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Quantifying Spatio-Temporal Land Surface Temperature and Biophysical Indices for Sustainable Management of Watershed: A Study of Vishwamitri Watershed of Gujarat

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Abstract: Spatio-Temporal Analysis of the nexus between vegetation dynamics and climatic parameters like surface temperature is essential in environmental and biophysical studies and for monitoring and management of watersheds. This study explored the spatio-temporal distribution of land surface temperature (LST), Normalised Difference Water Index (NDWI), and Normalized Difference Vegetation Index (NDVI) and the relationship between them in the Vishwamitri watershed of Gujarat for the Pre Monsoon and Post Monsoon of the Year 2001 and 2016 using Landsat dataset. The findings of the study showed that the LST of the Vishwamitri watershed. The mean LST value of the year 2001 was 46.19°C in the pre-monsoon season and 39.27°C in the post-monsoon season. Mean LST values for the year 2016 were 49.34°C in pre-monsoon and 35.21°C in the post-monsoon season as observed. The spatial distribution of NDVI and LST reflects an inverse relationship. A strong positive correlation between LST with NDVI is observed over highly dense built-up areas. In summary, the LST is greatly controlled by surface characteristics. The results of this study illustrate there has been a dynamic change in vegetation cover of the watershed in all seasons. There was also a negative correlation between LST and NDVI in the studied years. The study concludes that there has been a degradation of vegetation and intensification of LST in the year 2016 as compared with the year 2001. This study can be used as a reference for land use and environmental planning in a tropical city.

Keywords: LST, Biophysical Indices, Watershed, Vishwamitri Watershed

1. Introduction

The world is currently experiencing different environmental changes which are caused by both nature-induced and anthropogenic activities. India, like other parts of the world, is highly vulnerable to the impacts of these environmental changes. The country faces various problems in managing natural resources. Long-term degradation of vegetation is one of the major environmental challenges in various parts of the country. Serious vegetation degradation is highly influenced by human activities such as the conversion of vegetated and wetlands into agricultural, as well as residential and commercial areas (Chen et al., 2006).

Watersheds have been viewed as useful systems for planning and implementing natural resources and ecological development for many centuries. Urbanization accelerates the ecological stress by warming the local or global cities to a large extent (Foley et al., 2005; Fu, P. and Weng Q., 2016; Grimm et al. 2008; Liu H. et al. 2018; Liu Y. et al 2018; Peng J et al. 2018; Guha, S., and Govil, H. 2020). Presently, many urban areas are suffering from huge land conversion and resultant new heat zones (Patz et al.2005).

Population growth, widespread industrialization, and migration of the rural population to urban areas lead to urban population growth and expand the urban sprawls. Rapid urbanization also causes a drastic decrease in green cover, and water bodies, and a rapid increase in impervious areas. All this together modify the microclimate regime of an area. Urban growth and sprawl is a global phenomenon and has a significant influence on the biophysical environmental effects leading to severe ecological and environmental problems. Rapid and unplanned urbanization leads to changes in the land use/ land cover (LULC) of the area, especially reduction in vegetation cover, which in turn increased the built-up areas. Hence, impervious areas have increased and impervious surfaces can be considered a key indicator of the urban environment (Arnold and Gibbons, 2016). Natural vegetation and permeable soils have been replaced by impervious surfaces such as asphalt, bricks, and concrete, which lead to more sensible heat than heat flux. It could be argued that UHIs represent the most significant form of irreversible anthropogenically forced climatic change not only at the local scale but also at the regional and even global scale (Arnfield, 2003).

Such alterations are the main factors for global environmental change upsetting sustainable development. Land cover and land use (LCLU) changes induced by human and natural processes play a major role in global as well as regional-scale patterns of the climate.

The urban heat island (UHI) effect indicates the higher air and land surface temperature (LST) in urban areas in comparison to the surrounding rural area, generated by high levels of near-surface energy emission, solar radiation absorption of ground objects, and low rates of evapotranspiration (Buyantuyev and WuJ 2010).

Land surface temperature (LST) refers to the temperature of the soil, water, buildings, and the vegetation canopy on the land surface (Zhang and Liao 2014), is a key parameter for describing thermal conditions (Walawender, et. al. 2014) and is a common research topic in local and global environmental studies (Liu And Weng 2013). LST plays an important role in a variety of scientific studies, such as those on hydrology, ecology, and global climate change (Zhang and He. 2013). LST is calculated from emitted radiation measured by either ground or satellite-based instruments. Generally, remote sensing techniques require less time and a cheaper cost than field methods to investigate numerous phenomena on the land surface. Because of its repetitive nature and increasing spatial resolution, satellite imagery is becoming more and more a viable and preferred alternative to ground-based measurements of land surface characteristics (Alemu, 2019).

Increased LST in certain urban pockets in comparison to its surroundings consequent to the increase in paved surfaces is known as the urban heat island (UHI) phenomenon (Gallo and owen 1998). It is also observed that the vegetation and water body patches are having relatively low temperatures, which acts as a heat sink (Joshi and Bhatt 2012). The relationship between the LST and NDVI has been widely documented in the literature (Chen et. al, 2006; Weng, 2001 & Weng et.al, 2006).

The land surface temperature can be obtained from direct ground measurement (Chen et. al, 2006). With the availability of satellite remote sensing, thermal bands retrieved from the satellite can be used to estimate surface temperature. Several studies used the Land sat ETM+ imagery to develop LULC maps as well as for deriving the surface temperature. Accurate mapping of LST is becoming more significant in providing information about surface physical and the use of satellite images has become the predominant way to monitor LST on local and regional scales. Remote sensing-based indices have the advantages of being used effectively, being parameter-free, and being efficient in the applications of land surface information extractions.

