Assessing Environmental Degradation of Achanakmar-Amarkantak Biosphere Reserve and Its Ecosystem Using Google Earth Engine and Machine Learning

Anil Kumar[1], Dr. Hari Shankar Kumar[2]

[1]Assistant Professor, Department of Sociology, Bayalasi Degree College Affiliated Veer Bahadur Singh Purvanchal University, Jaunpur 222136
[2]Assistant Professor, Department of Geography, Faculty of Arts & Humanities, Kalinga University, Raipur, Chhattisgarh-492101

Abstract

Biosphere Reserve is a meso-type region of ecosystem; it represents the bio-geographic zones in the world. The Biosphere reserves suffer drastic environmental degradation, natural calamities, and anthropogenic activities, preventing ecological growth, shrinking, and exploiting the land due to extreme climatic conditions. In this study, the Achanakmar-Amarkantak Biosphere Reserve (AABR) area has been selected and represents a biodiversity-rich ecosystem in central India. It is a lush forest; however, it has seen large-scale devastation in the context of climate change, as evidenced by increasingly unpredictable rainfall and higher temperatures between 2002 and 2022. In this scenario, there is a need for the essential application of remote sensing and machine learning techniques to monitor environmental degradation and its ecosystem in AABR.

This study explores the nature of environmental degradation and its ecosystem in the study area. Using machine learning and Google Earth Engine, image classification techniques can reliably classify and map forest cover, land uses, and their spatial distributions. It will provide the long-term monitoring system by following six major spectral indices such as Land use and land cover, Normalized Difference Vegetation Index, Normalized Difference Water Index, Leaf Area Index, Normalized Difference Built-up Index, Soil Adjustment Vegetation Index, and Land Surface Temperature were determined based on the annual average between 2002 to 2022. As observed in the LST, proportionate to built-up land increases rapidly, and water bodies and vegetation cover decrease during 2002-2022. Globally, this study presents a robust methodology that can be applied to other sub-tropical regions. This study suggests appropriate conservation, management, and policies by identifying degradation and monitoring over time. Land use and climate variability changes necessitate implementing and protecting the AABR without sacrificing the natural environment.

Keywords: Environmental Degradation; Google Earth Engine; Achanakmar Biosphere Reserve; Spectral Indices

Introduction

Environmental degradation is a major challenge in India as well as in world, checking ecological growth and threatening to biodiversity. It is associated with changes in land use and climate variability. The Food and Agriculture Organisation shows that the world's soils have environmental degradation on a large scale, particularly in moonsoni tropical areas, reducing environmental services and impacting agriculture and livestock [1, 3, 5, 7].

Therefore, the objective was to evaluate the spatiotemporal dynamics of vegetation cover and land degradation in the Maso region of Central India through various remote sensing indices. Land use and land cover maps (LULC), Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and Normalized Difference Water Index (NDWI) were determined based on the annual average between 2003 to 2023. The water bodies and vegetation showed remarkable reductions between 2003 and 2023. As observed in the NDVI, from the year 2003 onwards, the LAI values were resilient. Determining vegetation indices associated with LULC maps and data allowed us to accurately validate the responses of the indices studied in the tropical region.

The approach highlights the Achanakmar-Amarkantak Biosphere Reserve's strong resilience. This study presents a robust methodology compatible with existing tropical regions worldwide.

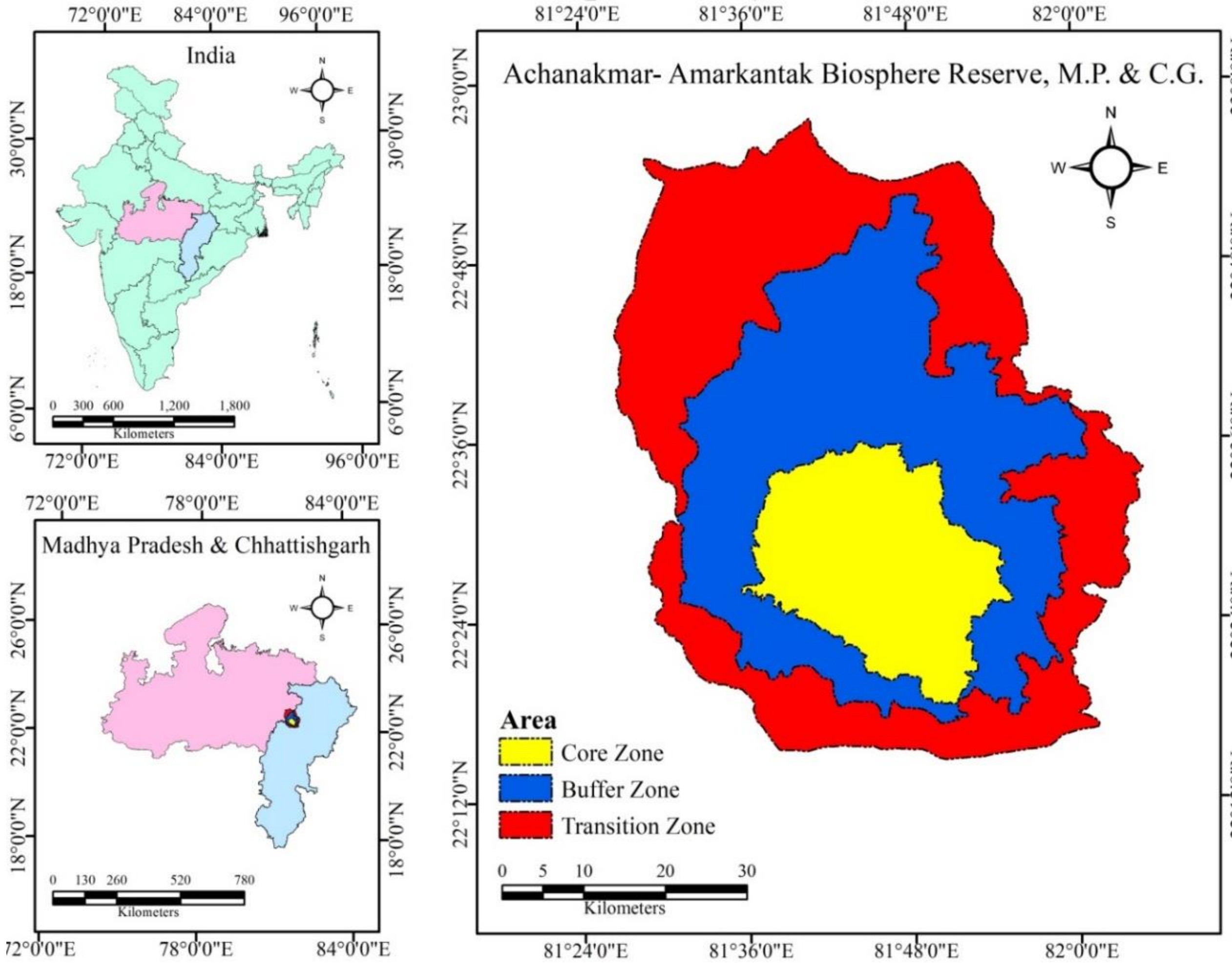
Objective

1. To study the temporal degradation of Achanakmar-Amarkantak Biosphere Reserve.
2. To analyses the INDICES of Achanakmar-Amarkantak Biosphere Reserve using Google Earth Engine.

Study Area

Achanakmar-Amarkantak Biosphere Reserve (AABR), the present paper deals with the worldview of Gond tribe for biodiversity conservation, was establish on 30th March 2005 [6]. The range of this biosphere reserve on *Anuppur, Dhindhori, Bilaspur and Mugeli* districts and adjacent areas of *Chhattisgarh and Madhya Pradesh* [4, 8, 9, 10]. This BR lies between $21^{0}15'$ North latitude $22^{0}58''$ North latitude and $81^{0}25'$ East longitude to $82^{0}5'$ East longitude [6]. It is spread over Maikal Hill range to the confluence of Satpura & Vindhyan Hill range in a triangular shape. Bilaspur, Gaurell-Pendra-Marwahi and Mugeli forest divisions of Chhatisgarh state & Anuppur and Dhindori forest division of Madhya Pradesh state surround the core zone of BR. Achanakmar Wildlife Sanctuary is located in this BR. It has been established in 1975 (Wildlife Protection Act, 1972) and declared a Tiger Reserve (Tiger Project-2009) [2].

Figure 1: Location Map of Study Area



Source: . Study Area: Achanakmar-Amarkantak Biosphere Reserve base map, 2023.

Data & Method of Study

GEE is a platform for processing up to 20 years' worth of global-scale satellite images. It enables users to use global satellite images and do intricate computations on the imagery. In the current study, particular study regions may be loaded, massive satellite images can be shown, and complicated geospatial operations can be carried out for the chosen data using the Google Earth Engine Playground (GEEP) programme (https://code.earthengine.google.com) [11,12,13 &14].

