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RESEARCH ARTICLE

EXPLORING NDVI AND NDBI RELATIONSHIP USING LANDSAT 8 OLI/TIRS IN KHANGARH TALUKA, GHOTKI

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ABSTRACT

Built-up is one of the most significant type of land use-cover linked with urbanization. Computing, classifying, and mapping the built-up areas by Landsat image, is on priority demand for municipal and policymakers to investigate urban extension. Thus, increasing population and conversion of agricultural land into urban is a major topic understanding the bond between both types of land use. In the context of this, this study investigates the relationship between Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) in Khangarh taluka. Therefore, satellite images of Landsat 8 OLI/TIRS 2014, 2016, 2018, and 2021 were downloaded freely from the USGS-GloVIS Earth Explorer website. The images were processed in the ArcGIS 10.3 environment. NDVI was calculated using the Near-Infrared NIR (band 5), Red (band 4) and for NDBI, Middle Infrared Reflectance MIR (band 6) and NIR (band 5) was used following the equation of both indices. The calculated values were then exported in SPSS software for correlation determination and scatter plot development. The results from the case showed that there was a linear and negative correlation between vegetation index and built-up index in all years over the study area. Furthermore, in 2014 the coefficient of correlation explicated R^2=0.96; in 2016 R^2=0.23, in 2018 R^2=0.34, and in 2021 R^2=0.22 which indicated that NDBI could be used to illustrate the evaluation of urban construction land. The all-over study recommends that built-up index NDBI not only can be used as a significant indicator for built-up or urban areas estimation but also deliver a consistent source for urban development and planning.

KEYWORDS

Correlation, NDBI, NDVI, Remote sensing, Khan Garh taluka

1. INTRODUCTION

The built-up area mapping is an essential indicator for urban growth, development, and urban sprawl. The demand for new housings, schools, hospitals, transportation, parks, and many other basic needs of communities are increasing with the increasing human population particularly in developing countries. Regular progress of urban hubs consumes cultivated land next to these, resulting in lower agricultural output. In view of these land use-cover dynamics and change detection on the earth's surface. Academics and Scientists are active and worked, an array of indicators together with Index based built-up index IBI, Urban Index, Normalized Difference Bareness Index (NDBaI), and Bare Soil Index BI for monitoring and mapping the built-up lands (Xu, 2008; Kawamura et al., 1996; Zhao and Chen, 2005; Rikimaru, 1997). The mapping process spread over several remote sensing (RS) data and spectral digits on the land use and land cover classes. Collectively increasing of built areas and fluctuation in vegetative lands, it is important to estimate the agricultural land, cropping area, forests for future planning to make availability and comfort zone for the population needs.

Enhanced Vegetation Index (EVI) and NDVI are the two main vegetation indicators for vegetation estimation and monitoring through remotely sensed technology. NDVI is mostly used in semi-arid areas for vegetation production and moisture estimation. It responds primarily in the high absorption red affected band. Thus, it is a dire need to monitor the vegetation areas and built-up indices. The indices are combinations of two or more bands associated with spectral appearances of vegetation (Matsushita et al., 2007). It has been found that the wide application in monitoring of cropping pattern, phenology, vegetation types and classes, and derivation of vegetative bio-physical constraints. A studies has described the vegetation index in their research work, NDVI lies between the ranges of -1 to +1 (Shah and Siyal, 2019). Waterbody, snow, barren land, and urban areas are under negative values. While the positive values indicate agricultural land, crops pasture, and are positively correlated with green vegetation. NDVI mostly used indices for vegetation and crop monitoring because it withdraws the huge portion of the noise produced by the topographic effects, clouds shadow, changing sun angles, and atmospheric conditions (Matsushita et al., 2007). It is accurate, reliable, simply calculated, and convenient for crop mapping, agriculture land

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mapping in tropical environments (Meera et al., 2015). Moreover, it is more saturated at high biomass levels and sensitive to canopy background variations (Gao et al., 2000). Vegetation Index and Built-up indices are the most used indices by remotely sensed techniques in past research work. Vegetative indicator NDVI is generally utilized to study the relationship between different indices correlation i.e., NDVI-NDBI (Macarof et al, 2017; Malik et al, 2019), LST-NDVI, and NDVI-NDWI (Weng et al, 2004; Smith et al, 1990; Julien et al, 2006; Stroppiana et al, 2014; Wen et al, 2017). Therefore, this study focuses to investigate the correlation between NDVI-NDBI in Khangarh taluka from 2014-2021.