In the earlier years, NOAA-AVHHR data and recently MODIS, LANDSAT, and ASTER data have been used for deriving land surfaces biophysical parameters such as vegetation abundances, built-up indices, and land surface temperature (*LST*) in many studies; which are good indicators of the situation of an urban ecosystem to investigate the urban heat formation (Gallo et. al 1993 Lu and Weng 2009; Sobrino et. al, 2014; Tooke et.al,2008; Zhang et al, 2009.). The distinctive LST patterns are associated with the thermal characteristics of the land cover types (Weng, 2001 and Lo et. al., 1997). It is necessary to further study the temperature changes by LULC for studying the effect of urbanization on the local thermal environment.

Numerous studies had been made to examine the effect of the vegetation on the LST, which showed that there was a negative correlation between LST and urban vegetation abundance measured by the Normal Difference Vegetation Index (NDVI) and the percent cover of urban vegetation (Sundara 2012; Mallik et.al, 2008; Gao, 1996). However, in India studies focusing on the relationship between urban vegetation and LST using Land sat ETM+ imagery are relatively scant.

Chen et al (2006) stated that appropriate indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Build-Up Index (NDBI), and Modified Normalized Difference Water Index (MNDWI) can be used to classify Landuse/land cover. The study consequently intends to quantify the dynamics of LST NDVI, NDWI 2001, and 2016 for the Vishwamitri watershed.

2. Study Area

The Vishwamitri River originates from Pavagadh hill at about 22º 28´ N latitude and 73 º 45´ E longitude at an elevation of more than 700 m with 601 sq. km. The watershed has two distinct regions upper half is comprised of industrial units along highways and wasteland parcels along the river. Whereas and lower part has high meandering under influence of rapid urbanization. The catchment area comprises 102 villages of Savali, Waghodia, and Vadodara Taluka of Vadodara District and Halol Taluka (Panchmahal District) with more than 12 lakh populations. The watershed is under the influence of the growing Vadodara city, the urbanization has resulted in the land cover change to a non-agriculture area. This change will make the shrinkage of the river channel and the floodplains, the green cover alongside the rivulets. Thus the chances of the development of the urban heat island are inevitable if goes unmonitored.

3. Objective

Analysis of the interaction between vegetation and waterbody's dynamics and climatic parameters like surface temperature is essential in environmental and ecological studies and for monitoring natural resources. The study of the health of the resource and its implication on other biophysical parameters is of utmost importance This study explores the interaction of spatio-temporal distribution of land surface temperature (LST), vegetation, and water distribution, using indices of Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) respectively. The study also addresses the temporal change during pre and post-monsoon for the years 2001& 2016 in the Vishwamitri watershed (Figure 1).

The present study aims to calculate the LST from Landsat dataset, NDVI and NDWI. Datasets of two different seasons (pre-monsoon, and post-monsoon) in the Vishwamitri watershed using a total of 12 Landsat satellite images for the years 2001 and 2016. Meanwhile, the LULC map has been generated using the Landsat dataset. The main aims of the study were (1) to analyze the seasonal variation of the spatial distribution pattern of the LST in the study area, (2) to determine the seasonal variation of LST, NDVI, and NDWI relationship for the study area, and (3) to explore the seasonal variation of LST, NDVI and NDWI relationship on different LULC types.

4. Methodology

For the present study, the methodology involves the preparation of NDVI and Land surface temperature maps and correlation analysis between LST and NDVI, and NDWI. The methodology involves the stages from Satellite data acquisition, LST retrieval, Land Use / Land cover Map generation, Assessment of NDVI, Assessment of NDWI, and determination of the relationship between, LST, NDVI, and NDWI over the study area.

4.1 Satellite image acquisition and processing

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensors (TIRS) data of 2016; Landsat 5 Thematic Mapper (TM) data of 2001 freely downloaded from the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov) Data Centre. Landsat 8 TIRS dataset has two TIR bands (bands 10 and 11) in which band 11 has uncertainty in calibration. Thus, only TIR band 10 (100 m resolution) has been recommended for the present study. Landsat 5 TM data has only one TIR band (band 6) of 120 m resolution that has been used for the present study. The spatial resolution of visible to near-infrared (VNIR) bands of the two types of Landsat datasets is 30 m which has been used for the NDVI and NDWI Indices generation.

4.2 Land surface temperature (LST) retrieval

Land surface temperature is the temperature at the interface of the earth’s surface with its atmosphere. The LST gives the relative information of the surface heat disseminated at any given point in time.

4.3Retrieval of LST from Satellite Image (Landsat TM)

The at-sensor spectral radiance is the amount of energy received by the satellite sensor. Spectral Radiance (L_λ) has been computed through the Conversion of the Digital Number (DN) into the radiance using equation.1. Digital Number (DN) of a pixel in an image is a numerical value that represents the brightness of that pixel in the image. In this step, each pixel of the Landsat images was converted from Digital Numbers (DN) to Spectral radiance (L_λ) using the following formula (Fathian et al., 2015; Wang et al., 2015).

$$L_\lambda = \left(\frac{L_{Max\lambda} - L_{Min\lambda}}{QCAL_{Max} - QCAL_{Min}}\right) * (QCAL - QCAL_{Min}) + L_{Min\lambda} \quad \ldots\text{(Equation.1)}$$

where;
L_λ = Spectral Radiance at the sensor's aperture in watts/(sq.m)
$LMAX_\lambda$ = the spectral radiance that is scaled to $QCAL_{Max}$ in watts/(sq. m)
$QCAL_{Min}$ = the minimum quantized calibrated pixel value (corresponding to $L_{MIN\lambda}$) in DN
$QCAL_{Max}$ = the maximum quantized calibrated pixel value (corresponding to LMAXλ) in DN

