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Towards Environmental Sustainability: Integrating RS and GIS for Ecology Assessment

Saurabh Singh[1], Mahesh Kumar Jat[2] and Sudhir Kumar[2]

ABSTRACT:
The environment provides numerous benefits for human well-being, such as ecosystem services. These services directly and indirectly depend on the physical state of the ecosystem. However, the over-exploitation of natural resources along with socio-economic factors, i.e. economic growth, poverty, agriculture expansion, population growth and weak environmental governance and regulation for fulfilling the human needs for food, fuel, and shelter, is leading to the degradation of the ecological health of an area. Therefore, monitoring and assessment of spatial and temporal changes in the ecology of a region in terms of vital ecological services is very critical and would help the decision-makers to develop and plan appropriate adaptation and mitigation measures for the conservation of natural ecosystems at various scales to ensure environmental sustainability.
The present study aimed to assess the ecological status of the Mahi Bajaj Sagar catchment area in Rajasthan (India) from the year 2000 to 2020, using remote sensing-based indices. Indicators such as greenness, dryness, and heat index have been selected as per the pressure-state-response (PSR) framework. Multi-spectral remote sensing data and image processing methods have been used to estimate these indicators, and a remote sensing-based Ecological Status Index (RSBI) has been generated by their integration using the principal component analysis (PCA) to assess the ecological status of the Mahi Bajaj Sagar catchment.
Findings from the study indicate a consistent decline in the overall ecological status of the Mahi Bajaj catchment, where decreased forest areas have a pronounced effect on ecological health. Interestingly, approximately 43.6% of the area displayed resilience to changes in ecological status; however, 36.4% of the area exhibited signs of ecological degradation.
Our study underscores the efficacy of a remote sensing-based approach in quantifying and detecting ecological changes, offering a promising methodology for monitoring and assessing the ecological health of large areas that can help promote environmental sustainability.

Keywords: Environmental Sustainability, Ecological Status, RSBI, Remote Sensing, PSR Framework,

1. Introduction

A sustainable environment seeks to provide essential ecosystem services to the present generation while safeguarding the needs of future generations. Policymakers must conduct thorough assessments and continuous monitoring of the environment to create comprehensive and effective policies to achieve this. The Millennium Ecosystem Assessment (MEA, 2005) defines the benefits provided by nature as "ecosystem services." These services are crucial in maintaining the ecological balance among ecosystem components, and any ecological degradation can diminish these services. For instance, forests offer services such as climate regulation, water filtration, food, timber, and medicines (Lambrechts et al., 2009; Anderegg et al., 2013). However, deforestation

| [1]Research Scholar, Department of Civil Engineering, Malaviya National Institute of Technology Jaipur (India)
[2]Professor, Department of Civil Engineering, Malaviya National Institute of Technology Jaipur (India)

negatively impacts these services, leading to the deterioration of ecological conditions. Similarly, increased urbanization from the conversion of agricultural land alters food production and shelter availability (Kanninen et al., 2007), thereby disrupting ecological balance.

A decline in ecological health results in a reduction of ecosystem services, leading to habitat loss and diminished socio-economic values. This deterioration adversely impacts community livelihoods and well-being because of a decline in the availability of ecological services. Environmental and ecological degradation can reduce agricultural productivity, increase health risks due to poor environmental quality, and lead to the erosion of culturally significant sites. Economic activities that rely on natural habitats, such as fishing and logging, are threatened, exacerbating poverty and food insecurity (MEA, 2005; Gordon et al., 2021). Essential ecosystem services like water purification, soil fertility, and pollination are critical to community well-being. Their loss increases resource management costs, reduces the availability of clean water and food, and disrupts traditional practices related to health and agriculture. This degradation not only affects economic stability and health but also weakens the traditional ecological knowledge that communities depend on for their sustainability (MEA, 2005). The erosion of cultural and socio-economic values undermines community identity and social cohesion. Traditional livelihoods associated with cultural practices can be lost, leading to economic instability and a decline in tourism revenues. Additionally, the disruption of cultural practices and social structures negatively impacts mental health and reduces community resilience (Berkes, 2008; Gordon et al., 2021). Therefore, accurate ecological quantification is essential for policymakers to frame and implement sustainable policies.