2. MATERIALS AND METHODS

2.1 Study area

This study was conducted in Khangarh taluka, district Ghotki. The taluka is situated on Latitude N: 28 02' 00' and Longitude E: 69 33' 00' with 77 meters above sea level. The total area covered by taluka is 1626.84 km² withholding 149,667 population (PBS, 2017; Shah and Siyal, 2019). The people of the taluka engaged in agriculture. The major crops in taluka are wheat, sugarcane, cotton, and some vegetables and fruits are excessively found. Qazi Wah irrigates the whole command area, it off takes from the Ghotki feeder canal. Desert minor also irrigated some agricultural land of the taluka (Shah et al., 2021). Government and private tube wells are also used during the shortage period of irrigation water in the study area.

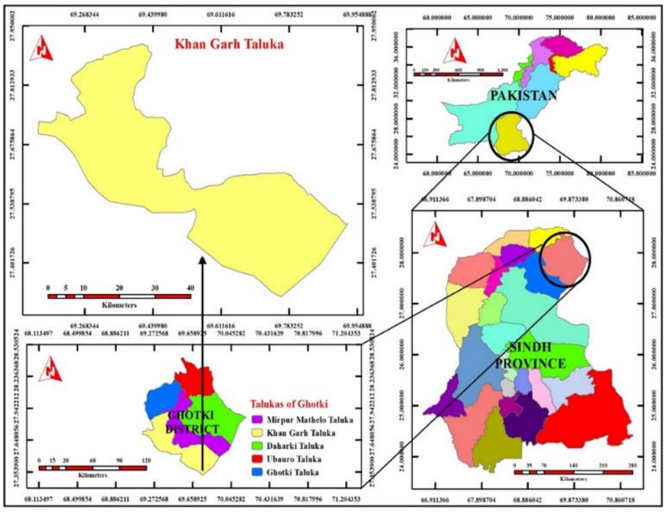

Figure 1: Layout map of Khangarh taluka, Ghotki, Sindh, Pakistan

2.2 Data Acquisition and Preprocessing

Remote sensing data from Landsat 8 OLI/TIRS was employed in this study for the years 2014, 2016, 2018, 2021. The data were freely downloaded from USGS-GloVIS (https://earthexplorer.usgs.gov/) web portal in Tagged Image File (TIF) format with 0% cloud cover. Remote sensing images were referenced to the (UTM) Universal Transverse Mercator projection system and covered one scene of Landsat 8 imagery from the worldwide reference system (WRS-2) of (path 151 row 41) presented in (Table 1). The acquired satellite images were processed in the geospatial tool ArcGIS 10.3 environment. Then shapefile of Khangarh taluka was taken out from the entire scene using the Extract by Mask tool.

Currently, many researchers have used NDVI for mapping and monitoring the vegetative zones with remotely sensed data (Sonawane and Bhagat, 2017; Chen et al, 2017; Shah and Siyal, 2019; Shah and Kiran, 2021). NDVI is mostly used for drought monitoring, timely prediction of crop production, predicting fire zones, and desert offensive maps worldwide. Since, it supports paying off for changes in lighting conditions, surface slope, exposure, and other peripherical factors. The range of vegetation index values between (-1 to 1) depends on the relative digital number DN of Near Infrared and red bands (Sonawane and Bhagat, 2017). The negative values indicate rocks, clouds, snow, surface water, bare land that normally falls within the 0.1-0.2 values corresponding to areas where plantation exists. Healthy and dense vegetation canopy always fall within 0.5 and sparse vegetation falls within 0.2-0.5. Moderate vegetation tends to differ from 0.4-0.6. Whatever above 0.6 values indicate the highest possible density of green leaves (Shah and Kiran, 2021; Malik et al, 2019). The NDVI is calculated from the following equation.1.

$$\text{NDVI}=\frac{\text{Near}-\text{Infrared (Band 5)}-\text{Red Band (Band 4)}}{\text{Near}-\text{Infrared (Band 5)}+\text{Red Band (Band 4)}} \tag{1}$$