The Google Earth Engine (GEE) was used to process and categories all four signs, utilizing various datasets, a variety of algorithms, and band rationing strategies.

Method, Matter and Process

The methodology for assessing environmental degradation of the Achanakmar-Amarkantak Biosphere Reserve using Google Earth Engine (GEE) and machine learning have outlined in the following steps:

Data Acquisition

Use Landsat 7 ETM+ and Landsat 8 OLI/TIRS satellite imagery as the primary source of environmental data. Obtain climatological data from relevant databases for atmospheric information.

Pre-processing
Perform pre-processing steps on the Landsat imagery to correct for atmospheric interferences, sensor noise, and other potential errors. Use the Shuttle Radar Topography Mission (SRTM) data for elevation and topographic information to aid in correcting surface reflectance values.

Surface Reflectance Calculation
Derive surface reflectance values from the pre-processed data to get accurate measures of the Earth's surface features.

Spectral Signature Analysis
Analyze the spectral signatures of the imagery to classify different types of land cover and land use. Calculate indices such as NDWI, NDVI, and NDLI to understand water content, vegetation health, and latent heat respectively.

Land Surface Temperature Calculation
Utilize the TIRS data from Landsat 8 to calculate the land surface temperature (LST). Determine albedo and soil heat flux as part of the process.

Index and Flux Analysis
Compute various vegetation indices for health and stress analysis. Calculate net radiation, sensible heat flux, and latent heat flux based on the climatological and Landsat data.

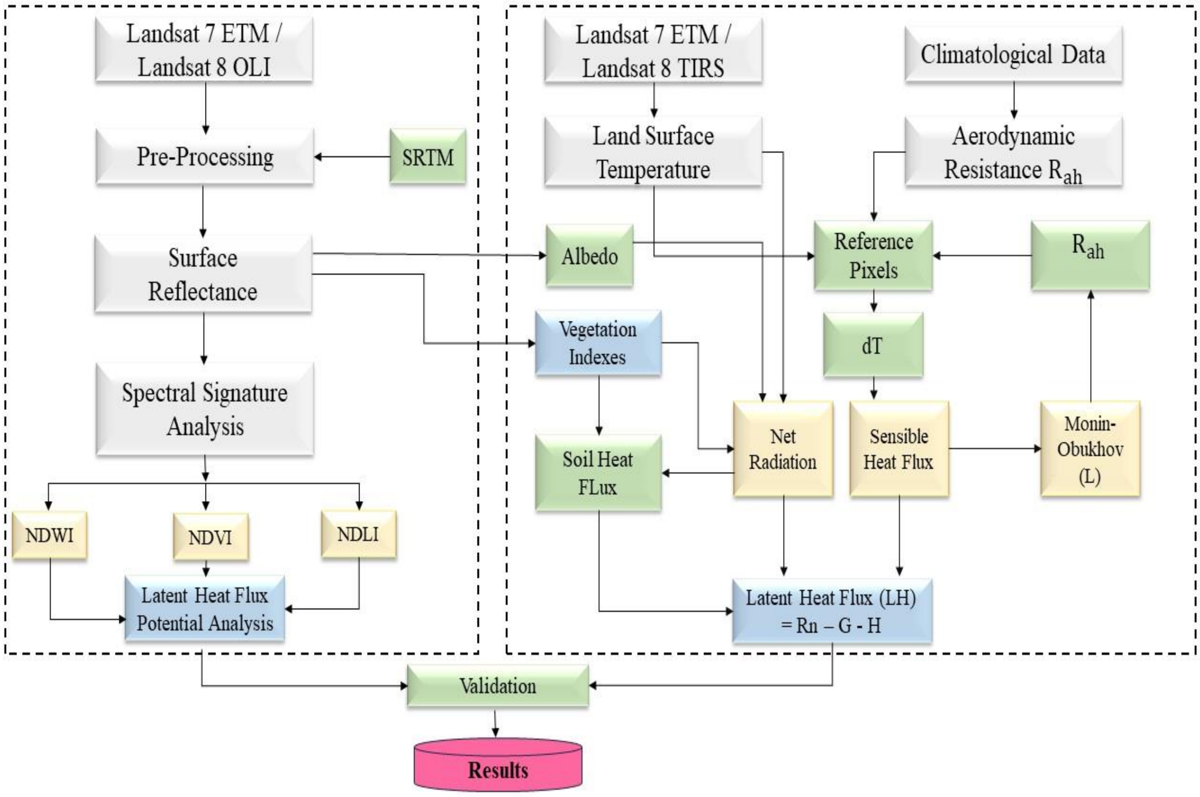
Machine Learning Application
Apply machine learning algorithms using GEE to analyze and predict patterns of environmental degradation. Use machine learning for classifying land cover changes, detecting shifts in vegetation health, and analyzing water stress indicators.

Validation
Validate the results using ground truth data or other reliable sources to ensure the accuracy of the analysis. This has include field surveys, historical data, or independent satellite measurements.

Results and Interpretation
Synthesize the validated data to assess the environmental degradation over time. Utilize the results to identify trends, hotspots of degradation, and potential recovery areas.

Iterative Refinement
Based on initial results, refine the machine learning models and reprocess the data as necessary to improve accuracy and reliability. This method integrates remote sensing data with machine learning within the Google Earth Engine platform, allowing for a comprehensive assessment of the environmental health of the Achanakmar-Amarkantak Biosphere Reserve over time. It harnesses the temporal capability of Landsat imagery and the computational power of GEE, along with the pattern recognition and predictive capabilities of machine learning, to understand and monitor the reserve's ecosystem dynamics.

Figure 2: Flowchart of Methodology



Source: Conceptual framework and Data Processing.

Data

Four indicators are used to measure the environmental degradation in the AABR region using a variety of factors (TI, HMI, EI, and SEI). These criteria are taken from several datasets and analyzed using the GEE platform. The elevation, slope, and aspect sub-factors from the Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global DEM, which has a spatial resolution of 30 m, are included in the terrain indicator. Environmental Indicators are produced using multi-seasonal composite Landsat images 8 (OLI), which have a spatial resolution of 30 m (2019). Several indices, such as the Enhanced Vegetation Index and the Normalized Difference Vegetation Index (NDVI), are frequently used to detect changes in the vegetation (EVI).

Landuse, the Normalized Difference Built-up Index (NDBI), and the Normalized Difference Water Index (NDWI) for water. Precipitation and land Surface Temperature (LST) are the sub-factors that make up the HMI. Annual and monthly precipitation data (2019) were gathered from CHIRPS V2 satellite gridded data and compiled by the Climate Hazards Group at a resolution of 0.05 arc degrees. Population density was calculated using Global gridded population 2020 (CIESIN, GPWv411).

Results and Disscusion

Table 1: Comparative data of Environmental Degradation

Indices	2002			2022		
	Min	Mean	Max	Min	Mean	Max
NDVI	-0.1	0.12	0.44	-0.25	0.09	0.53

SAVI	-0.15	0.18	0.66	-0.38	0.13	0.79
NDWI	-0.41	-0.16	0.09	-0.07	0.12	0.3
NDBI	-0.32	0.07	0.64	-0.48	0.12	0.72
NDBaI	-0.7	-0.46	0.92	-0.76	-0.53	0.98
BU	-0.7	-0.04	0.52	-0.77	-0.21	0.18
LST	12°C	26°C	37°C	16°C	28°C	38°C
NDLI	-0.08	-0.02	0.03	-0.1	-0.002	0.06

Source: Computed through Landsat- 7 and 8 in GGE-2023.

The proximity among socio-economic variables and the road network was calculated using the Global Roads Open Access Data Set, Version 1 (gROADSv1) dataset provided by CIESIN in 2013. In order to map plant type and its land use, the current study made use of a variety of cutting-edge machine learning picture classification techniques, including support vector machine (SVM), decision tree, and random forest classifiers, using cloud computing platforms like Google Earth Engine (GEE). It is an open access cloud-based tool for geospatial analysis. For the purpose of implementing mapping, Earth Engine offers a vast library of imaging data together with a number of pixel-based supervised and unsupervised classifiers, including machine learning-style techniques. Following the extraction of all the thematic layers using fuzzy linear member-based multi-criteria decision, weights and rankings were assigned and overlaid in a GIS environment at a standard pixel size of 30 m. Following investigation, the layer's environmental deterioration has been divided into five categories: Very High Degradation (VHD), High Degradation (VD), Moderate Degradation (MD), Slight Degradation (SD), and No Degradation (ND).