Today, global ecosystems face unprecedented human-induced disturbances, leading to significant environmental fluctuations (McDonnell et al., 2016). The increasing demands of human populations have driven a substantial expansion of built-up areas within natural landscapes, causing widespread disruptions to ecosystems at various scales (Williams et al., 2009). These large-scale disturbances have profound effects on the global carbon cycle (Baldocchi et al., 2008) and exacerbate climate change. Consequently, there is a growing need for models that can detect spatial and temporal variations in ecological status to inform policy decisions. Recent technological advancements have provided abundant earth surface data, enabling more effective ecosystem monitoring and offering robust insights into ecological conditions across different scales (Qiu et al., 2016).

There are multiple approaches to assessing and monitoring ecological status, including structure-based methods focusing on species, function-based methods related to goods and services, and process-based methods (e.g., nutrient cycling, photosynthesis, and primary productivity) (Zhang et al., 2023). While monitoring and evaluating one or more variables relevant to the regional ecosystem can provide historical information, these methods may not offer a complete picture. Therefore, there is a need to monitor ecosystems from various perspectives to obtain a comprehensive understanding of the status and level of degradation at regional scales. Interest in assessing ecological status has increased significantly in recent years (1990–2024), particularly with the growing application of remote sensing technology (Sishodia et al., 2020).

In contemporary times, remote sensing and Geographic Information Systems (GIS) have become essential tools for quantifying ecological status and aiding policymakers in resource management planning (Dahdouh-Guebas, 2002). These tools are commonly integrated to study various natural resources and their attributes (Patil et al., 2015; Rajitha et al., 2007; Saraf and Choudhury, 1998; Wilkinson, 1996). The combination of remote sensing and GIS provides valuable insights into the spatial distribution, extent, and potential of natural resources, which are crucial for formulating sustainable development strategies (Rao, 2000). These technologies have been employed to gather information on ecosystem functioning (Kasischke et al., 1997; Tang et al., 2017), soil characteristics (Mu et al., 2007), surface water (Bastiaanssen et al., 2000), groundwater (Minor et al., 1994), and land use/land cover mapping (Hansen and Loveland, 2012; Roy and Giriraj, 2008).

The Normalized Difference Vegetation Index (NDVI) by Rouse et al. (1973) was developed to assess ecological status and has become one of the most widely used indicators in ecological studies (Mishra et al., 2015). Another commonly used vegetation index is the Enhanced Vegetation Index (EVI). Alcaraz-Segura et al. (2017) highlighted the utility of EVI-derived Ecosystem Functional Attributes (EFAs) as predictors for Species Distribution Models (SDMs), offering an early and comprehensive response to vegetation performance under environmental pressures. Land surface temperature, extracted from thermal imagery captured by remote sensing, has been extensively utilized to examine regional thermal environments and has proven reliable in assessing the urban heat island effect. The combination of two or more remote sensing indices provides more comprehensive information than single indices, thus offering greater insights into ecological conditions. Tiner (2004) developed an aggregated index that integrates habitat properties such as disturbances and habitat extent to quantify ecosystem conditions. Similarly, the Forest Disturbance Index (DI) uses components of tasselled cap transformation of remote sensing data. Various authors have developed composite indices that incorporate multiple factors to quantify and monitor ecological changes using satellite images, overcoming the limitations of single-factor-based indices (Yu et al. 2024; Shao et al., 2023).

The Pressure-State-Response (PSR) framework, proposed by the Organization for Economic Cooperation and Development (OECD) in 1993, serves as a tool for decision-making and policy formulation. This framework can integrate multiple parameters, whether remote sensing-based or ground-based, using weighted methods. The PSR framework considers three scenarios: pressures exerted by human activities, environmental status (climate-related), and societal responses (socio-economic). It has a strong potential for defining ecological status when appropriate parameters are selected, such as those relevant to forest, soil, wetland, agricultural, water, and urban ecosystems (Santibáñez et al., 2015; Zhou et al., 2013; Lee et al., 2014). However, proper selection of indicators is crucial to understanding human pressures, environmental responses, and community actions within the PSR framework. The weighting of indicators may be influenced by subjective experience in practice.

In the current study, the ecological status of the Mahi Bajaj Sagar catchment area in Rajasthan from 2000 to 2020 was assessed using a remote sensing-based index (RSBI). For this assessment, three key indicators—greenness (NDVI), dryness, and heat index—were selected and used within the PSR framework with the help of principal component analysis (PCA) to obtain a composite ecology status index. Although other indicators may also be important in defining the ecological status of an area, this study focused on the three indicators that can be estimated using remote sensing. This index will be valuable for the rapid ecological assessment of relatively large areas, and it will assist decision-makers in developing frameworks for sustainable development that prioritize the conservation of natural ecosystems at various scales.

