Study of Green Indices of Smart City Ajmer using Remote Sensing and GIS

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Abstract.

Urbanization impacts the vegetation redundancy across the globe which turns and results into climate change manoeuvring. The paper particularly replicates the same on the basis of remote sensing data of vegetation for smart city Ajmer. Ajmer city had gone under lot of anthropogenic construction activities and few are still going on. These betterment activities for city are leading and shaking the vegetal cover of city. Entire year NDVI values are divided in four quarters and summer season and pre-summer season have lesser values of NDVI as compared to monsoon and winter season.

Keywords. Remote Sensing, Smart City, MODIS, NDVI, Variation.

1. INTRODUCTION

The physiological needs of component species and vegetation-modified environment link the vegetation and environment state spaces [1]. Most forest ecosystems need vegetation. Soil and water conservation are crucial [2]. Urban air pollution triggers 7 million premature deaths every year world - wide. In light of human pollutants, urban air quality is bad [3]. The vegetation barrier affected pollutant deposition dynamics and amplified the effect of plant hurdles against air pollution [4]. It may give insights for using new road clean infrastructures to ameliorate air quality [5]. Land cover influences and vegetation conditions govern the proliferation of vegetation types and forest sustainability includes determining the most effective variables [6]. Spatial and temporal soil complexity determines biodiversity distributions. Assessing the link between water and plants is vital for environmental restoration and management to show plant-environment interconnections. Satellite - derived datasets on growth of plants, gusto, and dynamism may be used in environmental monitoring, conservation of natural resources, agricultural production, lumber, urban green infrastructures, as well as other sectors. These categories of agricultural information provide a realistic framework for macro and resource management of agricultural production and, in many cases, crop yield forecasting and projections [7]. Nondestructive and noncontact remote sensing techniques capture crucial information via separated device (from target) for climate and environmental investigations [8]. Remote Sensing gets insight to response of a material with incident radiation on the basis of absorption, reflection, transmittance and scattering. Prospecting efforts in hyper spectral remote sensing platforms are indeed a vulnerable utility for land and climate monitoring applications like plant stress and chlorophyll content parameterization, surveillance of various vegetation classes along with water activity, mundialization of leaf pigment, change detection, and physical and biological crop yield. Spatial structural arrangement, biomass (live and senesced), moisture content is characterized by Leaf Area Index (LAI) in recognized spectral property determination by emphasizing processes for hypothesis testing of classified applications indulging new generation sensors like Compact Airborne Spectrographic Imager (CASI) and Airborne Visible Infrared Imaging Spectrometer (AVIRIS). In addition to that hyper spectral remote sensing provides a better approach for mapping, classifying, characterizing and modelling of green cover by inculcating Principal Component Analysis in best waveband selection. GIS helps organize, store, access, manipulate, update, and synthesize multi-sourced data related with geographic locations [9]. The Normalized Difference Vegetation Index (NDVI) is derived from the ratio of the amount of near-infrared light (NIR) reflected by leaf surface to the amount of red light (Red) reflected by leaf surface, recorded by a satellite sensor, and evaluated in a geographic information system (GIS) [10]. As a rule, leaves will soak up any sunlight that falls within the photo synthetically active radiation range. While green leaves strongly absorb blue and red spectral regions of incoming solar light, they do not considerably absorb NIR. This means that NDVI may be used to keep tabs on plant photosynthesis over time and to make quick work of comparing plant growth across different regions [11]. It may be used to map and anticipate the amount of land degradation, as well as to map and analyse the incidence and effect of disturbances including drought, fire, flood, and frost [12].