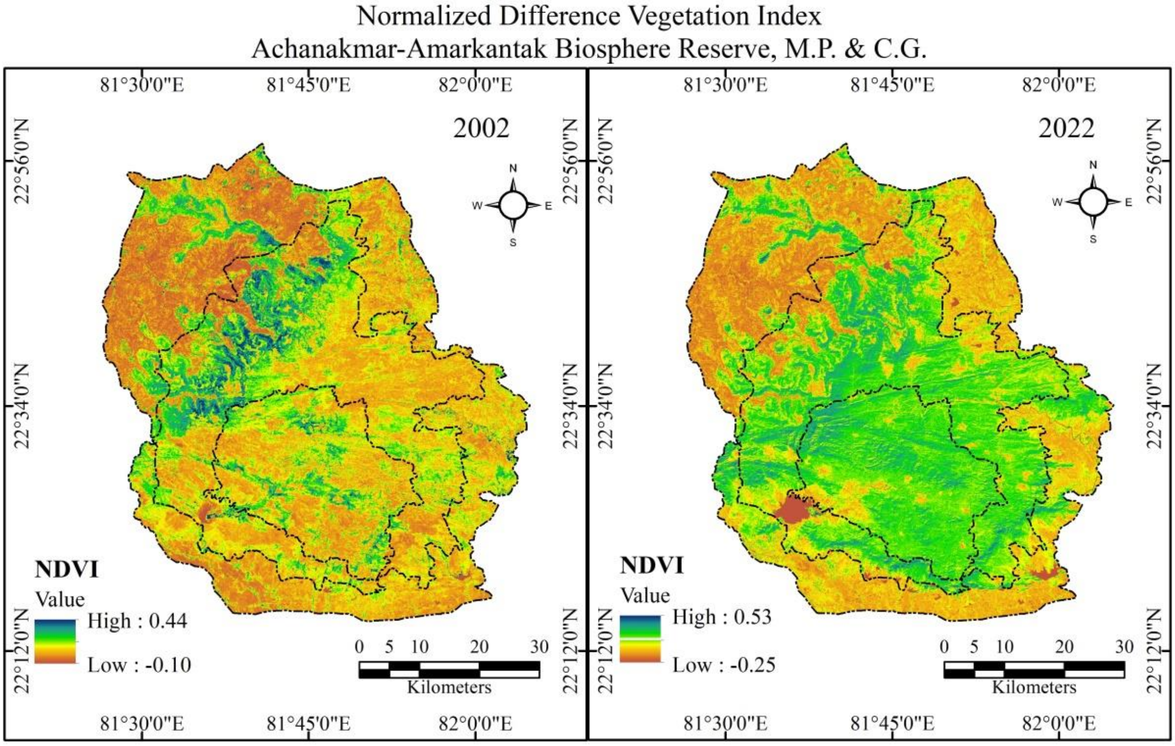
NDVI (Normalized Difference Vegetation Index)

NDVI quantifies vegetation health and density. Its range expanded from -0.10 to 0.44 in 2002 to -0.25 to 0.53 in 2022, indicating improved vegetation cover and health. The wider range suggests increased variability in plant growth, possibly due to climate variations, land use changes, or ecological shifts. In 2002, the mean NDVI was 0.12, indicating an average level of vegetation cover. In 2022, the mean NDVI was 0.09, suggesting a slightly lower average vegetation cover compared to 2002.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

NDVI is a measure of how green the vegetation is on the Earth’s surface. It is calculated by comparing the reflectance of near-infrared and red light from plants. Healthy plants reflect more near-infrared light and less red light than stressed or dead plants. NDVI values range from -1 to 1, where higher values indicate more greenness and lower values indicate less greenness or non-vegetated areas.
NDVI values have increased and become more variable over the past two decades. This means that the vegetation cover and health have improved overall, but there are also more differences in plant growth across regions and seasons. Possible reasons for this change include climate variations, land use changes, or ecological shifts. Climate variations can affect the temperature, precipitation, and sunlight that plants receive. Land use changes can alter the type, amount, and distribution of vegetation due to human activities such as agriculture, urbanization, or deforestation. Ecological shifts can occur when invasive species, pests, diseases, or natural disasters affect the native vegetation.

Figure 3: Normalized Difference Vegetation Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE

SAVI (Soil-Adjusted Vegetation Index)

SAVI, accounting for soil brightness, reflects vegetation vigor. The range increased from -0.15 to 0.66 in 2002 to -0.38 to 0.79 in 2022. Similar to NDVI, this points to enhanced vegetation growth and health, possibly due to better soil management and land practices. In 2002, the mean SAVI was 0.18, indicating a moderate level of vegetation cover. In 2022, the mean SAVI was 0.13, suggesting a slightly lower average vegetation cover compared to 2002.

The formula for SAVI is:

SAVI=(NIR−Red)(NIR+Red+L)×(1+L)\text{SAVI} = \frac{(NIR - Red)}{(NIR + Red + L)} \times (1 + L)SAVI=(NIR+Red+L)(NIR−Red)×(1+L)

- where:
- NIRNIRNIR is the reflectance in the near-infrared region.
- RedRedRed is the reflectance in the red region.
- LLL is a soil brightness correction factor.
- The value of LLL varies depending on the vegetation cover:
- For very high vegetation cover, LLL is close to 0.
- For intermediate vegetation cover, LLL is around 0.5.
- For very low vegetation cover, LLL is close to 1.

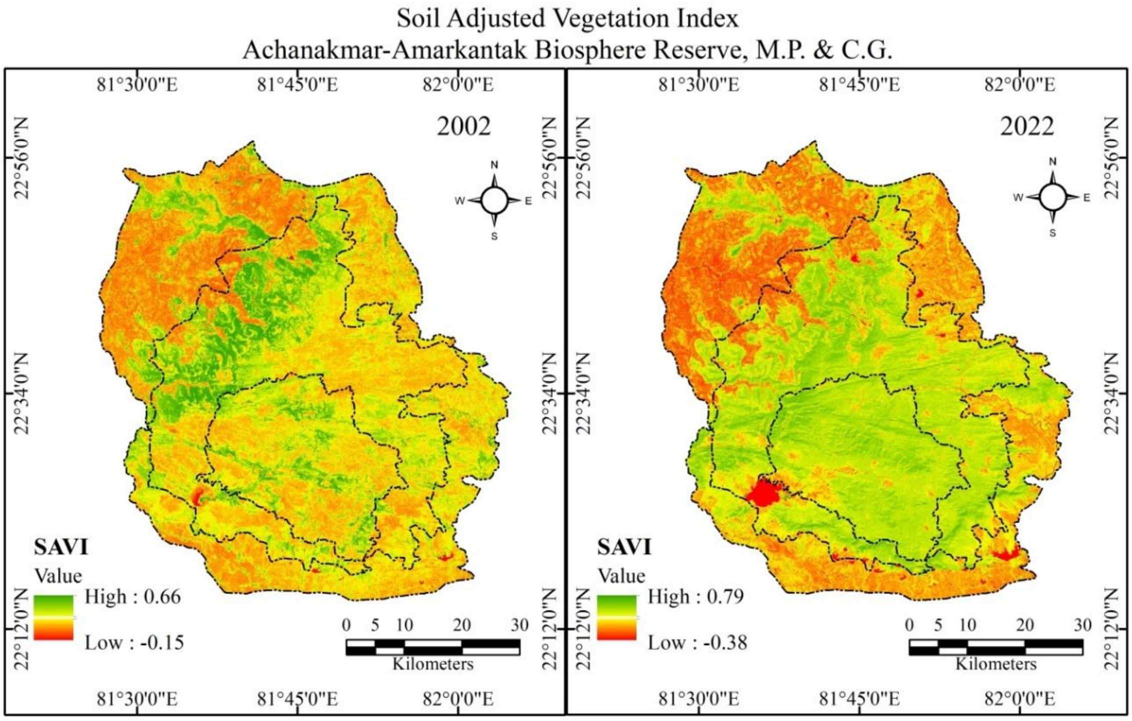
A commonly used value for LLL is 0.5, which is a compromise between minimizing soil noise and maximizing sensitivity to vegetation.

So, the formula used is:

SAVI=(NIR−Red)(NIR+Red+0.5)×1.5\text{SAVI} = \frac{(NIR - Red)}{(NIR + Red + 0.5)} \times 1.5SAVI=(NIR+Red+0.5)(NIR−Red)×1.5

SAVI (Soil-Adjusted Vegetation Index) is a measure of how green the vegetation is on the Earth's surface, adjusted for the effect of soil brightness. It is calculated by adding a constant factor to the NDVI formula, which reduces the influence of soil reflectance on the vegetation index. SAVI values range from -1 to 1, where higher values indicate more greenness and lower values indicate less greenness or non-vegetated areas.

Figure 4: Soil-Adjusted Vegetation Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE

SAVI values have increased and become more variable over the past two decades. This means that the vegetation growth and health have improved overall, accounting for soil brightness, which can vary depending on the moisture, texture, and color of the soil. Some possible reasons for this change are better soil management and land practices, such as irrigation, fertilization, erosion control, or crop rotation.

