Research Paper

Assessing the influence of elevation on satellite derived normalized difference vegetation index and land surface temperature in Rajasthan

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ABSTRACT

Land surface temperature (LST) and its interaction with normalized difference vegetation index (NDVI) are crucial for better understanding of environmental changes in current scenario. Therefore, the purpose of conducting this study was to examine, how LST and NDVI change as a function of elevation in Rajasthan. In present study, MODIS derived NDVI and LST and digital elevation model (DEM) from shuttle radar topography mission (SRTM) have been used. Results revealed that the LST and NDVI both were significantly influenced by elevation. Elevation, NDVI and LST varied from -6 to 1698 m, -0.09 to 0.65 and 24 to 45°C throughout the study region. In contrast to LST, which has a decreasing gradient from western to eastern portions, the spatial variability of NDVI has decreasing gradients from southern and eastern to western regions. The highest mean LST value (39.76 ± 0.2.9 ^{0}C) was obtained in elevation range of -6 to 168 m, whereas NDVI value (0.38 ± 0.06) in elevation ranges of 589 – 1698 m. The elevation has strong positive correlation with NDVI (R^2 = 0.26) and negative correlation with LST (R^2 = 0.28). Findings from this research can be utilized as a platform for environmental and land use planning for sustainable ecosystem management.

Keywords: Land surface temperature, Normalized difference vegetation index, Elevation, Rajasthan, Digital elevation model, Geospatial technique

Vegetation plays a crucial role in the recycling of materials and energy in terrestrial ecosystem by linking the hydrological, biogeochemical, and atmospheric cycles (Pei *et al.,* 2019). Vegetation is controlled by numerous factors such as land surface features, soil type, lithology, geology, and climate of a region (Bindajam *et al.,* 2020). But, topographical features of any terrain such as elevation, slope, aspect, surface curvature, play crucial role in the vegetation distribution.

Climate is another key aspect that contributes to changes in vegetation, particularly temperature and rainfall, both of which have a significant impact on the growth, development, distribution, and services provided from vegetation (Xu *et al.,* 2019). The land surface temperature (LST) is a key indicator that is used to investigate the terrestrial energy flux, climate change, and several other physical and chemical phenomena that occur in nature. The LST, also known as the surface skin temperature or simply surface temperature, refers to the surface soil temperature when there is no vegetation present and the temperature of the canopy surface when there is abundant vegetation (Khandelwal *et al.,* 2018). For instance, local topography parameters (elevation, slope, aspect, etc.), macro-geographical factors (longitude, latitude, macro-climatic background conditions, etc.), and underlying surface features (such as soil profile and different vegetation state) can all have an impact on surface temperature (Weng and Luo 1990).

Nowadays, climate anomalies have risen to the forefront as a result of the increasingly noticeable shifts in the global climate and earth ecosystem. Globally, the problems associated with changing climate have caused a hike in the LST, which will certainly induce variations in the vegetation dynamics and functions (Eleftheriou *et al.,* 2018). Therefore, it is of the utmost importance to assess the

effect of these variables and work towards improving the earth's environment, which is essential to the survival of mankind. The interrelationship between environmental factors like flora, land surface features, etc., and land surface temperature is currently being studied in many different ways. For instance, Garai *et al.,* (2022) assessed correlation between rainfall, NDVI and LST in Eastern India. Mathew *et al.,* (2022) studied the interaction between urbanization, water, and land surface temperature, and Sur *et al.,* (2018) and Yadav *et al.,* (2023) studied spatiotemporal variation of NDVI, rainfall, temperature and evapotranspiration over arid and semi-arid climate. But limited information is available on fluctuations of LST and vegetation with changing elevation.

Therefore, present study was carried out to analyse the vegetation–climate–topography relationship which is an important and crucial topic of ecological and geographic research. Remote sensing is the most cost-efficient and more reliable method for detecting changes in vegetation and surface temperature. The objectives of this investigation were (1) investigate the relationship between NDVI and elevation over Rajasthan (2) analyze spatial relation of LST with elevation (3) evaluate the interaction between the NDVI and the LST.

