INNSPUB

Journal of Biodiversity and Environmental Sciences (JBES)
ISSN: 2220-6663 (Print) 2222-3045 (Online)
Vol. 12, No. 6, p. 273-282, 2018
http://www.innspub.net

RESEARCH PAPER

OPEN ACCESS

Desertification vulnerability and risk analysis of Southern Punjab Region, Pakistan using geospatial techniques

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Article published on June 30, 2018

Key words: Desertification vulnerability assessment, Desertification difference index, Desertification degree, NDVI, LST

Abstract

Pakistan remains a frequent victim of desertification. This study aims to conduct an assessment of desertification vulnerability and desertification degree of district Bahawalpur, Rahim Yar Khan and Rajanpur, South Punjab, Pakistan, for the period 2001-2018. The datasets of three sensors of MODIS, namely MOD13Q1, MOD11A2 and MOD16A2, with a spatial resolution of 25m, were acquired for 2001, 2009 and 2018, for the study area, from USGS. The assessment of desertification vulnerability has been done by calculating Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Transformed Normalized Difference Vegetation Index (TNDVI), Moisture Stress Index (MSI), Potential Evapotranspiration (PET), Land Surface Temperature (LST) and Weighted Overlay analysis (WOL). The Desertification Difference Index (DDI) analysis concluded a 7.84% increase in area under vegetation and 7.74% decrease in barren land, from 2001 to 2018. However, a 6.87 rise in Max LST and a 3.06 rise in Min LST, from 2001-2018, left most of the increase in area under vegetation to be unhealthy, or dead. The Desertification Vulnerability Index (DVI) analysis presented an increase of 11.09% in the area covered by High desertification vulnerability category, i.e. from 7.4% in 2001 to 18.49% in 2018, whereas a 39.88% decrease was witnessed in the area covered by the Low desertification vulnerability category. An increase of 28.47% in the Medium desertification vulnerability category, in the study area was witnessed. Empirical support provided by the results, can help the future scientists and policy makers to work on mitigating this disaster to protect this climatically fragile region.

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Introduction

Desertification as a menace, has encompassed one quarter of the total area of the world (Idris *et al.*, 2011) and risked the lives of 1 billion people in 110 countries (UN, 2004) and directly affects more than 250 million people across the globe. 41% of the world's total land area is covered by drylands which are home to more than two billion people (Anjum *et al.*, 2010). United Nations Environment Program (UNEP) statistics share the terrible Fig. of loss of 20 million hm2 of global arable land to desertification each year. There is marked reduction in crop yields of about 12-21%, leading to a global economic loss of almost 26 million.

As it has impacts for over 250 million people of the world, the monitoring of this environmental disaster has become inevitable (Guan *et al.*, 2017). The literature affirms that the frequency, intensity and duration of droughts may increase due to anthropogenically induced shifts in climate (Kiem and Austin, 2013).

Although desertification is a global issue, however Pakistan is acutely affected by this phenomenon (Khan and Ali, 2016), as ¾th or 90% (Anjum *et al.*, 2010) of its land, is under the impact of desertification currently or vulnerable to it in near future. According to (Iftikhar and Mahmood, 2017) Pakistan's economy is heavily dependent on agricultural sector, as it contributes 19.8% to the Gross Domestic Product (GDP) of the country and 42.3% of the total work force is associated with this sector. Agriculture sector contributed 26% to the GDP, and its share in the export earnings was 80% in 2013 (Shahbaz *et al.*, 2013). Almost 68 million ha, out of a total of 79.6 million ha lie in areas receiving less than 300mm of rain annually (Anjum *et al.*, 2010).

According to World Bank 2013; (Aslam *et al.*, 2016), Pakistan is at high risk from the results of climate change, which include increase in higher average temperatures, glacial depletions and retreat, sea level rise and an increase in the frequency of floods and droughts episodes. The desert region of Pakistan is increasing due to deforestation, since forests cover merely 3.77% of the Pakistan's area.

Rapid urbanization, unsustainable management practices, overgrazing in rangelands and waterlogging and salinity are other factors triggering the process of desertification and leading to its intensification in Pakistan. Rangelands cover 26.77% of the country's land. The drylands suffer high diurnal range of temperature, scarce rainfall, high and intense incoming solar radiation, high wind velocity that leads to shifting of sand dunes and high rate of evapotranspiration further exacerbate the phenomenon (Anjum *et al.*, 2010).

Remote Sensing (RS) and Geographic Information System (GIS) provide the opportunity to assess desertification trends of remote areas, where human access is difficult. It is necessary to discover the sensitive areas by classifying their vulnerability before they undergo desertification and prioritizing these areas for protection or restitution.