2. DATA

This article calculates VI and NDVI for smart city Ajmer during 2003-2013. Data from the USGS Earth Resources Observation and Science Centre’s Land Processes Distributed Active Archive Centre (LP DAAC), part of NASA's Earth Observing System Data and Information System (EOSDIS), were utilized in this study (EROS) [13]. Canopy greenness is a metric of photosynthetic activity, chlorophyll, and canopy structure, and may be compared across space and time using MODIS vegetation indices [14]. With NOAA's AVHRR NDVI time series record, NDVI provides historical and climatic coherence. EVI diminishes oscillations between the canopy and the earth and increases sensitivity in dense foliage. The dynamics of vegetation on a global scale may be summed up in two components. Vegetation indices are calculated daily using the surface's bidirectional reflectance. VIs with low-quality pixels is removed by a MODIS-specific compositing process [15]. To composite, constrained view angle picks a pixel with one of the remaining high VI values (from the two highest NDVI values it selects the pixel that is closest-to-nadir) [16]. With the VI method, both MODIS data sets are integrated over a span of 16 days, with the resulting temporal resolution being improved. The latest version of Terra MODIS's vegetation indices (MOD13Q1) is produced every 16 days, with a spatial resolution of 250m. Two plants are included in MOD13Q1. NOAA-AVHRR NDVI uses NDVI as its continuity index [17]. EVI makes it possible to detect changes in high biomass areas with greater precision. A pixel's value is determined by the software and it is set to 16 days [18]. There were few clouds in the sky, and the NDVI/EVI values were high. Multi-day temporal resolution, temporal coverage beginning on February 18, 2000, worldwide coverage, sinusoidal coordinates, a 250m pixel size, and 12 Science Data Sets are all features of Terra MODIS (MOD13Q1.006-version 6) [19].

3. STUDY AREA

The research region is between 26°20′ N and 26°35′ N and 74°33′ and 74°45′ E. Ajmer is 132 kilometres from Jaipur, Rajasthan's capital, and surrounded by Aravalli hills. Ajmer is an important historical and educational centre in Rajasthan.

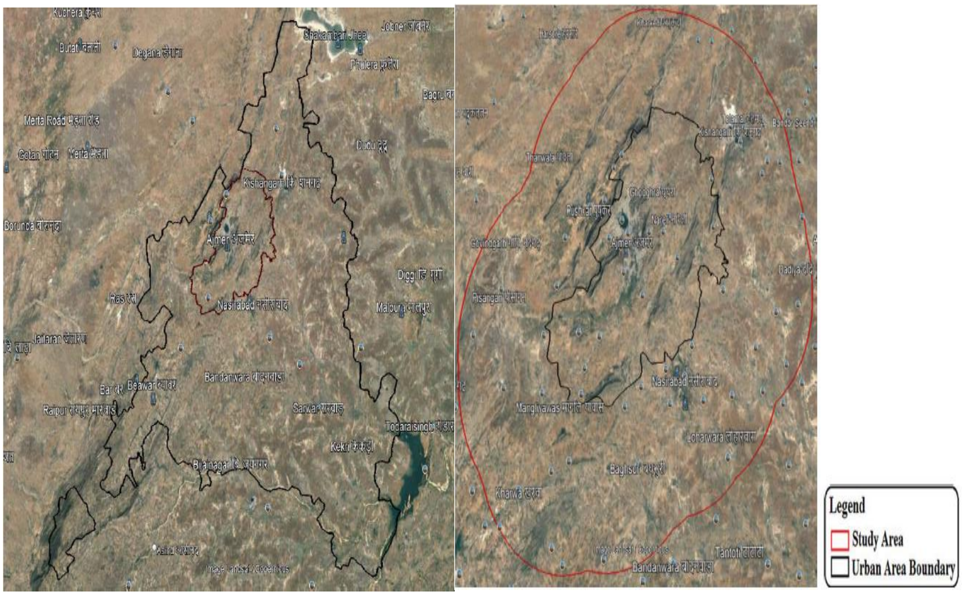

Figure 3.1. Geological Location of Study Area

Smart City has a semi-arid, hot summer and chilly winter environment, short monsoon. The Aravalli Mountain range in western India stretches 482 kilometres from northeast to southwest through Rajasthan. Ajmer district spans 8,481 square kilometres and is bordered by Nagaur, Jaipur, Tonk, Bhilwara, and Pali. Ajmer city is selected as study area due to mixed geographical conditions like hilly terrain, lake and desert area.

4. METHODOLOGY

The particular study of NDVI for Ajmer city using GIS and satellite data involves selection of Ajmer City coordinates sample along with creation of shape file of city area and buffer zone of 10kms. Afterwards the required data set for the time duration have been collected in Hierarchical Data Format (HDF) and then reformatted into Geo-TIFF format using MODIS re-projection tool (MRT) [20]. After quality checking and using a scale factor of 0.0001, the output data sets were operated under statistical analysis.