MATERIALS AND METHODS

Rajasthan, the largest state of the country, is situated in north-western region of India between 23° 30′ to 30° 11′ N latitudes and 69° 29′ to 78° 17′ E longitudes. It has a land area of 3, 42, 239 km^2, accounting for around 10.4 % of the entire geographical area of India. Rajasthan has 10 agro climatic zones. The typical Thar Desert in the north western part, sandy plains in the north eastern portion, the Aravalli Hills (extending from north east to south west) in the centre, and the south eastern plateau are among the state's topographic features. Rajasthan's climate is characterised by highly erratic and uneven rainfall distribution with low relative humidity, high wind speed, substantial evaporation losses, heat waves and temperature extremes.

In the current study, long-term (2001-2021) mean annual normalized difference vegetation index (NDVI) and land surface temperature (LST) were used to analyse the relationship with elevation in the Rajasthan state of India. Different used satellite datasets and their detailed specifications are provided in Table 1.

The DEM data from the shuttle radar topography mission (SRTM) was obtained from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov). After that, it was reprojected to Universal Transverse Mercator (UTM), 43N coordinate system in ArcGIS 10.5. The thematic layer was divided into five subclasses, namely, -6 to 168,168-267 267-387, 387-589, 589-1698 m, using the natural break method in ArcGIS. In the current research, Google Earth Engine (GEE) was used to acquire MODISMOD13Q1 NDVI data for a period of 21 years (2001–2021). NDVI is a dimensionless index and an important indicator of vegetative greenness of a region. It varies from − 1 to +1 where low and high score indicates stressed and healthy vegetation, respectively and it can be computed from near-infrared and red bands of satellite image using following equation

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

Downloaded data were re-projected to UTM 43 coordinate system and after that it was resampled to 30 m pixel resolution using bilinear interpolation approach in ArcGIS environment. After that, long term mean NDVI was computed from these data. In the present investigation, MODIS MOD11A2 LST data products were collected from GEE for the period of twenty-one years (2001-2021). The long term mean LST was calculated by computing the mean of images from 2001 to 2021. The datasets were re-projected to UTM 43 coordinate system and further resampled to 30 m pixel size in ArcGIS. Finally, the boxplots of NDVI and LST with different classes of elevation was computed in ArcGIS 10.5. The histogram depicting the distribution of pixel counts for LST and NDVI across various elevation classes was created using the R programming. In order to investigate the relationship between these parameters, the fishnet tool and multi-values to points function were employed in ArcGIS and the resulting correlation was computed.

RESULT AND DISCUSSION

Elevation

The elevation of Rajasthan is varying from -6 to 1698 m and classified into 5 classes such as first class (-6 to 168 m), second class (168-267 m), third class (267-387 m), fourth class (387-589 m) and fifth class (589-1698 m) using natural break method in ArcGIS 10.5 (Fig. 1A). The maximum portion of the study area came under first and second class of elevation. Highest elevated portion comes under sub humid southern plain agro climatic zone and lowest elevated portion of study area in the arid and hyper arid western plain.

Normalized difference vegetation index (NDVI)

Fig. 1B represents the spatial variation of long-term mean annual NDVI for the last 21 years (2001-2021) and it ranges from -0.09 to 0.65. Higher NDVI directly relates to the abundance of vegetation and lower NDVI represents vegetation browning or fewer vegetation in the study region. The spatial variability of NDVI has decreasing gradients from southern and eastern to western regions. Most of the areas with high NDVI values has come under the four ACZ viz. Humid south eastern plain, Humid southern plains, Sub-humid southern plains, semi-arid eastern plains and Flood prone eastern plain, While the region that falls under ACZs like the Arid Western Plain and Hyper Arid Partial Irrigated Zone had the lowest NDVI values. This variation in vegetation greenness was caused by Rajasthan's uneven rainfall distribution. This kind of spatial variability has arisen primarily due to the uneven distribution of monsoonal rainfall (Kumari *et al.,* 2021).

