ENVIRONMENTAL SUSTAINABILITY ASSESSMENT OF A HIMALAYAN CATCHMENT WITH LAND COVER INDICES AND LST RELATIONSHIP USING PRINCIPAL COMPONENT ANALYSIS – A GEOSPATIAL APPROACH

[1]*M. Sathyaseelan, [1]Sanjay Kumar Ghosh, [1]Chandra Shekhar Prasad Ojha

[1]Department of Civil Engineering, Indian Institute of Technology Roorkee, Uttarakhand - 247 667, India.
*msathyaseelan@ce.iitr.ac.in, sanjay.ghosh@ce.iitr.ac.in, c.ojha@ce.iitr.ac.in

KEY WORDS: Land Cover Indices, Land Surface Temperature, Principal Component Analysis, Sustainability .

ABSTRACT:

Environmental sustainability assessment is a crucial part of the management of natural resources. Remote Sensing based environmental land cover indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), Normalized Difference Moisture Index (NDMI), and its associated Land Surface Temperature (LST) are the major governing factors for the environmental processes that happen on the surface of the earth. These NDVI, NDWI, NDBI, NDMI, and LST are generated for 2020 using the Landsat satellite datasets. The process-based relationship among them is complex and involves various parameters but may be easily represented by multiple linear regression models. Principal Component Analysis (PCA) is one such type that efficiently handles and evaluates the contribution of each of these factors to each other based on the sampling units. The study area is the upper Ramganga catchment in the Indian Himalayas, consisting of 117 sub-catchments. These catchment units (samples) are entangled with these environmental factors. The results of the PCA reveal the relationship between each of the environmental factors and their priority. Based on the uncorrelated factors priority suggestion from the PCA, catchment units were classified as high, moderate, or low categories based on their dominance in the relationship among the factors. These spatial variations in the environmental factors can help to assess the sustainability of resources in the Himalayan catchment.

1. INTRODUCTION

1.1 Environmental Sustainability Assessment

Environmental sustainability assessment is an essential part of the conservation and management of natural resources of a region for the existence of life. Remote Sensing based land cover indices help feature extraction of land and water resources and are used for modelling various environmental and ecosystem processes concerning environmental sustainability (Robinson et al. 2017). Remote Sensing based Land Surface Temperatures (LSTs) play a vital role in monitoring and modelling the global or local Surface Energy Balances (SEBs) and water exchange processes at the land-atmosphere interactions (Zhao et al. 2019). The land cover indices and LST are useful in studying water resources management, agrobiodiversity conservation, soil health, climate change mitigation and adaptation strategies, and environmental sustainability (Singh et al., 2021). As per the United Nations (UN) Global Sustainable Development Report (GSDR, 2019) and the Sustainable Development Goals Report (SDGR, 2022), it is essential to formulate policy-making and implementation of SDGs at the local stakeholder level. The effects of climate change and land use changes need to be benchmarked in river basins (regional scale) so that the role of global trends versus local changes can be assessed and factored into decision-making (Lawford et al., 2013). Monitoring and managing natural resources at the local/regional scale as sub-catchments, administrative blocks or village levels is the current implementation scenario required for several policy-making. Science, economic viability, and community expectations is varying significantly over time. There is subsequently an increase in model complexities and difficulties in evaluating the sustainability of river basins (Horne, 2017). It is important to understand the interactions of societal factors that influence people's preferences in policy-making or decisions for sustainability (Roobavannan et al., 2020). Several studies were reported on the environmental sustainability aspects such as Eco-Hydrological sustainability (Khatun et al., 2021; Shiran et al., 2021), eco-environmental vulnerability (Nguyen et al., 2016; Liou et al., 2017; Venkatesh et al., 2020; and Kurniawan et al., 2022), vegetation dynamics (Qureshi et al., 2020), Soil moisture-LST based drought characterization (Saha et al., 2018). Several hydrological, ecological, environmental, and socio-economic problems and their solutions have been addressed by analyzing the Remote Sensing based land cover changes for environmental sustainability (Liou et al., 2017; Venkatesh et al., 2020; Kurniawan et al., 2022; Saleh et al., 2022). It includes changes in the built-up area, wetlands, forest cover, agricultural cropping patterns, and hydrological responses. The applicability and usage of those studies may vary based on the geographical prevalence of the study area and its spatial scales.

The Himalayas are notable for the richness of resources in terms of water, biodiversity, and varied ecosystems (Khare and Ghosh, 2016; Singh et al., 2021; Taloor et al., 2021; Gurjar et al., 2022; Piyoosh and Ghosh, 2022). Himalayan catchments are prone to several natural, anthropogenic, and other environmental problems associated with the hydrological cycle and the impact of climate change on the resources (Gurjar et al., 2022). In this study, using the geospatial approach, the assessment of environmental sustainability of the Upper Ramganga catchment has been carried using various land cover spectral indices and their relationship with LST. The study area has been delineated into 117 sub-catchments through the Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM). Remote Sensing datasets efficiently monitor and manage these changes at variable scales. The Google Earth Engine (GEE) Platform has been used for data extraction from Landsat 8 for 2020. The land cover indices, such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), Normalized Difference Moisture Index (NDMI) and LST, are chosen as major land Remote Sensing based environmental variables that help to regulate the environmental flows, their vulnerabilities and sustainability of natural resources (Nguyen et al., 2016; Firozjaei et al., 2021; Khatun et al., 2021; Kurniawan et al., 2022). The results of these indices and LST are used to delineate the sub-catchment units as the sampling units. The threshold limits of the results are based on statistical measures such as minimum, maximum, mean, and standard deviation of the factors. The results of the indices and LST have been classified into low, moderate, high, and very high classes.