Next, Thermal radiance values were converted from spectral radiance to brightness temperature using the thermal constants with the equation.2. (Sobrino et al., 2004): The brightness temperature presumes that the Earth's surface is a completely black body i.e spectral emissivity is 1.

$$BT = \frac{K2}{\ln\left(\frac{K1}{L_\lambda} + 1\right)} - 273.15 \qquad \ldots(Equation.2)$$

Where;
BT= The ToA brightness temperature in°C
K_2 = Calibration constant 2 from metadata
K_1 = Calibration constant 1 from metadata
L_λ = Spectral radiance in watts/(sq. m)

$$LST = \frac{BT}{1 + (\lambda * BT/\rho) * \mathrm{Ln}\varepsilon} \qquad \ldots.(Equation.3)$$

Where,
BT= Satellite rightness temperature (Kelvin),
λ= Wavelength of emitted radiance (11.5 μm),
ε= Land surface emissivity,
$\rho = h * c/\sigma$= 1.438*10-2mK (σ= Boltzmann constant= 1.38*10-23 J/K, h= Planck’s constant= 6.626*10-34Js, c= velocity of light= 2.998*108 m/s).

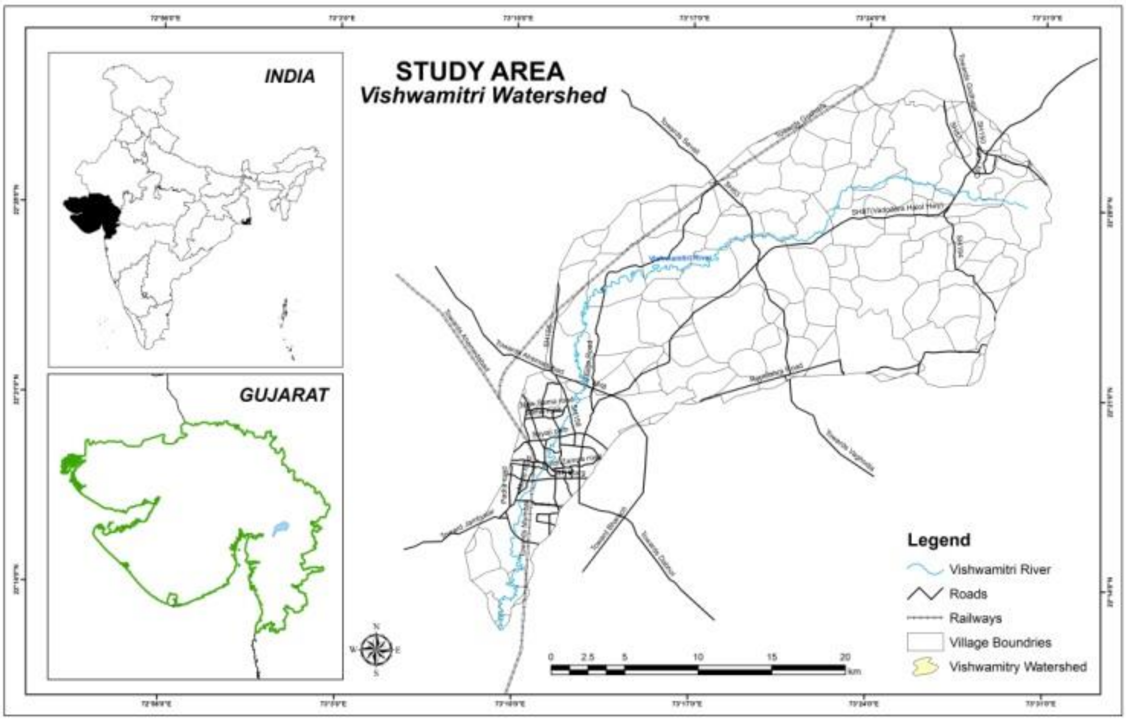

Figure 1. Study area

4.3 Calculation of Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is essential to estimate the amount of above-ground green vegetation cover. It is calculated from measurements of red and near-infrared reflectance using equation.4.

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad \dots (Equation. 4)$$

where; NIR and RED are the near-infrared and red band pixel values respectively. The value of NDVI ranges between -1.0 and 1.0.

4.4 Calculation of Normalized Difference Water Index (NDWI)

The NDWI is the most suitable index for water body mapping. Water bodies have strong absorbability and low radiation in the range from visible to infrared wavelengths. The index uses the green and NIR bands of the remote sensing images based on this phenomenon. The NDWI can enhance the water information effectively in most cases. It is sensitive to built-up land and often results in over-estimated water bodies. NDWI was calculated as follows using an equation.5 (McFeetemrs, 1996)

$$NDWI = \frac{Green - NIR}{Green + NIR} \qquad \dots (Equation. 5)$$

5. Results and discussion

Spato-Temporal variation of LST

Figure 2 illustrates the LST variation in the study area for the pre-monsoon and Post-monsoon years 2001 and 2016. LST represents the temperature of an object within a pixel, which may include several land cover types. LST maps are prepared to show the spatial distribution of LST within the study area. The maximum LST was observed as 49.41 °C and the minimum LST was observed as 35.85°C in the pre-monsoon of the year 2001; similarly, 42.33°C maximum and 31.21°C LST in the post-monsoon season was observed in the year 2001 (Figure 2). Spatial distribution of LST for pre-monsoon of the year 2016 shows the maximum and minimum LST is 53.43°C and 35.39°C respectively (1^{st} May); whereas for post-monsoon of the year 2016 shows the maximum is 38.45°C and minimum is 29.03°C (29^{th} October). The results also show that there are variations in the LST of the area due to variations in land use/land cover classes of the study area. The different cover has different conductivity of the heat owing to which a regional flow of thermal energy can be seen. The statistics showing the minimum & maximum values of LST are given in Table 1.