2. Methods and Materials

2.1 Study area

Mahi Bajaj Sagar reservoir is located near the village Borekhera, about 16 km from Banswara city. The Mahi Bajaj Sagar catchment is located between east longitudes 72˚15' to 78˚15' and north latitudes 22˚0' to 22˚40' N, respectively, with a watershed area of 6149 sq. km (Figure 1). The dam was built across the Mahi River, which has its source in the Amarkantak of the Dhar district in Madhya Pradesh. It is the biggest multipurpose project for the tribal area of Rajasthan as it facilitates the irrigation, hydro-power, and water supply.

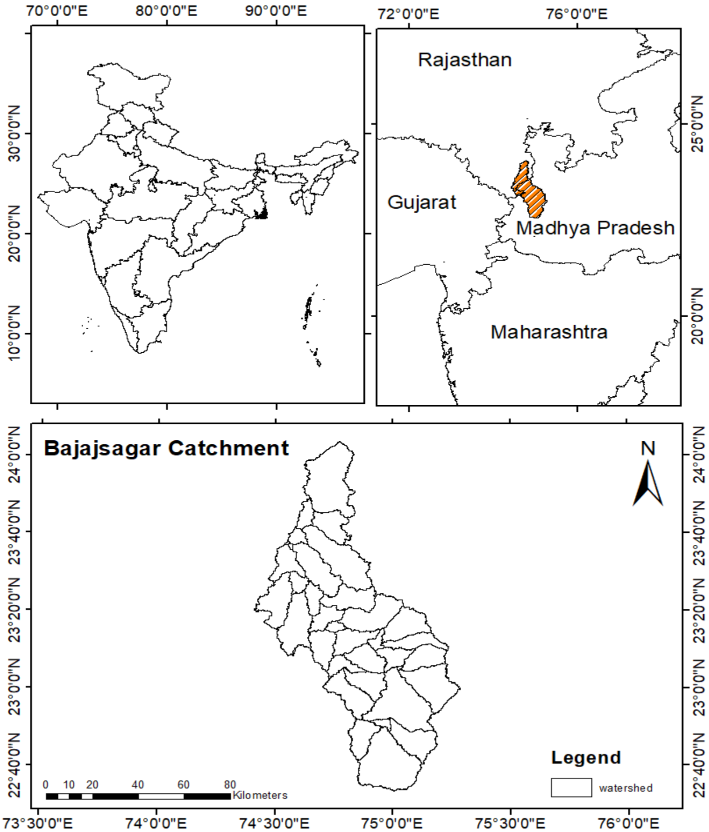

Figure 1: Study area showing Mahi Bajaj Sagar Catchment

2.2 Data used

Multi-spectral satellite images obtained from the Landsat satellite are used in the present study. These images were acquired in October for both the years 2000 (ETM+) and 2020 (OLI/TIRS) from USGS (https://glovis.usgs. gov/). The images were digitally processed, and necessary information was captured.

2.3 Land use land cover (LULC) extraction

A supervised classification method was employed to classify satellite images for the preparation of LULC maps for the years 2000 and 2020. The maximum likelihood classification algorithm, a frequently utilized technique in remote sensing image classification, has been endorsed by numerous researchers (e.g., Srivastava et al., 2012). The LULC of 500 randomly selected locations in classified maps was compared with a high-resolution reference dataset obtained from Google Earth to assess the accuracy of the LULC maps. The overall accuracies of the land use classifications for 2000 and 2020 are expressed in terms of Kappa values, derived by comparing Google Earth-based observations with the LULC classified data.