The relationship between these factors considering the catchment unit as samples is established using statistical measures such as Pearson's correlation coefficient, Regression analysis and Factor analysis, including the Principal Component Analysis (PCA). Since the number of factors is five, the PCA method is applicable and efficiently analyses the relationship among them. It is clear to identify the influencing factors using the eigenvector values and their percentage of variance among the principal component (PCs) (Qureshi et al., 2020; Abhir and Saha, 2021; Kumar et al., 2021). The results of the classification of the indices and LST are ranked based on the conceptual relation to the idea of sustainability and weighted based on the PCA results. These results are taken into the Geographical Information System (GIS) as layers, and the overlay operation is performed. The results show the variations of environmental sustainability classes such as low, moderate, high, and very high for the sub-catchments. The study is unique and deviates from other works by portraying a catchment unit-based geospatial approach for analyzing environmental sustainability results.

2. MATERIALS

2.1 Study Area

The study area is the Upper Ramganga Catchment in the Western Himalayas, which partially covers the states of Uttarakhand (53%) and Uttar Pradesh (47%) of India. It is one of the major tributaries of the Upper Ganga Basin. The geographical location of the study area lies between 28°15' 32.55" N to 30°6'32.42" N latitude and 78°15'45.37" E to 79°50'45.74"E longitude, as shown in Figure 1. The geographical area is about 18,000 km^2, and the elevation ranges from 76 m to 3000 m. As per the revised Koppen climate classification system, it falls under the categories of sub-tropical humid (cfa) and monsoonal (cwa). The mean annual rainfall varies from 2200mm to 800mm, and the average temperature ranges from 5°C to 25°C in winter and from 20°C to more than 40°C in summer. The average annual pan evaporation rate for Ramganga Basin is 4.88mm/day. The major towns such as Bareilly, Moradabad, Pilibhit, Rampur, and Shahjahanpur have populations ranging from 1 to 10 lakhs (Ramganga Basin Plan, 2020).

2.2 Datasets Used

The Digital Elevation Model (DEM) is one of the preliminary datasets for catchment or basin-level studies since any river pattern follows the topography. The catchment delineation for the study area has been obtained from the recent NASADEM_HGT version 1 an updated version of Shuttle Radar Topographic Mission (SRTM) DEM data of one arc-second resolution (~30m spatial resolution) with improved accuracy in height (Tran et al., 2023). The GEE platform has been used in this study to get the Landsat 8 Operational Land Imager (OLI) / Thermal Infrared Sensors (TIRS) Surface Reflectance (SR) collection products for 2020. Since the data is mostly available in the pre-processed format, there is no requirement for atmospheric and radiometric correction to the datasets. A known error exists in the Landsat Surface Temperature retrievals relative to clouds and possibly cloud shadows. These issues have been characterized by Cook et al., 2014. However, the presence of cloud cover in the data could be a problem. So, the cloud masking procedure has been included in the GEE program to remove 10% of the cloud cover in the data. Land cover indices such as NDVI, NDWI, NDBI, NDMI, and LST are derived from the pre-processed Landsat 8 datasets in the GEE platform.

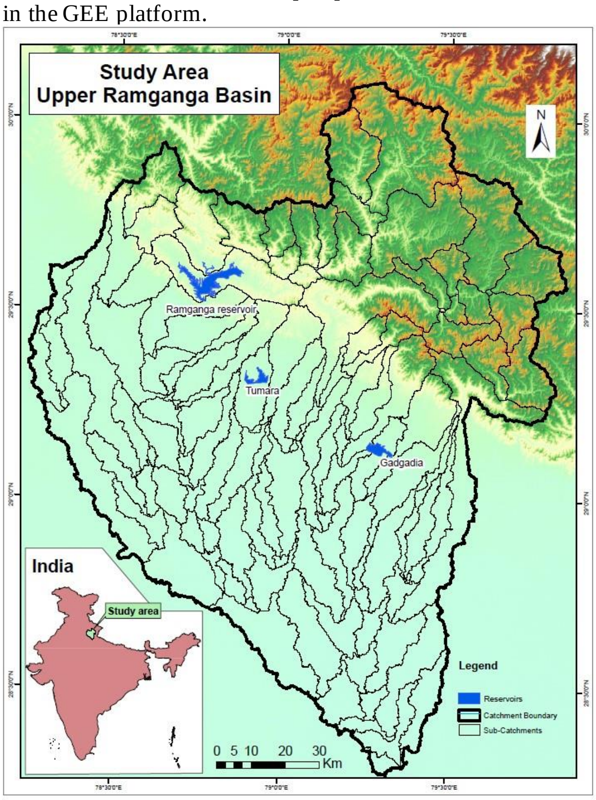

Figure 1. Study Area

Satellite Datasets Used	Band(s) used for analysis	Data Resolution
NASADEM (updated SRTM in Height measurements)	Single band raster NASADEM_HGT dataset	1-Arc Second (about 30m Ground Sampling Distance (GSD))
Landsat 8 OLI(LC08) Collection-2 Tier-1 Level-2 SR datasets	Band 4 – Red; Band 5 - Near Infrared (NIR); and Band 6 – Shortwave Infrared 1 (SWIR1)	30m X 30m GSD
Landsat 8 TIRS (LC08) Collection-1 Tier-1 Level-1 datasets accessed before 30th December 2022.	Band 10 – TIRS (this is used because USGS suggests band 10 for LST estimation rather than band 11(with uncertainty)	Resampled from 100 m to 30 m GSD data using the cubic convolution technique.