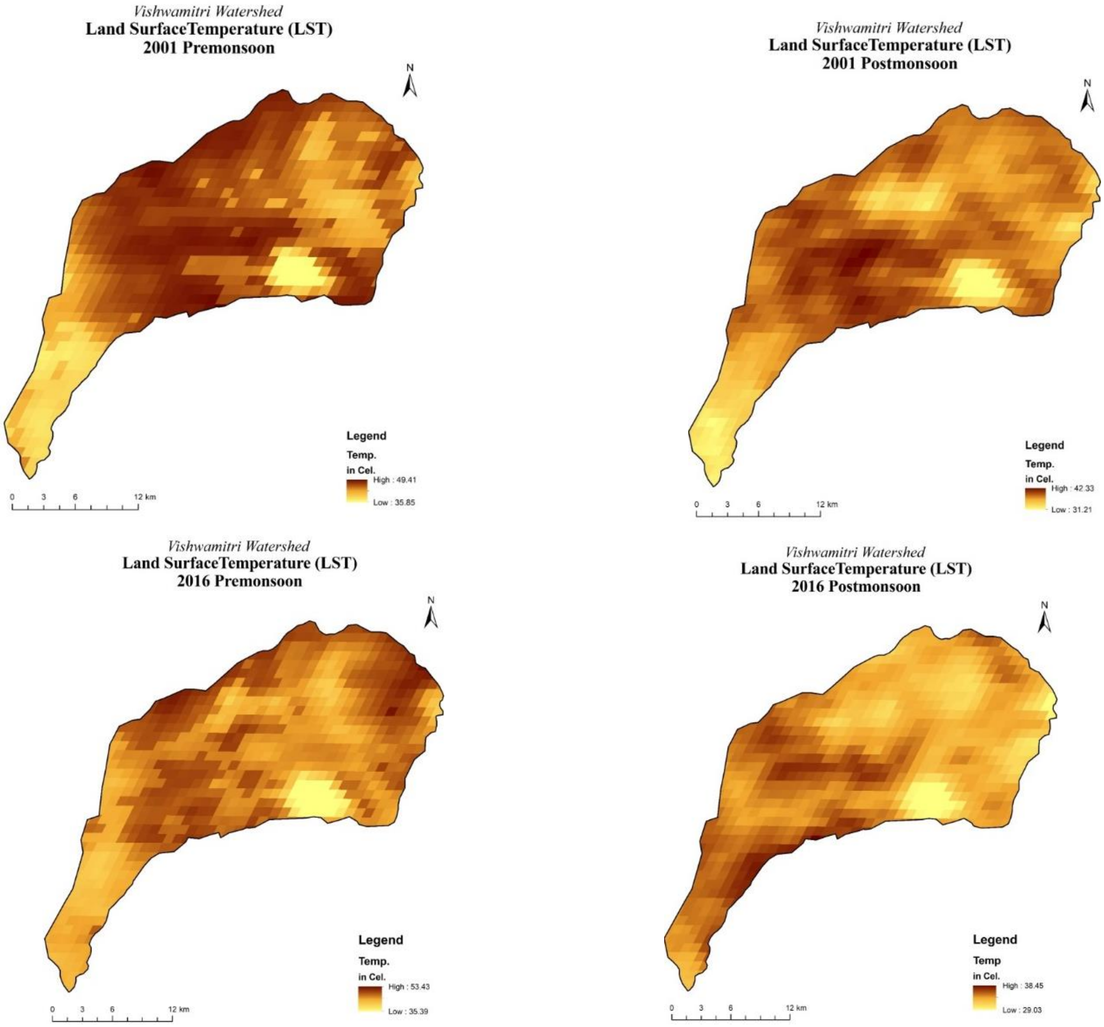

Figure2. Spatial and Temporal Variation of the LST

Table 1 . Variation of LST.

Year	Season	Temperature(°C)		
		Max.	Min.	Mean
2001	Pre-monsoon	49.41	35.85	46.19
	Post-monsoon	42.33	31.21	39.27
2016	Pre-monsoon	53.43	35.39	49.34
	Post-monsoon	38.45	29.03	35.21

It is observed that the pre-monsoon maximum temperature is 53.43^{0}C which has increased by 4.02 ^{0}C. The surface temperature of the region for the same period of the year suggests that the temperature is warmer in the Pre-monsoon as compared to the Post monsoon. The scenario of the Landuse also suggests the agricultural practice of current fallow and harvested land also leads to warmer surfaces. The increase in the temperature is accounted for based on the dry surface or the surface covering having a high affinity to hold heat like road and concrete structures.

Spatial and Temporal Variation of the NDVI:

Many vegetation indices have been developed to assess vegetation conditions. Among them, the normalized difference vegetation index (NDVI), which was proposed by Rouse et al. (1973), is applied in the study. Normalized Difference Vegetation Index (NDVI) is an index that describes the vegetation proportion by measuring the difference in the near-infrared portion of the electromagnetic spectrum which is strongly reflected by green vegetation and the red portion of the spectrum which is absorbed by vegetation.