2.4 RSBI ecological index

2.4.1 Indicators used in RSBI

Remote Sensing Based Indicator (RSBI) is developed to monitor and assess the ecological status of an area. This index is based on the PSR framework, and parameters are clubbed using Principal Components Analysis (PCA). The three ecological indicators used in the PSR framework are greenness as pressure indicator, heat as environmental status and dryness as socio-economic pressure. In the present study, three important indicators, which can be captured from remote sensing, have been used to assess the ecological status; however, consideration of other important indicators like marine ecology, species-based (plant and animal) ecosystems, and other socio-economic factors etc., may also be advantageous. These three indicators are easily estimated using satellite data. The RSBI can be expressed as a function of the PSR indicators:

$$\text{RSBI} = f(\text{Greenness, Dryness, Heat}) \qquad \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Greenness as a pressure indicator is estimated using vegetation cover and captured in terms of NDVI (Normalized Difference Vegetation Index). NDVI is a globally accepted vegetation index for monitoring vegetation growth over an area. Consequently, NDVI has long served as an alternative for ecosystem assessment. The NDVI is calculated using the following formula:

$$\text{NDVI} = (\text{NIR Band} - \text{Red Band})/(\text{NIR Band} + \text{Red Band}) \qquad \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where NIR represents near-infrared (NIR) bands of the Landsat image.

Dryness, indicative of built-induced land-surface desiccation, is defined by the Index-Based Built-up Index (IBI). Human activities exert a significant influence on ecological status, with the conversion of existing pervious or vegetative areas into built-up areas being a notable negative consequence that leads to land surface dryness. Consequently, the IBI is chosen to capture this effect. The IBI index is calculated using the following formula:

IBI = (2SWIR Band/(SWIR Band + NIR Band) − [NIR Band /(NIR Band + Red Band) + Green Band /(Green Band + SWIR Band)])/(2SWIR Band /(SWIR Band + NIR Band) + [NIR Band /(NIR Band + Red Band) + Green Band /(Green Band + SWIR Band)]) …………………………(3)

Where SWIR Band, NIR Band, Red Band, and Green Band are the satellite data captured in respective wavelengths.

Heat as an environmental indicator is estimated in terms of Land Surface Temperature (LST). LST is a widely accepted parameter, and its change over some time indicates a change in land and water interaction with the atmosphere. It can be estimated using remote sensing data. LST is calculated using the Single Channel (SC) algorithm through a Python code using thermal band satellite data.

2.4.2 Integration of the indicators

Rather than employing a conventional weighted approach, the statistical approach, i.e. Principal Component Analysis (PCA) is used to integrate three ecological indicators to estimate RSBI (Remote Sensing-based Ecological Status Index). The first component of PCA (PC1) was selected to represent RSBI since PC1 accounts for more than 78% of the total variation within the dataset. Each metric's significance to RSBI is determined by its loading onto PC1. PCA approach avoids the subjective optimization of weights. Accordingly, initial RSBI, $RSBI_0$, is denoted by PC1:

$RSBI_0 = PC1[f(NDVI, IBI, LST)]$ ……………………….…....(4)

The thematic map of all three indicators is prepared, and from the maps, the metrics of each indicator are extracted and transformed into three 3-band images to find the covariance matrix. Using ArcGIS software, the covariance matrix is calculated to estimate the first component of PCA as PC1. Due to unit difference and range of data variation for each ecological indicator, reclassification of values from 0 to 100 is done initially before applying PCA. The lower value of RSBI0 indicates good ecological status; similarly, a higher value of $RSBI_0$ indicates poor ecological status. Ecology status can be assumed to be good for a higher value of RSBI and bad for a lower value of RSBI. The $RSBI_0$ values are subtracted from 100 to get the RBSI index.:

$RSBI = 100 - RSBI_0$ ……………..(5)

Further, normalization between 0 and 100 of the RSBI value was done to understand the result better. Depending on the RSBI value from 0 to 100, ecological status can be easily estimated. Finally, the RSBI values are classified into five levels, i.e. Level 1 (0–20) indicates the very poor status of ecology; level 2 (20–40) indicates a poor level of ecology; level 3 (40–60) indicates an acceptable level of ecology; level 4 having RSBI value from 60 to 80 indicates the good status of ecology and Level 5 having RBSI values between 80 and 100 represents very good status of the ecology.

2.4.3 Integration of the Indicators

A simple image differencing method was used to assess and monitor the temporal change in ecology, considering classified RSBI maps:

$$\Delta RSBI = RSBI_{2020} - RSBI_{2000} \qquad \text{……………………………………..(6)}$$

The negative change represents a degradation in the ecological status, whereas the positive value indicates an improvement in ecological status.

3. Results

The maximum likelihood classifier algorithm and supervised classification method have been used to classify the multi-spectral satellite images for extraction of land use land cover (LULC) information for years 2000 to 2020. The study area has seven LULC classes, i.e. forest, water, cropland, shrubs, built-up area, barren, and rocky have been identified and extracted from the image classification. The LULC maps and changes in land use land cover from 2000 to 2020 have been shown in Figure 2 and Table 1.