Table 1. Datasets Used

3. METHODS

Remote Sensing based degree of Environmental Sustainability has been assessed at the sub-catchment level through a workflow as shown in Figure 2.

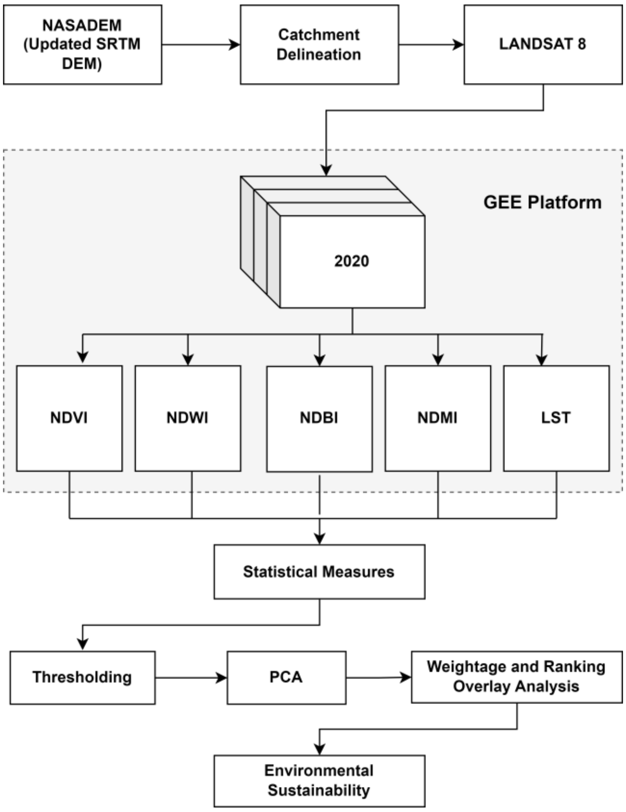

Figure 2. Flow Chart showing the methodology adopted.

3.1 Catchment delineation and Land Cover Spectral Indices

The catchment delineation has been carried on the upgraded NASA SRTM DEM with improved height measurements. Several approaches have been proposed for studying the various aspects of environmental sustainability. It is observed that the spectral indices such as NDVI, NDWI, NDBI, NDMI, and LST are used frequently, and that the same has been chosen in this study with catchment units as sampling units. Landsat 8 data has been chosen for the year 2020, with the catchment boundary as the area of interest in the GEE platform. The NDVI, NDWI, NDBI, NDMI and LST are derived from the GEE platform using the formulas suggested by Gao (1996); Weier and Herring (2000); Stathopoulou and Cartalis (2007); He et al. (2010); Khare et al. (2016); Piyoosh and Ghosh (2020) and Taloor et al. (2021) respectively.

3.2 Land Surface Temperature (LST)

The LST is calculated using the Single Channel Algorithm (SCA) (Jimenez-Munoz et al., 2014), which follows the spectral radiance of the Landsat 8 band 10. Since USGS recommends using band 10 Landsat 8 TIRS-1 datasets for the LST estimation, the same has been adopted for this study. The readily available Surface Temperature (ST) products from Collection-2 L2 ST is not used since it uses the emissivity derived from ASTER NDVI datasets which is of coarser resolution when compared with NDVI derived from Landsat 8 SR products (Table 1). The calculation of LST also exhibits known inaccuracy to pixel dimensions, clouds, and cloud shadows, which was characterized by Cook et al. (2014). So, a minimal cloud coverage of 10% has been chosen for the analysis. The prior knowledge of Land Surface Emissivity (LSE) is necessary for calculating LST (Chander et al., 2009; Valor and Caselles, 1996; Sobrino et al., 2004). So, an operational procedure to estimate LSE (i.e., ε) using the NDVI-based proportion of vegetation as proposed by Sobrino et al. (2008) and Van de Griend and Owe (1993). It has been used with the NDVI values of study area. Sobrino et al. (2004) proposed LSE calculation for the mixed pixels of vegetation. In case of unknown vegetation and soil, the emissivity values are taken as $\varepsilon_v = 0.985$ and $\varepsilon_s = 0.960$ (Valor and Caselles, 1996; Sekertekin and Bonafoni, 2020), respectively. The proportion of vegetation is also referred to as fractional vegetation cover, which is used for determining the surface emissivity of the area. In this study, the resulting emissivity is calculated by the above methods as 0.981. Based on the emissivity value, the Land Surface Temperature (LST) is calculated using the formula given by Stathopoulou and Cartalis (2007); Piyoosh and Ghosh (2020).

3.3 Thresholding

The factors contributing to the environmental sustainability are quantitatively assessed by the zonal statistical measures for the catchment unit areas. The thresholding of the statistical measures is based on the standard deviation from the mean of the histogram of data. The factors are classified as low, moderate, high, and very high based on the thresholding classes for each of the sampling catchment units in relevance to the concept of sustainability.

3.4 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a multivariate statistical technique that applies a linear transformation to the original data to study the complex relationship between those environmental and ecological variables (Estornell et al., 2013; Jolliffe and Cadima, 2016; Firozjaei et al., 2021; Kurniawan et al., 2022; Kumar et al., 2022). PCA also reduces the dimensionality of the data matrix through Singular Value Decomposition (SVD) algorithm, and to segregate the dominant information in the data (Zhou et al., 2018; Qureshi et al., 2020). The uncorrelated linear principal components (PCs) after the orthogonal transformation gives the variance relationship between the components. The PCA is also supported by the Pearson's correlation coefficient to study the linear one-to-one relationship between the factors.