The values of NDVI indicates the variations of green and healthy vegetation type in the given area. The higher the NDVI value the denser the vegetation and the lower the NDVI the less dense or absent vegetation cover. The normalized difference vegetation index (NDVI) was derived for the years 2001 and 2016 for pre-monsoon and post-monsoon.Given the changes occurring in cities and the fact that they will continue to expand, the study of urban land cover changes and their impacts on thermal patterns and NDVI values has a critical interest, Since the urban thermal environment is related to the reduction of evapotranspiration from the surface vegetation cover, it is useful to recognize the relationship between surface vegetation cover and water availability.

The Normalized Difference Indexes are commonly used to characterize the land cover types and in this study, they were used to evaluate the relationship between land cover types and heat formation.

The NDVI gradually increased in especially post-monsoon season in the period between the years 2001 and 2016 as shown in table 2 and figure 3. for the entire region. One of the reasons can be the availability of water from the Narmada branch canal. The mean NDVI was 0.25 observed in the year 2001 pre-monsoon period, which slowly increased to 0.28 in 2016, and the post-monsoon mean NDVI increased from 0.43 to 0.51 from the year 2001 to 2016 (Table 2).

Areas, where NDVI exhibited standard trends, were primarily located near the foothills and along the young stage of the Vishwamitri River. NDVI from 2001 to 2016, decreased continuously over the impervious area, although significant fluctuations were observed during this period.

4.4 Spatial and Temporal Variation of the NDWI

Normalized different water indices (NDWIs) derived from satellite images are commonly and successfully utilized in surface water body detection and mapping. NDWI has been calculated to draw to the wetland index in the watershed. The minimum and maximum and mean NDWI index found in the watershed varies from - 1 to 1. In recent times, several researchers are applying image processing methods for the extraction of water features from satellite data. Gao, (1996) developed the Normalized Difference Water Index from a near-infrared channel and a short-wave infrared channel; which is more sensitive to monitor changes in the water content of leaves. One such important method is the normalized difference water index (NDWI) which could be used for the extraction of water features from Land sat imageries (McFeetemrs, 1996).

The results from NDWI are indices that have a range of values of -1 for non-water bodies and 1 for water bodies.
The spatial variation of the NDWI is analyzed for extracting the water bodies from the watershed area. Ajwa Lake, Sur sager Lake, and Narmada canal were extracted over the watershed in the years 2001, and 2016 (Figure 4). Whereas other water bodies viz., Vadadala, Dhanora, Bodidra, and Pratapura are the lakes where there is seasonal fluctuation in boundaries, especially in pre-monsoon and post-monsoon seasons. Table 3 illustrates the maximum, minimum, and mean NDWI values of the study area for pre-monsoon and post-monsoon seasons of the years 2001 and 2016.

Table 2. Variation of NDVI

Year	**Season**	**Max**	**Min**	**Mean**
2001	Pre-monsoon	0.54	-0.20	0.25
	Post monsoon	0.76	-0.19	0.43
2016	Pre-monsoon	0.56	0.04	0.28
	Post monsoon	0.77	-0.20	0.51

Table 3 . Variation of NDWI

Year	Season	Max	Min	Mean
2001	Pre-monsoon	0.66	-0.58	0.31
	Post-monsoon	1	0.32	0.52
2016	Pre-monsoon	0.17	-0.50	-0.21
	Post-monsoon	0.17	-0.49	-0.23

