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Remote Sensing-Based Framework For Ecological Assessment: A Case Study Of Mahi Bajaj Sagar Dam Catchment, Rajasthan, India

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Abstract
Ecological assessment is crucial for sustainable management of resources and human wellbeing. However, Assessing the ecological condition of a region is highly complex, as it is influenced by numerous factors and dynamic processes. In current study, a remote sensing based ecological framework is proposed to quantify the ecological status considering 10 indicators derived directly or indirectly from Landsat and SRTM DEM images, for Mahi Bajaj Sagar Dam catchment from year 2000 to 2020. These 10 indicators are selected as ecological indicators defining the landscape, habitant, topography and Hydrological condition of the ecology. The Mahi Bajaj Sagar Dam catchment is very important in providing the ecosystem services for human wellbeing in Banswara district of Rajasthan. Each indicator was evaluated, normalised and spatially mapped using analytical hierarchy process (AHP), Principal Component Analysis (PCA) and geographical information system (GIS). Using the proposed framework, ecological maps were prepared and presented in 5 levels consisting of very poor, poor, average, good and very good ecological status, representing 49.94%, 26.68%, 0.01%, 6.77 and 16.60% for year 2000 and 19.37%, 62.44%, 3.38%, 8.95% and 5.86% for year 2020, of the study area, respectively. It is identified that there is quantitively shift from very poor ecological areas to poor one from year 2000 to 2020 but 64.6% change in very good ecological conditions has been observed due to increase in anthropogenic activities. The proposed is feasible for evaluating long-term ecological change and quantification of ecological status. The proposed remote sensing based ecological framework integrates indicators using GIS, AHP and PCA for ecological monitoring and assessment is useful for ecosystem services, environmental protection and proper planning of available resources for future needs and provide the alarming locations for further developments.
Keywords: *indicator, PCA, AHP, GIS, ecological assessment*

1. INTRODUCTION

The rapid urbanization and industrialization have led to unmatched environmental degradation, threatening the foundation of ecological status and human well-being (2428; MEA, 2005). This environmental degradation resulting in reduced ecosystem services from the environment. Benefits obtained from ecosystem for human wellbeing are termed as ecosystem services (ES) (MEA, 2005). Monitoring and quantification of ecological status still a challenging area. Ecological status is crucial for understanding the relation between human encroachments and the ecosystem, and for framing effective policies for environmental sustainability (Liu et al., 2015). Ecological assessment helps in identifying the ecological status of any area in terms of indicators showing healthy or weak ecology, which are essential for policy makers and decision makers to frame policies for proper restoration of ecology and identify temporal change in ecology. (Singh et al,,2024; Wang et al., 2008; Tran et al., 2007; Adger, 2002, Nguyen et al., 2016).

Traditional field-based methods for ecological assessment have limitations of spatial coverage, temporal analysis, and cost-effectiveness (Turner et al., 2003). Remote sensing technologies serve as a powerful tool for collecting data on ecological parameters over large areas and long periods of time (Kerr & Ostrovsky, 2003; Pettorelli et al., 2014). Remote sensing-based ecological assessment involves the use of airborne or satellite images to evaluate the health and functioning of ecosystems, including vegetation cover, land use/land cover changes, and biodiversity (Skidmore et al., 2021). Recent studies have shown the application and effectiveness of remote sensing in monitoring ecological indicators such as vegetation productivity (Gao et al., 2020), water quality (Page et al., 2019), and ecological health (Singh et al., 2024).

Various researcher and authors have been developing indices or indicators like RSEI (Xu et al., 2019), RSBI (Singh et al., 2024), NDVI (Meneses-Tovar., 2011) and descriptive measures like vulnerability maps (Nguyen et al., 2016), landscape matrix based, benefit transfer based for ecological monitoring (Kuriqi et al., 2019; Trevisan et al., 2018; Moretti, 2007;Trevisan et al., 2016a ;Gustafsson and Parker, 1992). Still the precise and composite framework or index is missing to evaluate the ecological status considering the natural as well as man made factors. In current study ecological conditions like landscape, habitant, topographic and hydrological are considered and quantified using Landsat imageries and available digital elevation model.

Current study proposed a remote sensing-based ecological framework for ecological assessment for Mahi Bajaj Sagar Dam catchment located in Banswara district of Rajasthan, India. Ecological status has been monitored from year 2000 to 2020 to visualize the change over 2 decades. This study area is having a significant environmental concern due to its unique topography and climate. Singh et al., 2024 identified the 36.4% degradation in ecological status over the period of 2 decades based on RSBI index. To monitor and map the ecological status of the study area, an assessment framework consisting of 10 ecological indicators indicating Landscape, habitant, topographic and hydrological conditions is proposed. A variety of techniques are available to integrate the sub indicators into single indicator for quantifying the ecology. These techniques are ANN method, principal component analysis (PCA), analytical hierarchy process (AHP) and fuzzy analytic hierarchy process (FAHP)method (Park et al., 2004; Ying et al., 2007; Song et al., 2010; Li et al., 2009; Thanh and De Smedt, 2011). In current study AHP is partly used to integrate the sub indicators at initial stage i.e level 1 stage, later on PCA is used for ecological assessment at level 2 stage.

The proposed ecological assessment framework helps in identifying the ecological status and concern areas for decision makers and poly makers for restoration of ecology .This approach will give quick and precise status of ecology over a period to identify the change in ecological status also. So that decision-makers can obtain objective measurements and comparative context to support environmental decision-making and develop effective strategies for sustainable development in the Mahi Bajaj Sagar Dam catchment and this framework can be adopted for any type of areas.

2. MATERIAL AND METHODS

2.1. Study area

Mahi Bajaj Sagar Dam, located in Banswara district of Rajasthan, is one of the largest reservoirs in the country, serves as major source for water supply, electricity generation and irrigation. Constructed on the Mahi River, the reservoir has a significant impact on the surrounding ecosystem and supports the livelihoods. Despite its importance, the reservoir faces various challenges, including sedimentation, water quality degradation, and climate change impacts. The Mahi Bajaj Sagar Dam catchment spread over 6149 sq. km area. This study aims to investigate the ecological status of study area to better understand the dynamics of the catchment services and provide insights for decision makers for sustainable management.

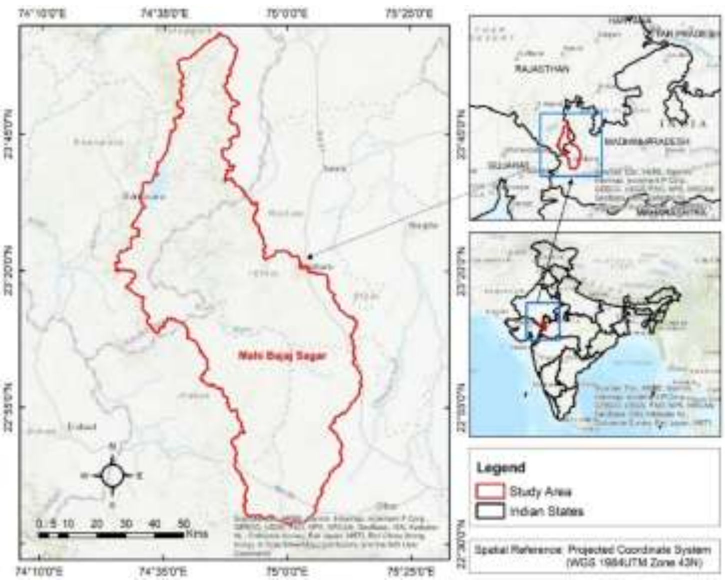

Figure 1: The map of India showing Mahi Bajaj Sagar Dam catchment

2.2. Materials

The primary and secondary/derived data used in study are shown in table 1.

Table 1: Details of primary and secondary data

Primary Data		
1.	Remotely sensed, October 2020 Landsat 8 OLI	U.S. Geological Survey (USGS).
2.	Remotely sensed, October 2020 Landsat 7 ETM+	
3.	SRTM Digital elevation model (DEM)	
Secondary Data		
1.	NDVI- Normalized Difference Vegetation Index	Landsat images
2.	LST- Land Surface Temperature	Landsat images
3.	NDBI- Normalized Difference Built-up Index	Landsat images
4.	NDMI- Normalized Difference Moisture Index	Landsat images
5.	LULC-Land Use Land Cover	Landsat images
7.	Slope	DEM
8.	Distance from Water Bodies	LULC and Arc GIS
9.	Distance from Built areas	LULC and Arc GIS
10.	Runoff coefficient	LULC based with Drainage guidelines

2.3. Methodology

The remote sensing based ecological assessment framework is shown in figure 2. Methodology deals with integration of multiple ecological indicators derived from both Landsat satellite data and Digital Elevation Model (DEM) sources. Key indicators from Landsat include LULC, NDVI, LST , distance from water bodies, distance from built-up areas, NDBI, NDMI, and runoff coefficient. From the DEM, slope and elevation data are incorporated. These parameters are systematically grouped into four major condition categories: landscape condition, habitant condition, hydrological condition, and topographic condition. The landscape condition is determined by land use/land cover and NDVI, while the habitant condition is influenced by LST, NDBI, proximity to water bodies, and built-up areas. Hydrological condition is evaluated using NDMI, and runoff coefficient, and topographic condition is assessed using slope and elevation. To ensure robust and comprehensive analysis, the indicators are first clubbed using the Analytic Hierarchy Process (AHP) at level 1 with internal weights as shown in table 2 maintaining consistency ration less than 5% to incorporate expert judgment and subjective weighting, and then further refined using Principal Component Analysis (PCA) at level 2 to objectively determine the ecological status. The combined results from these processes are then used to derive the overall ecological status, providing a scientifically sound and multi-dimensional evaluation of ecosystem health.