3.5 GIS Overlay

The weights of the GIS layers are obtained from PCA, and the corresponding conceptual ranking has been assigned to each of the layer classes relevant to the sustainability of environment. Later the intersection of GIS layers by overlay operation provides the final environmental sustainability with the threshold classes.

4. RESULTS

4.1 Catchment Delineation

The SRTM DEM with a spatial resolution of 1-arc second (approximately 30 m) is sufficient for this study and the catchment delineation threshold of about 30 km^2 area coverage.

This size is optimal for planning and managing catchment-level environmental sustainability studies, where the shape may vary subject to the village or block boundary. Also, the variations in the size of the catchments are subjective and relevant to the type of applications and planning purposes where it is implemented. Here, the number of catchment units delineated were 117 as given in Figure 1.

4.2 Results of the Spectral Indices and LST

NDVI is the most appropriate indices for studying vegetation cover in general and its characteristics. The NDVI values of zero or less than that indicate an area with no vegetation, such as barren lands or urban or water bodies. The results of the NDVI for the study area range from -0.126 to 0.898 and shown as in Figure 3 as NDVI (A) and NDVI (B). The results also show that the vegetation is higher along the stretch of lower hilly areas where the reservoirs are seen and along some portions of the higher elevations. All other areas are devoid of waterbodies, while urban areas show moderate vegetation cover. At the sub-catchment levels, lower vegetation is seen in fewer basins.

NDWI index segregates water bodies from the remote sensing datasets. The downside of the NDWI is reflectance observed in the green band from build-up or barren areas added to the calculation of the index with an overestimation of water bodies. However, from the results, it is observed that the NDWI can classify the waterbodies efficiently, but meanwhile, it is also considering the urban areas moderately to some extent in their index range. The NDWI is values range between -0.805 and 0.378. The thresholding of the NDWI class is based on statistical measures, and the results are illustrated in Figure 3 as NDWI (A) and NDWI (B). The results show that higher values represent as waterbodies, mostly the moderate values are found in the plain regions of the basin, and the higher vegetation regions show less water index values which is a downside of NDWI trade-offs.

NDBI is the mapping index for the build-up areas. The results are shown in Figure 3. It is observed from the results that NDBI classifies the barren land into the built-up area to some extent because of the reflectance observed in the SWIR and NIR band. Users should consider the trade-offs between the efficiency and accuracy of these indices when choosing between the actual performance of the indices to the desired application. The value of the NDBI ranges between -0.433 to 0.246. The results show that the NDBI segregates the build-up area at higher values and moderately classifies barren land or less/no vegetation areas. Some higher potential build-up areas are identified at the sub-catchment level based on the statistical thresholding of NDBI results.

The NDMI is a Remote Sensing based indices for calculating the overall moisture content in vegetation, soil, and water areas/wetlands. The NDMI is calculated using the same bands of NDBI with slight changes in the numerical operation of the bands. Also, it can overcome the drawbacks of the NDWI in calculating the waterbodies/wetlands or soil moisture area by taking advantage of the Shortwave Infrared band (SWIR1). The value of the NDMI ranges between 0.602 and -0.337, as illustrated in Figure 3 as NDMI(A) and NDMI(B).

