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Detecting NDVI & LST in the Municipalities of Al Jabal Al Akhdar Region – Libya using Remote Sensing and GIS

Talaat Abdel-Monem Hegazy[1], Mohamed Abd El Galil[1], Rasha M. Abou Samra[1], Mac Tar Mohamed[2] and Saleh S M Al Saleh[2*]

[1] Environmental Sciences Department, Faculty of Science, Damietta University, Egypt.
[2] Geography Department Faculty of Education, Omar Al-Mukhtar University.

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* Corresponding author's E-mail: saleh_197576@yahoo.com

Abstract

Human-induced land use/ land cover changes resulted in various impacts on the environment at various spatial and temporal scales. Conversion of natural resources for food, urbanization and other socioeconomic benefits have all exacerbated the problem. This paper aims to detect the relationship between NDVI and LST in Al Jabal Al Akhdar Region using remote sensing and GIS tools. The spatiotemporal dynamics of vegetation (NDVI) and LST were studied and understood using a geographic information system (GIS) techniques and remote sensing data in this work. The results showed that the area of dense vegetation decreased from 1207.9 km2 in 2010 to 673.9 km2 in 2020. In 2010, 52.9% of the total area had LST less than 40°C while 47.1% of the total area had LST more than 40°C. In 2020, 8.2% of the total area had LST less than 40°C while 91.8% of the total area had LST more than 40°C. The outcome of this research provides us with new knowledge that helps us better understand the spatiotemporal land use land cover changes and their impacts on LST.

Keywords: Degradation; Landsat images; Deforestation, NDVI, LST.

Introduction

The United Nations Decade on Biological Diversity is drawing to a close, at the same time forests are facing major challenges and increasing threats of deforestation at alarming rates. Globally, it is estimated that about 420 million hectares of forest are lost, and the rate of forest loss between 2015-2020 is about 10 million hectares (UNEP &FAO, 2020). Al - Jabal Al - Akhdar region constitutes 1% of the total area of Libya and contains 75% of the biodiversity i.e., 1100 plants of the total species registered in Libya. It is one of the main plant diversity areas on the southern coast of the Mediterranean Sea. This distinction is due to various geographical factors. The geographical location makes it more susceptible to the influence of altitude factors. It is gaining special importance, due to the natural resources, archaeological, historical sites, and beaches, in addition to the climatic features and tourist sites .

Many studies have been conducted on the natural vegetation cover of Al-Jabal Al-Akhdar. Confirming a reduction in the amount of natural vegetation, most of these investigations were based on fieldwork. The rugged terrain of the area made these studies limited. Recently, studies have adopted GIS and RS techniques. The area increasingly suffers from degradation of vegetation cover (Abedi, 2019). The qualitative and quantitative deterioration of vegetation of the region leads over time to the loss of national natural wealth that is difficult to compensate

There are many manifestations of land cover degradation that can be measured on many specific scales, such as reduced productivity of the plants that form the source of livelihood and income, changes in biomass, and the variety of micro and macro flora and fauna are unfavorable. The degraded locations are linked to inappropriate or over-intensive land use and land management practices (Thornton et al. 2005). In Libya, without a national monitoring program, vegetation will continue to change and deteriorate. According to studies, Al Jabal Al Akhdar is vulnerable to deforestation for agricultural development, urbanization, and other objectives (Estebanez, 2006). Deforestation in Al Jabal Al Akhdar region is generally considered as an important environmental challenge (Vasconcelos et al., 2018).

In the next 15 years, the region's woodlands will lose more than half of their natural cover (Omar Al-Mukhtar University, 2005). GIS technology represents, in tandem with remote sensing tools, the only practical means to obtain accurate, multispectral, temporal, and cost-effective data and can be used to analyze environmental change at different spatiotemporal scales. It is a base decision support system to prepare an environmental management plan accommodating most of the principles of ecosystem resource and components management planning concept (Daniel and Ayobami, 2007). The present technology of GIS and RS allows us to collect large amounts of spatial data quickly and regularly, as well as evaluate the data geographically and provide many alternatives. RS and GIS are valuable technologies that may be used independently or in combination in forestry and biodiversity research. For the creation of data, remote sensing techniques are quite valuable. They give a technique of acquiring a near-real-time synoptic view of the forest's state and condition (Tao Wang, 2016).