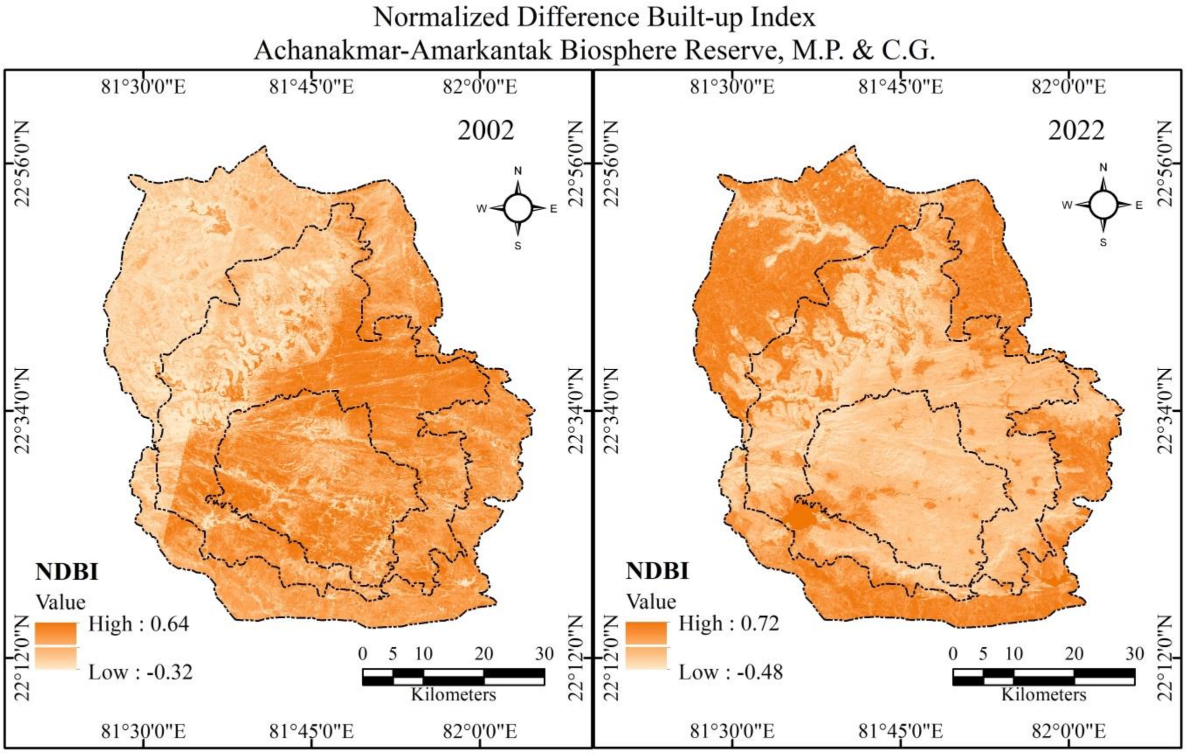
NDBI (Normalized Difference Built-Up Index)

NDBI gauges urbanization. The range changed from -0.32 to 0.64 in 2002 to -0.48 to 0.72 in 2022. The mixed shifts indicate variable urban expansion, while the narrower range implies stabilization in built-up areas between the two years. In 2002, the mean NDBI is 0.07, indicating a moderate level of built-up or urban areas. In 2022, the mean NDBI is 0.12, suggesting a slight increase in built-up or urban areas on average compared to 2002.

$$NDBI = \frac{(SWIR2 - NIR)}{(SWIR2 + NIR)}$$

NDBI is a measure of how urbanized the Earth's surface is. It is calculated by comparing the reflectance of near-infrared and shortwave infrared light from built-up areas or bare soil. Built-up areas reflect more shortwave infrared light and less near-infrared light than natural land cover. NDBI values range from -1 to 1, where higher values indicate more urbanization and lower values indicate less urbanization or non-urban areas.

Figure 5: Normalized Difference Built-Up Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE.

NDBI values have changed and become more variable over the past two decades. This means that the urbanization has changed in different ways across regions and seasons, while the overall range of urbanization has become narrower between the two years. Some possible reasons for this change are variable urban expansion, such as sprawl, densification, or redevelopment, or stabilization in built-up areas due to planning, regulation, or saturation.
Wooded, agricultural, arid, and aquatic zones were employed equation 2, to map the built-up areas.

NDBaI (Normalized Difference Bareness Index)
NDBaI monitors bare land. It expanded from -0.70 to 0.92 in 2002 to -0.76 to 0.98 in 2022. The changes suggest alterations in open spaces, with a wider range indicating diverse shifts in barren land conditions. In 2002, the mean NDBI is 0.07, indicating a moderate level of built-up or urban areas. In 2022, the mean NDBI is 0.12, suggesting a slight increase in built-up or urban areas on average compared to 2002.

Formula for NDBaI
NDBaI=(Band1−Band2)(Band1+Band2)\text{NDBaI} = \frac{(Band1 - Band2)}{(Band1 + Band2)}NDBaI=(Band1+Band2)(Band1−Band2)
where:

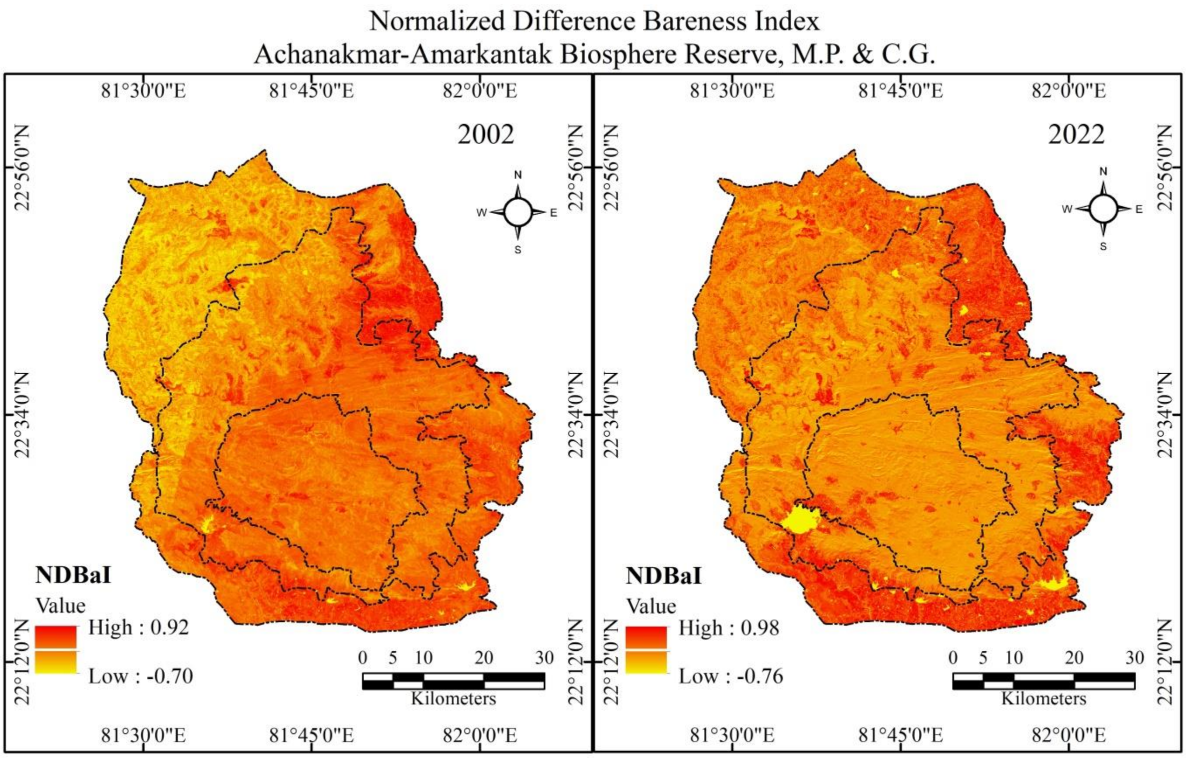
- Band1Band1Band1 and Band2Band2Band2 are reflectance values in selected spectral bands.

- The choice of Band1Band1Band1 and Band2Band2Band2 depends on the specific sensor used and the characteristics of the landscape being studied.

NDBaI (Normalized Difference Bareness Index) is a measure of how bare the Earth's surface is. It is calculated by comparing the reflectance of red and shortwave infrared light from bare land or sparse vegetation. Bare land reflects more shortwave infrared light and less red light than dense vegetation. NDBaI values range from -1 to 1, where higher values indicate more bareness and lower values indicate less bareness or non-bare areas.