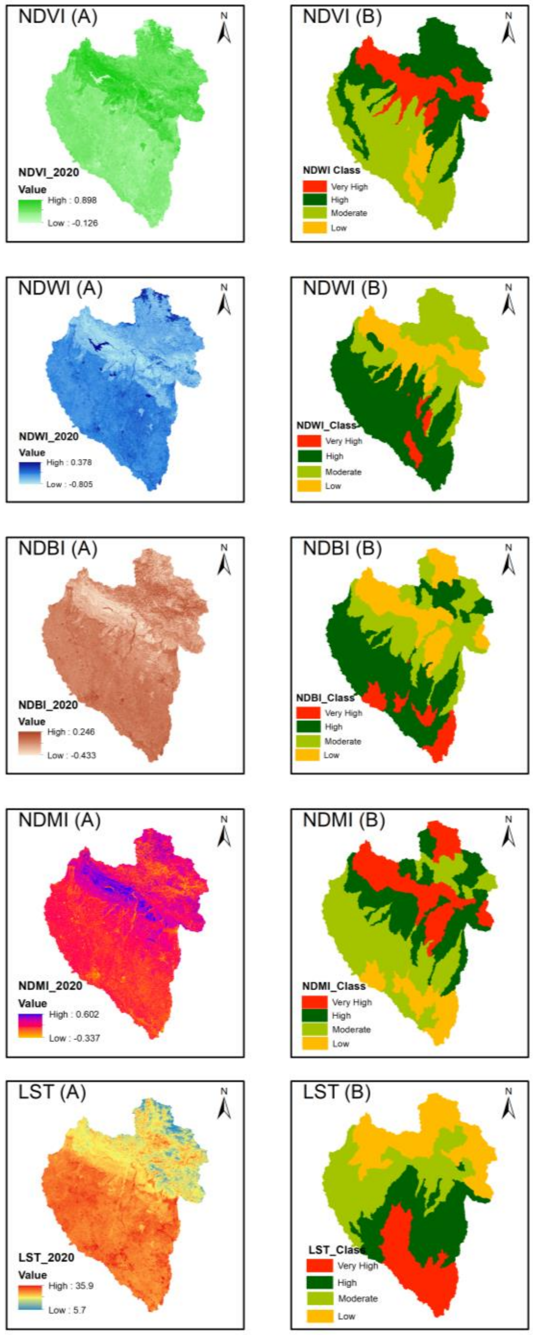

Figure 3. Land Cover Indices and LST

The Land Surface Temperature (LST) results show that it varies from 5.7°C to 35.9°C for 2020. It is calculated from the NDVI-based Land Surface Emissivity (LSE) given in Section 2. of the paper. The build-up areas show higher temperature ranges, and mostly the plain areas where the agricultural cover and waterbodies/wetlands show moderate to higher temperature ranges. The hilly areas with higher elevations show lower temperature ranges. The results of the LST are illustrated in Figure 3.

4.3 Results of the Statistical thresholds

The results of the thresholding based on the zonal statistical measures for the catchment unit corresponding to the factors is given in Table 2.

Factors	Threshold values	Category	Rank	Weight
NDVI	< 0.362	Low	IV	0.216
	0.362 < 0.463	Moderate	III	
	0.463 < 0.564	High	II	
	0.564 < 0.720	Very High	I	
NDWI	< -0.542	Low	IV	0.188
	-0.542 < -0.452	Moderate	III	
	-0.452 < -0.362	High	II	
	>-0.362	Very High	I	
NDBI	< -0.165	Very High	I	0.203
	-0.165 < -0.118	High	II	
	-0.118 < -0.0071	Moderate	III	
	>-0.0071	Low	IV	
NDMI	< 0.122	Low	IV	0.259
	0.122 < 0.174	Moderate	III	
	0.174 < 0.226	High	II	
	> 0.226	Very High	I	
LST	< 17.416	Very High	I	0.187
	17.416 < 21.7	High	II	
	21.7 < 25.984	Moderate	III	
	25.984 < 29.502	Low	IV	

Table 2. Threshold values for factors

4.4 Results of the Correlation and the PCA analysis

The results of the correlation matrix given in Table 3. shows a strong negative correlation between the NDVI-LST; NDMI-LST and a good positive correlation between the NDWI-LST; NDBI-LST, respectively.

The NDVI has a strong negative correlation with all the factors except NDMI, which has a strong positive correlation. It is observed that the NDWI can classify the waterbodies efficiently while also classifying the urban areas moderately. It is important to note that, the NDWI has a strong negative correlation with the NDVI. In general comparison it may seems to be a wrong correlation, here, the results of the land cover indices are given as a mean of the catchment units and hence, the correlation takes the average of the pixels of NDWI apart from the water pixels, it also considers the non-water pixels areas, resulting in a strong negative correlation.

Factors	**NDVI**	**NDWI**	**NDBI**	**NDMI**	**LST**
NDVI	1				
NDWI	-0.95	1			
NDBI	-0.70	0.48	1		
NDMI	0.71	-0.51	-1.00	1	
LST	-0.70	0.60	0.62	-0.64	1

Table 3. Correlation Matrix of the factors

So, a positive correlation is seen among the NDWI-LST, and it must be noted that seasonal factors also play a role in defining the correlation results (Guha and Govil, 2021). However, here only the annual data have been considered for this study. The results of the NDMI show a positive correlation with the NDVI negative correlation with NDWI, NDBI, and LST. Here, the NDMI and the NDBI use the same bands with slight changes in the sign operations; hence, there is a strong negative correlation of -1 between them. Meanwhile, there is a negative correlation between the NDBI-NDVI and a positive correlation between NDBI-NDWI and NDBI-LST, respectively.

The relationship between the factors can be further studied more accurately using the PCA technique. The eigenvalues corresponding to each principal component (PCs) provides the hierarchy of the components in the relation. The eigenvalues of PC factors, their corresponding variances, and the cumulative variances are given in Table 4.

PCs	**Eigenvalues**	**Standard deviation**	**Proportion of Variance**	**Cumulative Proportion of Variance**
PC1	3.778	1.943	0.755	75.555
PC2	0.798	0.893	0.159	91.521
PC3	0.410	0.639	0.081	99.712
PC4	0.013	0.115	0.002	99.977
PC5	0.001	0.034	0.000	100.000

Table 4. Results of all major PCs and its variance

Based on these results, the PC1 with an eigenvalue greater than one with a higher variance of about 75.60% is considered for the weightage analysis.

Factors	**PC 1**	**Component Score Coefficients**	**Corresponding Weights Calculated with Sum=1**
NDVI	-0.936	-0.248	0.216
NDWI	0.815	0.216	0.188
NDBI	0.881	0.233	0.203
NDMI	-0.894	-0.237	0.206
LST	0.813	0.215	0.187

Table 5. Weightage of the factors using PC1 score coefficients.

The scores of the PC1, as given in Table 5., are rescaled to the weightage of the factors with sum equals to one.

4.5 Results of the Environmental Sustainability Assessment

Based on the results of PCA, the weights of the factors that contribute to the Environmental sustainability are calculated as given in Table 5. is then assigned to the corresponding factors as given in Table 2.