Normalized Difference Built-up Index (NDBI) differs from vegetation index NDVI. It deals with the extraction, mapping, and monitoring of built-up/settlements areas from the remotely sensed data. Whereas NDVI only deals with vegetation extraction. The NDBI map and values were extracted from Landsat 8 OLI/TIRS. In contrast to the other land cover surfaces, built-up and settlements lands have higher reflectance in the MIR wavelength range 1.55~ 1.75μm than in the NIR wavelength range 0.76~ 0.90μm. Built-up range from (-1 to 1). The greater the built-up values, the higher the proportion of built-up areas. NDBI has been computed using the equation. 2.

$$\text{NDBI} = \frac{\text{MIR(Band6)}-\text{NIR(Band5)}}{\text{MIR(Band6)}+\text{NIR(Band5)}} \tag{2}$$

Here, MIR=Middle Infrared Reflectance (Band 6), NIR=Near Infrared reflectance (Band 5)

Table 1: Illustrate the information of downloaded Landsat images 2014, 2016, 2018 and 2021

S. No	Landsat Name	Landsat scene ID	Path/ Row	DOY	Image acquisition Date
1	Landsat 8 (OLI/TIRS)	LC81510412014203LGN01	151/41	202	2014-07-22
2	Landsat 8 (OLI/TIRS)	LC81510412016353LGN02	151/41	352	2016-12-18
3	Landsat 8 (OLI/TIRS)	LC81510412018214LGN00	151/41	213	2018-08-02
4	Landsat 8 (OLI/TIRS)	LC81510412021174LGN00	151/41	173	2021-06-23

3. RESULTS AND DISCUSSION

3.1 Computation of Normalized Difference Vegetation Index (NDVI)

NDVI values of 2014 imagery (Figure. 2) indicate the highest and lowest vegetation 0.40 to -0.13. The maximum values indicate the vegetation canopy over an area is highest, and the minimum values are displayed on the water body, barren land, and sandy areas. While the NDVI of 2016 imagery shows that the maximum value of 0.44 and observed as healthy vegetation, and the minimum value is -0.14 over the study area. The imagery 2018 NDVI represents the highest value on agricultural crop and pasture 0.43, on the other hand, minimum values showed the NDVI -0.05 over the sandy, barren and built-up area. The vegetation index of 2021 showed the maximum value 0.42 and minimum value -0.02 observed on barren land and sandy area over the Khangarh taluka. Comparing NDVI of 2014-2021, the vegetation canopy is highest in 2016 with full greenery on the agricultural land. While the lowest NDVI was computed in 2021 imagery.

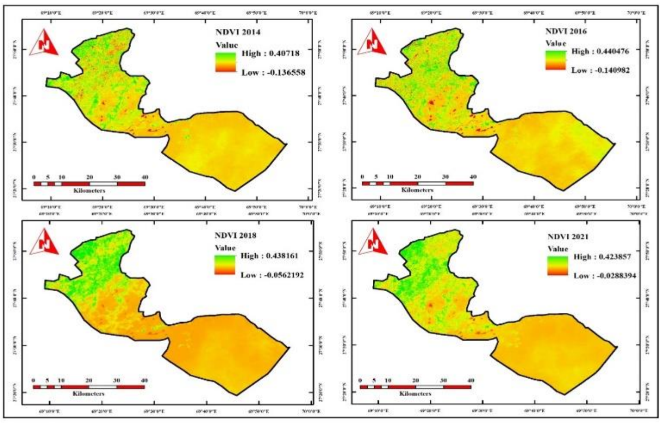

Figure 2: Represents NDVI of 2014-2016-2018-2021

3.2 Computation of Normalized Difference Built-up Index (NDBI)

NDBI values of 2014 imagery (Figure.3) indicate the highest and lowest built-up values 0.08 to -0.31. The maximum values indicate the dense built-up and barren areas, and the minimum values are displayed on the water body, and vegetative areas. While the NDBI of 2016 imagery shows that the maximum value of 0.55 and observed as the highest built-up, and the minimum value is -0.31 over the study area. The imagery 2018 NDBI represents the highest value on settlement, sand, and barren land 0.08, on the other hand, minimum values showed the NDBI -0.31over the crops, vegetation, and pasture. The built-up index of 2021 showed the maximum value of 0.07 and a minimum value of -0.28 observed on vegetation and waterbody areas over the Khangarh taluka. Comparing NDBI of 2014-2021, the built-up is highest in 2016. While the lowest values were computed in 2021 imagery. Hence, NDBI was found to be a good index for distinguishing the built-up areas from OLI data. The barren index could be active in several applications concomitants with the application of the geospatial information, mainly in the subject of municipal remote sensing.