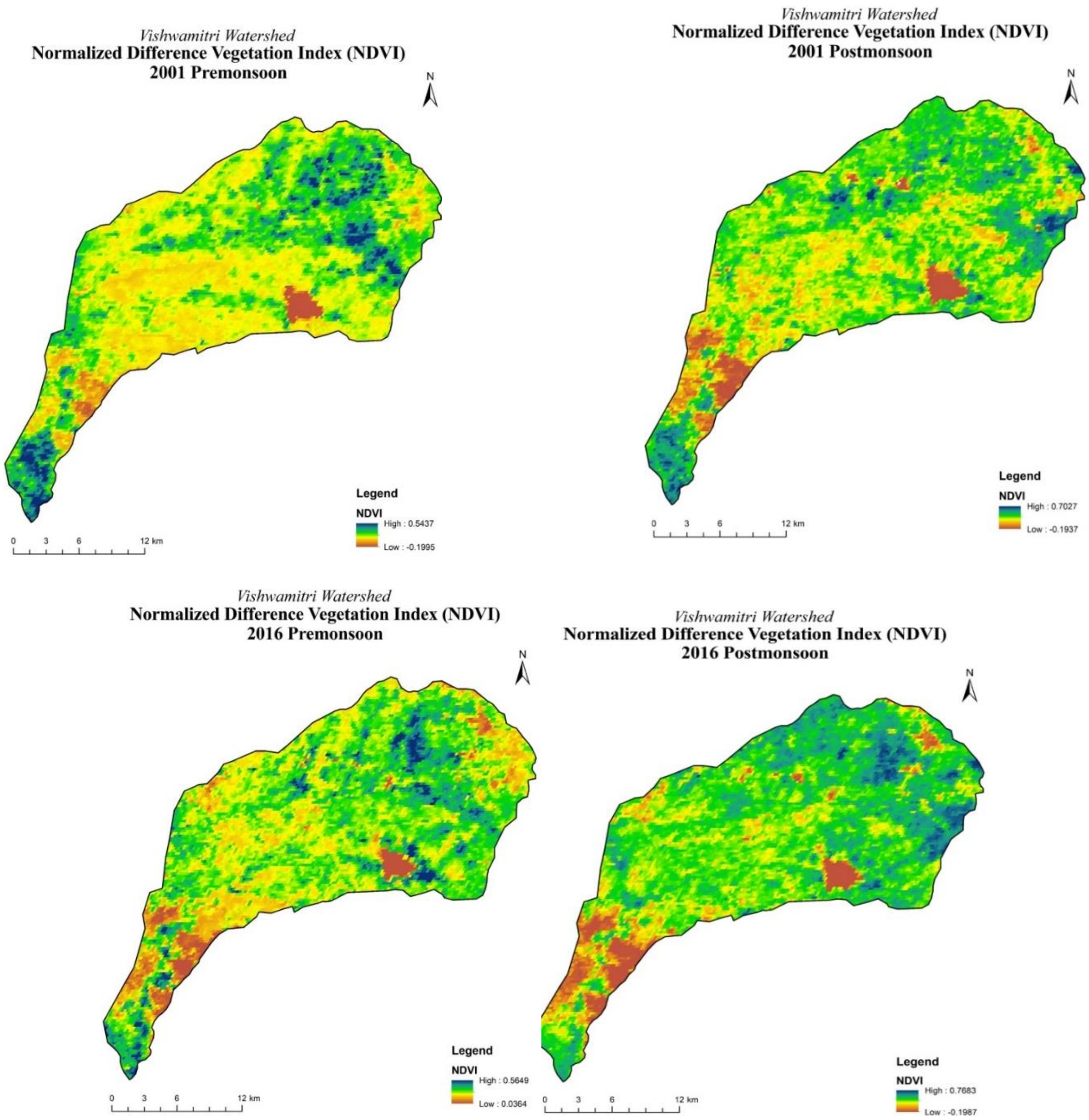

Figure 3. Spatial and Temporal Variation of NDVI

Relationship of LST with NDVI, and NDWI

Land surface temperature (LST) is sensitive to vegetation cover. As shown in table 4, the biophysical indices(NDVI and NDWI) have a negative correlation with LST. In general, it is observed that urban and water body classes of LULC are negatively correlated with NDVI in 2001. Negative relationships between LST and NDVI have been reported in other studies using thermal sensors for urban and rural environments (Dousset and Gourmelon 2003; Lo et al., 1997). Thus, it can be attributed to the fact that higher levels of latent heat fluxes may correspond to the areas characterized by vegetation cover in comparison to areas with sparse or no vegetation cover and low surface moisture availability. Table 4 describes the correlation of LST and biophysical indices for the year 2001.

Whereas the correlation of LST with NDWI shows that the NDWI is effective to water surfaces, this index was originally designed for use in non-urban settings. The threshold of NDWI values eliminated rooftop pixels and other non-water surfaces from the areas contained within the residential parcels themselves. NDVI shows a higher negative correlation with LST in the pre-monsoon period, and NDWI shows a lower negative correlation with LST in the pre-monsoon season for the year 2001. Similarly for the Post monsoon season of the year 2001 NDVI reflects a higher negative correlation with LST as compared to the NDWI.