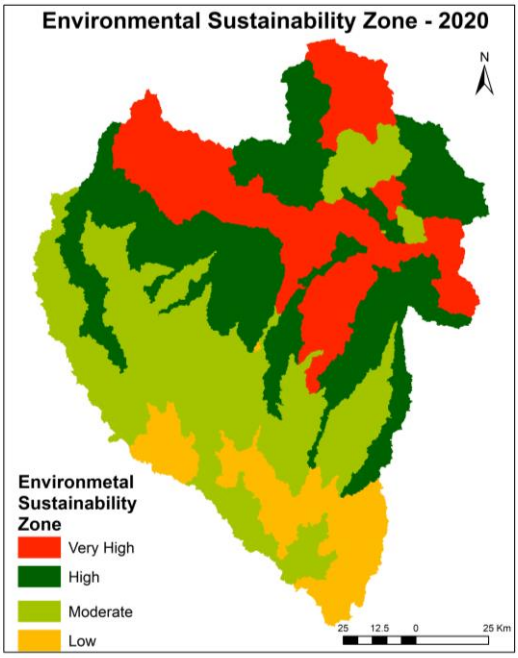

Figure 4. Environmental Sustainability Zones

All the factors that contribute to the analysis are classified as low, moderate, high, and very high classes based on the Table 2. The factors are taken into the GIS platform, where the layers are weighted, based on the PCA results and the corresponding ranks have been assigned to each class in all the layers, and the GIS overlay operation is performed. The final environmental sustainability zones for the sub-catchments were identified and classified as low, moderate, high, and very high classes based on the GIS overlay result, as shown in Figure 4. The results show that the low sustainability catchments are identified at the lower region of the basin, very high sustained zones are identified at the higher elevation regions, and along the stretch of the lower hilly regions of the Himalayas, where the reservoirs and dams are located. Higher sustainable catchment zones are found on either side of the very high sustainable zones. Most of the moderate zones of sustainable catchments are identified in the plain areas, and few are in the hilly areas.

5. DISCUSSION

The results of the land cover indices, such as the NDVI, NDWI, NDBI, NDMI, and LST, are studied for 2020 only. Their seasonal relationship with the factors also plays an important role in the seasonal assessment. However, this study has not considered it, which is one of the limitations. The results of NDWI in the zonal statistics with catchment areas yield a negative correlation with the NDVI which may leads to contradictory results because of considering the non-water areas in calculating the mean. The other limitations are that the number of factors contributing to environmental sustainability assessment is less. The limitation of the study includes the watershed prioritization based on the morphometric characteristics, several other socio-economic statuses of the region, and demographic factors, like population density and migration is not included and may be considered in future works. The correlation and the PCA technique uses the relationship the uncorrelated factors with eigenvalues and eigenvectors, where the relationship is established among of one-to-many factors has been established, and the individual factor contribution is identified. Since the number of PCs that is more than the eigenvalue of 1 is only one principal component, and hence there is no rotated component matrix exists for the same. If the number of significant components is more than 1, then we should consider the rotated component matrix for determining the weight of the factors contributing to environmental sustainability. Based on the environmental sustainability assessment results, the regions at the lower elevation or plain areas are identified as low sustainable catchment zones, where the presence of built-up and the LST are higher and favorable for the likelihood of urban agglomeration. The moderately sustainable catchments are the region where there is a need for mitigation measures to ensure or stop the degradation of environmental sustainability. The higher and very high zones are less vulnerable to the degradation of sustainability.

6. CONCLUSION

The overall study uses minimal remote sensing-based land cover indices and LST for the analysis. Despite the limitations discussed above, this study tried to assess the environmental sustainability of a catchment based on the remote sensing inputs at the sub-catchment level. The results of the PCA analysis their relationship between the factors helps in modelling the scenario and may help in prediction of future conditions using the Machine Learning (ML) algorithms. This study may help planners and decision-makers to formulate strategies and adaptation policies or measures for environmental sustainability under climate change initiatives.

ACKNOWLEDGEMENTS

The authors sincerely thank the Department of Civil Engineering, IIT Roorkee, India and the Ministry of Education, Government of India, for providing the MHRD Fellowship.

REFERENCES

Abir, F. A., & Saha, R. (2021). Assessment of land surface temperature and land cover variability during winter: a spatio-temporal analysis of Pabna municipality in Bangladesh. *Environmental Challenges*, *4*, 100167. https://doi.org/10.1016/j.envc.2021.100167

Chander, G., Markham, B. L., & Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote sensing of environment*, *113*(5), 893-903. https://doi.org/10.1016/j.rse.2009.01.007

Cook, M., Schott, J. R., Mandel, J., & Raqueno, N. (2014). Development of an operational calibration methodology for the Landsat thermal data archive and initial testing of the atmospheric compensation component of a land surface temperature (LST) product from the archive. *Remote Sensing*, *6*(11), 11244-11266. https://doi.org/10.3390/rs61111244

Estornell, J., Martí-Gavilá, J. M., Sebastiá, M. T., & Mengual, J. (2013). Principal component analysis applied to remote sensing. *Modelling in Science Education and Learning*, *6*, 83-89. https://doi.org/10.4995/msel.2013.1905

Firozjaei, Mohammad Karimi, Solmaz Fathololoumi, Majid Kiavarz, Asim Biswas, Mehdi Homaee, and Seyed Kazem Alavipanah. "Land Surface Ecological Status Composition Index (LSESCI): A novel remote sensing-based technique for modeling land surface ecological status." *Ecological Indicators* 123 (2021): 107375. https://doi.org/10.1016/j.ecolind.2021.107375