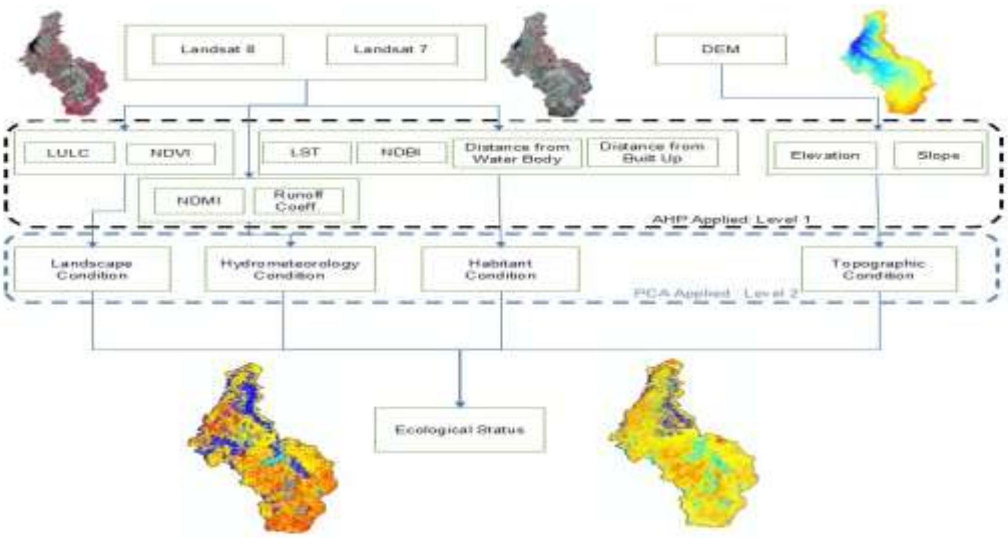

Figure 2: The proposed ecological assessment framework

Table 2: Inter weights of indicators at level 1 for AHP process with dependency of indicators on ecology

S.No.	Factors	Indicators	Weights	Dependency
1.	Landscape	LULC	0.667	Directly
		NDVI	0.333	Directly
2.	Habitant	LST	0.467	Indirectly
		NDBI	0.16	Indirectly
		Distance from water Body	0.095	Indirectly
		Distance from Built up	0.277	Directly
3.	Hydrological	NDMI	0.5	Directly
		Runoff Coefficient	0.5	Indirectly
4.	Topography	Elevation	0.6	Indirectly
		Slope	0.4	Indirectly

Landscape condition

Landscape plays a dominating role in safeguarding and protecting various diversities, human well being and improving the ecological quality. Natural pervious land cover act as very good ecological indicator showing healthy ecosystem as compared to impervious land covers for ecological assessment. Impervious land cover such as built up, rocky lands increases surface runoff resulting in sedimentation, change in instream flow patterns and increase in temperatures. Many researchers identifies that lower portion of impervious land cover significantly affect ecological health (Wang and Yin, 1997; King et al., 2011). Two ecological indicators were selected to quantify the landscape condition i.e LULC and NDVI.

Habitant Conditions

The ecological status of habitats depends on the surrounding landscape and temperature. The potential for various living beings to migrate in catchments for search of water and peace i.e. away from built up areas serve as an indicator of the habitat condition. Four ecological indicators were selected to quantify the habitant condition i.e LST, NDBI, Distance from water bodies and distance from built area.

Hydrological Conditions

Hydrology deals with relationship between atmosphere and hydrological processes. Impact of hydrology on ecology is very vast, but in current study, NDMI and runoff potential based on LULC is used as hydrological indicator to to quantify the hydrological conditions.

Topographic Conditions

To assess the topographical characteristics of the area, both terrain elevation and slope angle were integrated using the Analytic Hierarchy Process (AHP). Slope angle serves as a reliable indicator for factors such as soil erosion, flooding risk, inundation, and construction management. Changes in elevation can greatly influence processes like evapotranspiration, transportation, soil properties, regional climate, and other factors that may contribute to environmental vulnerability.

3. RESULTS AND DISCUSSION

Based on the framework shown in methodology landscape condition, habitant condition, hydrological condition, and topographic condition were identified using AHP at level 1 stage and finally integrated using PCA to monitor ecological status at level 2 stage. Before using the indicators, all the indicators are normalized from 0 to 1 showing the value 0 for poor ecological status and value 1 for good ecological status based on criteria discussed in Table 6 of appendix section.

3.1. Landscape condition

The ecological assessment of landscape condition between the years 2000 and 2020 reveals notable shifts across all condition classes. In 2000, 25.99% of the landscape was categorized as "Very Poor," but this decreased significantly to 13.83% by 2020. Conversely, the proportion of the landscape in "Poor" condition rose sharply from 49.64% in 2000 to 68.10% in 2020, indicating a general decline in landscape quality. The "Average" condition class saw a modest increase, moving from 1.00% in 2000 to 3.25% in 2020. Areas classified as "Good" also increased, rising from 6.77% to 8.95% over the two decades. However, the percentage of landscape in "Very Good" condition dropped substantially, from 16.60% in 2000 to just 5.86% in 2020. These changes suggest that while there has been some improvement in the most degraded areas, there has been an overall shift toward poorer landscape conditions, with a marked reduction in the extent of high-quality landscapes

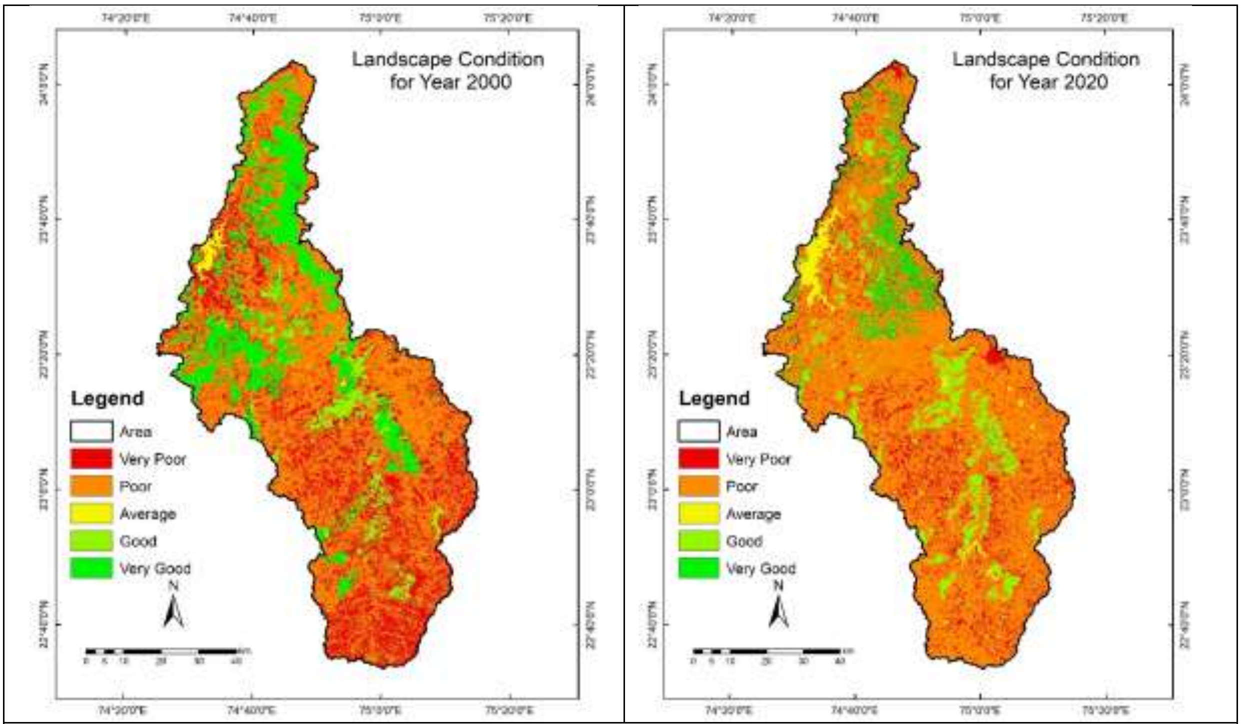

Figure 3: Landscape conditons of study area for the year 2000 and 2020

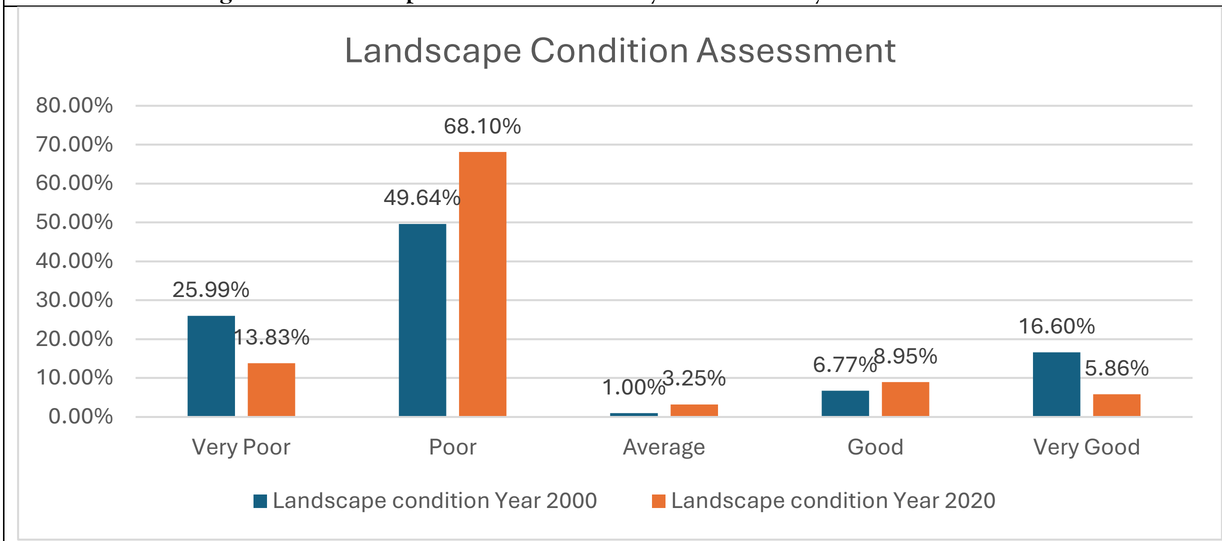

Figure 4: Comparative analysis of ecological status for landscape condition from year 2000 to 2020