The big area of Bahawalpur, Rajanpur and Rahim Yar Khan in southern Punjab makes the desertification study difficult based solely on field studies. Alternatively, remote sensing can provide the necessary wide-area data at adequate temporal and spatial resolutions, and GIS applied science can be utilized to examine the information. This technique is effectively cheap in cost, also time-efficient and valuable for mapping the risks of land degradation, and allows an assessment of land degradation, including desertification, at local, regional, and even national scales (Bakr *et al.*, 2012; Lam *et al.*, 2011; Vicente-Serrano *et al.*, 2015; Ladisa *et al.*, 2012).

Multi-temporal remote sensing data allow monitoring of long-term trends and the spatial distribution of land degradation or desertification (Salvati and Bajocco, 2011). Through collaboration with GIS, remote sensing can rapidly and accurately identify areas of land degradation or desertification and link them to the physiographic setting (Van Lynden and Mantel, 2001). Aerial photographs and Moderate resolution Imaging Spectroradiometer (MODIS) images are useful and reliable data source to assess and map desertification (Orare, 2000).

The present study aims to analyze the desertification vulnerability for south Punjab, Pakistan for the period 2001-2018. The study works on mapping various indices affecting the desertification of a region and the weighted overlay analysis provides final desertification vulnerability maps that will be helpful for decision makers to identify the areas at higher risk where proper mitigation measures must be incorporated beforehand.

It also aims to calculate the Desertification Difference Index (DDI), in order to assess desertification degree of the study area.

Materials and methods

Study Area

Study area comprises of three districts, i.e. Rajanpur, Rahimyar Khan and Bahawalpur that lie at the southern tip of Punjab province, Pakistan (Fig. 1). Coordinates of District Bahawalpur are 29.3544°N, 71.6911°E, district Rahim Yar Khan 28.4212°N, 70.2989°E and District Rajanpur 29.1044°N, 70.3301°E. The study area covers a total area of 44, 445.23 62 sq. km (Google Earth).

Data Acquisition

For the assessment of desertification in any region remote sensing technique became an indispensable tool in the last decades, four sets of remotely sensed data are applied to analyze aridity in the subject region (Table 1). In order to find out the condition of desertification in the main regions of southern Punjab (Bahawalpur, Rahim Yar Khan and Rajanpur), three MODIS dataset images of the study area are acquired for 2001, 2009 and 2018. These images were obtained from United States Geological Survey (USGS) an Earth Observatory website. Methodology work flow is presented in (Fig. 2).

Table 1. Characteristics of remotely sensed data used for Desertification analysis.

Sr. No.	Year	Satellite	Sensor	Spatial Resolution
1	2000	MODIS	MOD13Q1 MOD11A2 MOD16A2	250m
2	2009	MODIS	MOD13Q1 MOD11A2 MOD16A2	250m
3	2018	MODIS	MOD13Q1 MOD11A MOD16A2	250m