Gao, B. C. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote sensing of environment*, *58*(3), 257-266. https://bpb-us-w2.wpmucdn.com/sites.udel.edu/dist/d/1835/files/2014/06/NDWI-A-Normalized-Difference-Water-Index-for-Remote-Sensing-of-Vegetation-Liquid-Water-From-Space-1ko95nn.pdf

Guha, S., & Govil, H. (2021). An assessment on the relationship between land surface temperature and normalized difference vegetation index. *Environment, Development and Sustainability*, *23*, 1944-1963. https://doi.org/10.1007/s10668-020-00657-6

Gurjar, S. K., Shrivastava, S., Suryavanshi, S., & Tare, V. (2022). Assessment of the natural flow regime and its variability in a tributary of Ganga River: Impact of land use and land cover change. *Environmental Development*, *44*, 100756. https://doi.org/10.1016/j.envdev.2022.100756

He, C., Shi, P., Xie, D., & Zhao, Y. (2010). Improving the normalized difference built-up index to map urban built-up areas using a semiautomatic segmentation approach. *Remote Sensing Letters*, *1*(4), 213-221. https://doi.org/10.1080/01431161.2010.481681

Jiménez-Muñoz, J. C., Sobrino, J. A., Skoković, D., Mattar, C., & Cristobal, J. (2014). Land surface temperature retrieval methods from Landsat-8 thermal infrared sensor data. *IEEE Geoscience and remote sensing letters*, *11*(10), 1840-1843. https://doi.org/10.1109/LGRS.2014.2312032

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical transactions of the royal society A: Mathematical, Physical and Engineering Sciences*, *374*(2065), 20150202. https://doi.org/10.1098/rsta.2015.0202

Khatun, R., Talukdar, S., Pal, S., Saha, T. K., Mahato, S., Debanshi, S., & Mandal, I. (2021). Integrating remote sensing with swarm intelligence and artificial intelligence for modelling wetland habitat vulnerability in pursuance of damming. *Ecological Informatics*, *64*, 101349. https://doi.org/10.1016/j.ecoinf.2021.101349

Khare, S., Ghosh, S. K., Latifi, H., Vijay, S., & Dahms, T. (2017). Seasonal-based analysis of vegetation response to environmental variables in the mountainous forests of Western Himalaya using Landsat 8 data. *International journal of Remote Sensing*, *38*(15), 4418-4442. https://doi.org/10.1080/01431161.2017.1320450

Kumar, A., Singh, S., Pramanik, M., Chaudhary, S., Maurya, A. K., & Kumar, M. (2021). Watershed prioritization for soil erosion mapping in the Lesser Himalayan Indian basin using PCA and WSA methods in conjunction with morphometric parameters and GIS-based approach. *Environment, Development and Sustainability*, 1-39. https://doi.org/10.1007/s10668-021-01586-8

Kurniawan, R., Saputra, A. M. W., Wijayanto, A. W., & Caesarendra, W. (2022). Eco-environment vulnerability assessment using remote sensing approach in East Kalimantan, Indonesia. *Remote Sensing Applications: Society and Environment*, *27*, 100791. https://doi.org/10.1016/j.rsase.2022.100791

Lawford, R., Bogardi, J., Marx, S., Jain, S., Wostl, C. P., Knüppe, K., ... & Meza, F. (2013). Basin perspectives on the water–energy–food security nexus. *Current Opinion in Environmental Sustainability*, *5*(6), 607-616. https://doi.org/10.1016/j.cosust.2013.11.005

Liou, Y. A., Nguyen, A. K., & Li, M. H. (2017). Assessing spatiotemporal eco-environmental vulnerability by Landsat data. *Ecological indicators*, *80*, 52-65. https://doi.org/10.1016/j.ecolind.2017.04.055

Nguyen, A. K., Liou, Y. A., Li, M. H., & Tran, T. A. (2016). Zoning eco-environmental vulnerability for environmental management and protection. *Ecological Indicators*, *69*, 100-117. https://doi.org/10.1016/j.ecolind.2016.03.026

Nguyen, B. Q., Vo, N. D., Le, M. H., Nguyen, Q. D., Lakshmi, V., & Bolten, J. D. (2023). Quantification of global Digital Elevation Model (DEM)–A case study of the newly released NASADEM for a river basin in Central Vietnam. *Journal of Hydrology: Regional Studies*, *45*, 101282. https://doi.org/10.1016/j.ejrh.2022.101282

Piyoosh, A. K., & Ghosh, S. K. (2022). Analysis of land use land cover change using a new and existing spectral indices and its impact on normalized land surface temperature. *Geocarto International*, *37*(8), 2137-2159. https://doi.org/10.1080/10106049.2020.1815863

Qureshi, S., Alavipanah, S. K., Konyushkova, M., Mijani, N., Fathololomi, S., Firozjaei, M. K., ... & Kakroodi, A. A. (2020). A remotely sensed assessment of surface ecological change over the Gomishan Wetland, Iran. *Remote Sensing*, *12*(18), 2989. https://doi.org/10.3390/rs12182989

Ramganga Basin Plan. (2020). http://www.swaraup.gov.in/BAPS%20Reports/Ramganga%20Basin%20Plan%20Final/Ramganga%20Basin%20Plan%20(March%202020)%20Vol-1.pdf

Robinson, D. A., Panagos, P., Borrelli, P., Jones, A., Montanarella, L., Tye, A., & Obst, C. G. (2017). Soil natural capital in Europe; a framework for state and change assessment. *Scientific reports*, *7*(1), 6706. https://doi.org/10.1038/s41598-017-06819-3