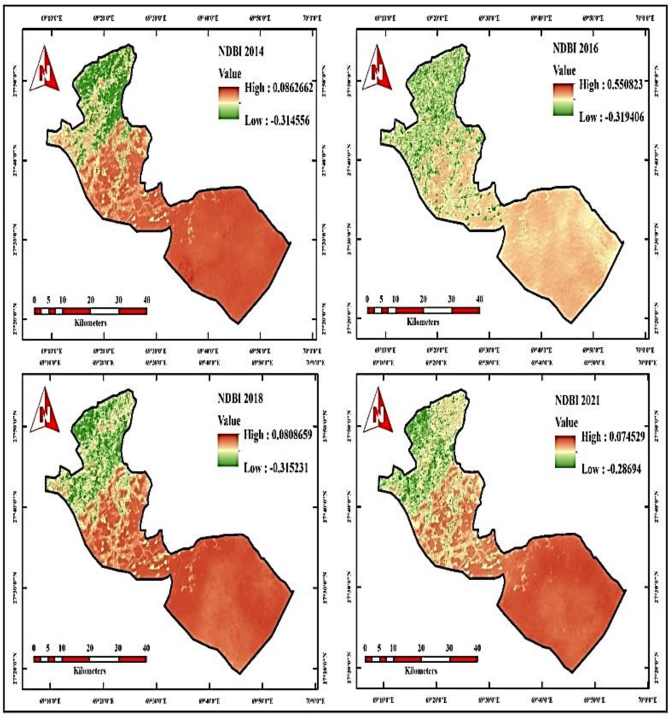

Figure 3: Represents NDBI of 2014-2016-2018-2021

Table 2: Illustrate NDVI-NDBI values of 2014-2016-2018-2021 imageries								
Indices	2014		2016		2018		2021	
	High	Low	High	Low	High	Low	High	Low
NDVI	0.40	-0.13	0.44	-0.14	0.43	-0.05	0.42	-0.02
NDBI	0.08	-0.31	0.55	-0.31	0.08	-0.31	0.07	-0.28

3.3 Relationship between NDVI-NDBI 2014, 2016, 2018, 2021

The correlation between NDVI-NDBI is depicted in (Figure. 4) which indicates that the NDVI is negatively correlated with NDBI in all years. The NDVI-NDBI relationship in 2014, 2016, 2018, 2021 were computed as R^2=0.20, R^2=0.44, R^2=0.91, and R^2=0.76. The statistical scatter plots explained the correlation values. Whereas, in 2018-2021 graphs indicated there is a strong negative relationship between vegetation index and built-up index. There is a linear and negative correlation between the vegetation index and the built-up index during 2014 and 2016. Hence, it is clear that NDBI can be employed to illustrate the evaluation and expansion of the built-up index. The linear relationship of NDVI-NDBI is displayed in the scatter plots for all selected years (Figure.4).