There are many indicators for vegetation detection. NDVI is one among over 150 spectral vegetation indices that were defined in the literature. However, NDVI remains the most successful in identifying areas of vegetation, characterizing live green vegetation canopies in multispectral remote sensing data (Kirkpatrick, 2014). NDVI is an indicator of the health of the vegetation cover because the degradation of the vegetation cover of an ecosystem will be reflected in a decrease in the value of NDVI. If the amount of biomass in different forest ecosystems can be quantified by NDVI, then the degradation processes can be monitored (Scheftic ,2014).

NDVI is estimated based on the effect of terrain, elevation, and slope, by analyzing the relationship between variables using single and multiple linear regression (Sara et al., 2013). Studying the influence of topographical factors on NDVI&LST provides a scientific basis for building the ecological environment and creating suitable living spaces for humans (Xiaoxue et al.,2020).

Javed (2014) reported the effect of terrain on LST&NDVI. The values were determined based on the elevation and slope. The relationship between variables was analyzed using single and multiple linear regression, and a quantitative model was created describing the relationship between the variables. The spatial and temporal resolution of every satellite sensor is inherently controlled by the surface configurations. LST has an inverse connection with vegetation in general. LST is determined by NDVI, and some research has utilized the LST-NDVI correlation to assess the NDVI distributional pattern. Many recent types of research have used a multimodal approach to evaluating the LST-NDVI association (Mallickm et al., 2013) .Using the NDVI index is possible to estimate the earth surface temperature anywhere on the globe in a convenient and fast way. It is calculating the LST. The NDVI -LST correlation has been utilized in certain research to assess the distributional pattern of LST (Weng et al., 2004). The effect of natural factors was investigated using GIS and RS in a study, such as vegetation cover, altitude above sea level, and distance from the sea on the land surface temperature, in the AL Jabal Al Akhdar region, compared between 1986 and 2014. The study showed that the vegetation cover is the most influenced by changes in LST in the studied region (Mactar and Jumma, 2018). A study showed that there is a significant relationship between the NDVI and climate variables. A study showed distinction GWR in analyzing the relationship between patterns of NDVI and precipitation and the other factors (Usman et al., 2013).

Alexis et al., (2012) mentioned that the GWR is effective for describing the changing spatial relationship between land cover classes because GWR estimates regression coefficients locally using spatially dependent weights, under the assumption that the effect of the predictor variables on the dependent variable will vary continuously.

The purpose of this research is to estimate the relationship between NDVI and LST in Al Jabal Al Akhdar Region using remote sensing and GIS techniques.

Materials and Methods

Study area

The Green Mountain region (Al Jabal Al Akhdar) is located in the northeast of Libya. AL- Jabal Al Akhdar (Green Mountain) region is located in the northeast of Libya. It lies between 21° 31′ 4″ E to 21° 54′ 35″ E and 32° 41′ 40″ N to 32° 55′ 33″ N, it represents only 1% of the total area of Libya. The study area constitutes part from AL-Jabal Al Akhdar Region, which covers a total area of 2354,74 km^2. Al Jabal Al Akhdar is a NE–SW to ENE–WSW-trending mountainous belt that extends for approximately 360 km in length and 60–75 km in width along the Mediterranean coast. Regionally, Al Jabal Al Akhdar consists of three escarpments and defines a doubly plunging anticlinorium with its main axis plunging gently to the northeast and southwest.