3.2. Habitant Conditions

Analysis of the habitat condition data over two decades reveals a notable shift toward improved ecological status in the study area. In 2000, 11.87% of the area was classified as "Poor," 85.76% as "Average," and 2.36% as "Good," with no areas in either the "Very Poor" or "Very Good" categories. By 2020, the proportion of "Poor" habitat decreased to 5.28%, while "Average" condition increased substantially to 92.31%, and "Good" remained nearly unchanged at 2.41%; "Very Poor" and "Very Good" categories continued to be absent1. The reduction in "Poor" areas and the increase in "Average" habitat suggest a general improvement in ecological conditions, likely due to better land management, conservation efforts, or natural regeneration processes. The stability in the "Good" category and continued absence of extreme classes indicate that while severe degradation has been avoided and moderate recovery achieved, significant gains toward high-quality habitats have yet to occur.

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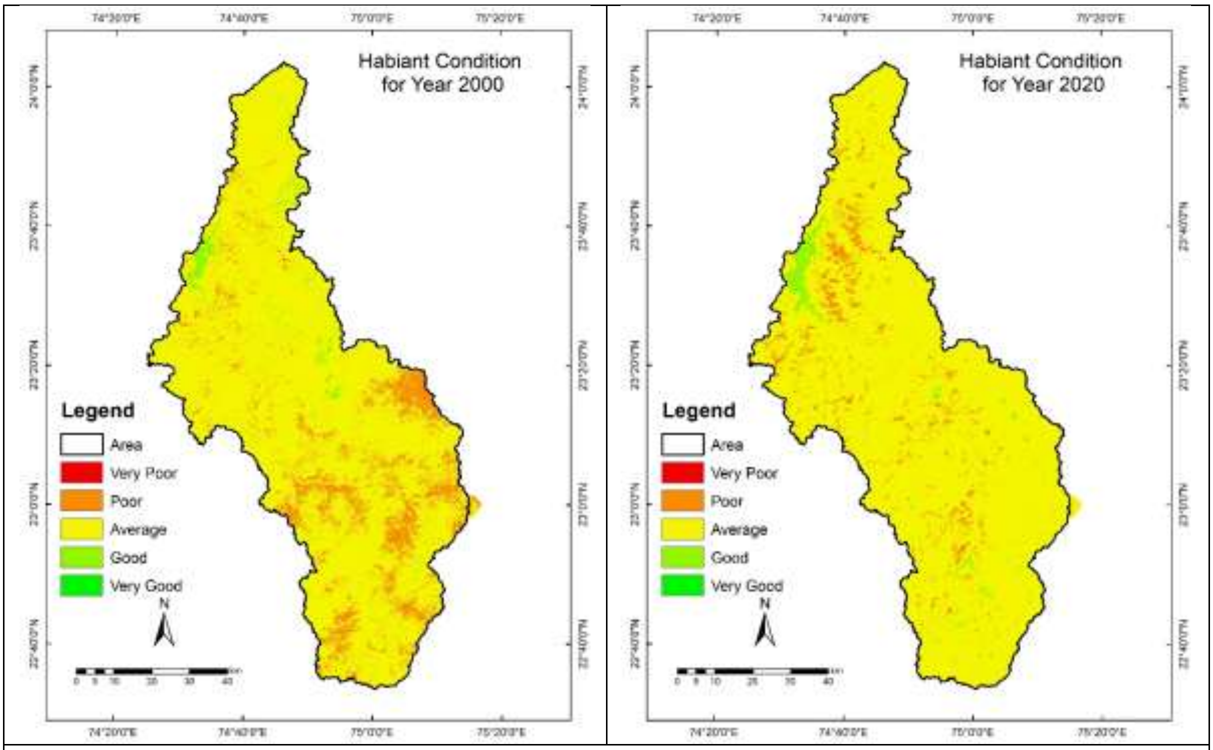

Figure 5: Habitant conditons of study area for the year 2000 and 2020

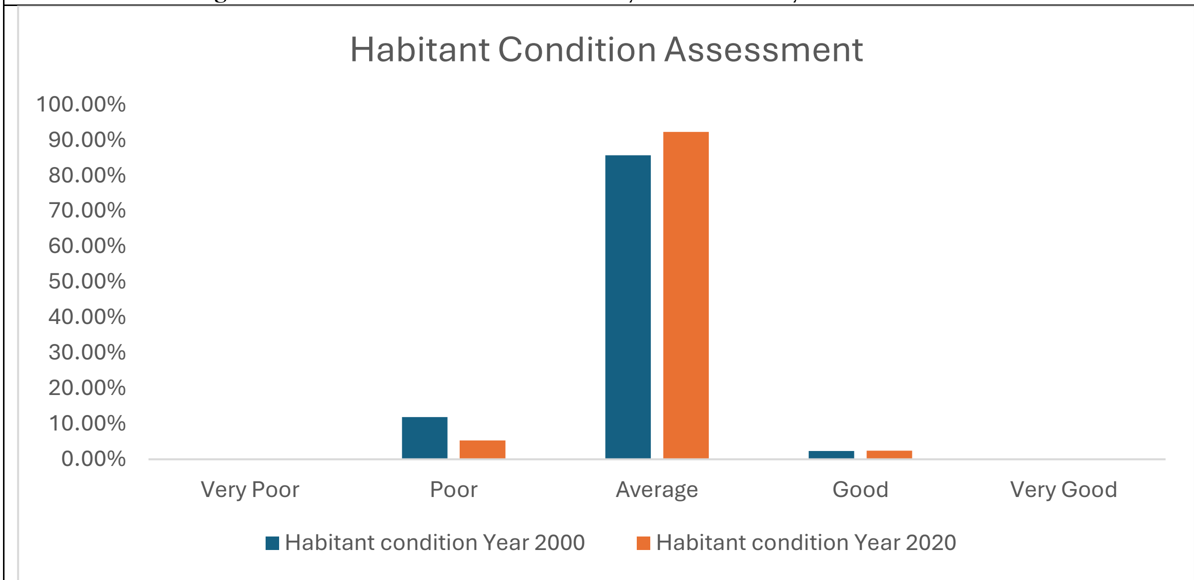

Figure 6: Comparative analysis of ecological status for habitant condition from year 2000 to 2020

3.3. Hydrological Condition

The hydrological assessment of the Mahi Bajaj Sagar catchment, based on the ecological condition classes from 2000 to 2020, reveals several notable trends. In 2000, the majority of the catchment (49.34%) was in "Average" hydrological condition, with 24.24% classified as "Good" and 25.43% as "Poor." Only 0.99% of the area was in "Very Poor" condition, and there were no areas rated as "Very Good."

By 2020, the proportion of the catchment in "Average" condition remained almost unchanged at 48.93%. However, the area in "Good" condition increased significantly to 36.81%, indicating improvement in hydrological health in a substantial portion of the catchment. The percentage of the landscape in "Poor" condition decreased markedly to 11.11%, suggesting successful mitigation of some hydrological stressors. Conversely, the "Very Poor" category increased to 3.15%, indicating localized areas of worsening hydrological condition. The "Very Good" class remained absent in both years.

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Overall, the hydrological assessment indicates a positive shift, with a decrease in "Poor" areas and an increase in "Good" condition, although some areas have deteriorated to "Very Poor." The persistence of a large proportion of the area in "Average" condition suggests ongoing challenges, but the overall trend points toward gradual improvement in hydrological health within the Mahi Bajaj Sagar catchment.