NDBaI values have expanded and become more variable over the past two decades. This means that the bareness has changed in different ways across regions and seasons, with a wider range indicating diverse shifts in barren land conditions. Some possible reasons for this change are alterations in open spaces, such as desertification, deforestation, mining, or agriculture.

Figure 6: Normalized Difference Bareness Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE.

NDLI (Normalized Difference Landscape Index)

NDLI characterizes non-vegetated areas. It shifted from -0.08 to 0.03 in 2002 to -0.10 to 0.06 in 2022, showcasing minimal fluctuations. These changes suggest relatively stable patterns in non-vegetated areas over the observed period. In 2002, the mean NDBI is 0.07, indicating a moderate level of built-up or urban areas. In 2022, the mean NDBI is 0.12, suggesting a slight increase in built-up or urban areas on average compared to 2002.

NDLI=(B1+B2)/(B1−B2)

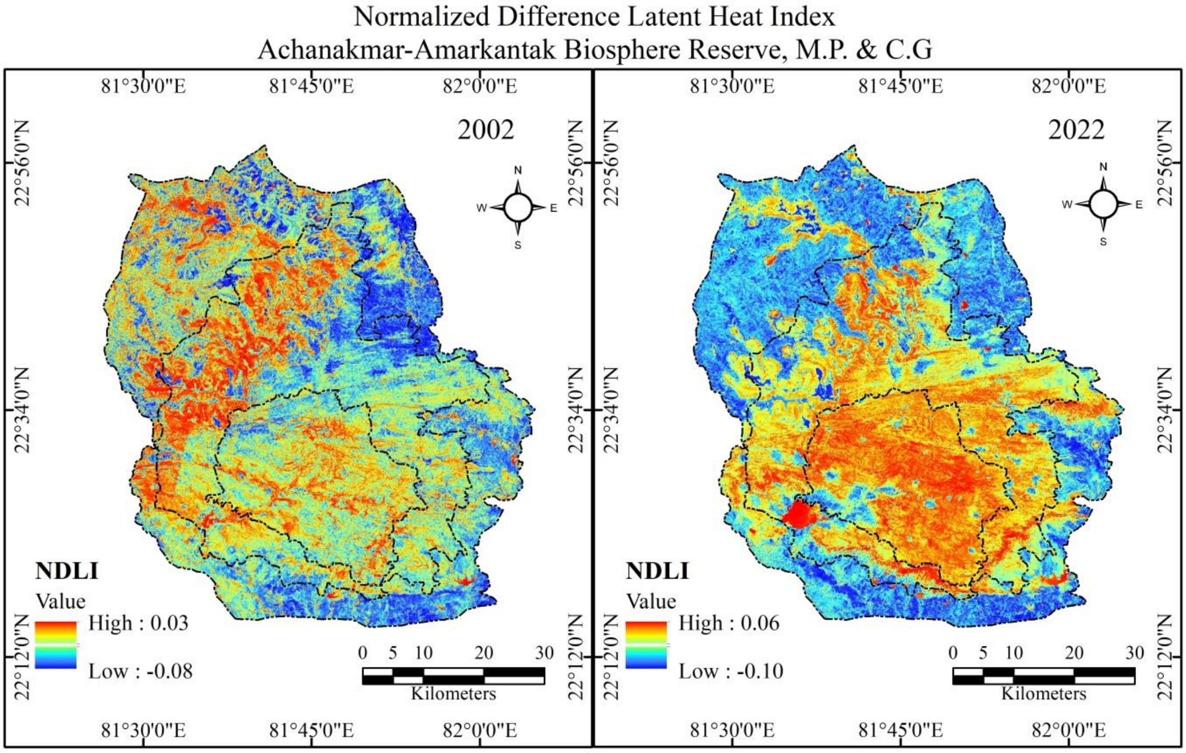
where:

- B1B1B1 and B2B2B2 are reflectance values in different spectral bands, chosen to highlight specific landscape features or land cover types.
- The choice of B1B1B1 and B2B2B2 depends on the characteristics of the landscape being studied and the spectral sensitivity of the sensor.

NDLI is a measure of how non-vegetated the Earth's surface is. It is calculated by comparing the reflectance of red and thermal infrared light from non-vegetated areas or sparse vegetation. Non-vegetated areas reflect more thermal infrared light and less red light than dense vegetation. NDLI values range from -1 to 1, where higher values indicate more non-vegetation and lower values indicate less non-vegetation or non-non-vegetated areas.

NDLI values have shifted slightly over the past two decades, showing minimal fluctuations. This means that the non-vegetation patterns have remained relatively stable over the observed period, with little change in the amount or distribution of non-vegetated areas. Some possible reasons for this stability are constant land use or cover, natural equilibrium, or resilience to disturbances.

Figure 7: Normalized Difference Landscape Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE.

BU (Built-Up Index)

BU assesses urban expansion. The range shifted from -0.70 to 0.52 in 2002 to -0.77 to 0.18 in 2022. The mixed changes hint at varying rates of urban growth, while the narrower range implies controlled development or more balanced expansion. In 2002, the mean NDBI is 0.07, indicating a moderate level of built-up or urban areas. In 2022, the mean NDBI is 0.12, suggesting a slight increase in built-up or urban areas on average compared to 2002.

$$NDBI=(SWIR+NIR)(SWIR-NIR)$$

For instance, using the Normalized Difference Built-Up Index (NDBI):

- Extract NIR and SWIR bands from satellite imagery.
- Calculate NDBI using the formula: NDBI=(SWIR−NIR)(SWIR+NIR)\text{NDBI} = \frac{(SWIR - NIR)}{(SWIR + NIR)}NDBI=(SWIR+NIR)(SWIR−NIR)
- Apply a threshold (e.g., NDBI > 0.3) to classify pixels as built-up or non-built-up.

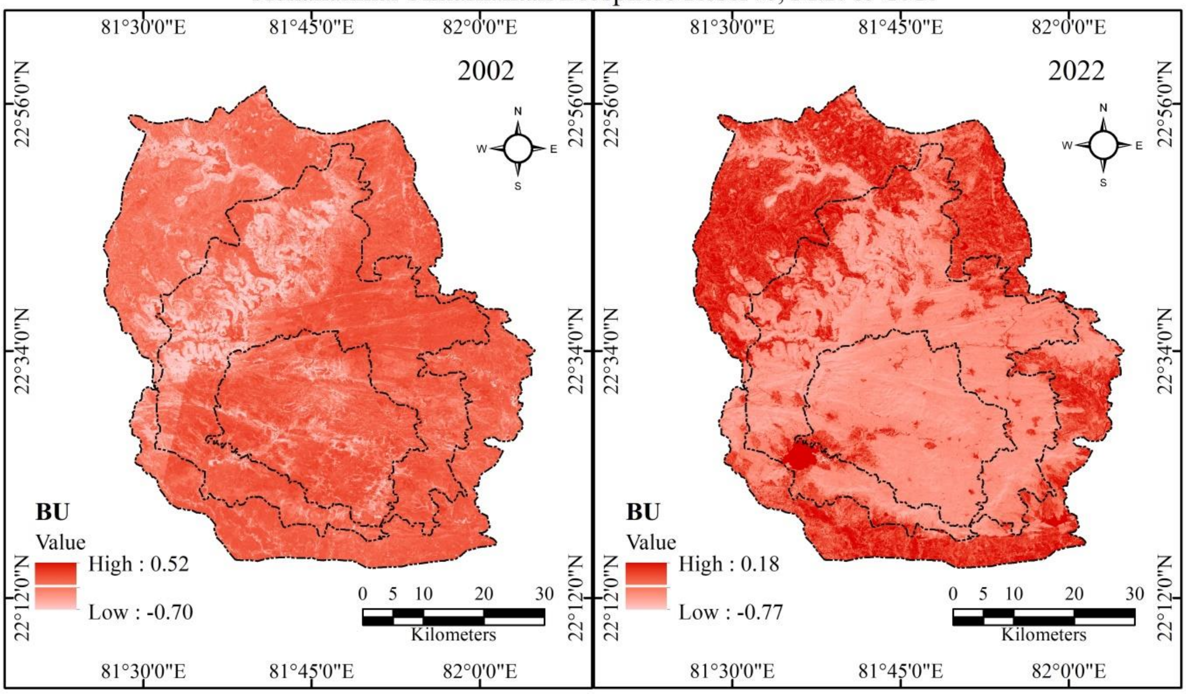
High values of NDBI indicate built-up areas due to the high reflectance of urban materials in NIR and low reflectance in SWIR.

BU (Built-Up Index) is a measure of how urbanized the Earth's surface is. It is calculated by comparing the reflectance of red and near-infrared light from built-up areas or natural land cover. Built-up areas reflect more red light and less near-infrared light than vegetation or water. BU values range from -1 to 1, where higher values indicate more urbanization and lower values indicate less urbanization or non-urban areas.