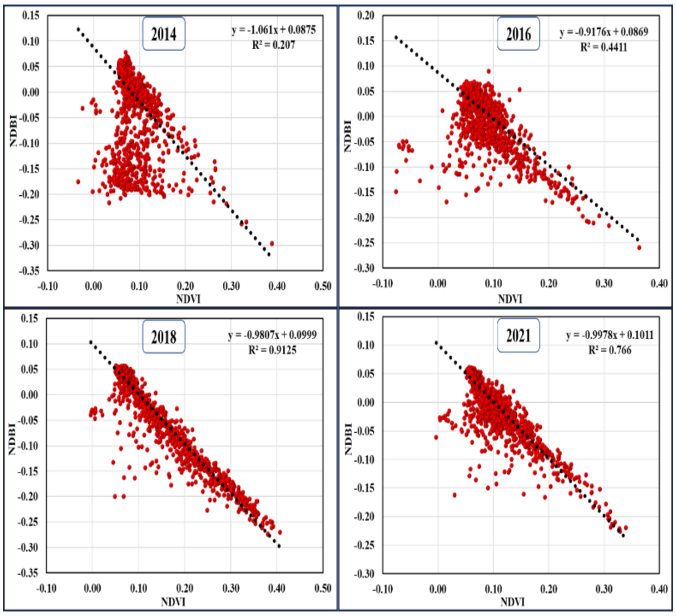

Figure 4: Represents Correlation between NDVI-NDBI 2014, 2016,2018, 2021

4. Discussion

Globally, the increase in built-up areas is due to the different actions of humans i.e., land-use change, urbanization, population growth, and industrialization. It has been confirmed from the satellite images, ground trothing survey and from past literature, the rapid increase in the population, unplanned built-up, industrialization, and commercialization have affected the vegetative areas especially agricultural land as well as environmental factors. Land use-cover dynamics have given away to vary greatly in their effects on vegetation indices, and built-up areas. While computing the NDVI-NDBI in the study area from 2014-2021, it has been confirmed through correlation that due to the spatial size of the cities, and vegetation cover there has negative relation between vegetation index and built-up index. Hence, we have tried to discuss and compare the results of both indices in four years (2014, 2016, 2018, and 2021).

NDVI values of 2014 indicated the highest and lowest vegetation 0.40 to -0.13. The maximum values indicate the vegetation canopy over an area is highest, and the minimum values are displayed on the water body, barren land, and sandy areas. While the vegetation index of 2016 imagery shows that the maximum value of 0.44 and observed as healthy vegetation, and the minimum value is -0.14 over the study area. The 2018 imagery represents the highest value on cropping and pasture areas as 0.43, on the other hand, minimum values recorded -0.05 over the barren land, settlements, and sandy area. The vegetation index of 2021 showed the maximum value 0.42 and minimum value -0.02 observed on sand, built-up and barren areas over the Khangarh taluka. Comparing NDVI of 2014-2021, the vegetation canopy is highest in 2016 with full greenery on the agricultural land. While the lowest NDVI was computed in 2021 imagery.

On the other side, NDBI values of 2014 indicate the highest and lowest built-up values 0.08 to -0.31. The maximum values indicate the dense built-up and barren areas, and the minimum values are displayed on the water body, and vegetative areas. The Landsat 2016 imagery shows that the maximum value of 0.55, observed as the highest built-up, and the minimum value is -0.31 over the study area. The imagery 2018, built-up index represents the highest value on settlement, sand, and barren land 0.08, while, minimum values showed -0.31over the crops, vegetation, and pasture. The built-up index of 2021 displayed the maximum value 0.07 and minimum value -0.28 observed on vegetation and water body areas.

Furthermore, the correlation between both indices has been computed to find what relations occur either positive or negative. The NDVI-NDBI relationship in 2014, 2016, 2018, and 2021 was computed as 0.20, 0.44, 0.91, and 0.76. The scatter plots in (Figure.4) clearly showed there was linear and strong negative relation in all years. It is obvious from the results that vegetation and urban lands are inversely proportional to each other as one grows, the other decrease simultaneously. Now researchers turn to work on this perception of sustainable management as with the up-to-date step, the urban growth may just cross out the vegetation and availability of resources. This would lead to havoc creating cases of jeopardizing and enormous harm of bio-diversity in the existing ecosystem.

5. Conclusion

In the present study, NDVI-NDBI has been derived using Landsat 8 OLI/TIRS data and the relationship between both indices has been investigated over the Khangarh taluka. It has been observed that most of the settlement, barren land, and sandy areas have high NDBI values and on vegetation, low values were recorded during the selected years. There was a strong negative relationship between the vegetation index and the built-up index from 2014-2021. From the results, it has been concluded that NDVI and NDBI can be used as good parameters for monitoring vegetation, cropping area estimation, built-up, and urban areas. In conclusion, a built-up index was anticipated for mapping the built-up areas in the study area using OLI/TIRS bands, and the result of the research study would appearance municipal and cities designers to distinguish evaluate growth for sustainable performs of the urban land system. It is expected from Government and policymakers that they should encourage researchers to conduct more studies on these indices with environmental parameters and provide more knowledge about the current land use cover dynamics particularly urban areas and agricultural lands. Other factors including rapid population growth, landscapes, and socio-economics parameters should be considered in their research studies.

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