Table 1: Land use land cover in the study area during the year 2000 and 2020

S. No.	Class	Year 2000 (%)	Year 2020 (%)
1	Water	5.7	3.36
2	Forest	17.47	7.78
3	Rocky	16.47	15.05
4	Crop Land	51.52	61.9
5	Shrub	8.12	9.14
6	Built up Area	0.54	2.75
7	Barren	0.14	0.01

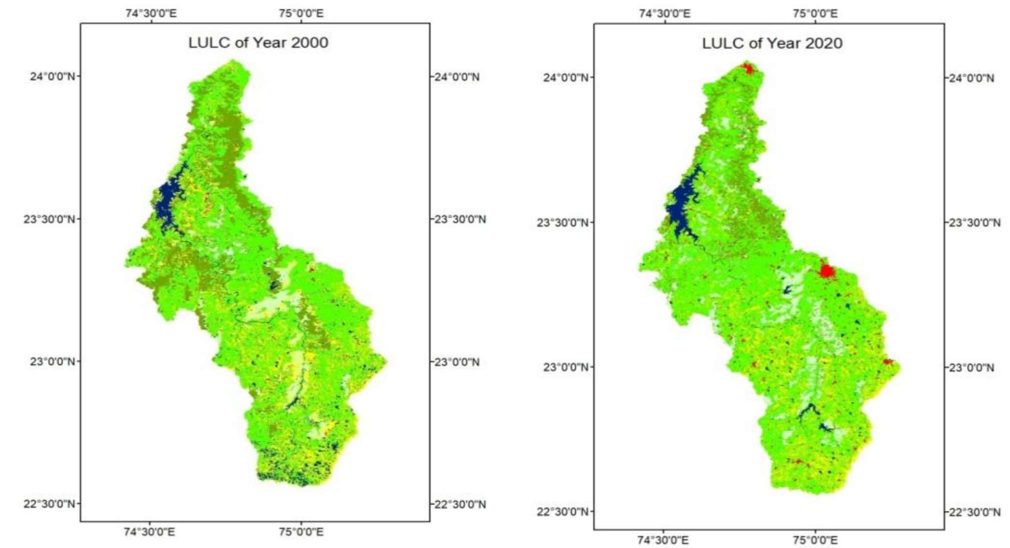

Figure 2: LULC map of Mahi Bajaj Sagar Catchment for the years 2000 and 2020

Classification accuracy was assessed using randomly selected 500 locations, for which the LULC class obtained from the image classification was compared with reference information captured from high-resolution Google Earth images. The overall accuracies of the LULC classifications for both years 2000 and 2020 were found to be 82% and 88%, respectively, with Kappa values indicating a high level of agreement.

Further, three remote sensing metrics of greenness (vegetation, NDVI), heat (Land Surface Temperature, LST), and dryness (impervious area, IBI) are estimated from the satellite data for both the years i.e., 2000 and 2020 using equations 1, 2, and 3. Indicator values are further normalized, as discussed in the methodology section. The average values of the three ecological indicators are presented in Table 2. Further, PCA has been performed to integrate the three ecological indicators to obtain the RSBI, a composite index that indicates the ecological status of Mahi Bajaj Sagar catchment.

From year 2000 to 2020, the average changes in normalized indicators for the study area are shown in Table 2. The greenness index decreased by 12%, whereas the heat index and dryness index increased by 54.6% and 24.32%, respectively. The average value of RSBI has also reduced by 12.88%, indicating the degradation of ecology over two decades. The normalized RSBI results are shown in Figure 3.

Table 2: Mean values of normalized ecological indicators for the Mahi Sagar catchment

S.No.	Index	Year 2000	Year 2020	Change
1	Greenness	45.71	39.82	-12.88
2	Dryness	53.65	66.7	24.32
3	Heat	41.46	64.1	54.6
4	RSBI	71.26	51.44	-27.81

