Loam	2
	Agriculture	3		Sandy Clay Loam	3
	Rangeland	4		Sandy Loam	4
	Bare	5			
Slope (°)	0-7	1	Bulk Density (kg/m^3)	756-1036	1
	7-15	2		1036-1133	2
	15-25	3		1133-1216	3
	25-55	4		1216-1290	4
	55-77.57	5		1290-1425	5
SOC (g/kg)	55-81	1			
	46-55	2			
	36-46	3			
	27-36	4			
	16-27	5			

— Development of Pairwise Comparison Matrix

Table 3-2 Pairwise Comparison Matrix

Criteria	Soil Erosion	NDVI	LULC	Slope	SOC	Precipitation	LST	Soil Texture	Bulk Density	Weightage
Soil Erosion	1	2	0.5	2	4	3	6	7	9	**0.20**
NDVI	0.5	1	0.5	3	4	3	5	8	8	**0.19**
LULC	2	2	1	0.5	3	5	8	5	8	**0.22**
Slope	0.5	0.333	2	1	5	2	6	7	9	**0.18**
SOC	0.25	0.25	0.333	0.2	1	2	6	4	7	**0.08**
Precipitation	0.333	0.333	0.2	0.5	0.5	1	3	6	7	**0.07**
LST	0.167	0.2	0.125	0.167	0.167	0.333	1	2	5	**0.03**
Soil Texture	0.143	0.125	0.2	0.143	0.25	0.167	0.5	1	4	**0.02**
Bulk Density	0.111	0.125	0.125	0.111	0.143	0.143	0.2	0.25	1	**0.01**
Sum	**5.004**	**6.366**	**4.983**	**7.621**	**18.06**	**16.64**	**35.7**	**40.25**	**58**	**1 (Checked)**

After the formation of the pairwise comparison matrix, computation of the criteria weights has been done.

— Estimation of the Consistency Ratio

Then the next step was to calculate a consistency ratio (CR) to measure how consistent the judgments have been relative to large samples of purely random judgments.

Table 3-3 Computation of Consistency Vector

Criteria	Soil Erosion	NDVI	LULC	Slope	SOC	Precipitation	LST	Soil Texture	Bulk Density
Weighted sum vector	2.087	1.962	2.195	1.842	0.840	0.732	0.321	0.252	0.141
Consistency Vector	10.580	10.83	10.218	10.502	10.13	9.887	9.48	9.494	9.976

lambda (λ) = 10.124

Where Lambda (λ) is the average of the consistency vector.

$$CI = (\lambda - n)/(n - 1) \quad \textbf{3. 1}$$

= (10.124-9)/ (9-1)

=0.140

The random index is the consistency index of a randomly generated pairwise comparison matrix of order 1–10 obtained by approximating random indices using a sample size of 500 (Saaty, 1990).

Table 3-4 shows the value of R.I. sorted by the order of the matrix. The consistency ratio (CR) is designed in such a way that if CR<0.10, the ratio indicates a reasonable level of consistency in the pairwise comparisons; if, however, CR>0.10, then the values of the ratio are indicative of inconsistent judgments. In such cases, one should reconsider and revise the original values in the pairwise comparison matrix.

Table 3-4 Random Index

Order Matrix	1	2	3	4	5	6	7	8	9	10
R. I	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

$$CR = CI/RI \quad \textbf{3. 2}$$

=0.14/1.45 (Since, RI= 1.49 for n=9)

=**0.096**

(**Consistency ratio CR (0.099) <0.10 indicated a reasonable level of consistency in the pairwise comparisons**). Therefore, the values obtained satisfy the said conditions, which denote that the weights obtained are agreeable.

4. RESULTS AND DISCUSSION

From the AHP model, it was found that LULC had the highest priority in land degradation zone identification, with a weight value of 22%, followed by soil erosion (20%), NDVI (19%), slope (18%), SOC (8%), and Precipitation (7%). In this study, with the help of the AHP and the GIS-based modeling approach, five land degradation zones: very low, low, moderate, high, and very high. The study area is mainly composed of moderate degradation (57.49%), followed by low degradation (40.21%), then high degradation (2.25%), very high degradation (0.03%), and very low degradation occurs the least (0.02%). Very high degradation is mainly concentrated in the western part, and very low and low erosion is found in the northern part of the study area.

The land degradation was then classified for each municipality of the Khotang district shown in Table 4-1. The classification illustrates Halesi Tuwachung followed by Rupakot, Saakela, Jantedhunga, Diprung, and Khotehang were observed to be more vulnerable to land degradation whereas Rawabesi, Kepilashgadhi, Aaiselukharka, and Barahapokhari shows low extent of land degradation.