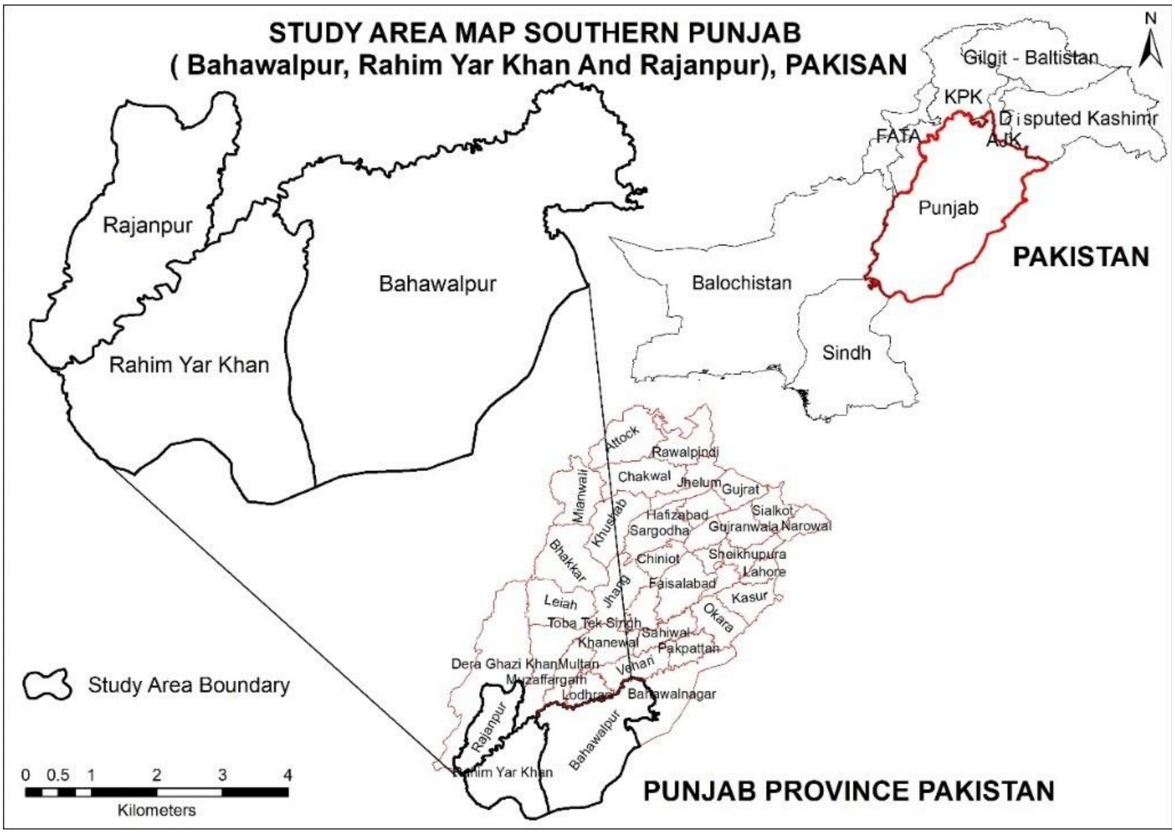

Fig. 1. Study Area Map.

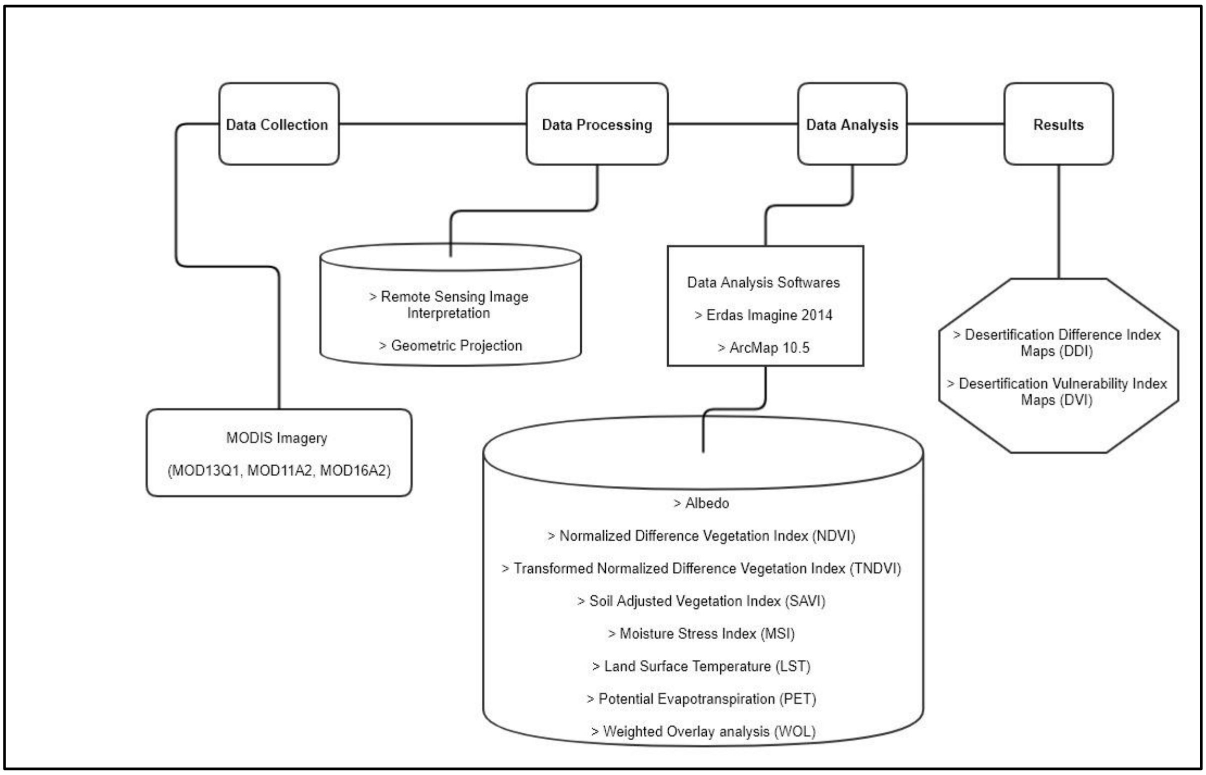

Fig. 2. Methodological Framework.