Land surface temperature (LST)

Land surface temperature (LST) is an important measure for energy flux and environmental studies. Fig. 1C depicted the spatial representation of long-term mean annual LST for the 21 years' period (2001 to 2021) and it varies from 24 to 45°C. It is observed that western parts have higher temperatures compared to

Table 1: Dataset used in the study and their specifications

Sr. No.	Dataset	Variable	Temporal resolution	Spatial resolution	Time period
1	MODIS MOD13Q1	NDVI	16 days	250 m	2001-2021
2	MODIS MOD11A2	LST	8 days	1 km	2001-2021
3	SRTM DEM	Elevation	-	30 m	-
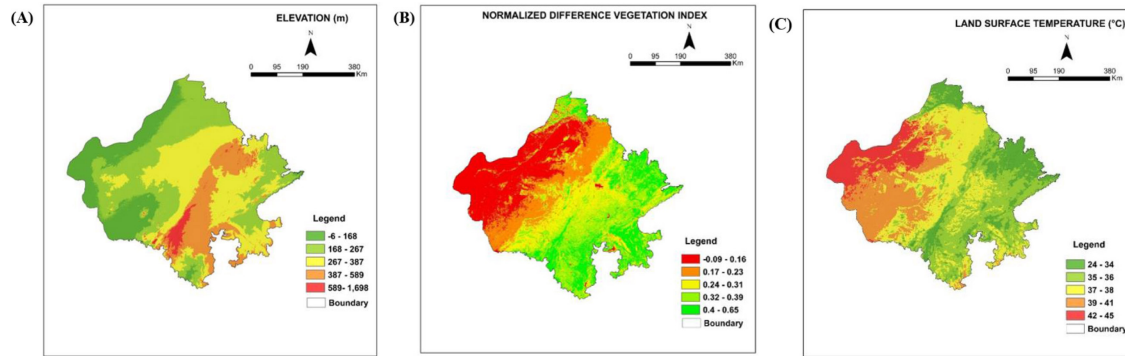
Fig. 1: Representation of variation in (A) Elevation (B) NDVI and (C) LST over Rajasthan

eastern and southern portion of Rajasthan. The agro-climatic zones viz. hyper arid partially irrigated zone and arid western plains show maximum variation while sub-humid southern plains show least LST value. Apart from elevation, vegetation type and its growth also affects LST of a region. Our findings are very compatible with those of the research of Phan *et al.,* (2018) who observed that barren land has the higher mean LST value in comparison to many others land use land cover (LULC) classes. The western part of Rajasthan has unsuitable soil conditions and texture, low vegetation cover, and arid climatic conditions (Dutta and Chaudhuri 2015). Therefore, this zone has higher LST as compared to the eastern and southern parts. Additionally, certain higher LST zones are associated to parts of the Aravali Mountains and isolated hills in the research region. Due to their higher emissivity, exposed rock surfaces should have a higher LST than dry soil and plants (Khandelwal *et al.,* 2018). Surface roughness and albedo are also factors that influence LST. This can be observed by the fact that built-up regions have lower roughness and a lower albedo than vegetation, which results in built-up areas having a higher LST.

Variation of LST with elevation

In this study, interrelationship between LST and elevation were studied. For each elevation category, we calculated the average, maximum, minimum and standard deviation (SD) of LST values (Table 2). All elevation classes have slight variations in the distribution of LST. Lowest and highest minimum LST was observed in elevation class of 267-387 (24.42 ℃) and -6 to 168 (28.28 ℃), respectively while lowest and highest maximum LST was observed in elevation class of 589-1698 (37.82 ℃) and -6 to 168 (44.83 ℃), respectively. The maximum mean LST (39.76 ℃ ± 2.9 SD) was observed in elevation class of -6 to 168 m and lowest (32.93 ℃ ± 1.46 SD) was observed in elevation class (589 – 1698 m).

Elevation class (267 to 387 m) showed highest fluctuation of LST, which comes under transitional plain of inland drainage and humid southeaster plain ACZ of Rajasthan. Whereas, lowest fluctuation was observed in fifth elevation class (589-1698 m) and this elevation class is represented by Humid southern plains ACZ. The impact of elevation was evaluated by correlating LST and elevation as shown in Fig. 2. It indicates negative statistical correlation with r^2 of 0.28 and intercept of -0.0117. The regression equation between LST and elevation is given below:

LST = -0.0117×Elevation + 40.255

Fig. 4 depicts histogram and it represents the number of pixels for particular elevation class. It can be seen from the histograms that density of pixels is varying with LST under all elevation classes. The highest frequency of pixels was observed at 39, 38, 37, 35, and 32 ℃ in elevation class of -6 to 168, 168-267, 267-387, 387-589, 589-1689 m, respectively. Based on the results, it seems that there may be a more noticeable shift in LST as elevation increases. The negative correlation proves that surface temperature and topography have a well-known interrelationship (Bindajam *et al.,* 2020; Khan *et al.,* 2020). In fact, LST decreases with increasing elevation for two major reasons: air temperature decreases with elevation and surface vegetation is good and it tends to be vertically organized (Deng *et al.,* 2018). Moreover, in this study area, area relates to higher elevation generally has high the surface coverage and solar radiation received at higher elevation primarily spreads as latent heat and the LST is low (Deng *et al.,* 2018). The zones of more topographic variation and higher elevations also have fewer human activities. That is to say, the proportion of LST attributable to human-caused heat emissions has decreased as human activity has decreased. Meanwhile, the duration and intensity of solar radiation differed among different slope directions, which corresponds to LST variation in high elevations (Moradi *et al.,* 2018). The regression analysis between elevation and LST showed R^2 value of 0.28 which suggesting another local factor such as vegetation and slope may have strong influence on LST. Phan *et al.,* (2018) observed a much stronger correlation between land surface temperature and elevation (R^2 ranges from 0.372 to 0.748) throughout the year at both day and

Table 2: Relationship between elevation (m) and LST (°C) values

Elevation	LST (°C)			
	Min	Max	Mean	SD
-6 to 168	28.28	44.83	39.76	2.9
168-267	26.62	43.61	37.23	2.84
267-387	24.42	42.87	36.39	1.85
387-589	26.16	39.90	35.03	1.45
589-1698	26.72	37.82	32.93	1.46

Table 3: Relationship between elevation (m) and NDVI values

Elevation	NDVI			
	Min	Max	Mean	SD
-6 to 168	-0.06	0.53	0.17	0.08
168-267	-0.09	0.65	0.24	0.11
267-387	-0.09	0.60	0.29	0.09
387-589	-0.06	0.60	0.35	0.06
589-1698	0.05	0.64	0.38	0.07

$$y = -0.0117x + 40.255$$
$$R^2 = 0.2819$$
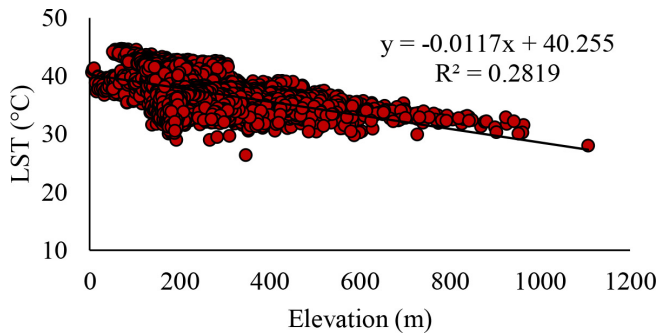
Fig. 2: Regression analysis of LST and elevation in the study area
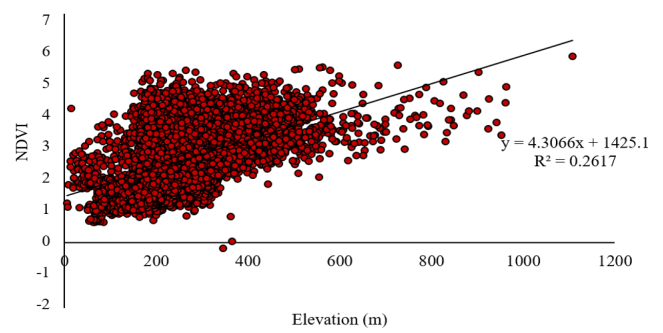
$$y = 4.3066x + 1425.1$$
$$R^2 = 0.2617$$