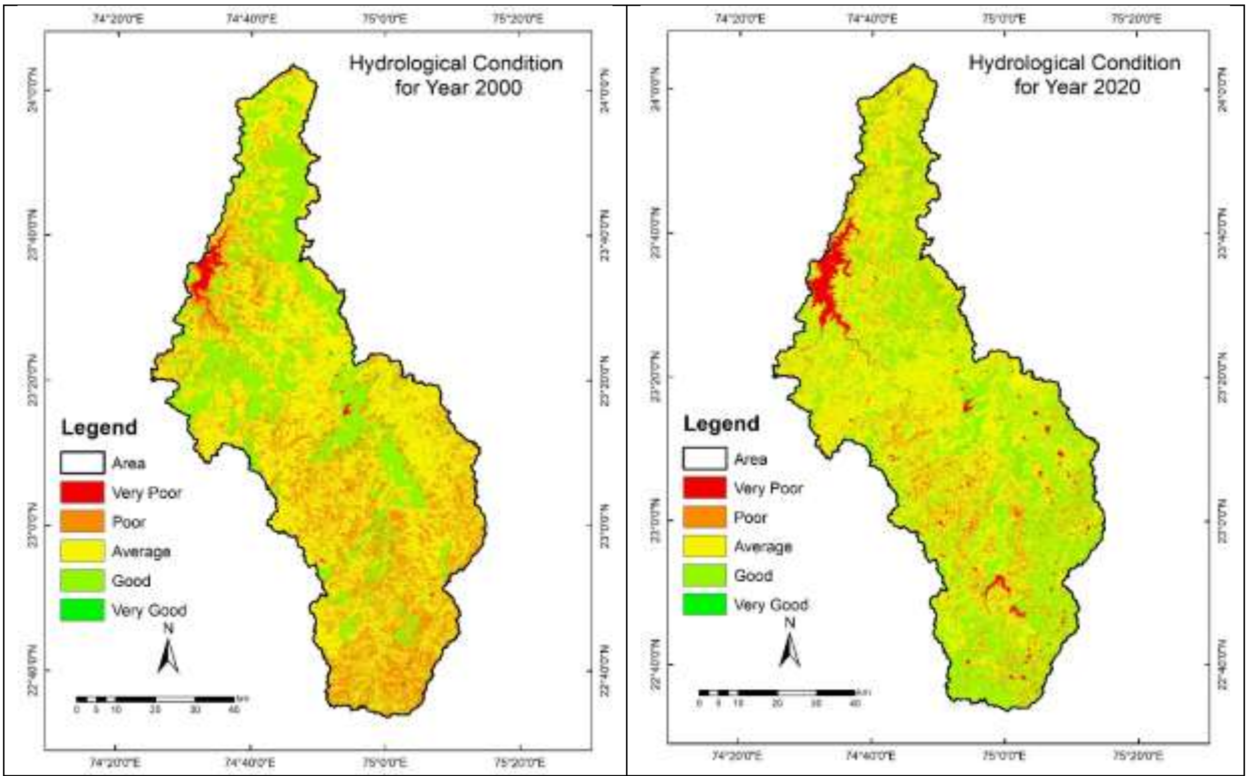

Figure 7: Hydrological conditons of study area for the year 2000 and 2020

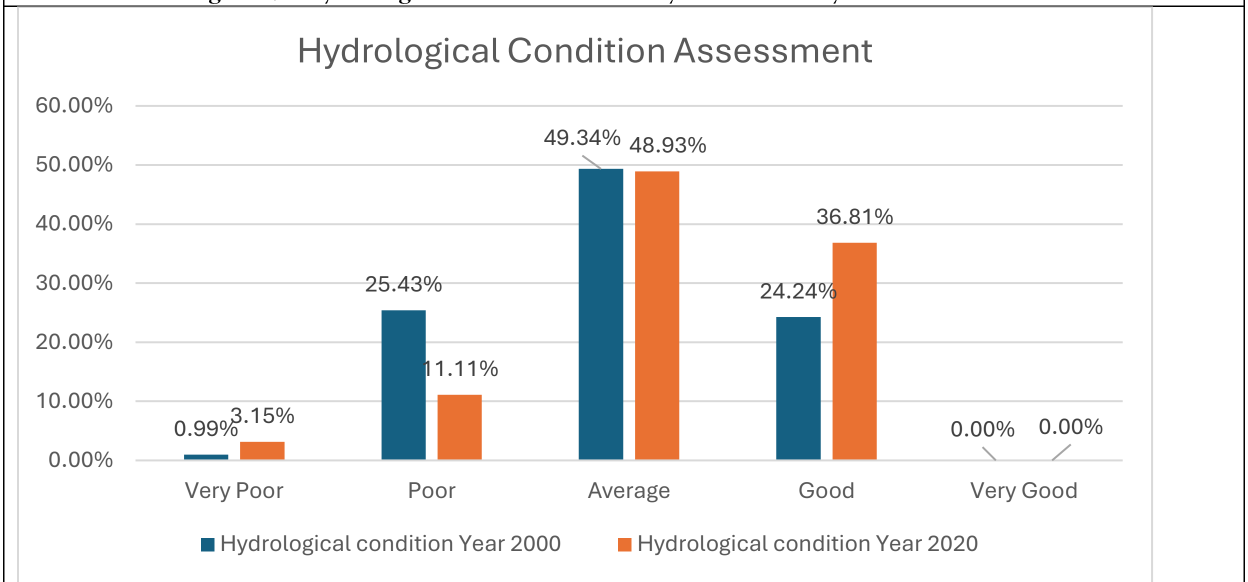

Figure 8: Comparative analysis of ecological status for hydrological condition from year 2000 to 2020

3.4. Topography

The topographic condition assessment of the Mahi Bajaj Sagar catchment indicates a predominantly favorable landscape profile. According to the data, the majority of the catchment area falls under "Good" topographic condition, covering 54.73% of the region. "Average" conditions account for 35.05%, while "Very Good" conditions constitute 9.88%. Only a small fraction of the area is classified as "Poor" (0.32%) or "Very Poor" (0.01%). This distribution suggests that the catchment is largely characterized by stable and suitable topographic features, which are likely to support effective water movement, soil stability, and overall ecological health. The minimal extent of "Poor" and "Very Poor" areas indicates limited topographic constraints, reducing risks such as erosion or waterlogging and favoring both ecological processes and land management within the catchment.

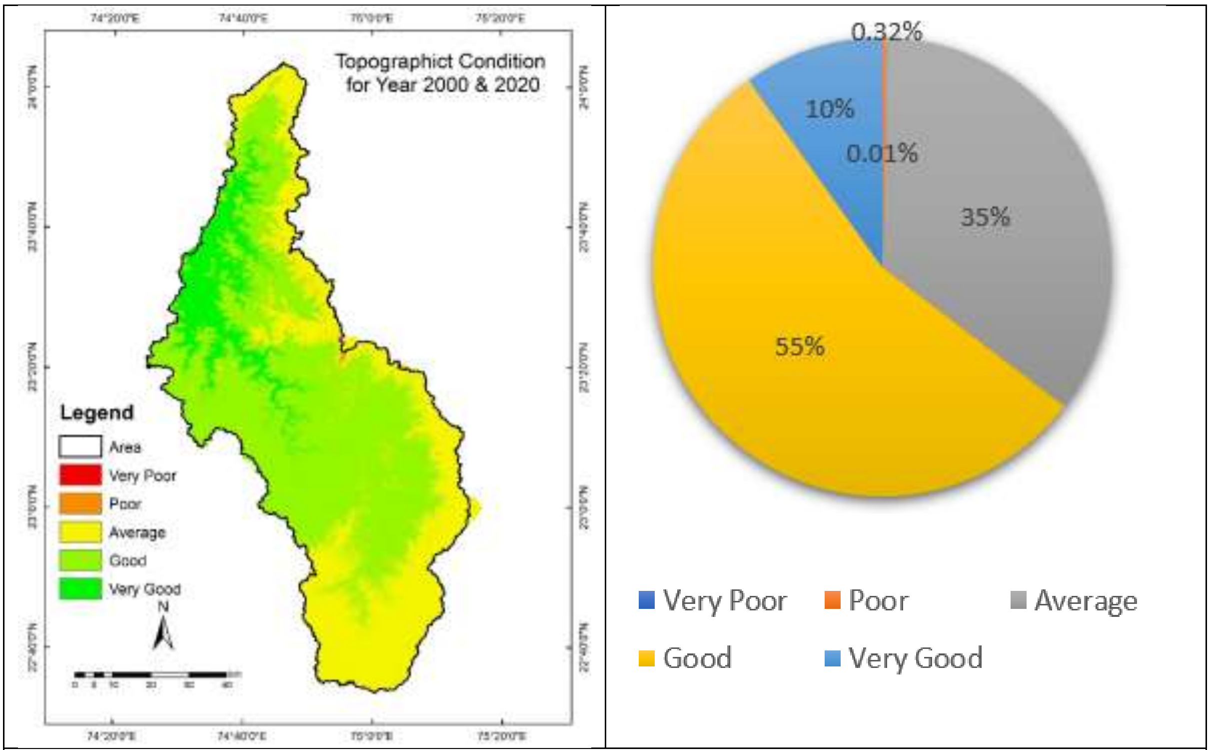

Figure 9: Topographic condition of study area with percentage assessment

Table 3: Ecological status of each indicator for two decades after AHP integration

	Landscape condition		Habitant condition		Hydrological condition		Topographic Conditions
Class/LULC	2000	2020	2000	2020	2000	2020	
Very Poor	25.99%	13.83%	0.00%	0.00%	0.99%	3.15%	0.01%
Poor	49.64%	68.10%	11.87%	5.28%	25.43%	11.11%	0.32%
Average	1.00%	3.25%	85.76%	92.31%	49.34%	48.93%	35.05%
Good	6.77%	8.95%	2.36%	2.41%	24.24%	36.81%	54.73%
Very Good	16.60%	5.86%	0.00%	0.00%	0.00%	0.00%	9.88%

The correlation matrix of indicators extracted from Landsat data reveals several important relationships among LST, NDBI, NDVI, and NDMI. LST shows a high positive correlation with NDBI (0.63), indicating that areas with more built-up surfaces tend to have higher temperatures. This is likely due to property of built up areas having concrete and asphalt structures, retains more heat than natural surfaces. LST is negatively correlated with both NDVI (-0.33) and NDMI (-0.59), which means that areas with more vegetation and higher moisture content are generally cooler; this can be attributed to the cooling effect of vegetation through shading and evapotranspiration, as well as the moderating influence of moisture. NDBI has a very high negative correlation with NDVI (-0.86) and an even stronger negative correlation with NDMI (-0.94), reflecting that urbanized, built-up areas typically replace vegetated and moist surfaces, leading to drier and less green landscapes. The strong positive correlation between NDVI and NDMI (0.81) indicates that areas with more vegetation also tend to have higher moisture content, which is expected since healthy vegetation is often associated with better soil and surface moisture. These observed correlations are consistent with established urban ecological processes, where urbanization leads to a loss of vegetation and moisture, resulting in increased surface temperatures and altered local microclimates.