Analysis

Desertification Difference Index (DDI)

DDI is based on NDVI-α relationship and reflectivity analysis, and it proves a negative relation between desertification types. The higher the albedo value, the lower the vegetation cover. High albedo values also correspond to bare soil patches on ground (Becerril-Piña *et al.*, 2016). According to vegetation growth pattern, the maximum vegetation coverage and minimum soil coverage are the key ingredients to assess desertification. With the aim of obtaining the factors, the yearly NDVI can be acquired by Maximum Value Composite method, while yearly albedo is synthesized by Minimum Value method.

Albedo = -0.67137 x NDVI + 0.38439 (1).

Based on above equation (1) desertification assessment can be characterized by the desertification difference index (DDI) (Zeng *et al.*, 2006) a linear formula of NDVI and albedo. Then, desertification thematic products are completed, which is utilized for mapping and evaluating the southern Punjab desertification from 2001 to 2018.

DDI = 1.4895x NDVI – Albedo (2).

(Becerril-Piña *et al.*, 2016) suggest that land degradation is indicated by an increase in α and it proves that albedo has a strong impact on both vegetation and soil moisture. There exists a negative correlation of NDVI-α with desertification, i.e. an increase in albedo corresponds to a low vegetation cover or bare soil. Two general conditions of DDI were identified in this paper, high and low.

Desertification Vulnerability Index

Desertification Vulnerability Assessment was performed by calculating Desertification vulnerability Index (DVI), which was carried out by calculating NDVI, TNDVI, SAVI, MSI, PET and LST indices from MODIS images. Later weighted overlay analysis was performed over the acquired results to produce desertification vulnerability index maps. The brief detail about the indices is provided below:

Normalized Difference Vegetation index (NDVI)

NDVI in remote sensing is the estimation for greenery in a particular region or area. It is the combination of spectral bands that depends upon reflection, assimilation and transmission of vegetation.

It is derived from satellite-based optical sensor images that allow us to monitor the growth of green vegetation in land surfaces over large areas and a quantitative index of the relative abundance and natural action of green vegetation. NDVI employs the red (R) and Near Infrared (NIR) wavelengths and its value ranges from -1 to +1 (Epiphanio and Huete, 1995).

NDVI = (NIR-R) / (NIR+R) (3).

Soil Adjusted Vegetation Index (SAVI)

In this research article, NDVI is correlated with Soil Adjusted Vegetation Index (SAVI). SAVI is an alteration of NDVI that shows vegetation as soil, it is a central index for compensating soil brightness where vegetation cover is down. It is as same as NDVI but with the addition of Red wavelength as L is "Soil Brightness Correction Factor" (Gilabert, 2002).

$SAVI = NIR - (RED/NIR+RED+L) * (1+L)$ (4).

Transformed Normalized Difference Vegetation Index (TNDVI)

The transformed normalized difference vegetation index (TNDVI) is a symbol of vegetation biomass and it's a ratio between near-IR reflection and red reflection.

The TNDVI is computed following the equation:

TNDVI = √(((Infrared-Red))/((Infrared+Red))) +0.5 (5)

According to (Greenland 1994) TNDVI is "an integrated part of photosynthesis, leaf area and evapotranspiration". The total quantity of biomass has indirect and direct relation to the surface energy balance, surface temperature consistent with the interference of sunlight, canopy cover ratio and with evapotranspiration cooling effect. (Friedl and Davis, 1994; Sandham and Zietsman, 1997; Yang *et al.*, 2008).

Moisture Stress Index (MSI)

Moisture Stress Index (MSI) is a water ratio index that finds the water content in vegetation or leaf relative. Soil moisture plays a significant part in growing vegetation from the roots rather precipitation (Soni *et al.*, 2017). It is normally estimated from MODIS data that uses SWIR band instead of MIR because of band's sensitivity to moisture.

Ratio between SWIR and MIR reduces scattering effect and dominate water variation in vegetation (Zhang, 2013).

MSI = RSWIR6 / RNIR (6).

Potential evapotranspiration (PET)

Accurate and timely estimates of PET are essential for agricultural and water resource planning as well as for understanding the impacts of climate variability on terrestrial systems. Potential evapotranspiration (PET) is specified as the utmost ability to disappear under the presumption of a well-watered surface (Thornthwaite, 1948; Brutsaert, 1982; Shuttleworth, 1993). The Terra-MODIS platform provides an opportunity to supervise several environmental variables influencing evapotranspiration that were previously unavailable. Which based on the Priestley–Taylor equation (7) that also contain daily net radiation model during cloudless days.