BU values have shifted and become more variable over the past two decades. This means that the urbanization has changed in different ways across regions and seasons, while the overall range of urbanization has become narrower between the two years.

Figure 8: Built-Up Index

Built-up Index
Achanakmar-Amarkantak Biosphere Reserve, M.P. & C.G.



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE.

Some possible reasons for this change are varying rates of urban growth, such as fast, slow, or negative growth, or controlled development or more balanced expansion due to planning, regulation, or demand.

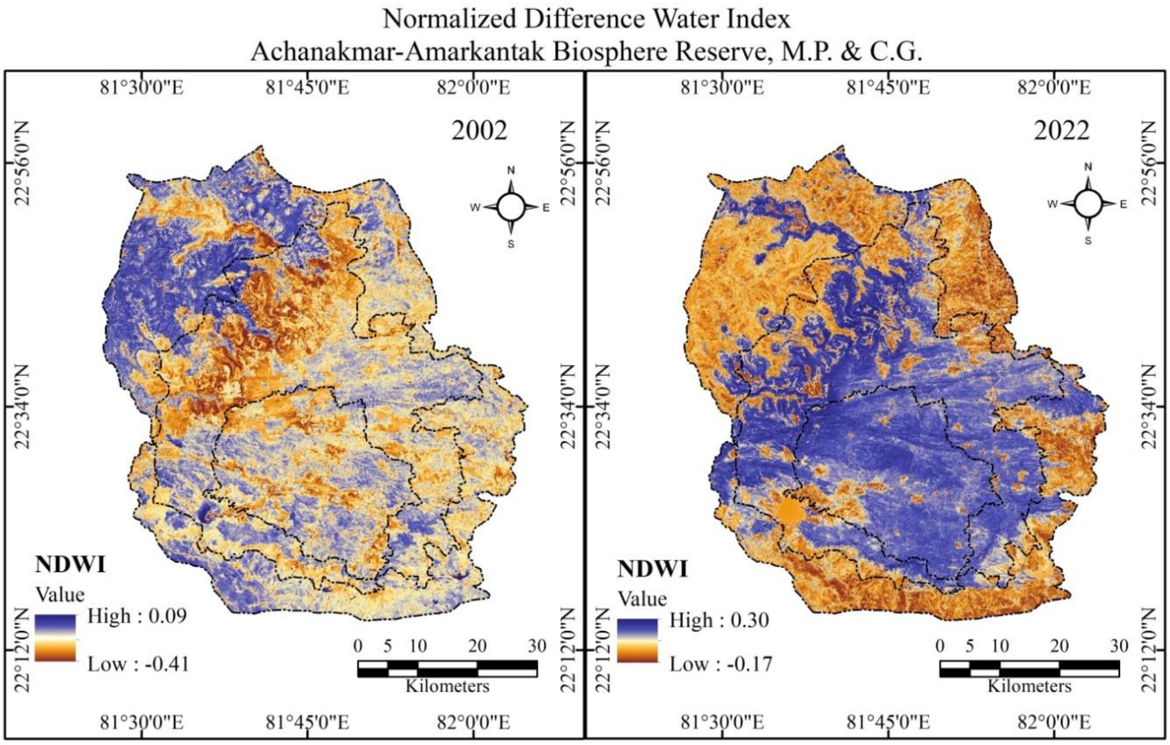
NDWI (The Normalized Difference Water Index)

NDWI is a measure used to identify and quantify water content in natural surfaces. It's calculated as the normalized difference between the near-infrared (NIR) and green bands of remotely sensed data, typically from satellite or airborne sensors. NDWI values typically range from -1 to 1, with values closer to 1 indicating high water content and values closer to -1 indicating low water content. This index is commonly used in hydrological applications, such as monitoring water bodies, assessing drought conditions, and tracking water quality changes.

$$NDWI = \frac{(G - NIR)}{(G + NIR)}$$

The provided images show comparative Normalized Difference Water Index (NDWI) maps of Achanakmar-Amarkantak Biosphere Reserve in Madhya Pradesh and Chhattisgarh, India, for the years 2002 and 2022. NDWI is an index used to monitor changes in water content on the Earth's surface and is useful for the detection of water bodies and the assessment of the moisture content in vegetation.

Figure 9: Normalized Difference Water Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE.

The color scale for NDWI values ranges from blue (indicating higher water content) to orange and brown (indicating lower water content). In 2002, the range of NDWI values was from -0.41 to 0.09 with a mean of -0.16. This suggests that, on average, there were more areas with low water content, which could be indicative of less surface water or drier vegetation conditions across the biosphere reserve. By 2022, the range of NDWI values had shifted to span from -0.17 to 0.30 with a mean of 0.12. This shift to more positive values indicates an increase in water content, suggesting there may be more water bodies or higher moisture content in vegetation than in 2002.

Comparing the two images, the 2022 map shows a broader area of blue, especially in the central and southern parts of the reserve, which aligns with the increased NDWI values indicating more water presence.

Possible reasons for this increase include

1. More frequent or intense rainfall events over the past two decades.
2. Changes in land management practices leading to better water retention in the soil and vegetation.
3. Conservation efforts that have resulted in the recovery of water bodies and improved hydrological conditions in the biosphere reserve.

LST (Land Surface Temperature)

LST increased slightly, from a range of 12°C to 37°C in 2002 to 16°C to 38°C in 2022. This aligns with overall temperature trends, indicating a modest rise in land surface warmth over the years. In 2002, the mean NDBI is 0.07, indicating a moderate level of built-up or urban areas. In 2022, the mean NDBI is 0.12, suggesting a slight increase in built-up or urban areas on average compared to 2002.

LST (Land Surface Temperature) is a measure of how warm the Earth's surface is. It is derived from the thermal infrared radiation emitted by the land surface, which depends on the surface type, cover, and moisture. LST values vary depending on the time of day, season, and location, but typically range from below zero to above 50°C.

LST values have increased slightly over the past two decades. This means that the land surface warmth has risen modestly over the years, in line with the overall temperature trends. Some possible reasons for this change are global warming, urban heat island effect, or changes in land cover or albedo**.**

A simplified outline of the steps and the final formula for LST calculation:

Steps for LST Calculation:

1. **Radiance Conversion**: Convert digital numbers (DN) from the satellite image to radiance (LλL_\lambdaLλ): Lλ=ML×DN+ALL_\lambda = M_L \times DN + A_LLλ=ML×DN+AL where MLM_LML and ALA_LAL are provided in the metadata of the satellite image.
2. **Brightness Temperature Calculation**: Convert radiance to brightness temperature (TbT_bTb) using the Planck's law inverse: Tb=K2ln(K1Lλ+1)T_{b} = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}Tb=ln(LλK1+1)K2 where K1K_1K1 and K2K_2K2 are calibration constants specific to the thermal band of the satellite sensor.
3. **Emissivity Correction**: Correct the brightness temperature for surface emissivity (ϵ\epsilonϵ): LST=Tb1+(λ⋅Tb/ρ)lnϵLST = \frac{T_b}{1 + \left(\lambda \cdot T_b / \rho \right) \ln \epsilon}LST=1+(λ⋅Tb/ρ)lnϵTb where:

- LSTLSTLST is the Land Surface Temperature in Kelvin.
- λ\lambdaλ is the wavelength of the emitted radiance (typically around 10-12 micrometers for TIR bands).
- ρ\rhoρ is a proportionality constant related to the physical constants hhh, ccc, and σ\sigmaσ.
- ϵ\epsilonϵ is the surface emissivity, which can be estimated from NDVI or other methods.