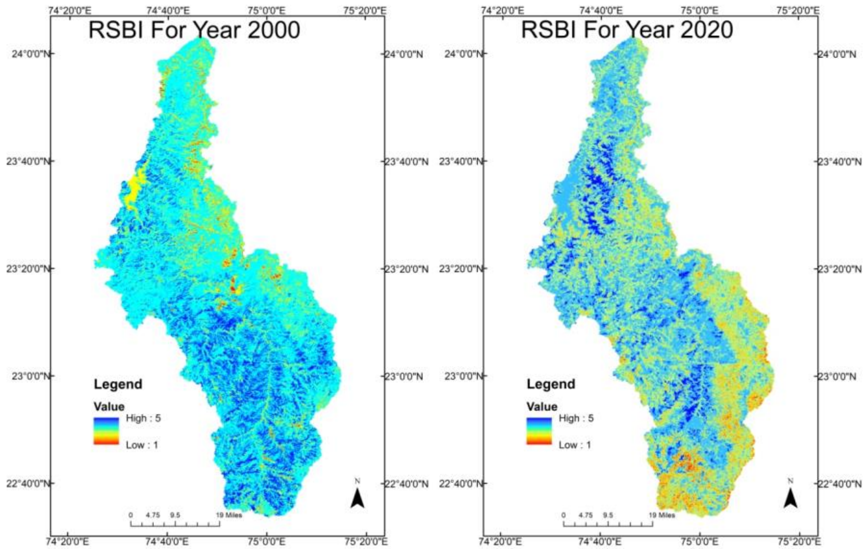

Figure 3: RSBI values for the year 2000 and 2020

RSBI results indicate that in the year 2000, the areas with very poor/ poor ecology were relatively small, approximately 77 km^2 area, which has increased to 826 km^2 by the year 2020. Further, the RSBI of 2020 is subtracted from the RSBI values of the year 2000 to analyze the change in the ecological status of the area. Changes in ecological status of the area is shown in Table 3, and the potential causes of the ecological changes were identified. There were eight kinds of results in the ecological change status, namely, − 3, − 2, − 1, 0, 1, 2, 3, and 4, with respect to the relative change in RBSI values, as shown in Figure 4. It is observed that 43.62 % of the area remains unchanged in terms of RSBI value, indicating a resilient nature. Resilient nature is defined as the ability of the ecosystem to maintain or resist change in its ecological services under the impact of climate change, urbanization, and natural disasters. The possible reasons for such resilience are no changes in ecology because of stable vegetation, sufficient water availability, low urbanization, adaption to climate change and successful implementation of environmental policies. Meanwhile, 36.4% showed degradation due to changes in LULC over time and an increase in urban areas. The ecology of the degraded regions can be restored by framing and implementing proper policies of green infrastructure and limiting the rate of urbanization by policymakers to enhance sustainable developments.

Table 3: Change analysis of ecological status from the year 2000 to 2020.

Nature	Change	Change from year 2000 to 2020	
		Area (sq km)	Percentage Area
Degraded	-3	0.50	0.008
	-2	9.16	0.14
	-1	2221.27	36.20
Unchanged	0	2676.75	43.62
Improved	1	411.40	6.70
	2	701.19	11.42
	3	109.93	1.79
	4	5.90	0.09

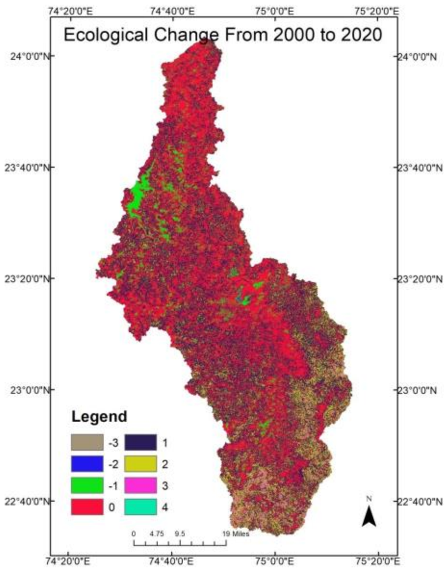

Figure 4: Magnitude of ecological changes from year 2000 to 2020

4. Discussion

It has been observed from LULC classification that forest area decreased by 55.4%, cropland increased by 201.18%, and built-up area increased by 409% from the year 2000 to 2020. There are many reasons for LULC change, including urbanization, agricultural expansion, deforestation, infrastructure development, natural disasters, climate change, land use policies and regulations, and socio-economic drivers. An increase in built-up area as well as agricultural land has a significant impact on local climate and biodiversity because of a change in natural land cover, i.e., local native plant species, shrubs, or forests may change into agricultural land, leading to adverse effects on biodiversity. Conversion of pervious surfaces into impervious surfaces as a result of an increase in built-up activities may change the energy balance between land and atmosphere, leading to changes in climate like reduction in latent heat flux and increase in sensible heat flux. In terms of local climate change, an increase in built-up and croplands results in increased temperature, altered rainfall intensities, and changes in wind patterns, whereas habitat loss, changes in species compositions, disruption of ecosystem services, and instability of wildlife are observed in the case of biodiversity. Thoughtful planning and suitable practices can help mitigate the adverse impacts of increased LULC changes and provide a holistic approach between humans and the ecosystem.