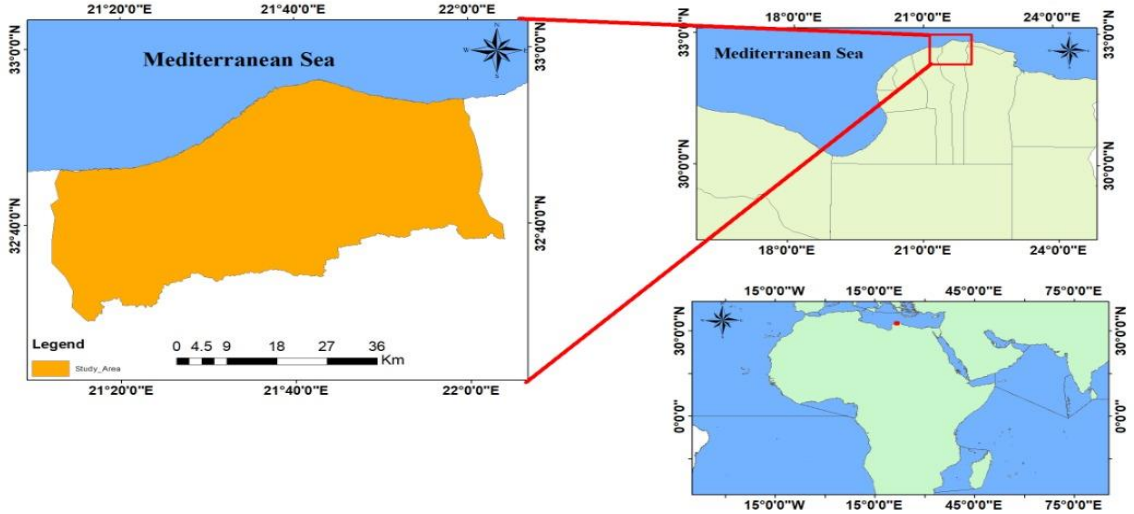

Figure: (1) Location of Al Jabal Al Akhdar in North East of Libya

The study area consists of four Municipalities, Al-Baydah, Shahat, AL Sahel, and Werdamah, previously it was called Al- Jabal Al-Akhdar Governorate. Al Jabal Al Akhdar (The Green Mountain) is a low to medium mountainous landscape (Hegazy et al., 2011). It has three borders as well as two long terraces that run parallel to the coast. The width and length of the terraces vary from one place to the next. The Sedi Al Homri (800 meters above sea level) is the highest point on the ridge of Al Jabal Al-Akhdar, and it stretches for 40 kilometers along the watershed of Al Jabal Al-Akhdar. Many vast valleys fall from Al Jabal Al-watershed Akhdar's through the mountain's north and south interfaces, eventually reaching the sea in the north and the desert in the south (Omar Al-Mukhtar University, 2005). The climate of the study area is characterized by the Mediterranean climate, which is warm and rainy in the winter, hot and dry in the summer, and the prevailing winds are north to northwest in the winter, northeast, and occasionally southern in the summer.

Methodology

The data sources

In order to accomplish the objectives of the present study, a group of satellite images were used (Landsat TM 5, Landsat ETM+ 7, and Landsat OLI 8). These images were downloaded from the United States Geological Survey Earth Explorer gateway (https://earthexplorer.usgs.gov/). The images are for the path/row 181/40 and 177/38 and are dated 2010, 2015, and 2020. Each image consists of 11 spectral bands including the visible, near infrared, middle infrared, and thermal infrared portions of the spectrum (Table 1). The images have geo-rectified to the Universal Transverse Mercator (UTM) with the datum WGS 1984.

Table (1) satellite images

Satellite	Acquisition date	resolution
Landsat 5 TM	12-08 2010	30-60 m
Landsat 7 OLI, TIRS	25-07-2015	30 m
Landsat 8 OLI, TIRS	8-09-2020	30 m

Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is one of the most famous indices applied to highlight the vegetation spectral signature in the image. As coastal wetlands are dominated by aquatic vegetation, the NDVI is then important as a proxy to the green vegetation in the image. The NDVI = (NIR - Red)/ (NIR + Red). The NIR is the near infrared reflection, and the R is the red reflection in the Landsat images. The NDVI values ranges from -1 to +1 with vegetation having values close to +1.). It is expressed as (O'Callaghanm, 1980; Fensholt and Proud, 2012; Tao Wang, 2016)
NDVI= (NIR-RED)/ (NIR+RED
Where NIR is the near infrared band value of the cell and RED is the red band value. The values are ranged from -1 to 1, with -1 and 1 referring to non-existence and existence, respectively.
NDVI can be calculated in ArcGIS by applying the given Formula:

$$NDVI = \frac{B1 - B2}{B1 + B2}$$

Where: Band5 = Infrared Band, Band4=Red band.