Roobavannan, M., Kandasamy, J., Pande, S., Vigneswaran, S., & Sivapalan, M. (2020). Sustainability of agricultural basin development under uncertain future climate and economic conditions: A socio-hydrological analysis. *Ecological Economics*, *174*, 106665. https://doi.org/10.1016/j.ecolecon.2020.106665

Saha, A., Patil, M., Goyal, V. C., & Rathore, D. S. (2018). Assessment and impact of soil moisture index in agricultural drought estimation using remote sensing and GIS techniques. *Multidisciplinary digital publishing institute proceedings*, *7*(1), 2. https://doi.org/10.3390/ECWS-3-05802

Saleh, S. K., Sanaei, A., Amoushahi, S., & Ranjbar, S. (2022). Effect of landscape pattern changes and environmental indices on land surface temperature in a fragile ecosystem in southeastern Iran. *Environmental Science and Pollution Research*, 1-17. https://doi.org/10.1007/s11356-022-24602-4

Sekertekin, A., & Bonafoni, S. (2020). Land surface temperature retrieval from Landsat 5, 7, and 8 over rural areas: Assessment of different retrieval algorithms and emissivity models and toolbox implementation. *Remote sensing*, *12*(2), 294. https://doi.org/10.3390/rs12020294

Shiran, M., Mozzi, P., Adab, H., & Asadi, M. A. Z. (2021). Remote sensing assessment of changes of surface parameters in response to prolonged drought in the arid zone of central Iran (Gavkhoni playa). *Remote Sensing Applications: Society and Environment*, *23*, 100575. https://doi.org/10.1016/j.rsase.2021.100575

Singh, R., Patel, S. K., Tiwari, A. K., & Singh, G. S. (2021). Assessment of flood recession farming for livelihood provision, food security and environmental sustainability in the Ganga River Basin. *Current Research* *in Environmental Sustainability*, *3*, 100038. https://doi.org/10.1016/j.crsust.2021.100038

Sobrino, J. A., Jiménez-Muñoz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from LANDSAT TM 5. *Remote Sensing of environment*, *90*(4), 434-440. https://doi.org/10.1016/j.rse.2004.02.003

Sobrino, J. A., Jiménez-Muñoz, J. C., Sòria, G., Romaguera, M., Guanter, L., Moreno, J., ... & Martínez, P. (2008). Land surface emissivity retrieval from different VNIR and TIR sensors. *IEEE transactions on geoscience and Remote Sensing*, *46*(2), 316-327 https://doi.org/10.1109/TGRS.2007.904834

Stathopoulou, M., & Cartalis, C. (2007). Daytime urban heat islands from Landsat ETM+ and Corine land cover data: An application to major cities in Greece. *Solar Energy*, *81*(3), 358-368. https://doi.org/10.1016/j.solener.2006.06.014

Taloor, A. K., Manhas, D. S., & Kothyari, G. C. (2021). Retrieval of land surface temperature, normalized difference moisture index, normalized difference water index of the Ravi basin using Landsat data. *Applied Computing and Geosciences*, *9*, 100051. https://doi.org/10.1016/j.acags.2020.100051

The Global Sustainable Development Report (GSDR). (2019). The future is Now: Science for Achieving Sustainable Development. https://sdgs.un.org/sites/default/files/2020-07/24797GSDR_report_2019.pdf

The Sustainable Development Goals Report (SDGR). (2022). The United Nations. https://unstats.un.org/sdgs/report/2022/The-Sustainable-Development-Goals-Report-2022.pdf

Tran T.-N.-D, Nguyen, B. Q., Vo, N. D., Le, M. H., Nguyen, Q. D., Lakshmi, V., & Bolten, J. D. (2023). Quantification of global Digital Elevation Model (DEM)– A case study of the newly released NASADEM for a river basin in Central Vietnam. *Journal of Hydrology: Regional Studies*, *45*, 101282. https://doi.org/10.1016/j.ejrh.2022.101282

Valor, E., & Caselles, V. (1996). Mapping land surface emissivity from NDVI: Application to European, African, and South American areas. *Remote sensing of Environment*, *57*(3), 167-184. https://doi.org/10.1016/0034-4257(96)00039-9

Van de Griend, A. A., & Owe, M. (1993). On the relationship between thermal emissivity and the normalized difference vegetation index for natural surfaces. *International Journal of remote sensing*, *14*(6), 1119-1131. https://doi.org/10.1080/01431169308904400

Venkatesh, R., Abdul Rahaman, S., Jegankumar, R., & Masilamani, P. (2020). ECO-ENVIRONMENTAL VULNERABILITY ZONATION IN ESSENCE OF ENVIRONMENTAL MONITORING AND MANAGEMENT. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, *43*. https://doi.org/10.5194/isprs-archives-XLIII-B5-2020-149-2020

Weier, J., & Herring, D. (2000). Measuring Vegetation (NDVI & EVI). NASA Earth Observatory. *Washington, DC, USA*. URL:https://earthobservatory.nasa.gov/features/MeasuringVegetation

Horne, J. (2017). The politics of water reform and environmental sustainability in the Murray–Darling Basin. *Water International*, *42*(8), 1000-1021. https://doi.org/10.1080/02508060.2017.1412201

Zhao, W., He, J., Wu, Y., Xiong, D., Wen, F., & Li, A. (2019). An analysis of land surface temperature trends in the central Himalayan region based on MODIS products. *Remote Sensing*, *11*(8), 900. http://dx.doi.org/10.3390/rs11080900