LULC change has a significant impact on ecosystem services, as shown in Table 4. If natural forest is converted into agricultural land, urban areas, or other LULC classes, the ability of an ecosystem to provide services is compromised. LULC changes can provide short-term benefits like food, fodder and fuel; however, they often lead to the degradation of essential ecosystem services.

Table 4: Summary of LULC change impacts on ecosystem services and their possible mitigation and adaptation strategies.

S.No.	Services	Change	Impact	Mitigation and adaptation strategies
1	Provisioning services	Deforestation for agricultural area	It may increase food production but reduces the availability of clean water and forest products.	1. Sustainable land management Policies promoting agroforestry, conservation tillage and integrated water resource management. 2. Protected areas and conservations - Marking and maintenance of protected areas can conserve critical habitats and biodiversity. 3. Restoration ecology - Restoring degraded ecological areas can help to recover lost ecosystem services, such as restoration projects that enhance carbon sequestration and water regulation. 4. Urban green infrastructure - Integrating green spaces, urban forests, and sustainable drainage systems in urban planning can help maintain regulating services in cities.
2	Regulating services	Conversion of forest, wetlands	Increased carbon emission, reduced water quality, higher risk of floods and droughts	
3	Cultural services	Natural landscapes to other classes	Depletion of opportunities for recreational activities and eroding the cultural significance of natural areas for local communities	
4	Supporting services	Conversion of forest, wetlands	Habitat loss and fragmentation reduce biodiversity, disrupt natural processes and lead to the decline of endangered species.	

Due to uncontrolled LULC changes over the decades, ecology has degraded, which is indicated by the decreasing values of RSBI. The RSBI index shows a degradation in ecological status from the year 2000 to 2020 as its value has reduced by 27.81%. A decrease in RSBI value indicates Habitat Loss and Fragmentation, loss of ecosystem services, and loss of cultural and socio-economic values.

It is observed that 43.62 % of the area remains unchanged in terms of RSBI value, indicating a resilient nature. Resilience nature is defined as the ability of the ecosystem to maintain or resist change in its ecological services under the impact of climate change, urbanization and disasters. The reasons behind unchanged ecology are stable vegetation, sufficient water availability, low urbanization, adaption to climate change and successful implementation of environmental policies. Meanwhile, 36.4% showed degradation due to changes in LULC over time and an increase in urban areas. The ecology of the degraded regions can be restored to a certain extent by framing and implementing proper policies for green infrastructure, rewarding owners for maintaining the ecosystem on their lands, and limiting the rate of urbanization by policymakers to enhance sustainable developments.

Habitat Loss results in the degradation of biodiversity and ecology and negatively impacts communities by reducing access to critical resources such as food, water, and raw materials. LULC changes, landscape disturbances, and other anthropogenic activities reduce agricultural productivity, increase health risks from poor environmental quality, and the erosion of cultural sites that hold spiritual or historical significance. Economic activities dependent on natural habitats, like fishing and logging, face declines, exacerbating poverty and food insecurity. Ecosystem processes, such as natural water purification, soil fertility, and pollination, are vital for community well-being. Their loss can increase costs for resource management, reduce the availability of clean water and food, and disrupt traditional practices related to health and agriculture. This degradation impacts economic stability and health outcomes and diminishes conventional ecological knowledge that communities rely on for sustainability. The erosion of cultural and socio-economic values undermines community identity and social cohesion.

Habitat loss is quantified by detecting degraded areas using vegetation cover and built areas, as well as urban expansion from the encroachment of natural habitat areas. The results indicate the impact of human activities on habitats. RSBI helps in the early detection of habitat conditions, allowing policymakers to prevent further habitat loss and guiding environmental policymakers in strategizing land use planning to minimize landscape disturbances. Benefits obtained from the ecosystem are termed ecosystem services. Changes in RSBI values indicate the changes in ecosystem services. For example, a decrease in vegetation cover tends to decrease carbon sequestration capacity, resulting in an increase in temperature corresponding to poor local climate regulation service. Policymakers should prioritize areas with lower values of RSBI for restoration, conservation, and sustainable management of ecosystems.