$PET = \propto (Rn - G) \frac{\Delta}{\Delta + \gamma}$, (7)

In above equation (7) Δ is the derivative of saturated vapor pressure in terms of temperature (Pa K^{-1}), Δ is the psychrometric constant (Pa K^{-1}), and ∝ is the "Priestly–Taylor parameter" that accounts for the complex effects of evapotranspiration. Net radiation is Rn and G is soil heat flux (Kim and Hogue, 2007).

Land Surface Temperature (LST)

LST is one of the crucial problems faced globally, it is highly accelerated by the deprivation of vegetation, loss of ground moisture content, increased temperature activated with anthropogenic activities (Xiao and Xu, 2010). LST is one of the global challenge that can be highly correlated with urban development activities that hinders sustainable development (Baba, Tifwa, and Achoba 2017).

DN * 0.02 – (273.15) (8).

In above equation (8) calculated Digital Number (DN-values) acquired from the United States Geological Survey (USGS) was accumulated and the average was taken out. Firstly, DN was converted to Radiance by multiplying by (0.02) and then subtracted by (273.15) as shown in Eq. (8). Secondly, for the conversion of radiance, Kelvin values into degree Celsius values were used.

Weighted Overlay Analysis

Weighted Overlay is a technique in which various dissimilar inputs are assigned a common measurement scale of value, in order to create an integrated analysis (EDN' Esri developer network). In overlays several rasters use a joint quantity scale of weights given according to importance (ESRI, 2016). In this analysis through weighted overlay of NDVI, SAVI, MSI, TNDVI, PET and LST Desertification vulnerability index for south Punjab was extracted.

Results and discussion

Desertification Difference Index (DDI)

DDI 2001 (Fig. 3) analysis presented 98.47% of the study area to have no vegetation, merely 1.07% area was covered by vegetation, while 0.45% of the study area was covered by water bodies. In a sharp contrast stood the DDI 2009 (Fig. 5) analysis, where 95.42% area had no vegetation, 4.02% of the study area was covered under vegetation and 0.56% of the study area was under water bodies. Moreover, in 2018 (Fig. 7), the areas under vegetation had increased to 8.91%, and the barren land had reduced to 90.73% from 95.42% in 2009. The area under water bodies had reduced in 2018 to 0.36% from 0.56% in 2009.

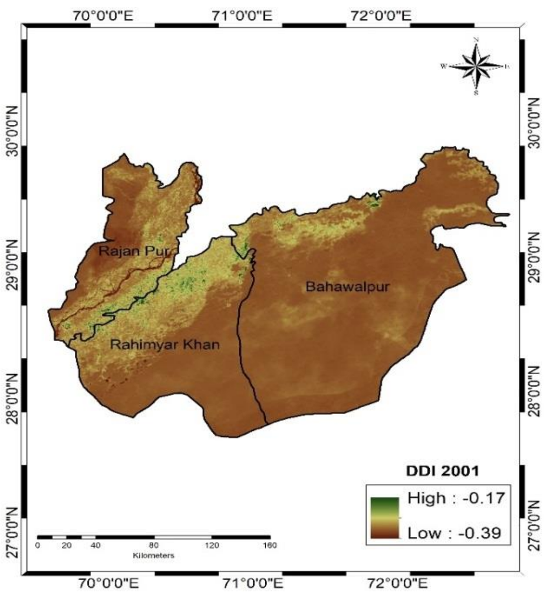

Fig. 3. DDI 2001.

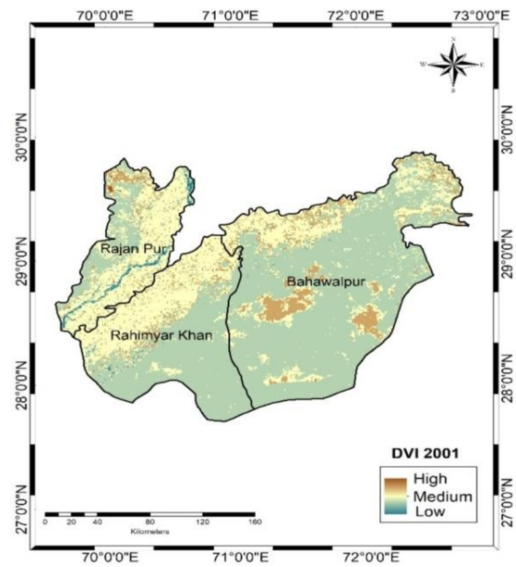

Fig. 4. DVI 2001.