Vegetation change detection

The vegetation delineation tool was used to identify the presence of vegetation and to visualize its level of vigor. Five classes based on the presence of vegetation were categorized into dense (NDVI > 0.70), moderate represented by NDVI value falling between (0.50 and 0.70), low between (0.25 and 0.50), very low between (0 and 0.250) and no vegetation between (-1.0 and 0). These classes were transformed to shapefiles, and then the differences between each class were measured using Arc Map. The NDVI images were detected using change detection analysis for 2010, 2015 and 2020. Then the map was created to visualize the changes over 10 years.

Land Surface Temperature

Landsat images were used to generate LST data in the study area. Images acquired on August 12, 2010, June 25, 2015, and August 9, 2020, respectively. In order to extract the LST maps, the brightness temperature (TB) can be estimated from the spectral radiance (Lλ), and the emissivity (ε) based on NDVI (Sultana and Satyanarayana, 2018) using the following steps:

(1) Conversion to TOA Radiance

For Landsat images, the LST of the study area was derived using NASA procedures on the thermal bands. Top of Atmosphere spectral radiance $L\lambda$ was estimated using the following equation:

$$L\lambda = M_{L\times}Q_{cal+}A_L,$$

where M_L is a band-specific multiplicative rescaling factor from the metadata file Q_{cal} that corresponds to the thermal band, and A_L is a band-specific additive rescaling factor from the metadata file.

(2) Conversion to Top of Atmosphere Brightness Temperature

Thermal band data can be converted from spectral radiance to the top of atmosphere brightness temperature using the thermal constants in the MTL file.

$$T = \frac{K2}{In\left(\frac{K1}{L_\lambda} + 1\right)}$$

where K_1 and K_2 are band-specific thermal conversion constants from the metadata file.

Results and discussion

NDVI detection

The vegetation in the study region was converted from dense and moderate types to low, very low, and no vegetation types, as shown in Table (2) and Figures (2). The area of dense vegetation decreased from 1,207.913 km^2 in 2010 to 673.92 km^2 in 2020 (44.4%) and the total area of reduction is 533.10 km^2.

Table (2): Changes and percentage change in vegetation from 2010-2020 years by km^2

years	No vegetation	%	Very low Vegetation	%	Low vegetation	%	moderate Vegetation	%	Dense Vegetation	%
2010	31.67945	32	340.1899	18	573.3464	35.27	201.543	21.7	1207.913	44
2015	32.83428	33	638.6344	34.6	465.5451	31.95	363.6151	39.2	854.0432	31
2020	34.4796	34.8	865.9795	46.9	418.0479	28.69	362.0479	39	673.9155	24.6
Change km^2	2.8	0.028	525.7896	28.5	-211.2985	-15	160.5049	17.3	-533.9975	-19.5

This decrease was at the expense of increasing the area of no vegetation from 31.67945 km^2in 2010 to 34.4796 km^2 in 2020.The total increase amounted to 2.8 km^2 (8.83%) and the distribution area to 362.0479 km^2 in 2020, a total increase of 160.5049km^2 (79.6%).

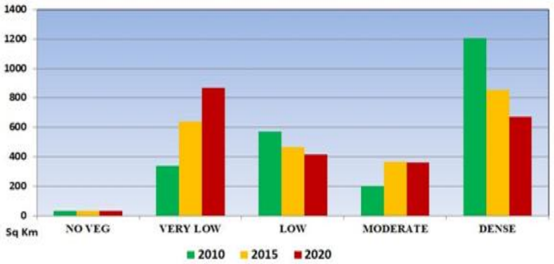

Figure (2): Vegetation distribution and changes during 2010-2020 period

The very low vegetation distribution area increased from 340.1899 km^2in 2010 to 865.9795 km^2in 2020.The total increase amounted to 525.7896 km^2(79.6%). It was also noted that the area of the low vegetation cover decreased from 573,3464 km^2in 2010 to 418,0479 km^2in 2020, and the total area of reduction was 211.2985km^2(44.4%).