Final Formula for LST

LST=K2ln(K1ML×DN+AL+1)LST = \frac{K_2}{\ln\left(\frac{K_1}{M_L \times DN + A_L} + 1\right)}LST=ln(ML×DN+ALK1+1)K2

This formula combines the radiance conversion and brightness temperature calculation steps into a single equation, using the satellite-derived values for MLM_LML, ALA_LAL, K1K_1K1, and

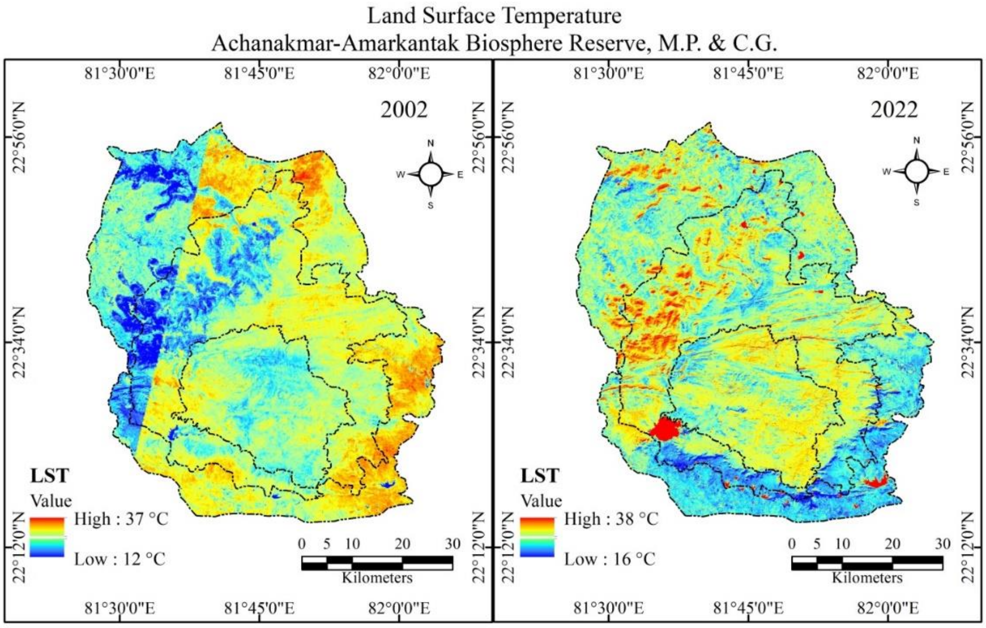
K2K_2K2. It assumes that emissivity is either known or estimated separately and applied in the correction step.

Notes

- **Calibration Constants**: K1K_1K1 and K2K_2K2 are specific to the satellite sensor and thermal band used. They are provided in the sensor's calibration data.
- **Surface Emissivity**: Accurate estimation of emissivity is critical for precise LST calculations and can significantly affect the results.
- **Atmospheric Corrections**: Depending on atmospheric conditions and study requirements, additional corrections may be necessary to account for atmospheric effects on thermal infrared measurements.

The provided image shows two Land Surface Temperature (LST) maps of the Achanakmar-Amarkantak Biosphere Reserve in Madhya Pradesh and Chhattisgarh, India, from the years 2002 and 2022. The LST is an important climatic variable that represents the temperature of the earth's surface.

Figure 10: Land Surface Temperature



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE.

2002 LST Map: The range of temperatures is from 12°C (low) to 37°C (high). The northern part of the reserve is predominantly cooler, as indicated by the blue color, suggesting that this area might be covered with dense vegetation or higher elevation. Central areas show moderate temperatures, and there are patches of warmer temperatures (yellow to orange) scattered across the reserve.

2022 LST Map: The temperature range has shifted slightly higher, from 16°C (low) to 38°C (high). The overall map appears warmer, with more areas of red, indicating a general increase in surface temperatures across the reserve. The northern part still remains relatively cooler compared to the rest of the reserve, but the cooler area seems reduced compared to 2002.

Comparative Observations

There appears to be a warming trend over the 20-year span. The lowest temperature in 2022 is higher than the lowest in 2002, which has suggest milder conditions during the coolest times of the year or changes in land cover, such as deforestation or urbanization, that tend to increase LST. The highest temperatures are relatively similar, but the area that experiences the highest temperatures has expanded, particularly in the central and southern parts of the reserve. Such a warming trend have impact the biosphere reserve's ecosystem, potentially affecting biodiversity, altering habitats, and changing the phenology of plant and animal species.

NDLI (Normalized Difference Latent Heat Index)

The Normalized Difference Latent Heat Index (NDLI) is an index designed to estimate the latent heat flux, which is a measure of the amount of energy transferred by evaporation and transpiration processes. It is similar in concept to other normalized difference indices like NDVI but focuses on the thermal properties related to latent heat.

The formula for NDLI is:

NDLI=(TIR−MIR)(TIR+MIR)\text{NDLI} = \frac{(TIR - MIR)}{(TIR + MIR)}NDLI=(TIR+MIR)(TIR−MIR)

where:

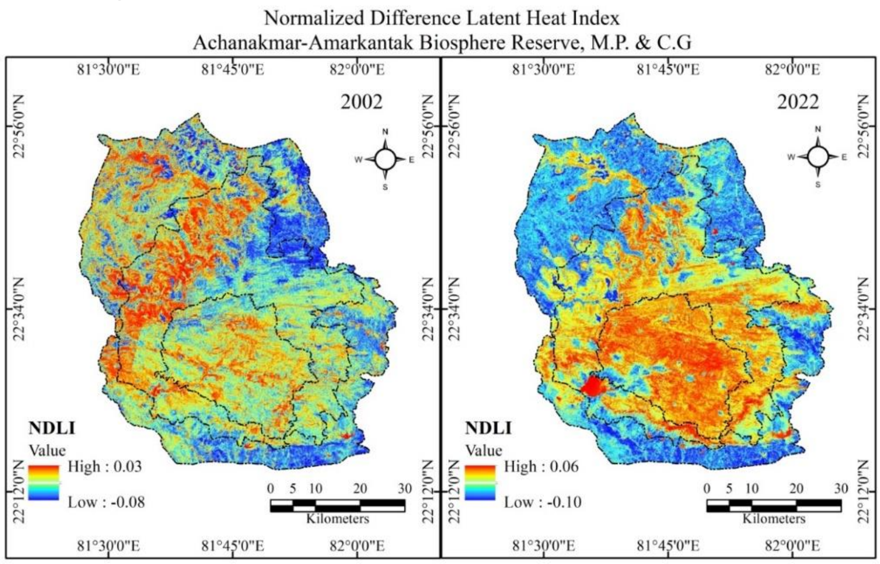
- TIRTIRTIR is the thermal infrared band reflectance.
- MIRMIRMIR is the mid-infrared band reflectance.

This formula helps to highlight the differences in thermal properties that are related to latent heat flux

The presented image in **Figure 11** compares two maps of the Achanakmar-Amarkantak Biosphere Reserve, located in Madhya Pradesh and Chhattisgarh, India, using the Normalized Difference Latent Heat Index (NDLI) for the years 2002 and 2022. The NDLI is a satellite-derived index that has used to assess vegetation stress and water content in plants; it is typically related to the amount of latent heat in the environment, which is associated with evapotranspiration.

The NDLI values are represented on a color scale, with blue indicating lower values (lower latent heat and likely lower vegetation water stress) and red indicating higher values (higher latent heat and likely higher vegetation water stress).

Figure 11: Normalized Difference Latent Heat Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE

The map for 2002 shows a relatively mixed pattern of NDLI values, with no extensive areas of high values, indicating a relatively balanced distribution of latent heat across the biosphere reserve. In contrast, the 2022 map shows a significant increase in areas with high NDLI values, particularly in the central part of the reserve. This could imply an increase in vegetation stress, possibly due to factors such as deforestation, changes in land use, climate change, or decreased precipitation. The expansion of higher NDLI values over the 20-year period could suggest that the biosphere reserve is experiencing increased environmental stress, leading to higher levels of evapotranspiration and potential changes in the ecosystem.
The LST is connected to every process occurring on the lithosphere, hydrosphere, and biosphere. The Land Surface Temperature may be estimated using the following formulas. It entails the following 5 steps:
Step: I, Digital number to spectral radiance
$L\lambda = ML^{*}Qcal + Al$
Step: II, Spectral radiance to bright temperature
Step: III, Proportion of Vegetation

$$PV = \left\{\frac{NDVI - NDVI_{min}}{NIR_{max} - NDVI_{min}}\right\}$$

Step: VI, Land Surface Emissivity

$$LSE = 0.004^{*}PV + 0.986$$

Step: V, Land Surface Temperature

$$e_j = \frac{-1}{1n(m)} \sum_{i=j}^{m} n_{ij} In(n_{ij})$$

The degree of diversity (d) possessed by each criterion is evaluated as equation 7.
$d_j = 1 - e_{ij}, j = 1,2,3$
The weight objective for each criterion is expressed in equation in equation 8.
$w_j = \frac{d_i}{\sum_{i=1}^{n} d_1}$

These indices collectively depict improved vegetation health, increased water presence, mixed urban expansion, subtle land warming, and relatively stable non-vegetated areas. The variations in index ranges provide insights into changing environmental dynamics and human impacts on the landscape between 2002 and 2022.