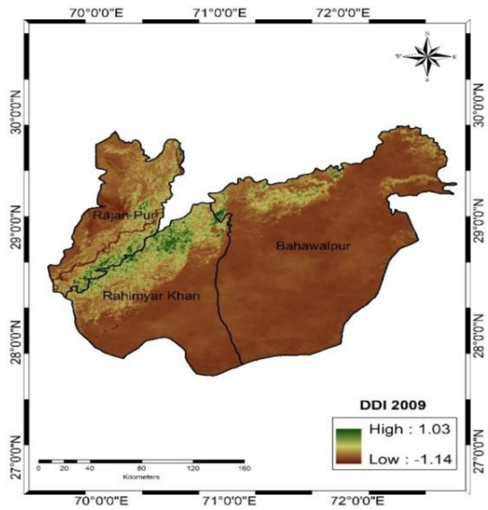

Fig. 5. DDI 2009.

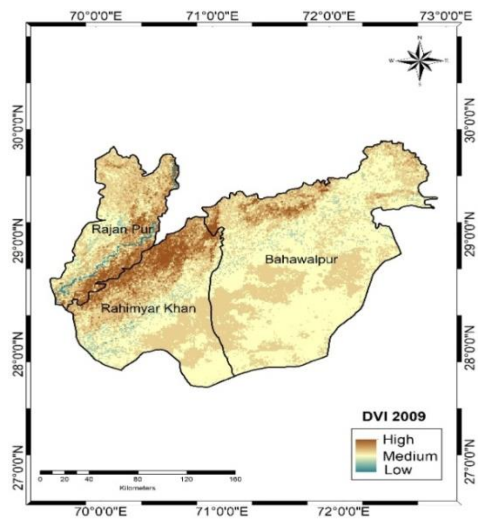

Fig. 6. DVI 2009.

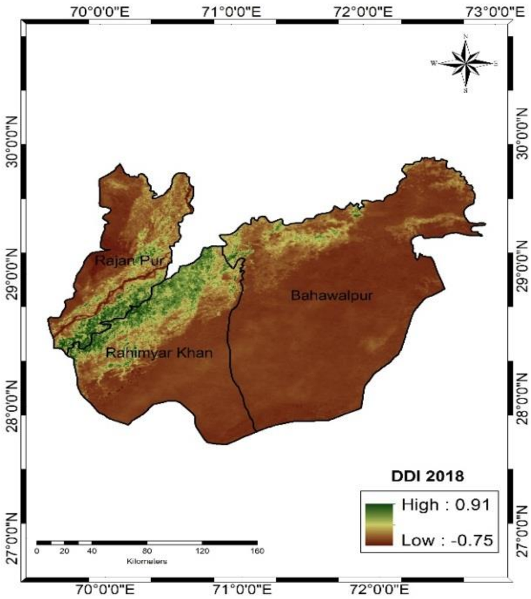

Fig. 7. DDI 2018.

Although percentage of vegetation cover proves that area under vegetation has increased in the study time period of 17 years, from 1.07% to 8.91%, the NDVI and image analysis present the fact that most of this vegetation cover consisted of dead vegetation due to higher LST. In 2001 max LST value was of 53.13 which increased to 60 in 2018. Similarly, there was a drastic rise in min value of LST from 32.09 in 2001 to 35.15 in 2018. This rise in max and min LST led to harmful impacts on vegetation. Therefore, spatial increase in area under vegetation became meaningless as it added to the area's vulnerability to desertification. Moreover, DDI 2001 had greater Low DDI value of -0.39 than Low DDI value of 2018 i.e. -0.75. The increase in Low category in the 2018 image is worth concern, since the intensity has increased in this category with darker shades of brown covering the eastern expanse of the study area.

Desertification Vulnerability Index

The results of WOL presents that the DVI values show that the vulnerable area with higher risk of desertification in the study area had drastically increased from 7.4% in 2001 (Fig. 4) to 18.49% in 2018 (Fig. 8), low desertification vulnerability had reduced spatially from 61.60% in 2001 to 21.72% in 2018, while medium desertification vulnerability class increased from 30.96% in 2001 to 59.43% of the study area, in 2018. The higher and lower values of DVI in 2001 and 2018 present the alarming situation of desertification in the study area.

In 2001 the high desertification vulnerability class only existed as a small spot on north western corner of the study area, this spot expanded as a complete zone on the area covered by vegetation, along River Indus, as shown in Fig 4.

The high vulnerability class besides covering the same zone, as in 2009 image, extended to south-western portion of the study area. The high DDI values corresponded with the high DVI values. Similarly, the medium vulnerability class expanded dramatically from western part to entire east and southern part of the study area, from 2001 to 2009.

The low class seems to have almost disappeared from 2001 to 2009. The north western, north eastern and southern portions of the study area were replaced from medium DVI category by low DVI or bare soil category in 2018.

Combined DDI and DVI Analysis

When compared with one another, in 2001, high DDI corresponds to medium DVI, while in 2009 and 2018, high DDI corresponds to high DVI. While low DDI values correspond with the low DVI values. Thus, proving that there exists a relation between the two, i.e. higher the DDI higher, greater the desertification vulnerability.