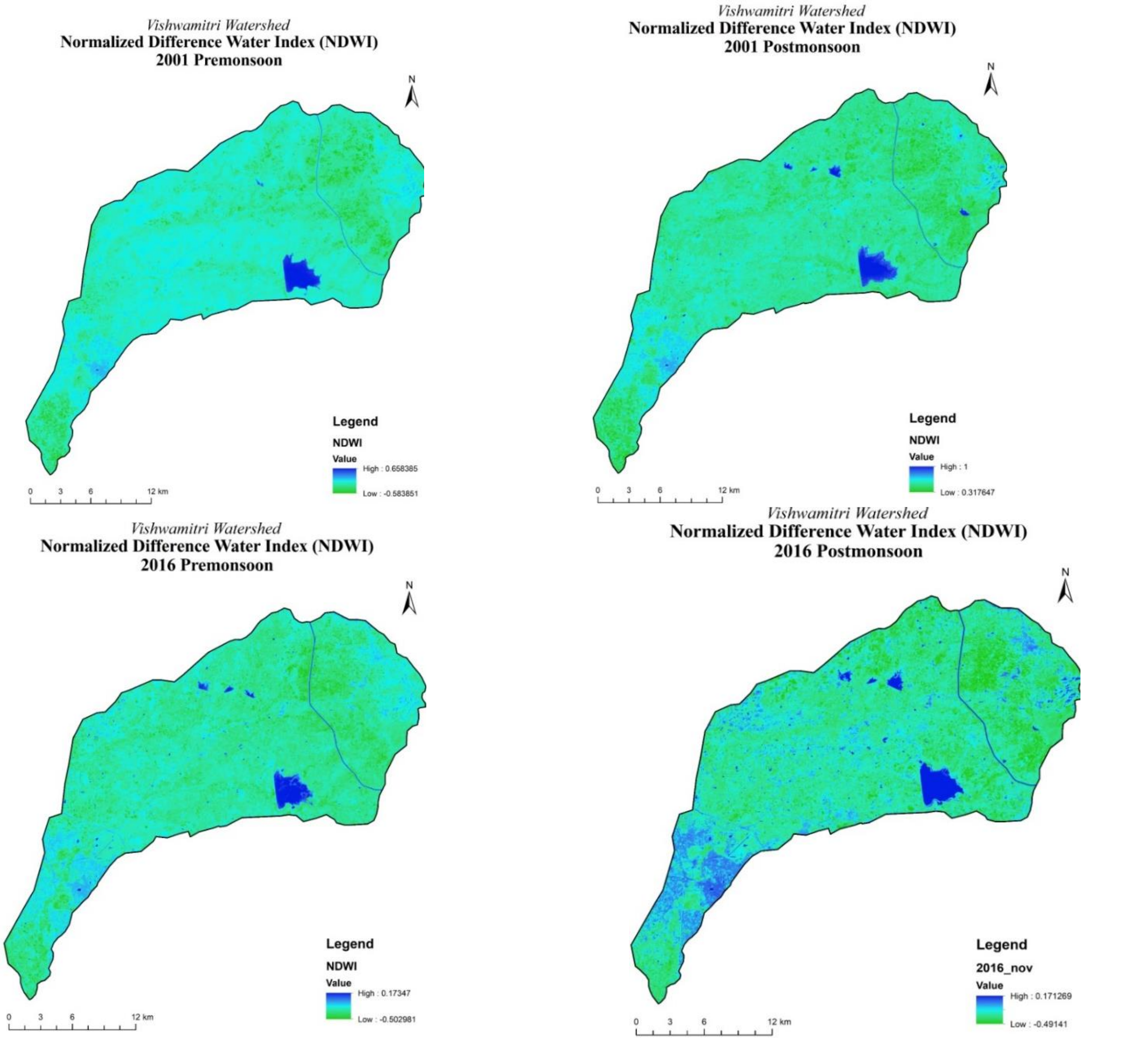

Figure 4. Spatio-temporal Variation of NDWI

Table 4. Correlation of LST and biophysical indices (2001)

2001	Pre Monsoon			Post Monsoon		
Indices	**LST**	**NDVI**	**NDWI**	**LST**	**NDVI**	**NDWI**
LST	**1**			**1**		
NDVI	**-0.158**	**1**		**-0.155**	**1**	
NDWI	**-0.023**	**-0.512**	**1**	**-0.005**	**-0.551**	**1**

The NDVI shows a strong negative correlation with LST in the post-monsoon period, and NDWI is less Negative correlation with LST in the pre-monsoon season. In the year 2016, NDVI shows a strong negative correlation with LST in the post-monsoon period, and NDWI is less Negative correlation with LST in the pre-monsoon season as indicated in table 5.

Table 5. Correlation of LST and biophysical indices for the year 2016

2016	Pre-Monsoon			Post-Monsoon		
Indices	**LST**	**NDVI**	**NDWI**	**LST**	**NDVI**	**NDWI**
LST	**1**			**1**		
NDVI	**-0.259**	**1**		**-0.472**	**1**	
NDWI	**-0.003**	**-0.247**	**1**	**0.182**	**-0.447**	**1**

Land use/ land cover (LULC) map derivation

The mapped land-use change and the land-use statistics of the catchment are derived using the Landsat dataset (Figure 5). The land-use pattern indicates that the expansion of Vadodara city is sinking the flood plains of the river and the vegetation cover adjoining the river. Also due to the non-perennial nature of the river, the current fallow usage is considerably high owing to which the pre and post-monsoon interaction of the usage has its impact in defining the micro biophysical variation of the region. As noticeable in figure 6. In the period of the study, it is evident that the area under the built-up has almost doubled, reducing the open land, current fallow, and vegetation coverage.

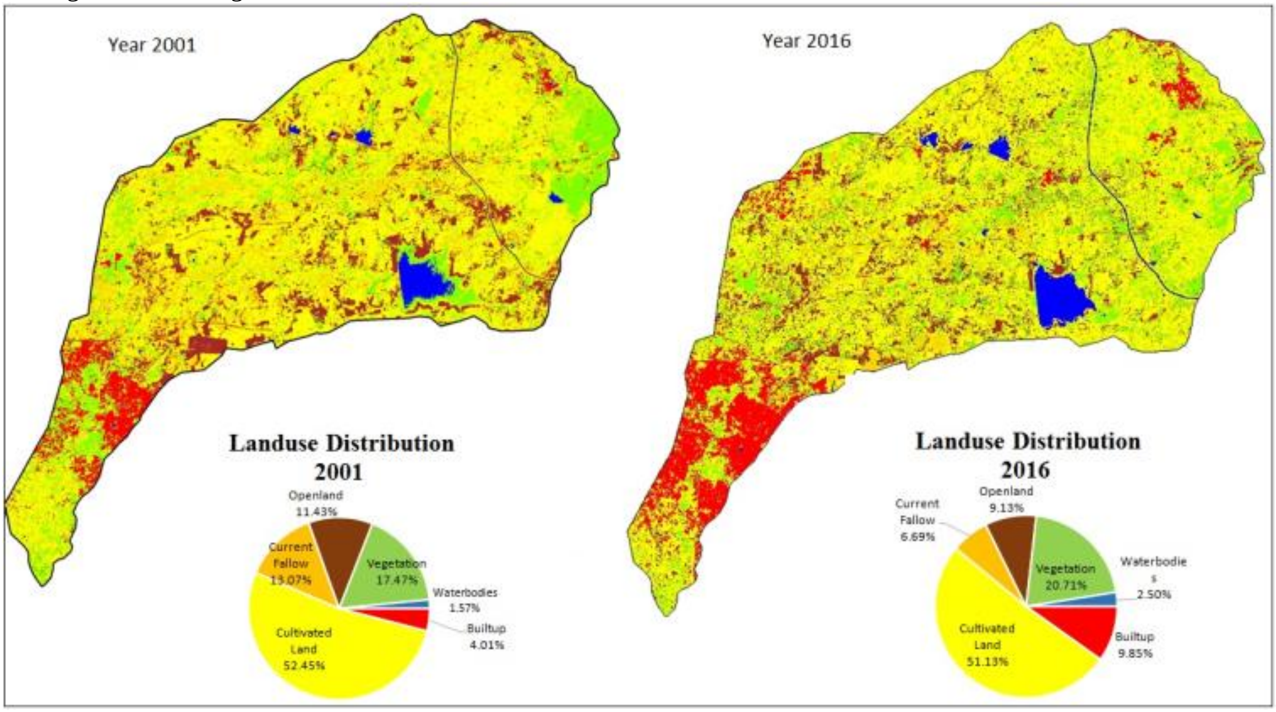

Figure 5: Landuse of the Vishwamitri River catchment area.