Fig. 3: Regression analysis of NDVI and elevation in the study area
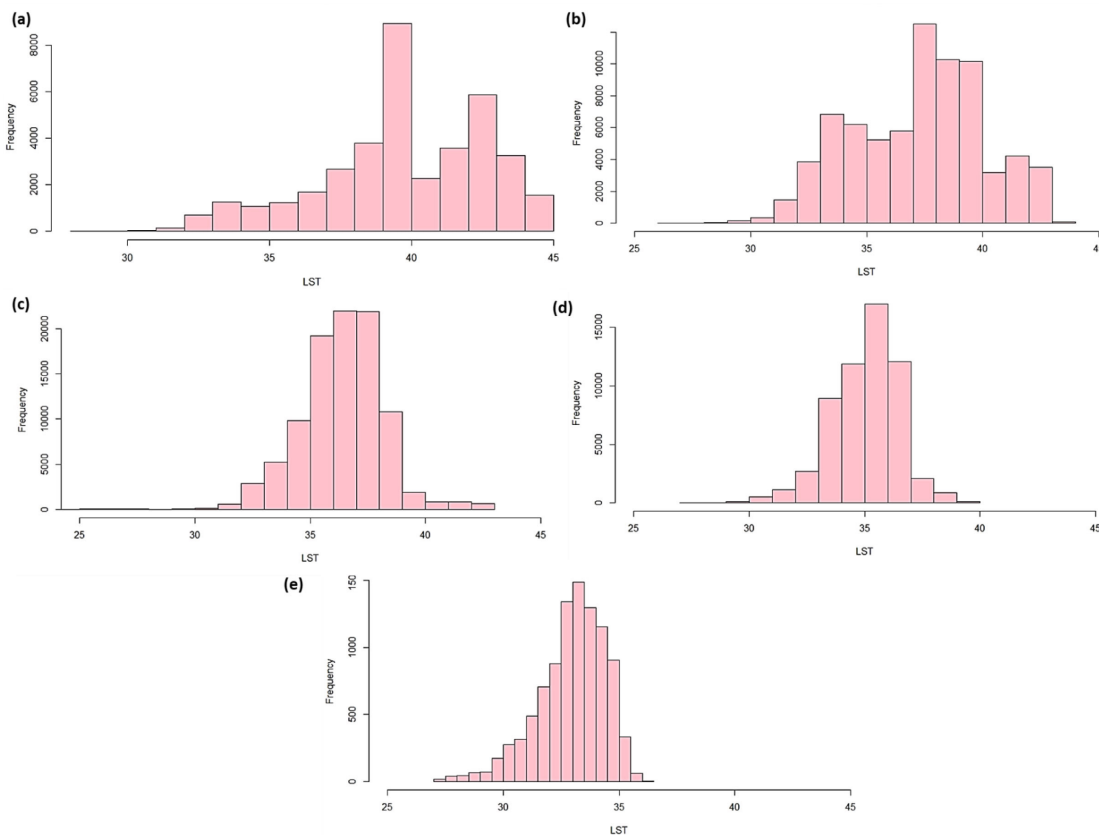
Fig. 4: Histogram of number of pixels for LST under elevation class (a) -6 to 168 (b) 168-267 (c) 267-387 (d) 387-589 (e) 589-1698 m

night time in Northwest Vietnam. Similarly, Deng *et al.,* (2018) and Bindajam *et al.,* (2020) also observed positive correlation between LST and elevation.