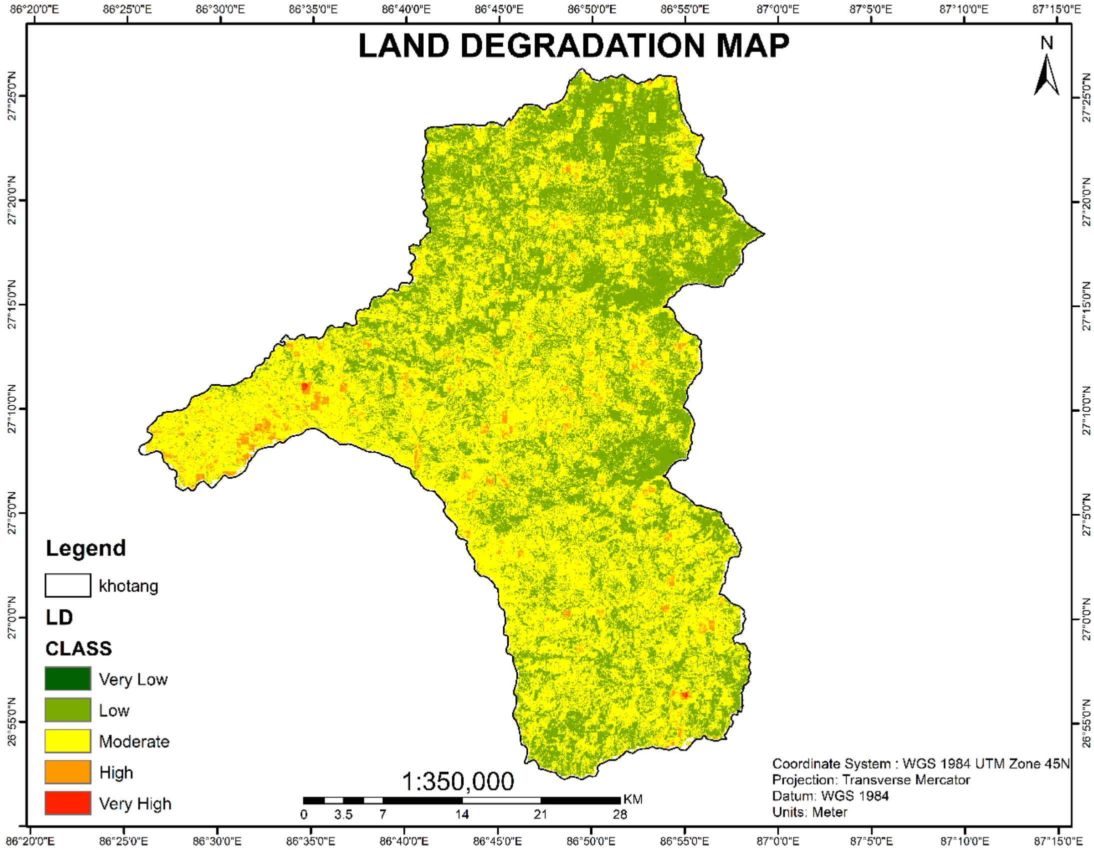

Figure 4-1 Land Degradation Map

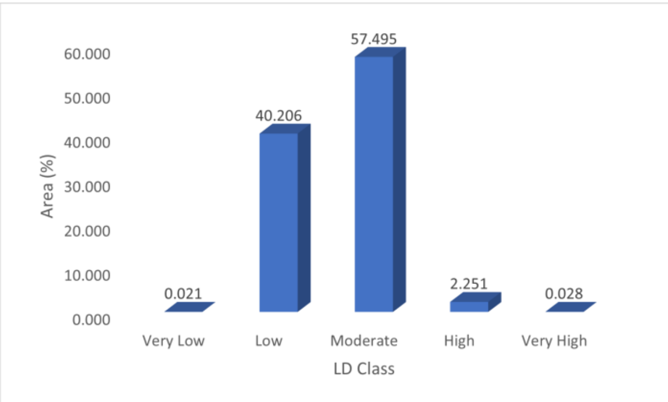

Figure 4-2 Degredaded Area (%)

Table 4-1 Municipality Level Land Degradation Area (%)