The RBSI may help assess vulnerable communities through its integration with socio-economic indicators, i.e., income levels or population density, resulting in the identification of more vulnerable areas for ecological degradation. The RBSI can check the efficacy of existing policies or assist in planning new policies to balance environmental sustainability. For example, areas with low economic development but high RSBI value should be targeted first for sustainable development to maintain the balance between both ecological and socio-economic outcomes. Economic valuation of natural resources: economic values of natural resources, such as forests, could be validated using RSBI values supporting livelihood through tourism. These RSBI findings will assist in environmental sustainability when planning land use policies. Climate resilience: socio-economic stability is identified by a change in RSBI values. For example, areas with lower RSBI values are more vulnerable to climate-related disasters like drought, floods, etc, impacting local economies and livelihoods. RSBI values directly and indirectly affect socio-economic and human well-being by influencing ecological status (Table 5).

Table 5: Applications of RSBI Index

S. No.	Parameter	Quantification	RSBI	Impact
1	Agriculture Productivity and food security	Monitoring vegetation health	Low	Soil degradation or drought resulting in low crop yields
2	Health and well-being	Air quality, Heat stresses, disease vector control,	Low	Higher temperatures and lower vegetation result in heat stress, poor air quality and the spread of diseases.
3	Economic Stability	Resource-based livelihoods	Low	The lower value of RSBI results in lower ecological status, promotes resource depletion and reduces the income and economic stability of people habitants depending on fisheries, forestry or tourism.
		Disaster risk reduction	Low	Identify areas prone to natural disasters such as floods or droughts.
		Tourism	Low	Lower RSBI negatively impacts natural beauty and bio-diversity-dependent communities.

The RBSI index can help in maintaining environmental sustainability in a multifaceted way. It can guide policymakers in deciding the land use policies and help regulate land use change. It can also help identify the characteristics of the affected ecosystem and determine the socio-economic context. The study is successful in estimating the change in the status of the ecology of the Mahi catchment over 20 years. Further, the study successfully demonstrated the application of remote sensing and GIS for the ecology assessment of larger areas.

Over-exploitation of natural resources for food, fuel, and shelter is degrading ecological health. This exploitation of resources can be reduced by framing and implementing proper policies, i.e. limiting and preventing over-harvesting of resources, making reserve or protected areas, taxes and subsidies, payments for preserving ecosystems, sustainable forestry and agriculture, strict enforcement of laws, community-based resource management, public awareness and educating people about ecosystems.

Policymakers can use the RSBI to make policies and prioritize the areas for policy implementation while considering the human and ecological aspects of sustainability. RSBI serve as an important tool in creating and guiding holistic approaches for environmental policymaking, which promotes greenery, protection of critical habitats and improved ecosystem services.

Integration of multiple indicators such as air quality index, water quality index, biodiversity indicators, region-specific indicators, and socio-economic indicators using machine learning and AI techniques with higher resolution and temporal data will enhance RSBI accuracy, flexibility, and relevance at various scales from global to local for ecological assessment and decision making. Such issues can be studied in the future research.

5. Conclusion

RSBI, based on the PSR framework, is used in the present study to assess the ecological status of the Mahi catchment in terms of three critical ecological indicators, i.e., greenness, heat, and dryness and successfully quantified the changes in ecology during the years 2000 and 2020. The RSBI values over the Mahi catchment showed that the catchment experienced ecological deterioration during the study period from 2000 to 2020, with the mean RSBI value which decreased from 71.26 in 2000 to 51.44 in 2020. The development of RSBI is aimed at assessing ecological status using three indicators that are strongly correlated to general ecological conditions. This remote sensing data-derived index will be helpful for quick ecological assessment as it integrates environmental factors and helps decision-makers develop or plan a proper framework for sustainable development that considers the conservation of natural ecosystems at various scales. Further, refining the RSBI will assist the policymakers in urban planning, environmental monitoring, water resource management, flood risk management, post-disaster ecological assessment, drought monitoring, ecological policy development and many more at various scales. The study has also demonstrated the successful application of spatial technologies, i.e., remote sensing and GIS, in environmental studies.

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