Table 2. Results of DDI.

Classes	2001		2009		2018	
	Sum Area-km	Sum Percentage	Sum Area-km	Sum Percentage	Sum Area-km	Sum Percentage
Barren Land	43765.02	98.47	42391.61	95.42	40323.93	90.73
Vegetation	476.73	1.07	1784.63	4.02	3962.04	8.91
Water body	202.21	0.45	249.36	0.56	158.18	0.36

Table 3. Results of WOL.

Class	2001		2009		2018	
	Sum Area-km	Sum percentage	Sum Area-km	Sum percentage	Sum Area-km	Sum percentage
High	3285.16	7.44	7560.64	17.11	8182.36	18.49
Low (Bare Soil)	27013.62	61.15	1440.22	3.26	9610.33	21.72
Medium	13677.08	30.96	34948.57	79.07	26292.04	59.43
Water Body	202.21	0.45	249.36	0.56	158.18	0.36

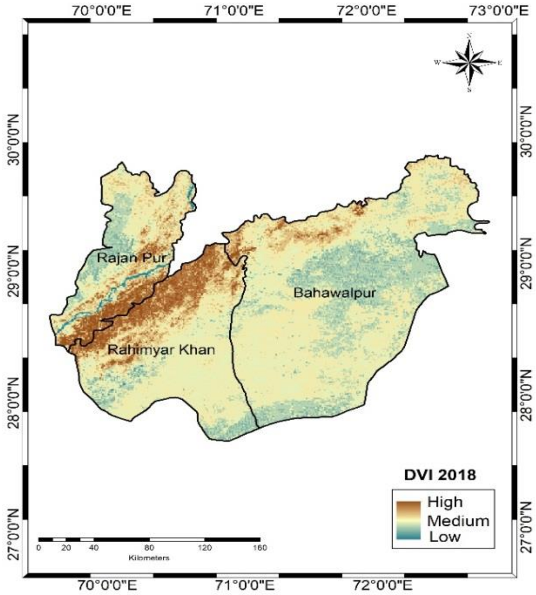

Fig. 8. DVI 2018.

Conclusion

Monitoring spatio-temporal variability of desertification vulnerability is extremely significant in arid, semi-arid regions that are persistently under the threat of climate induced extreme weather events. This study calculated various climate indices using geospatial techniques to investigate the desertification vulnerability in south Punjab, Pakistan. The present study used MODIS datasets of the sensors MOD13Q1, MOD11A2 and MOD16A2, with 25m resolution to compute NDVI, SAVI, TNDVI, MSI, PET, LST and WOL.

The resultant DDI and DVI maps concluded a direct relationship between DDI and DVI, i.e. higher the desertification difference, higher the desertification vulnerability and vice versa. DDI analysis concludes that area under vegetation had increased spatially from 1.07% in 2001 to 8.91%, in 2018, while barren land had reduced from 98.47% in 2001 to 90.73% in 2018.

However, the intensity of barrenness had dramatically risen as shown by darker shades of brown in the DDI maps. Higher vegetation as shown by DDI in 2018, can be related to presence of dead vegetation due to significant shifts in max and min LST values for the study area. Max value of LST in 2001 was 53.13 which increased to 60 in 2018. A significant rise in min value of LST was also observed i.e. from 32.09 in 2001 to 35.15 in 2018. The DVI analysis presents the alarming situation where the vulnerable area with higher risk of desertification in the study area had increased from 7.4% in 2001 to 18.49% in 2018, low desertification vulnerability had reduced from 61.60% in 2001 to 21.72% in 2018, whereas, the medium desertification vulnerability class had increased from 30.96% in 2001 to 59.43% of the study area, in 2018. The Fig.s conclude the expanding high zones of desertification vulnerability in the study area especially, along the right bank of River Indus. The analysis applied in this study will help the policy makers, disaster managers and researchers to better understand the shifting trends of desertification vulnerability and desertification degree, in the region.

References

Amin AA. 2004. The extent of desertification on Saudi Arabia. Environmental geology **46(1),** 22-31.

Anjum SA, Wang LC, Xue L, Saleem MF, Wang GX, Zou CM. 2010. Desertification in Pakistan: Causes, impacts and management. Journal of Food, Agriculture and Environment **8(2),** 1203-1208.

Aslam AQ, Ahmad RS, Hussain YI, Hussain SM. 2016. Vulnerability and impact assessment of extreme climatic event: A case study of southern Punjab, Pakistan. Science of The Total Environment 580 (Supplement C), 468-481.