Table 4: Correlation of remote sensing based indicators for ecological assessment

	NDBI	NDMI	NDVI	LST
NDBI	1			
NDMI	-0.94	1		
NDVI	-0.86	0.81	1	
LST	0.63	-0.59	-0.33	1

3.5. Ecological Assessment

The ecological assessment using Principal Component Analysis (PCA) for the years 2000 and 2020 integrates landscape, habitat, hydrological, and topographic conditions to provide a comprehensive view of ecosystem status in the study area. The first principal component (PC1) accounts for 58.25% of the total variance, indicating that the majority of ecological variability across these four dimensions is effectively captured by this single axis dominated by landscape and hydrological conditions, which represents a robust summary of overall ecological condition.

In 2000, the assessment shows that nearly half of the area (49.94%) was in "Very Poor" ecological status, with 26.68% classified as "Poor," 6.77% as "Good," and 16.60% as "Very Good." There were no areas in the "Average" category. By 2020, there is a marked shift: the "Very Poor" class drops significantly to 19.37%, while the "Poor" category rises sharply to 62.44%. The "Average" condition appears for the first time at 3.38%, and "Good" and "Very Good" categories decrease to 8.95% and 5.86%, respectively.

This pattern suggests a substantial reduction in the most severely degraded areas, but also a pronounced expansion of areas with suboptimal ecological status ("Poor"). The decrease in "Very Good" and "Good" areas indicates that, while extreme degradation has lessened, high-quality habitats have also diminished over time. These trends may be attributed to factors such as intensified land use, ongoing anthropogenic pressures, partial ecological restoration, and shifts in water and habitat management practices. The emergence of the "Average" category in 2020 reflects some improvement and stabilization, likely due to targeted interventions or natural recovery processes, but the overall ecological quality remains a concern, with the majority of the area still falling into the "Poor" class.

In summary, PCA proves to be a powerful tool for integrating diverse ecological indicators and tracking changes over time, providing actionable insights for ecosystem management and highlighting the need for continued restoration and protection efforts to improve ecological status across the landscape.

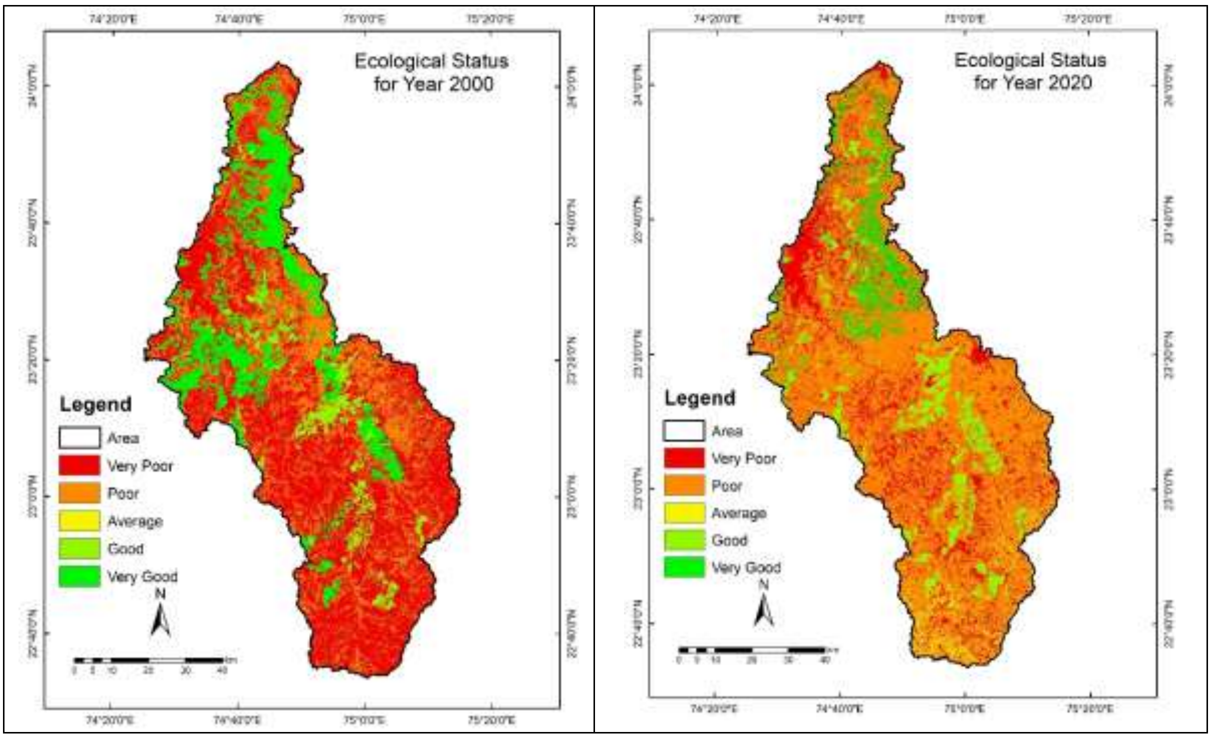

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Figure 10: Ecological status of study area from year 2000 to 2020

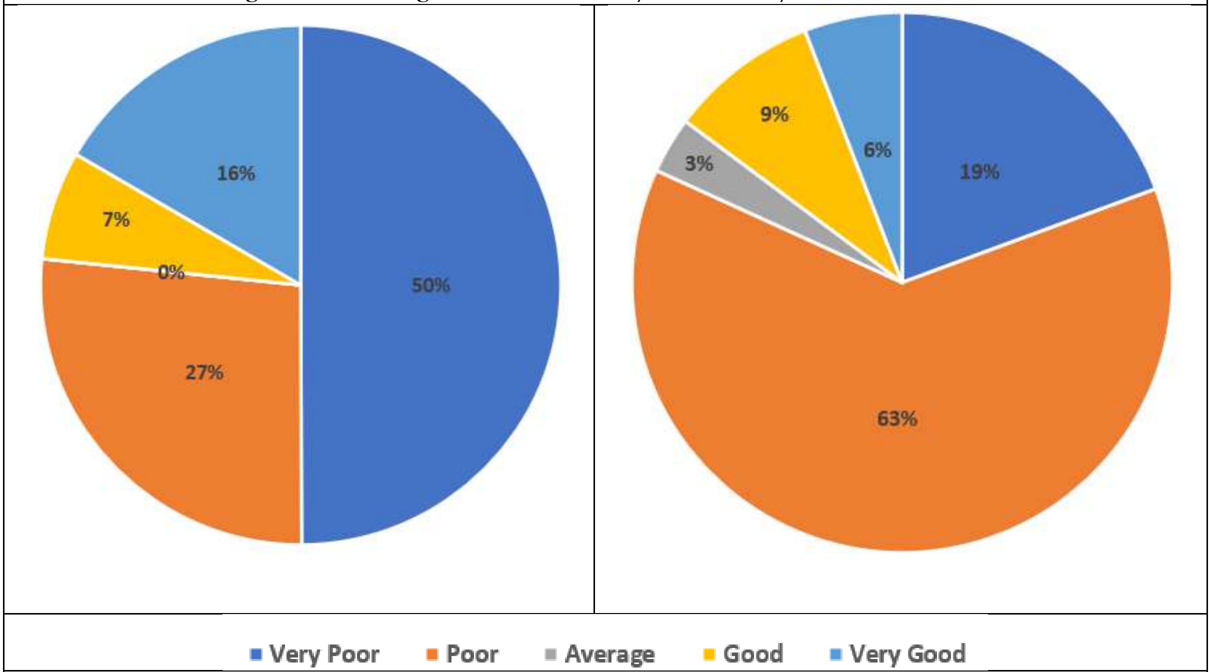

Figure 11: Comparative analysis of ecological status from year 2000 to 2020

4. CONCLUSION

The ecological assessment of the study area from year 2000 to year 2020, considering landscape condition, habitat condition, hydrological condition, and topographic condition, demonstrates that Principal Component Analysis (PCA) is an effective and robust tool for integrated ecological evaluation. The PCA method efficiently synthesizes multiple ecological indicators into composite indices, capturing the complex interactions and overall trends in ecosystem health over time. The data reveal notable shifts in condition classes: for example, the landscape condition shows a decrease in "Very Poor" areas from 25.99% to 13.83%, while "Poor" areas increase, indicating changes in degradation and recovery patterns. Habitat condition remains largely stable in "Average" and "Poor" classes, with slight improvements in "Good" condition. Hydrological condition improves with a rise in "Good" condition from 24.24% to 36.81%, and topographic condition is predominantly stable, with over half the area in "Good" condition.

Importantly, the ecological status derived from these multiple dimensions reflects these shifts, with the "Very Poor" ecological status decreasing from 49.94% to 19.37%, and the "Poor" status increasing to 62.44%, highlighting ongoing ecological pressures despite some improvements. This integrated ecological status metric, which PCA helps to derive, provides a clear, quantitative summary of ecosystem health that can guide management and restoration efforts.