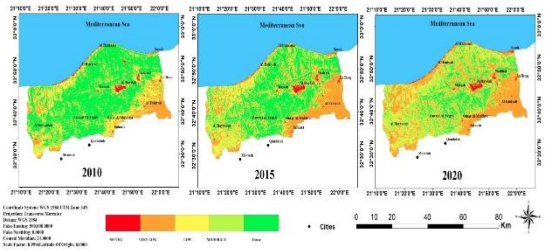

Figure (3): Spatial distribution of NDVI in 2010, 2015 and 2020

The erosion of the vegetation cover occurred in the northern direction near the sea, as shown in Fig. (3). It may be as a result of its effect, a gradual southward decline is observed due to the influence of the desert climate and logging, because some residents of the area consider cutting trees as their source of livelihood. Cities appear without vegetation cover due to illegal urbanization and the construction of green spaces in and around cities. It seems that the erosion of the vegetation cover is more significant in the first terrace than the second, although the population density, urban communities, economic and service activities are more significant in the second terrace; this can be explained because the population seized land in the second terrace and the erosion of vegetation cover. It is also quite clear that the management of these natural resources through local governments in the study area is weak.

LST detection

As illustrated in Table (3) & Figure (4) , land surface temperature is significantly increased during the study interval. In 2010, minimum LST was 23 - 37 °C and covered an area of 327.4 km^2 (13,9%). While maximum LST was 41- 47°C and covered an area of 609.1 km^2 (25.8%). In 2015, minimum LST was 24- 41 °C and covered an area of 107.09 km^2(4.547%). Maximum LST was 44-50 and covered an of area 476.8 km^2(20.2%). In 2020, minimum LST was 29 - 40 °C and covered an area of 210.35 km^2(8.9%). Maximum LST was 45- 51 °C, and covered an area of 1087.7 km^2(46%). The study showed that LST decreases near the seacoast as indicated in Figure (5), the influence of the sea can explain this. The surface temperature increased with the years (2010–2020), which could be explained by the decline in the vegetation cover areas in the study area between 2010 and 2020. There was an inverse relationship with a statistical significance between NDVI and LST. The results also showed that the lowest temperatures in 2010 were in the first terrace, and in 2020 it increased to record levels and covered a large area. This is evidence of a significant decline in vegetation cover and increased negative human activities. The increase in surface temperature in the second terrace is related to extensive human activities. The study area has significant temporal and spatial changes in LST, explaining the local authority's poor control and management of natural resources. The strong negative correlation between LST and vegetation is found. Comparing LST with NDVI show that the peaks of the LST are usually the areas with no vegetation cover. LST values are relatively higher in the built-up or suburban area with no vegetation cover It can be said that the strong negative relationship between vegetation cover and surface temperature makes the adoption of LST an essential indicator for successful building a long-term monitoring program for vegetation cover and environmental changes in the region.

Table (3) LST Changes in 2010, 2015 and 2020

	2010			**2015**			**2020**	
°Cclass	Km^2	%	°Cclass	Km^2	%	°Cclass	Km^2	%
23-37	327.45	13.9	24-41	107.09	4.547	29-40	210.35	8.93
37-40	929.33	39	41-43	1240.71	52.69	40-43	193.28	8.2
40-41	488.8	20.7	43-44	530.0575	22.5	43-45	863.33	36.6
41-47	609.14	25.8	44-50	476.88	20.2	45-51	1087.777	46

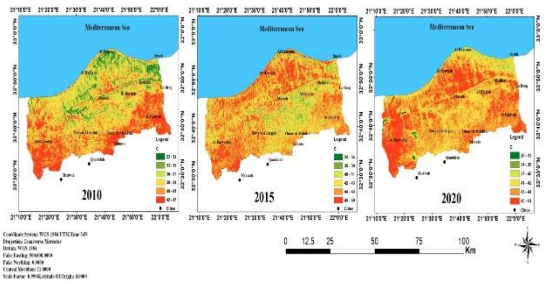

Figure (4): Spatial distribution of LST in 2010, 2015 and 2020

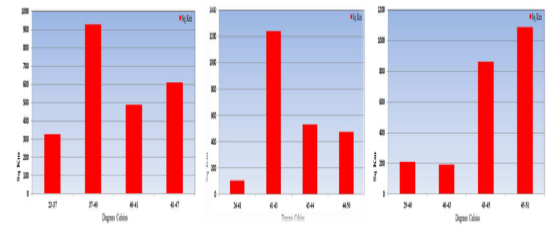

Figure LST Change detection 2010 LST Change detection 2015 LST Change detection 2020