Class	Area%									
	Rup akot	**Halesituw achung**	**Dipr ung**	**Khote hang**	**Kepilash gadhi**	**Aaiseluk harka**	**Ra wa Bes i**	**Jantedh unga**	**Barahap okhari**	**Saa kela**
Very Low	0.012	0	0.05	0	0.054	0.032	0.0 1	0	0	0.1
Low	40.14	19.52	38.72	30.2	65.54	59.02	44. 71	34.64	39.23	50.5 6
Mode rate	57.66	74.13	59.37	68.46	33.63	40.2	54. 78	63.33	59.79	47.5 2
High	2.18	6.25	1.86	1.329	0.766	0.75	0.5	2.018	0.968	1.82
Very High	0	0.1	0	0	0	0	0	0.119	0.006	0
Total (High & Very High)	2.18	6.35	1.86	1.33	0.77	0.75	0.5	2.14	0.97	1.82

5. VALIDATION OF DEGRADED ZONES

To ensure the accuracy of our land degradation map, we used a validation methodology which involved selecting specific sites representing varying degrees of degradation—high, moderate, slight, and no degradation—based on the classification output from our model. (Tolche et al., 2021)(Mzuri et al., 2022) These sites were visually validated using high-resolution Google Earth images.

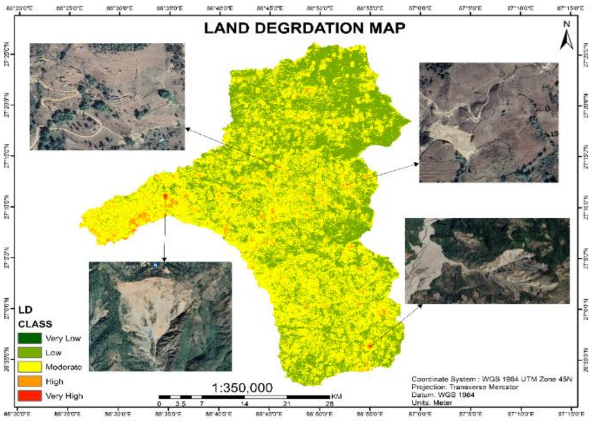

Figure 5-1 Validation of degraded classes

The selected LD classes when overlayed with the high-resolution Google Earth images of the year 2023 indicates that the degree of land degradation characteristics of Google Earth images of the selected areas is well in agreement with the results of AHP- and GIS-based model output of the study.

Purano Gaun of Halesi Tuwachung Municipality - 11, Rajapani of the district remained empty due to the water scarcity. As the water scarcity peaks, only four houses remained in the village out of a total of 55 households that were damaged and the remaining houses were also about to be damaged (Bhattarai, 2023). From this article also we can relate our research that, almost 6.35%of the total area of Khotang District named Halesi Tuwachung Municipality had been affected by land degradation for which the reasons might be the water scarcity and migration of the people from the place. This insight might be the reference for the validation of our research findings with ground reality.

Figure 5-2 Validation of Degredaded Areas

6. CONCLUSION AND RECOMMENDATION

In conclusion, the land degradation assessment in Khotang District, utilizing GIS- and AHP-based models, identified that 3554 hectares of the total study area fall into high and very high categories of land degradation (LD), while 89,698 hectares are in the moderate LD category. The study revealed that 57.49% of the area experiences moderate land degradation, followed by low degradation (40.20%), high degradation (2.25%), very high degradation (0.02%), and very low degradation (0.02%). The most severe degradation was concentrated in the western part of the district, while the northern part exhibited very low to low erosion. The analysis at the municipal level showed that Halesi Tuwachung Municipality had the highest percentage of degraded area at 6.35%, followed by Rupakot, Saakela, Jantedhunga, Diprung, and Khotehang. Conversely, municipalities such as Rawabesi, Kepilashgadhi, Aaiselukharka, and Barahapokhari showed lower extents of land degradation. A case study in Purano Gaun, Halesi Tuwachung Municipality - 11, Rajapani, highlighted the severe impact of land degradation, where only 4 out of 55 households remain due to water scarcity and drought conditions, directly linked to land degradation. The RUSLE model further emphasized that soil erosion is a significant problem in many parts of the study area. The validation of moderate, high, and very high LD classes using high-resolution Google Earth imagery confirmed the accuracy of the AHP-GIS model-based approach.

Overall, the findings suggest an urgent need for land conservation and management, particularly in the degraded parts of Khotang District. Collaborative efforts involving the government, non-governmental organizations, researchers, and local farmers are essential to address the ongoing challenges of land degradation and to ensure sustainable land use and management in the region.

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