Overall, the proposed remote sensing-based method by incorporating GIS, AHP and PCA proves to be a valuable approach for ecological assessment in the catchment because it consolidates diverse environmental variables into meaningful components, enabling clear detection of spatial and temporal trends. The use of ecological status as a synthesized indicator further supports targeted decision-making by highlighting areas of concern and improvement. This comprehensive assessment underscores the dynamic nature of the catchment's ecology and the importance of continuous monitoring using advanced multivariate techniques like PCA to inform sustainable ecosystem management.

Appendix

A-1. Preparation of LULC

A supervised classification methodology incorporating the maximum likelihood classifier algorithm was employed to analyse multi-spectral satellite data spanning 2000–2020, enabling the identification of land use and land cover (LULC) patterns. Six primary LULC categories—forest, water bodies, agricultural land, shrubland, urban settlements, and barren/rocky terrain—were delineated across the study region. The spatiotemporal

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changes in these categories over the 20-year period are visualized in Figure 12 and quantitatively detailed in Table 5.

To assess classification precision, 500 randomly sampled points were cross-verified against high-resolution Google Earth datasets. The analysis yielded overall accuracies of 82% (2000) and 88% (2020), with supporting Kappa coefficients demonstrating strong agreement between classification outputs and ground-truth references. These metrics underscore the methodological consistency and validity of the LULC mapping process.

Table 5: Details of Land use land cover in the study area for the year 2000 and 2020

S.No.	Class	Year	
		2000	2020
1.	Forest	16.60%	5.86%
2.	Rocky Terrain	25.43%	11.17%
3.	Crop Land	49.64%	68.14%
4.	Shrubs	6.77%	8.95%
5.	Water	1.00%	3.15%
6.	Built Up	0.56%	2.73%

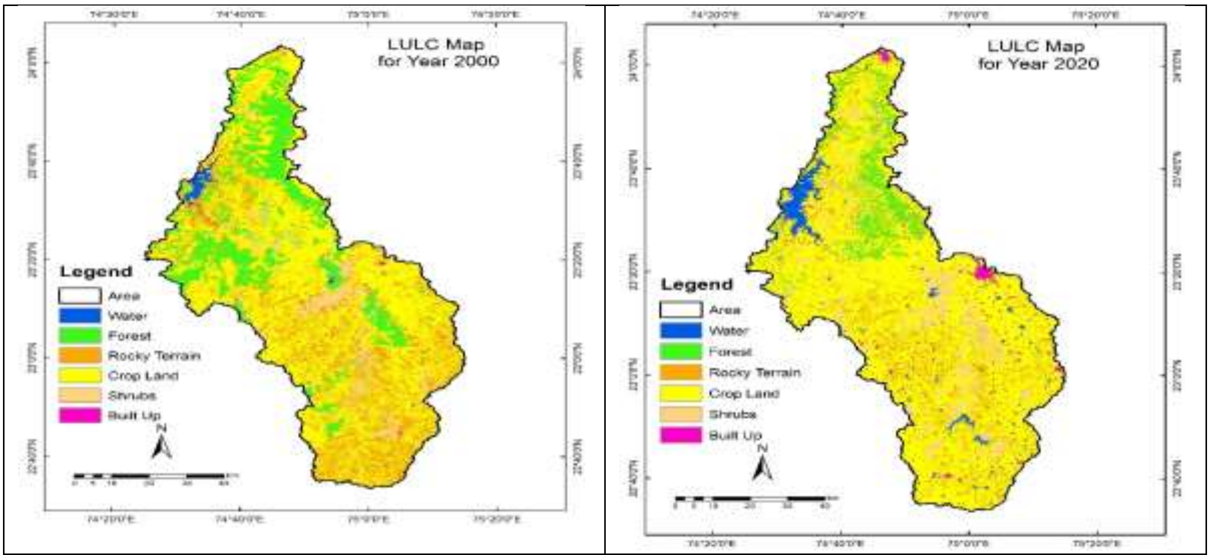

Figure 12: Land use land cover map of study area for the year 2000 and 2020.

For ecological assessment, LULC classes are given weightage according ecosystem services. Based on LULC based ecosystem services as suggested by Costanza et al., 1997, weightage of each class is assigned as shown in table 6.

A-2 NDBI-Normalized Difference Build-Up Index

The NDBI is a popular remote sensing tool for detecting and mapping urban and built-up areas. It is calculated using the following equation (Zha et al., 2003):

$$NDBI=(SWIR2-NIR)/(SWIR2+NIR)$$

In this formula, SWIR2 represents the shortwave infrared band, and NIR stands for the near-infrared band. Built-up regions typically yield positive NDBI values, indicating the presence of buildings and urban infrastructure, while negative values are usually associated with non-urban features such as vegetation or water bodies. This index is widely utilized for identifying human settlements and mapping urban development. Table 6 shows the range of NDBI and its normalised values for ecological assessment.

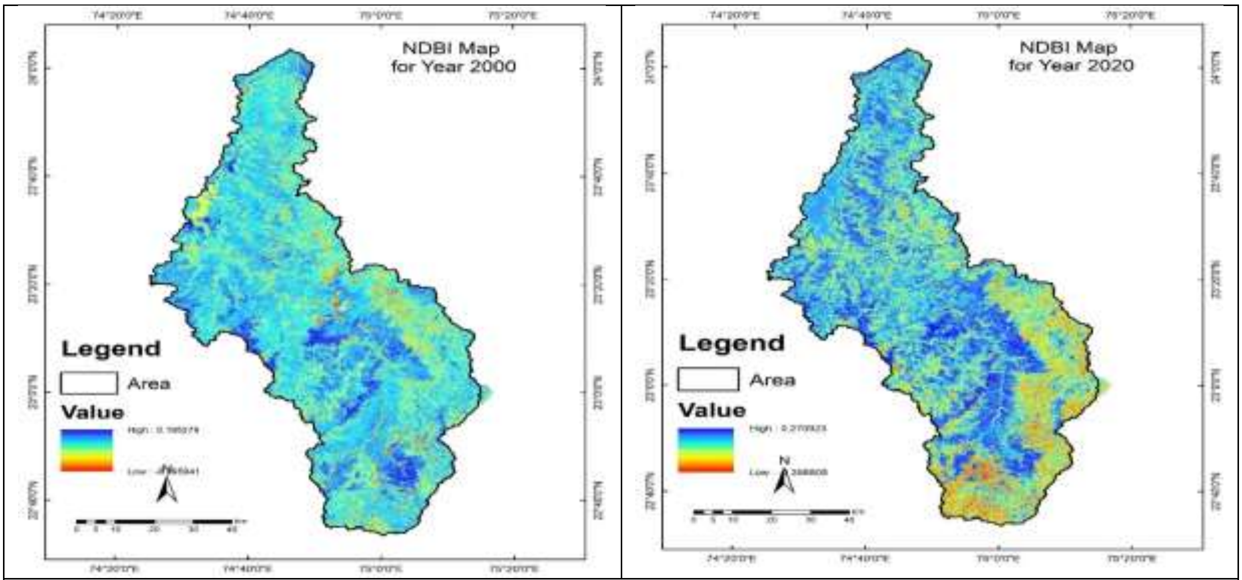

Figure 13: NDBI map of study area for the year 2000 and 2020

A-3 NDMI-Normalized Difference Moisture Index

The Normalized Difference Moisture Index (NDMI) is designed to assess variations in moisture content across different landscape features, particularly focusing on soils, rocks, and vegetation. NDMI is calculated using the following formula:

$$NDMI=(NIR-SWIR)/(NIR+SWIR)$$

where NIR stands for near-infrared and SWIR for short-wave infrared reflectance. NDMI values typically range from -1 to +1. Higher NDMI values (above 0.1) indicate areas with greater moisture content, while values approaching -1 signify low moisture levels. This index is widely used for monitoring vegetation water status, detecting drought conditions, and evaluating overall landscape moisture. Table 6 shows the range of NDMI and its normalised values for ecological assessment.

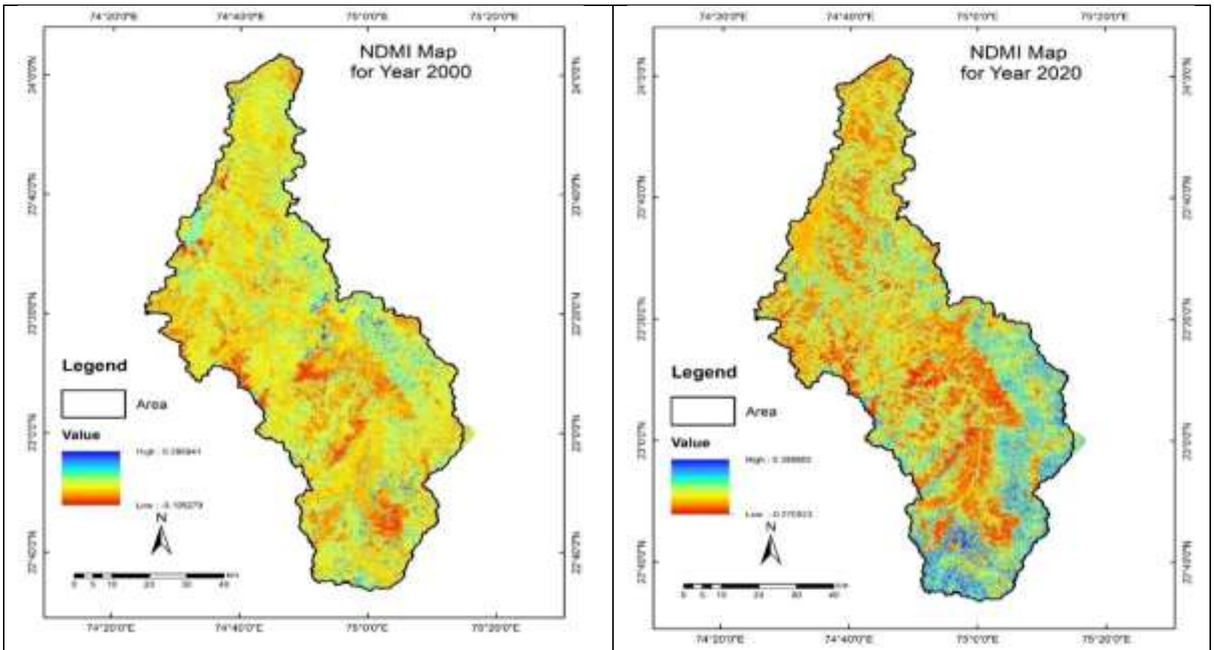

Figure 14: NDMI map of study area for the year 2000 and 2020

A-4 NDVI-Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is a widely used indicator for assessing the presence and health of vegetation using remote sensing data. NDVI is calculated with the formula:

$$NDVI=(NIR-RED)/(NIR+RED)$$

where NIR represents the reflectance in the near-infrared band and RED is the reflectance in the red band. NDVI values range from -1 to +1. Negative values typically indicate water or non-vegetated surfaces, values near zero correspond to bare soil or sparsely vegetated areas such as grasslands, and values approaching +1 signify dense, healthy vegetation. This index is a reliable tool for monitoring vegetation cover and evaluating plant vigor across various landscapes. Table 6 shows the range of NDMI and its normalised values for ecological assessment.

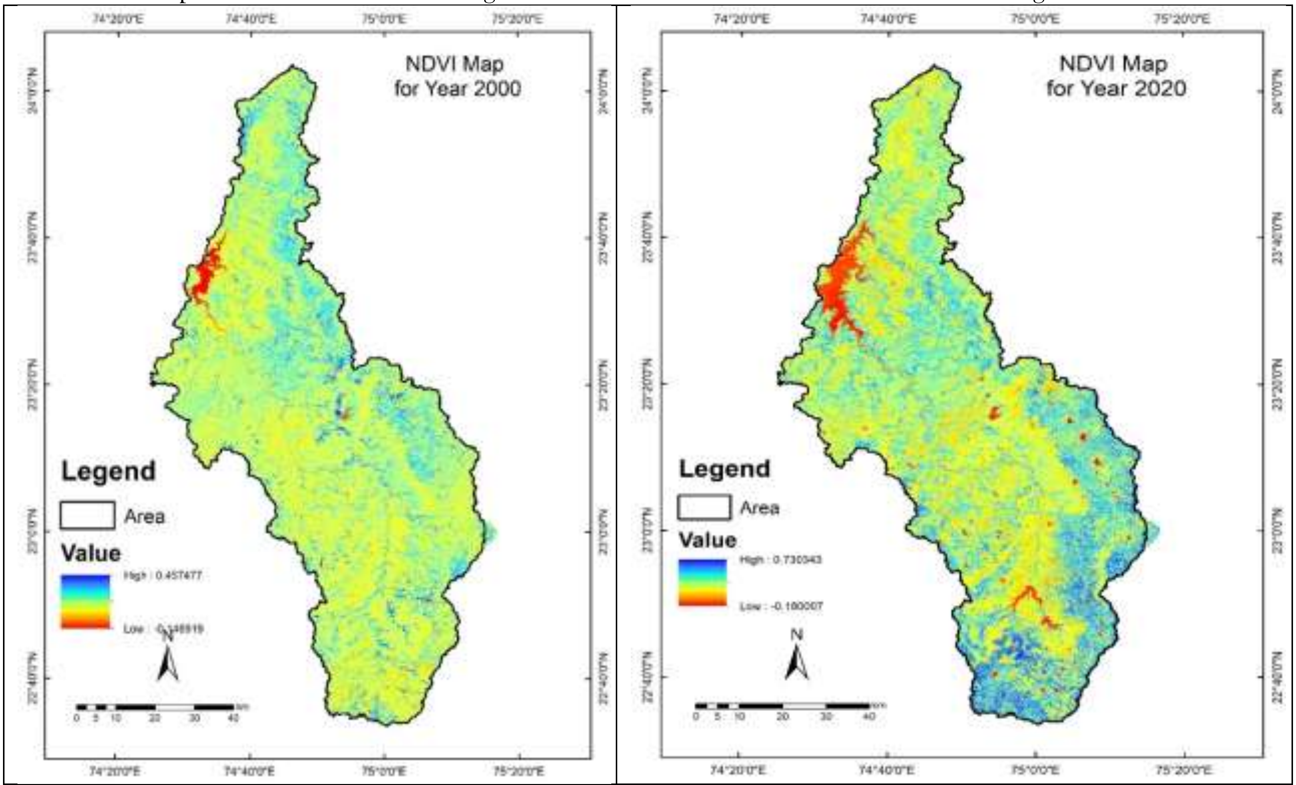

Figure 15: NDVI map of study area for the year 2000 and 2020

A-5 LST- Land Surface Temperature

Land Surface Temperature (LST) is an important environmental metric used to evaluate heat levels on the Earth's surface. It captures the dynamic relationship among land, water, and atmospheric elements, and fluctuations in LST over time can indicate shifts in these interactions. Remote sensing—especially using thermal infrared data from satellites—has become a standard approach for measuring LST, making it possible to observe temperature patterns over vast and varied landscapes.

The estimation of LST often employs the Single Channel (SC) algorithm, which relies on thermal bands captured in satellite images. This method generally involves transforming thermal band readings into radiance values and then computing the brightness temperature. The entire process can be efficiently executed with Python programming or Geographic Information System (GIS) tools, providing a streamlined and repeatable way to derive LST from satellite data. Table 6 presents the observed LST values along with their normalized counterparts, which are useful for ecological evaluations.

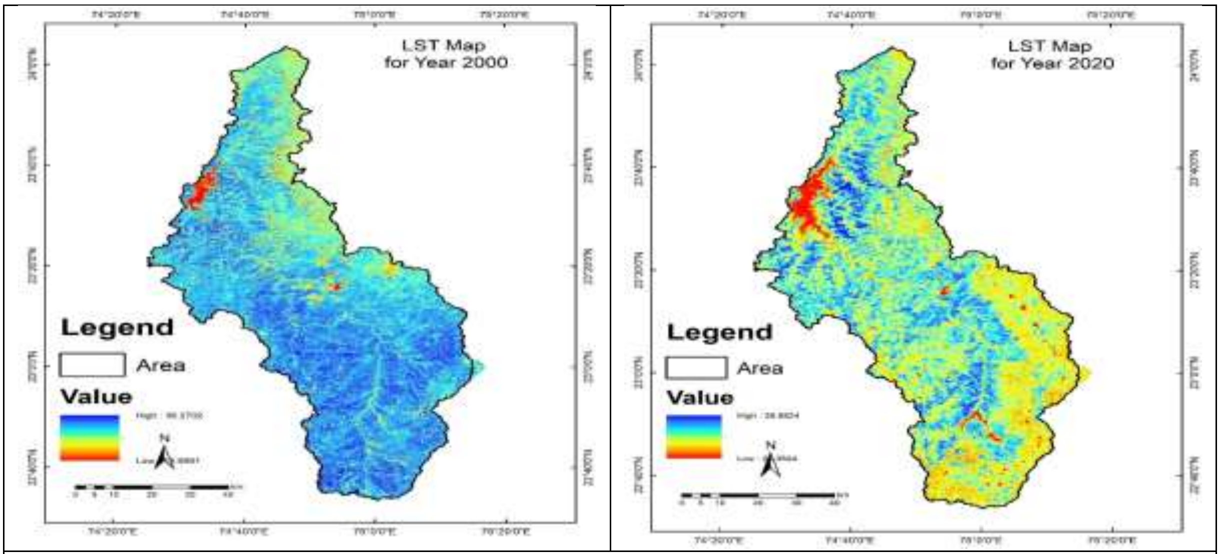

Figure 16: LST map of study area for the year 2000 and 2020

A-6 Distance from residential areas

This indicator reflects the extent of human development and urbanization patterns. Typically, residential zones can contribute to various forms of pollution, including household waste disposal and emissions from vehicle traffic. To assess this factor, buffer zones were established around residential areas and then using GIS interface distance of each pixel from residential areas is calculated on a grod of 30 x 30 m. Table 6 displays the range for this indicator along with its normalized values, which are used for ecological analysis.