Figure (5) Comparison LST changes in 2010, 2015 and 2020

The study area has significant temporal and spatial changes in LST, explaining the local authority's poor control and management of natural resources. When comparing LST to NDVI, it is clear that the LST peaks are typically places with no vegetation cover. The built-up or suburban areas have higher LST values with no vegetation cover. It can be said that the strong negative relation between land cover and LST makes the adoption of LST is a critical indication for establishing a long-term monitoring program for the region's vegetation cover and environmental changes.

Conclusion

Undesirable land use/ land cover changes are major drivers of environmental changes at different scales. Various impacts of these changes can be manifested by disturbance of ecosystem, degradation of soil, hydrology, and climate change which, is highly linked with LST. The results of this study showed that significant changes in land use/ land cover have been undergone in the research areas for the last 10 years. The land surface temperature in addition showed an increasing trend in this time period, and this is linked with the change in LU/LC. RS and GIS are effective vibes for mapping natural resources. The outcome of this research provides us with new knowledge that helps us better understand the spatiotemporal land use land cover changes and their impacts on LST.

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الملخص العربي

عنوان البحث: تتبع الغطاء النباتى وحرارة سطح الارض فى بلديات الجبل الاخضر، ليبيا باستخدام الاستشعار عن بعد ونظم المعلومات الجغرافية

طلعت عبد المنعم[١]، محمد عبد الجليل[١]، رشا أبوسمرة[١]، مختار العشري[٢]، صالح سعيد[١]*
[١] قسم علوم البيئة، كلية العلوم، جامعة دمياط، مصر
[٢] قسم الجغرافية، كلية التربية، جامعة عمر المختار، ليبيا

على مدى العقود القليلة الماضية ، أدى التدخل البشري إلى تغيرات وتدهور في الغطاء النباتي الطبيعي، وعدم إدارته في بلديات الجبل الأخضر، وتفاقمت هذه المشكلة كنتيجة لتحويل الموارد الطبيعية للأغراض الغذائية والزحف العمرانى والمنافع الاجتماعية والاقتصادية الأخرى. ولفهم التغيرات الزمنية والمكانية للغطاء النباتي بالجبل الاخضر تم استخدام ثلاث صور للقمر الصناعي لاندسات ملتقطة فى أعوام ٢٠١٠، ٢٠١٥ و٢٠٢٠، ونظم المعلومات الجغرافية ((GISلحساب التغييرات في معامل الغطاء النباتى ((NDVIوحرارة سطح الارض ((LSTفي منطقة الدراسة بين عامي ٢٠١٠ و ٢٠٢٠. أظهرت النتائج تغييرات مهمة في NDVI، حيث انخفضت مساحة الغطاء النباتي الكثيف من ١٢٠٧,٩١٣ كلم٢ في عام ٢٠١٠ إلى ٦٧٣,٩٢ كم٢ في عام ٢٠٢٠، وبلغ إجمالي مساحة الغطاء النباتي المنخفض للغاية ٥٢٥,٧ كم٢ وبلغت المساحة المكشوفة بدون غطاء نباتي ٣٤,٤ كم٢ . ونتائج التغير في LST ، في عام ٢٠١٠ شكلت المساحة الإجمالية لـ LST أقل من ٤٠ درجة مئوية ، ٥٢,٩٪ من المساحة الاجمالية لمنطقة الدراسة ، بينما شكلت المساحة الإجمالية لـ LST أكبر من ٤٠ درجة مئوية ٤٧,١٪ من المساحة الاجمالية لمنطقة الدراسة ، في عام ٢٠٢٠ المساحة الإجمالية لـ LST أقل من ٤٠ درجة مئوية ، شكلت ٨,٢ ٪ ، في حين أن المساحة الإجمالية للـ LST أكبر من ٤٠ درجة مئوية شكلت ٩١,٨ ٪ من المساحة الاجمالية لمنطقة الدراسة.