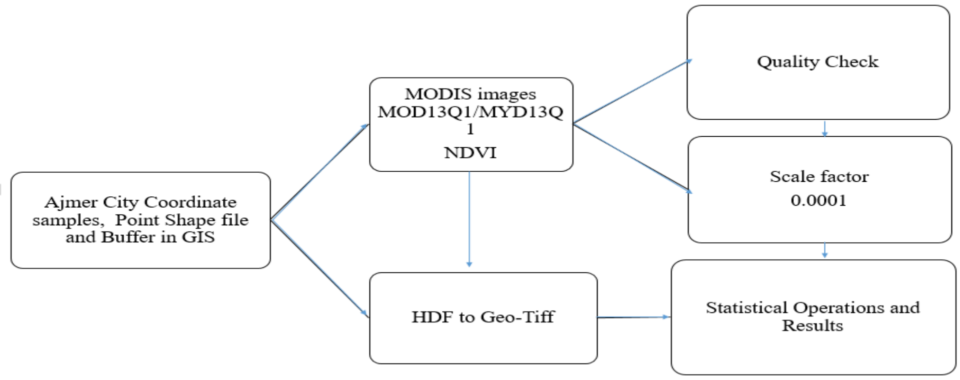

Figure 4.2. Methodological Layout

5. Results and Discussions

Normalized Difference Vegetation Index is calculated for the period of 2000-2022 by examining 23 images per year. These results are divided among the four quarters in a year to check the monthly as well as annual comparisons. Generally, NDVI values lies in between -1 to 1 and same range is established in the results. Trend analysis and correlation coefficient with maximum, minimum, average and variance values were also calculated as in Table5.1.

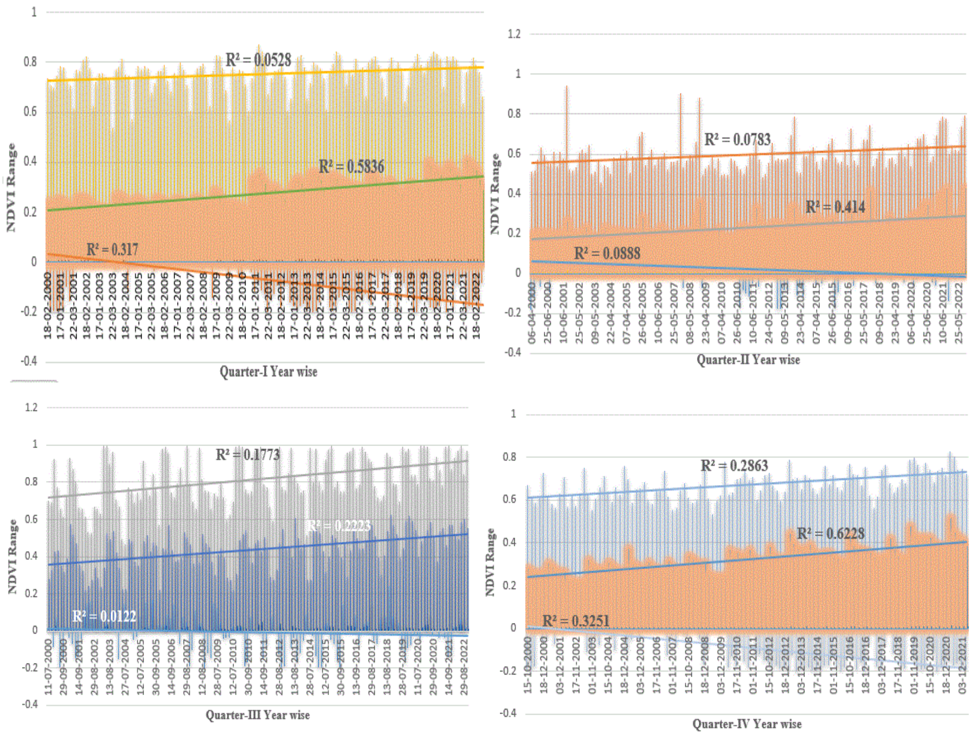

Figure 5.3. Quarter wise variation in NDVI from 2000-2022

After summers in all the years the average NDVI values for quarter III and IV showing increase on comparing previous quartes. The trend line and coffiecent of co-relations are 0.1773 and 0.2863 for Q-3 and Q-4 while Q-1 and Q-2 are having 0.0528 and 0.0783 for maximum NDVI values as shown in Fig.5.1.