Variation of NDVI with elevation

The variation of NDVI under each elevation classes is depicted in the Table 3. Results showed that NDVI has substantial
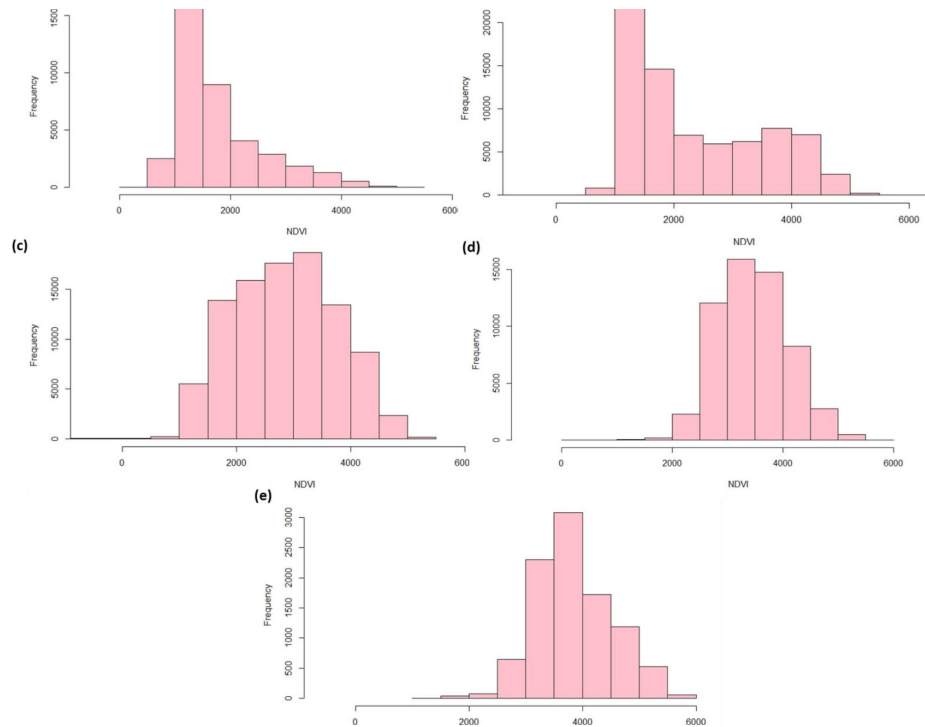
Fig. 5: Histogram of number of pixels for NDVI under elevation class (a) -6 to 168 (b) 168-267 (c) 267-387 (d) 387-589 (e) 589-1698 m
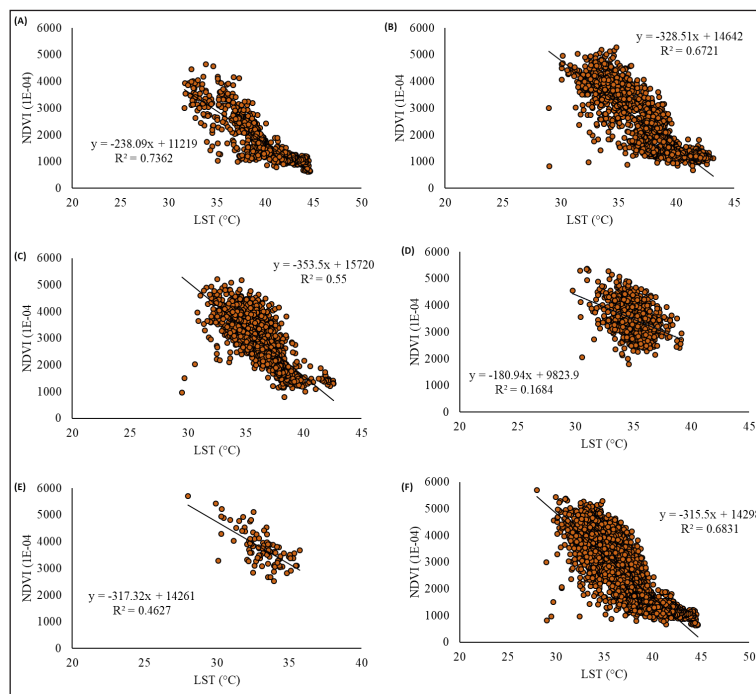

Fig. 6: Regression analysis between NDVI and LST under different elevation classes (A) -6 to 168 m (B) 168 to 267 m (C) 267 to 387 m (D) 387 to 589 m (E) 589 to 1698 m (F) Pooled data for all classes

variation with elevation in the study area. The mean NDVI values increase with increasing elevation. The maximum mean NDVI (0.38 ± 0.06) was obtained in fifth elevation class (589 – 1698 m) and minimum mean NDVI (0.17 ± 0.08) was observed in first elevation class (-6 to 168 m). Lowest and highest minimum NDVI was observed in elevation class of 267-387 m (-0.09) and 589-1698m (0.05), respectively while lowest and highest maximum NDVI was observed in elevation class of -6 to 168 (0.53) and 168-267 (0.65), respectively.