Pre - Monsoon and Post – Monsoon composite Characteristics

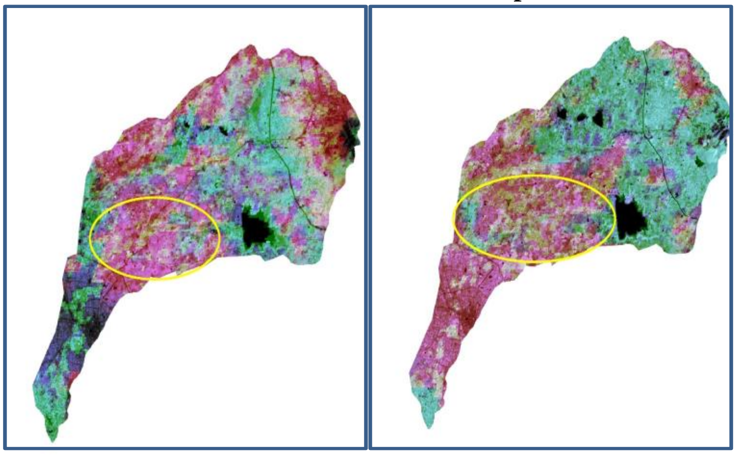

Figure 6: Landcover Variation in the Vishwamitri River catchment area. The central catchment area is showing a high variation of cropping as the water deficit

Conclusion:

A strong positive correlation between LST with NDVI is observed over the highly dense built-up area. A strong negative correlation between LST and NDVI implies that the higher the biomass a land cover has, the lower the surface temperature. On the other hand, the strong positive correlation between LST and NDVI implies that the lower the biomass of a land cover, the higher the surface temperature. Because of this causal relationship between LST and NDVI, the type of LULC influences LST through NDVI and consequently, it affects the microclimate of an area. The foregoing discussion reveals that NDVI effectively differentiates between the vegetation and non-vegetation land cover classes. A negative correlation between LST and NDVI means wherever there is high NDVI the surface temperature is low.

The results suggest that the bareness of the surface plays an important role in the overall surface temperature range. In biosphere interaction, water bodies and vegetation cover act as heat sinks preventing higher temperature fluctuation in the region. Normally, water bodies, vegetation, and damp soil are less warm compared to bare soil and built-up area. Consequently, there is a positive relationship between LST with urbanization. The period chosen was in line with the development the region is undergoing. The large-scale usage transformations are underway. The Middle basin region is relatively dry and post-monsoon and also it shows heterogeneity in land usage. This shows the disparity in the region. Also, the expanding city limits and disparity will be exerting tremendous pressure for transformation.

For sustainable management in the Vishwamitri watershed area, to adopt climatic changes, interventions are required for increasing the density of the vegetation and water body conservation. Especially, the central portion of the catchment area is required to be addressed as it is agricultural land but in the absence of water, the land becomes moistureless thus productivity is decreased. Owing to the less yield this land will be subjected to non-agricultural use which indeed will promote concretization. Also, the land serves as the hinterland for the city for the vegetable need, thus agro-technological inputs can be enhanced to promote horticulture. Along with the area planning approach to deal with provisioning of the water resource. The check dam and groundwater recharge well can be adapted to facilitate the region in maintaining soil moisture and healthy growth of the vegetation.

Dense built-up at the lower catchment and its expansion can pose a threat to becoming an urban heat island formation. Tree cutting, and conversion of wetlands and agricultural land into built-up areas have adverse effects on the micro-climate of the area which may result in several pockets of heat zones UHI over some time. Development of the region should be along with the usage of material having an emissivity of energy and higher reflection toward the infrared radiation.
Planning is essential to distribute suitable agricultural practices to incorporate the current fallow and open land with some biomass productivity. Climate change impact can be addressed by conservation of the hydrology. The river size and the wet perimeter are significantly less, to mitigate the rising temperature change. So water bodies are to be conserved also vegetation growth should be enhanced. Prior attention is needed to address the micro-climate changes of the area for sustainable management.

Based on the bio-physical indicators an areal regionalization concept has to be adapted by looking at the microclimatic impact. This region will cater as the environmental planning unit. Also, effective restoration of the vegetation and waterscapes will help the region to cope with future climate adversity. Thus leading to the climate resilience planning of the region.

The retrieved satellite LST was effectively validated with in-situ observations. The application of robust geospatial technology with freely available data such as Landsat has the potential to be effective in monitoring urban growth patterns, hot spot detection, and spatial-temporal climatic changes. The effective use of this technology for determining the normalized difference in water index, urban index, moisture index, drought index, and vegetation index has immensely enhanced the capability of human beings to further explore remote sensing data for quick and accurate results. This study shows that the watershed can be subdivided functionally for efficient ecologically sustainable planning and resource management.

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