Baba AN, Tifwa YH, Achoba IM. 2017. A Synergy between Urban Planning and the Public towards Achieving Sustainable Development Goals (SDGs). International Journal of Technical Research and Science.

Bakr N, Weindorf CD, Bahnassy HM, El-Badawi MM. 2012. Multi-temporal Assessment of Land Sensitivity to Desertification in a Fragile Agro-Ecosystem: Environmental Indicators. Ecological Indicators **15,** 271-280.

Becerril-Piña R, Díaz-Delgado C, Mastachi-Loza AC, González-Sosa E. 2016. Integration of remote sensing techniques for monitoring desertification in Mexico. Human and Ecological Risk Assessment: An International Journal. **22(6),** 1323-1340.

Epiphanio JN, Huete RA. 1995. Dependence of NDVI and SAVI on Sun Sensor Geometry and Its Effect on Fapar Relationships in Alfalfa. Remote Sensing of Environment **51(3),** 351-360.

Gilabert M, Piqueras GJ, Garciaa-Haro JF, Melia J. 2002. A Generalized Soil-Adjusted Vegetation Index. Remote Sensing of Environment. **82(2-3),** 303-310.

Guan Y, He B, Li X, Yin C, Qiu S. 2017. Desertification Assessment and Trend Analysis Using MODIS Data. Paper presented at the Geoscience and Remote Sensing Symposium (IGARSS): IEEE Geoscience and Remote Sensing Letters IEEE International. (pp. 5739-5742).

Idris MN, Rafee MM, Johar F. 2011. Drought and desertification management in arid and semi-arid zones of Northern Nigeria. Management of Environmental Quality: An International Journal **22(5),** 595-611.

Iftikhar S, Mahmood ZH. 2017. Spatial distribution of agricultural resources and food security: A case of Punjab Pakistan. Cogent Food & Agriculture **3(1),** 1357265.

Khan AN, Ali A. 2016. Desertification Risk Reduction Approaches in Pakistan. SPRINGER Verlag, JAPAN 161-173.

Kiem AS, Austin KE. 2013. Drought and the future of rural communities: opportunities and challenges for climate change adaptation in regional Victoria, Australia. Global Environmental Change **23(5),** 1307-1316.

Kim J, Hogue TS. 2008. Evaluation of a MODIS-based potential evapotranspiration product at the point scale. Journal of Hydrometeorology **9(3),** 444-460.

Ladisa G, Todorovic M, Liuzzi TG. 2012. A GIS-based approach for desertification risk assessment in Apulia region, SE Italy. Physics and Chemistry of the Earth **49,** 103-113.

Lam DK, Remmel KT, Drezner DT. 2011. Tracking desertification in California using remote sensing: A sand dune encroachment approach. Remote Sensing- Open Access Journal **3,** 1-13.

Orare AC. 2000. Wind erosion of volcanic soils, a reconnaissance study in the southern catchments of Lake Naivasha region, Kenya. MSc diss., ITC.

Salvati L, Bajocco S. 2011. Land sensitivity to desertification across Italy: Past, present, and future. Applied Geography **31,** 223-231.

Shahbaz M, Rafiq KM, Khan NT. 2013. Arid Land Development and Combating Desertification in Pakistan. In G. A. H. R. Squires (Ed.), Combating Desertification in Asia, Africa and the Middle East: Proven Practices 231-248.

Soni C, Vaishnav DD, Bairwa D, Mittal H, Vijayvargiya H, Vijavargiya A, Singh V. 2017. Automatic Irrigation System. International Journal of Technical Research and Science (IJTRS).

Van Lynden GWJ, Mantel S. 2001. The role of GIS and remote sensing in land degradation assessment and conservation mapping some user experiences and expectations. International Journal of Applied Earth Observation and Geoinformation **3,** 61-68.

Vicente-Serrano SM, Cabello D, Tomás-Burguera M, Martín-Hernández N, Beguería S, Azorin-Molina C. 2015. Kenawy, A.E. Drought variability and land degradation in semiarid regions: Assessment using remote sensing data and drought indices (1982-2011). Remote Sensing — Open Access Journal. **7,** 4391-4423.

Xiao K, Xu H. 2010. RS and GIS Based Analysis of Urban Heat Island Effect in Shanghai. In Geoinformatics, 2010 18th International Conference on (pp. 1-5). IEEE.

Zeng Y, Feng Z, Xiang N. 2006. Albedo-NDVI space and remote sensing synthesis index models for desertification monitoring. Scientia Geographica Sinica **26(1),** 75-80.

Zhang N, Hong Y, Qin Q, Zhu L. 2013. Evaluation of the Visible and Shortwave Infrared Drought Index in China, International Journal of Disaster Risk Science **4(2),** 68-76.