Elevation class (168-267 m) showed highest variability of NDVI from -0.09 to 0.65, which comes under sub humid southern plain ACZ of Rajasthan. Whereas, minimum variability of NDVI from 0.05 to 0.64 was observed fifth elevation class 589-1698 m) and this elevation class is represented by arid and hyper arid western plain ACZ. The correlation between NDVI/LST with elevation is slightly low compared to Phan *et al.,* (2018) and Bindajam *et al.,* (2020). It may be due to the use of mean annual NDVI/LST compared to monthly temperature (day and night) as observed by Phan *et al.,* (2018). Other reasons may be non-consideration of land use wise or masking out water bodies and habitant etc. The impact of elevation on vegetation was evaluated by correlating NDVI and elevation as shown in Fig. 3. It shows that there was a positive statistical correlation with R^2 of 0.26.

NDVI= 4.3066× Elevation + 1425.1

Fig. 5 depicts histogram and it represents the number of pixels for particular elevation class. It can be observed from the histograms that density of pixels is varying with NDVI under all elevation classes. The highest frequency of pixels was observed at 0.11, 0.13, 0.13-0.44, 0.27-0.41, and 0.33-0.39 in elevation class of -6 to 168, 168-267, 267-387, 387-589, 589-1689 m, respectively. In the present study, NDVI was high in areas having high elevation. The spatial variability of rainfall has been substantially influenced by topography, with annual precipitation generally increasing with altitude (Orographic impact) (Hasanean and Almazrou 2015). Higher elevation areas are mostly covered by perennial dense forest such as hilly region of humid southern plains ACZ. It may be one of the regions of high NDVI values (Mokarram and Sathyamoorthy 2015). However, NDVI was high in eastern portion of the Rajasthan state, which as low elevation because elevation is not the only factor in vegetation distribution. Other climatic and geographic factors, like temperature, pressure, geology and rainfall are also important. This analysis is highly consistent with Uhey *et al.,* (2020), who reported a positive correlation of NDVI with elevation.

Correlation of NDVI and LST Distribution

The functional relationships between land surface temperature and NDVI, as well as the effects of these variables on natural vegetation and ecosystem services, can only be understood by examining their whole spatial and temporal distribution. From the spatial distribution map (Fig. 1B &1C), it could be seen that pixels with high LST have low NDVI values. Scatterplot between NDVI and LST under different elevation classes showed significant negative correlation throughout the study area (Fig. 6).

Highest negative correlation was found in -6 to 168 m class (R^2=0.73) of elevation followed by 168 to 267 m (R^2=0.67), 267 to 387 m (R^2=0.55) and 387 to 589 m (R^2=0.17) classes, whereas highest elevation class 589 to 1698 m showed medium negative correlation (R^2=0.46) of NDVI with LST. There is a general declining trend in the LST as vegetation gets denser (exhibited by the higher value of NDVI). The dense layer of vegetation canopy provides an efficient barrier against the sun's incoming radiation and enhances the vegetation's evaporative cooling effect, which has a moderating effect on the rise in surface temperature (He *et al.,* 2019). Based on the inverse correlation between the NDVI and LST,

we can infer that vegetative land cover typically acts as a buffer against LST (Wang *et al.,* 2018). Bindajam *et al.,* (2020) and Sajan *et al.,* (2023) also observed a negative correlation between NDVI and LST.

High-resolution remote sensing products were used during this research to analyze relationship between LST and vegetation dynamics with elevation. But it's crucial to remember that there is some uncertainty about these products because of problems with quality. However, the main focus of the current study was conducting a preliminary examination of variation of land surface temperature and vegetation at different elevation over Rajasthan. Nevertheless, additional research is necessary to thoroughly examine the underlying mechanisms causing the reported inconsistencies.

CONCLUSIONS

The study investigated the interrelationship among NDVI and LST with elevation for Rajasthan state of India using satellite (MODIS and SRTM) derived remote sensing products. Elevation, NDVI and LST ranges from -6 to 1698 m, -0.09 to 0.65 and 24 to 45°C respectively throughout the area of study. Results indicates that there is a strong linear relationship between mean LST and elevation and a decreasing trend in LST is observed with increase in elevation from western to eastern portions, whereas increasing trend was observed in NDVI with increase in elevation. The statistical positive (R^2=0.26) correlation was found between NDVI and elevation and a negative correlation of NDVI with LST. This study provides an insight into response of land surface to climate change. Understanding the relationship between LST, NDVI and terrain attributes is of critical importance for sustainable ecosystem management, environmental protection and restoration of degraded land in Rajasthan.

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