Table 5.1: Annual Quarter wise distribution of NDVI

Year	NDVI values for Quarter-I			NDVI values for Quarter-II			NDVI values for Quarter-III			NDVI values for Quarter-IV		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
2000	-0.11	0.74	0.24	-0.02	0.56	0.19	-0.20	0.66	0.35	-0.17	0.59	0.26
2001	-0.19	0.79	0.24	0.01	0.94	0.26	-0.13	0.66	0.36	-0.07	0.56	0.27
2002	0.04	0.77	0.25	0.09	0.60	0.23	0.09	0.66	0.29	0.07	0.57	0.21
2003	0.11	0.75	0.21	0.03	0.54	0.23	-0.01	0.71	0.42	-0.04	0.61	0.27
2004	-0.03	0.78	0.26	0.07	0.57	0.20	-0.05	0.69	0.38	-0.10	0.66	0.27
2005	0.12	0.79	0.25	0.11	0.71	0.28	0.17	0.84	0.48	0.03	0.65	0.29
2006	-0.01	0.77	0.24	0.02	0.58	0.24	0.07	0.74	0.44	0.13	0.65	0.27
2007	0.12	0.75	0.24	-0.01	0.90	0.21	-0.19	0.79	0.47	-0.03	0.56	0.28
2008	0.04	0.78	0.25	0.10	0.88	0.35	-0.12	0.75	0.45	0.00	0.60	0.30
2009	0.01	0.83	0.27	0.05	0.58	0.23	-0.04	0.60	0.29	0.01	0.60	0.24
2010	0.06	0.75	0.22	0.08	0.54	0.17	-0.19	0.76	0.54	-0.18	0.70	0.35
2011	-0.12	0.79	0.32	0.08	0.67	0.33	-0.15	0.79	0.50	-0.12	0.60	0.31
2012	-0.13	0.77	0.30	0.08	0.57	0.24	-0.20	0.77	0.55	-0.17	0.64	0.33
2013	-0.17	0.75	0.32	0.02	0.79	0.33	-0.12	0.74	0.45	-0.20	0.70	0.37
2014	-0.20	0.80	0.35	0.00	0.64	0.23	-0.20	0.80	0.53	-0.20	0.65	0.36
2015	-0.18	0.77	0.34	0.02	0.68	0.28	-0.16	0.81	0.45	-0.18	0.66	0.32
2016	-0.20	0.75	0.30	-0.02	0.73	0.30	0.09	0.77	0.50	-0.19	0.71	0.37
2017	-0.15	0.80	0.34	0.10	0.74	0.41	-0.05	0.78	0.51	-0.18	0.62	0.32
2018	-0.04	0.82	0.32	0.07	0.58	0.28	0.08	0.80	0.57	-0.11	0.63	0.37
2019	-0.14	0.71	0.31	0.00	0.65	0.25	-0.08	0.84	0.59	-0.15	0.80	0.43
2020	-0.15	0.80	0.40	0.09	0.64	0.35	0.08	0.82	0.59	-0.20	0.74	0.39
2021	-0.20	0.82	0.38	0.08	0.78	0.42	-0.14	1.00	0.57	-0.17	0.80	0.45
2022	-0.20	0.76	0.41	0.10	0.79	0.43	0.02	0.97	0.56	-0.20	0.74	0.41

In the winters average NDVI values are found in Q-1 and Q-4 due to prevailing favourable environmental conditions for the growth of vegetation also the corelation coffiecient lies in the range of 0.58-062. The average NDVI values settled for all the quarters 0.3-0.85. The highest values for average NDVI values lies in Q-3 and Q-4. The minimum NDVI lasted 0 to -0.25 for Q-1, 0 to-0.5 for Q-2, 0 to -0.3 for Q-3 and 0 to -0.2 for Q-4 respectively. The cofficient of corelation for minimum NDVI values is highest i.e.0.3251 for Q-4 and lowest in the summer and post summer season 0.0122 along with 0.0888 for Q-2 and Q-3 respectively.

6. REFERENCES

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Biographies

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