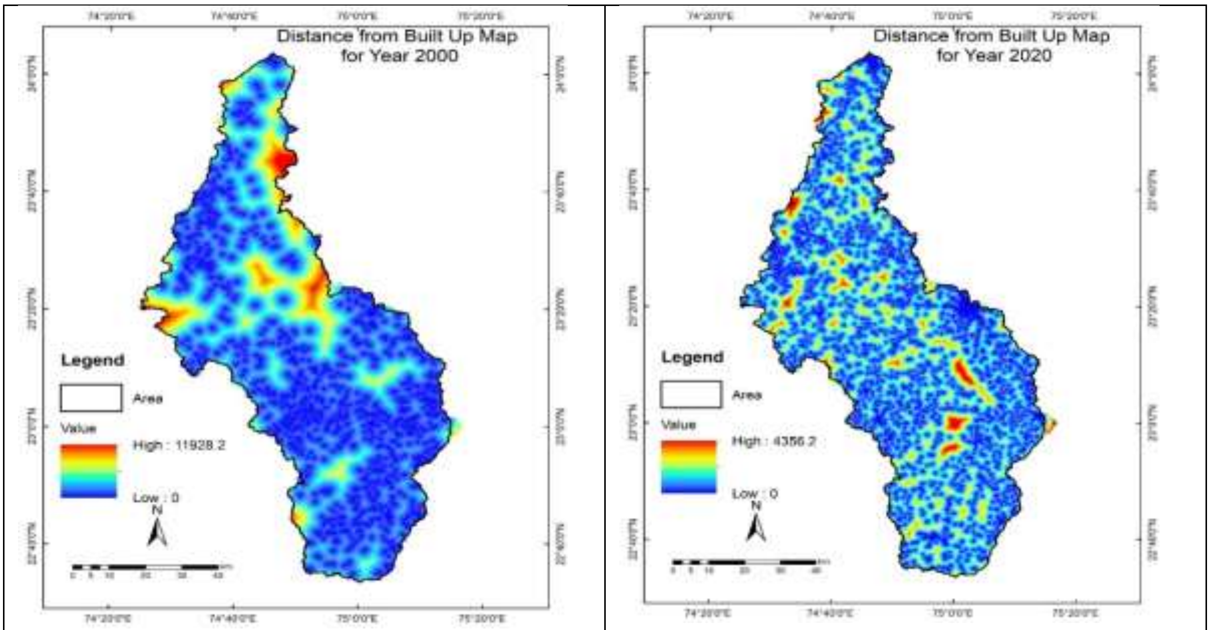

Figure 17:Distance from built up area map of study area for the year 2000 and 2020

A-7 DEM

A Digital Elevation Model (DEM) with a spatial resolution of 30 meters was employed in this study. The range of values for this indicator, as well as their normalized equivalents for ecological assessment, are presented in Table 6

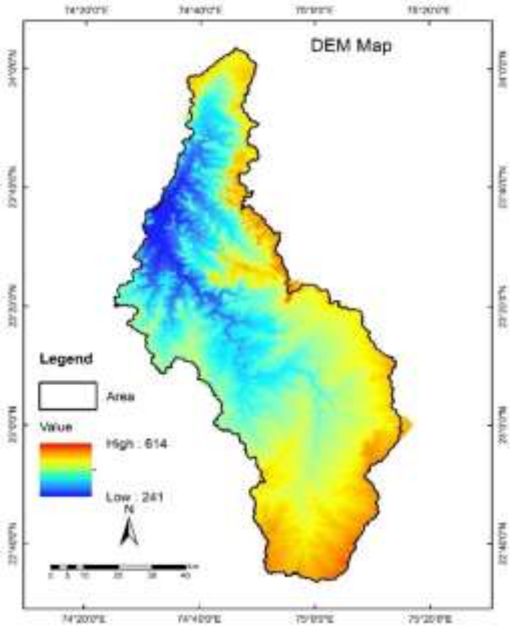

Figure 18: DEM map of study area

A-8 Slope angle

Slope angle is a fundamental parameter in assessing ecological status, as it influences the region's climatic conditions. In this study, slope angles were derived from the Digital Elevation Model (DEM), with values ranging from 0° to 52.17°. Table 6 provides both the range of slope angle values and their normalized forms, which are used for ecological evaluation.

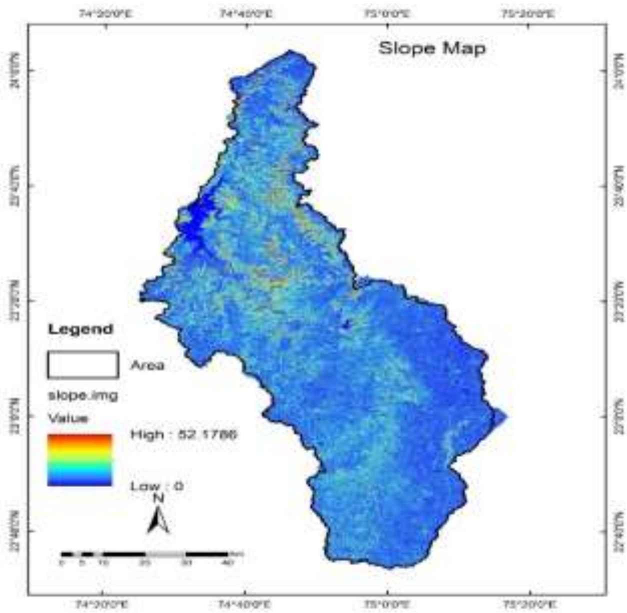

Figure 19: Slope map of study area created from DEM

A-9 Distances from hydrological network

This metric highlights regions with limited access to surface water, which are often linked to heightened ecological vulnerability. Dry areas are particularly prone to challenges such as desertification, landfill expansion, and wildfires. Table 6 outlines the range of distances from hydrological networks and their normalized values for ecological evaluation.

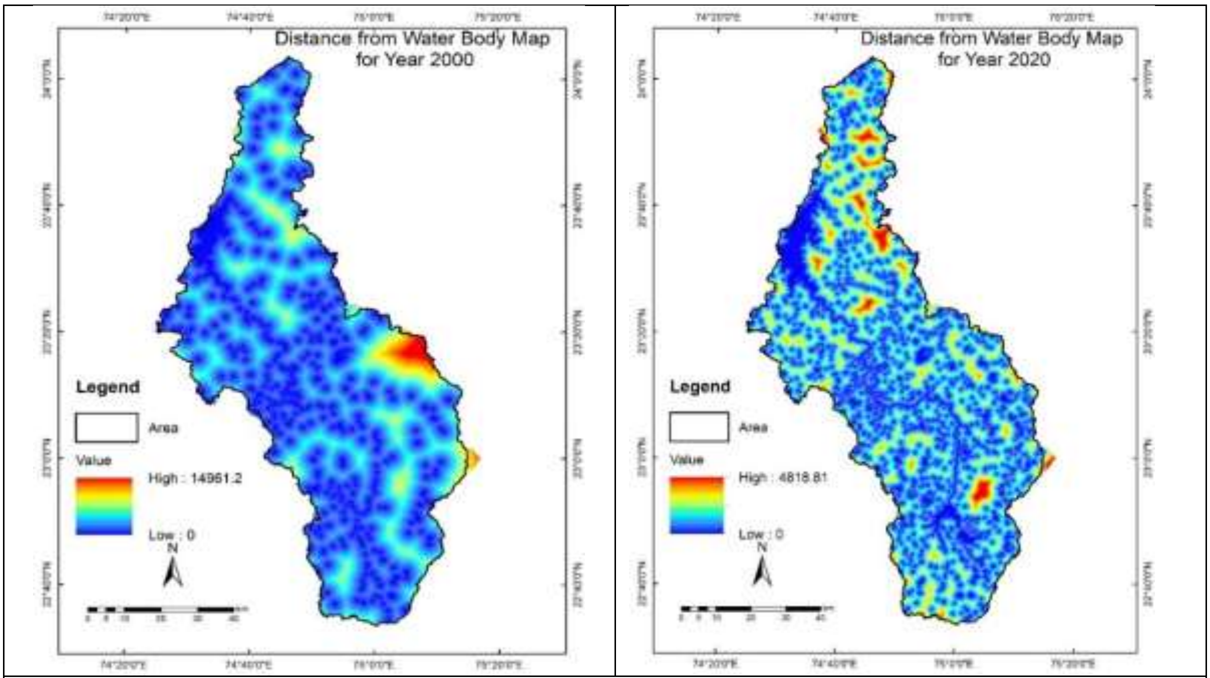

Figure 20: Distance from water bodies map of study area for the year 2000 and 2020

A-10 Runoff Coefficient

According to the CPHEEO guidelines for storm water drainage, the runoff coefficient is determined based on land use and land cover (LULC) characteristics. Table 6 presents the runoff coefficient values along with their normalized counterparts, which are used for ecological assessment.

Table 6: Indicators with range, normalised values and assigned weight for identification of ecological status

S.No.	Factors	Sub Class/Range		Value Obtained		Normalised Value		Global Weights
				2000	2020	2000	2020	
1	Landscape	LULC	Water	0.45	0.45	0.45	0.45	0.667
			Forest	1	1	1	1	
			Rocky Terrain	0	0	0	0	
			Crop Land	0.23	0.23	0.23	0.23	
			Shrubs	0.69	0.69	0.69	0.69	
			Built Up	0	0	0	0	
		NDVI	min	-0.14	-0.18	0.42	0.4	0.333
			max	0.45	0.73	0.728	0.86	
2	Habitant	LST	min	13.99	20.35	1	0.744	0.467
			max	36.27	38.88	0	0	
		NDBI	min	-0.29	-0.39	0.64	0.69	0.364
			max	0.195	0.27	0.4	0.36	
		Distance from water Body	min	0	0	1	1	0.095
			max	14961	4818.8	0	0.67	
		Distance from Built up	min	0	0	0	0	0.277
			max	11928	4356.2	1	0.365	
3	Hydrological	NDMI	min	-0.19	-0.27	0.4	0.36	0.5
			max	0.29	0.39	0.64	0.69	
		Runoff Coefficient	Water	1	1	0	0	0.5
			Forest	0.175	0.175	0.825	0.825	
			Rocky Terrain	0.8	0.8	0.2	0.2	

			Crop Land	0.35	0.35	0.65	0.65	
			Shrubs	0.25	0.25	0.75	0.75	
			Built Up	0.58	0.58	0.42	0.42	
4	Topography	Elevation	min	241	241	1	1	0.6
			max	614	614	0	0	
		Slope	min	0	0	1	1	0.4
			max	52.17	52.17	0	0	

- Normalized values 0 represent poor ecology and 1 represent good ecology.

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