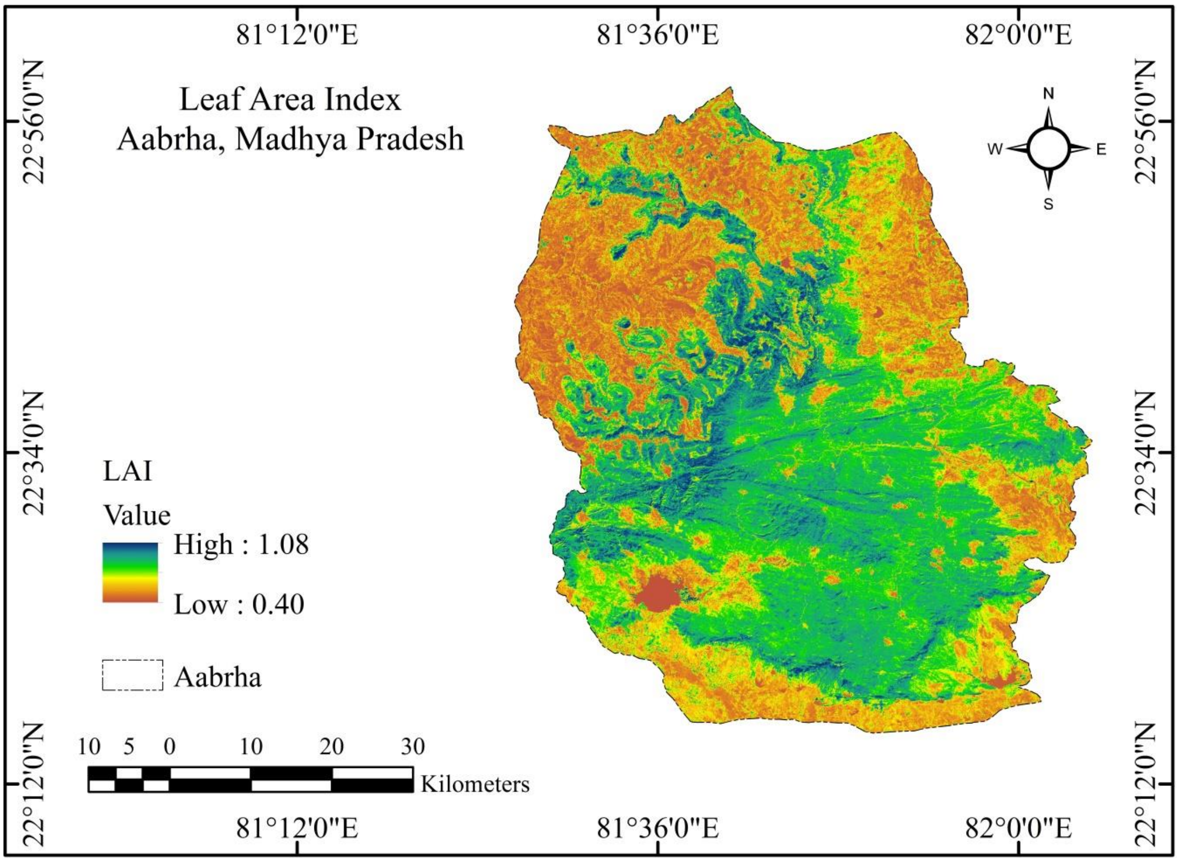
LAI (Leaf Area Index)
The Leaf Area Index (LAI) is a dimensionless value that characterizes the amount of leaf area in a given area. It is defined as the total one-sided area of leaf tissue per unit ground surface area. LAI can be estimated using different methods, including direct measurements, remote sensing, and various mathematical models. One common approach to estimate LAI from remote sensing data is using vegetation indices like the Normalized Difference Vegetation Index (NDVI).
This image **Figure 12** appears to be a map displaying the Leaf Area Index (LAI) for a region in AABR, India. The LAI is a measure of the leaf area per unit ground area and is used to estimate the amount of foliage in a region, which is critical for understanding photosynthesis, evapotranspiration, and the overall energy balance of an area. The color scale on the left indicates LAI values, with the low end at 0.40 and the high end at 1.08.

A common empirical formula to estimate LAI from NDVI is:
LAI=α·NDVI+β\text{LAI} = \alpha \cdot \text{NDVI} + \betaLAI=α·NDVI+β
where:

- α\alphaα and β\betaβ are coefficients that need to be determined through calibration for the specific vegetation type and conditions.

The relationship between LAI and NDVI can vary, and more sophisticated models may involve additional parameters and corrections for factors such as soil background, atmospheric conditions, and sensor-specific characteristics.

Figure 12: Leaf Area Index



Souece: Satellite Imagery of Landsat- 7 and 8 (2002 and 2022) processed in GEE.

The colors on the map range from green to red, with green areas indicating higher LAI values (more foliage or denser vegetation) and the orange and red areas indicating lower LAI values (less foliage or sparse vegetation). The dotted outline labeled "AABR" seems to delineate the boundary of the study area or a specific zone within the map. The north arrow and the longitude and latitude markers help orient the map geographically. The scale at the bottom gives a sense of distance, allowing viewers to estimate the size of the areas of interest.

Conclusion

AABR Reserve facing drastic environmental degradation, natural calamities, and anthropogenic activities, checking ecological growth, shrinking, and exploiting due to the extreme climatic conditions, which leads to land degradation to biodiversity. The Achanakmar-Amarkantak Biosphere Reserve is a lush green forest, but has witnessed large-scale devastation bearing the substance of climate change evident in increasingly unpredictable rainfall and higher temperatures from 2002 to 2022. This study identify the degradation and long-term monitoring and suggest the appropriate conservation, management, and policies, it is a time to implement and protect the Achanakmar-Amarkantak Biosphere Reserve without hindering the present stage of the natural environment sustainably. It is associated with changes in land use and climate variability. These indices collectively depict. The variations in index ranges provide insights into changing environmental dynamics and human impacts on the landscape between 2002 and 2022.

References

1. Baruah, J., & Jyoti Bhuyan, D. (2021). Environmental degradation and its impact on sustainable development: An analysis. *International Journal of Aquatic Science, 12*(03), 2021.
2. Chandrakar, S., Dixit, B., Singh, S., & Sahu, C. (2021). Studies on rare and threatened medicinal plants of Achanakmar-Amarkantak Biosphere Reserve (AABR), Chhattisgarh. *Chhattisgarh Journal of Science and Technology, 18*(4), 310–314.
3. Chopra, R. (2016). Environmental degradation in India: Causes and consequences. *International Journal of Applied Environmental Sciences, 11*(6), 1593–1601. http://www.ripublication.com
4. Choudhury, D. N. R. (2016). Report on monitoring of developmental activities Achanakmar-Amarkantak Biosphere Reserve in Chhattisgarh under Management Action Plan 2015-16. *Tropical Forest Research Institute (Indian Council of Forestry Research and Education)*, 4–4.
5. Hasnat, A., Sajjad, A., Usmani, M. A., Rehman, A. A., & Bi, S. (2012). Environmental degradation: Its causes, effects, and restoration. *S Iss, 11*(1), 1492–1501. www.ijfans.org
6. Joshi, K. C., & Tiple, A. D. (2010). Achanakmar-Amarkantak Biosphere Reserve. *Biosphere Reserves Information Series (BRIS), 2*(1-2)(October), 2. https://doi.org/10.13140/2.1.1634.4649
7. Maurya, P. K., Ali, S. A., Ahmad, A., Zhou, Q., da Silva Castro, J., Khane, E., & Ali, A. (2020). An introduction to environmental degradation: Causes, consequence, and mitigation. *Environmental Degradation: Causes and Remediation Strategies*, 1–20. https://doi.org/10.26832/aesa-2020-edcrs-01
8. N. Roychaudhury, K. C. J. (2011). Monitoring of development activities of Achanakmar-Amarkantak Biosphere Reserve in Chhattisgarh under Management Action Plan 2009-10.
9. Roychoudhury, N. (2020). Biosphere reserve under World Network of Biosphere Reserves: Scope and challenges (Indian Council of Forestry Research and Education). November 2012.
10. Roychoudhury, N., & Gupta, D. (2016). Achanakmar-Amarkantak Biosphere Reserve, India: A diverse tropical forest ecosystem. *Van Sangyan (ISSN 2395 - 468X), 3*(6)(June).
11. Bera, D., Chatterjee, N., Das, G., Ghosh, S., & Dinda, S. (2022). Recent trends of land surface temperature in relation to the influencing factors using Google Earth Engine platform and time series products in megacities of India. October. https://doi.org/10.1016/j.jclepro.2022.134735
12. Capolupo, A., Monterisi, C., & Tarantino, E. (2020). Landsat Images Classification Algorithm (LICA) to automatically extract land cover information in Google Earth Engine environment. *Remote Sensing, 12*(7). https://doi.org/10.3390/rs12071201
13. Liu, C., Li, W., Zhu, G., Zhou, H., & Yan, H. (n.d.). Land use/land cover changes and their driving factors in the northeastern Tibetan Plateau based on geographical detectors and Google Earth Engine: A case study in Gannan Prefecture. *Remote Sensing*.

14. Goldblatt, R., You, W., Hanson, G., & Khandelwal, A. K. (2016). Detecting the boundaries of urban areas in India: A dataset for pixel-based image classification in Google Earth Engine. *Remote Sensing, 8*(8), 634.