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Assessing The Vegetation Degradation Dynamics in Salt Mine Areas of District Chakwal, Pakistan

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ABSTRACT

The sustainability of human habitation is seriously threatened by land degradation and it is crucial to evaluate it quantitatively. This study aims to identify the spatiotemporal trends and vegetation degradation dynamics in the salt mine area of district Chakwal, Pakistan. One of the abandoned mines, the Chakwal salt mine, experienced subsidence as a result of the pillars dissolving from unmanaged leaching processes, which produced a large cavern in a horizontal direction. Changes in vegetation cover are influenced by the phenomenon of land deformation (landslides and subsidence). The goal of the current study is to employ multi-spectral remote sensing data to analyze the temporal alterations in vegetation brought on by salt mining. The study used Landsat-derived NDVI to model vegetation degradation dynamics over 30 years (1990–2020). The normalized difference vegetation index (NDVI), leaf area specific index (SLAVI), normalized difference water index (NDWI), and thermal index were used in the current investigation to construct detailed maps of the vegetation. The zones affected by land degradation, which has a direct impact on vegetation covering, are identified using the change detection approach in vectorial format on NDVI and all other factor data. As a result, an analysis of the NDVI for vegetation demonstrates that there has been a drastic decline from 0.5973 to 0.4321 between 1990 and 2020. The outcomes supported the viability of assessing the vegetation growing status in the salt mining area using remote sensing technology. Furthermore, the government must act right away to implement several prudent policies that will position it in the best possible position once the current environmental crisis has passed.

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1. Introduction

The vegetation status in opencast mining locations around the world can accurately indicate ecological damage and regeneration. Although mining makes a considerable contribution to the world's energy output, it has proven challenging to reduce its adverse effects on the environment (Zhengfu, Inyang, Daniels, Frank, & Struthers, 2010). The exploitation of coal mines has resulted in several environmental issues, including heavy metal contamination, soil erosion, plant degradation, and ground subsidence(Li, Lei, Cheng, Liu, & Wang, 2019). Many other aspects, such as human, geographical, climatic, and policy issues, have an impact on mining sites. By eliminating vegetation, destroying soil structure, changing the physical and chemical properties of the soil, accelerating soil water erosion, reducing soil microbial activity, and limiting vegetation growth, mining activities have the potential to abolish the structure and function of landscapes (Dejun, Zhengfu, & Shaogang, 2016). Regressive vegetation dynamics, or degradation of the vegetation cover in the environment, results in invasion and landscape closure because shrub-tree layers emerge (progressive vegetation dynamics), or it makes some places desert since the vegetation strata are lost in some locations. The equilibrium that preserves the savanna habitat is disturbed in both situations (Anyamba & Tucker, 2005).

Vegetation deterioration had no accepted definition across the board. It can be explained more broadly as "the decreasing process of viable vegetation growth in landscape variation under natural or artificial disruptions.". When opencast coal mines are employed in semi-arid regions, coal mining, coal gangue discharge, and vegetation restoration all have an impact on the characteristics of vegetation growth at the geographical and temporal scales. The spatiotemporal dynamics of vegetation throughout the opencast coal mine mining process, however, have received little attention from studies, and little is known about them. Traditional research, as stated by Kusimi (2008) and Zhang, Wang, and Li (2019) has mostly focused on the categorization of plant cover and the traits of vegetation spatiotemporal dynamics. The tension between coal production and related ecological issues can only be resolved through sustainable development (Chen et al., 2022).

In order to evaluate the state of land degradation (LD) under various land uses, MAE AbdelRahman, Natarajan, Hegde, and Prakash (2019) carried out a study. To interpolate the geographic distribution of soil physical, chemical, and biological properties, Geostatistical methods are applied. Indicators of salinity helped predict the salt-affected areas using hyperspectral and multispectral data. A map depicting the overall degradation of the research region was created in the Chamarajanagar district (CDK) of Karnataka, India, by integrating multiple LD techniques. When evaluating land resources, remote sensing data is an effective tool, particularly in difficult-to-access areas like mountains. Effective approaches for assessing and evaluating the susceptibility to land degradation include the Analytic Hierarchy Process (AHP), Geographic Information Systems (GIS), and reliable and trustworthy observation satellite datasets. Sandeep, Reddy, Jegankumar, and Arun Kumar (2021) employed AHP and GIS to analyze the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), rainfall, topographical features, and pedological restrictions in the semi-arid Rayalaseema region of southern India. Modeling and measuring the susceptibility to land degradation was the aim. Using geographic information systems and remote sensing techniques, the biological and environmental effects of gold mining may be spatially quantified.

IR Orimoloye (2020) evaluated land-use and land-cover changes in the gold mining region using Remote Pixel Databases, ArcGIS 10.4, programming, and geographic information systems. It has been noted that desertification and land degradation are the main environmental issues for the foreseeable future. The purpose of this study was to identify hotspots of desertification in the semi-arid Anantapur region of Southern India using the normalized difference vegetation index (NDVI). Using ground truth data, a supervised classification was performed on each of the six reflecting bands for the prior 28 years, or independently from 1990 to 2018. In order to evaluate the accuracy of the classification results, survey data and a land cover map from the years 2005 to 2006 were employed. The categorization results were further enhanced by using auxiliary statistics, visual clarification, and specialist data of the area through GIS. The changing image was created using cross-tabulation and the post-classification change detection method (Kumar, Babu, Rajasekhar, & Ramachandra, 2020).

The district of Chakwal, which is in North-West Punjab, Pakistan, also faces issues with vegetation degradation. This problem is caused by a number of things, including the major alteration of the original natural vegetation, which has increased the frequency of rock falls on slopes used for hayfields and meadows as well as the subsidence of arable land. Hedge growth on severely eroded lands also plays a stabilizing role. The district also contains salt mines in the southern portion of the area, which is susceptible to degradation as a result of explosive mining operations, the alteration of the forest into agricultural lands, construction engineering activities that pollute vegetation-covered areas, and last but not least, the expansion of urban and rural areas. Therefore, when exploring the causal association between vegetation cover and operating variables, examining the consequences of factors that trigger vegetation degradation, or encouraging regeneration of vegetation in coal mining areas, human-caused variables should be considered in addition to topographical and climate ones (Chen et al., 2022). Therefore, knowledge of and monitoring vegetation dynamics are necessary to comprehend the disturbance and recovery of regional ecosystems (Li et al., 2019). A major issue for agricultural production is vegetation degradation. The scientific community places a high priority on monitoring vegetation degradation. To this end, many researchers employ a variety of techniques, including repeated field surveys, measuring changes in species diversity, and concentrating on both small-scale and long-term vegetation changes (Zucca, Julitta, & Previtali, 2011). By incorporating remote sensing data into a GIS system, this study's primary goal is to analyze how mining activities affect vegetation covering in this setting. To monitor changes in vegetation coverage as a sign of vegetation degradation, Landsat satellite data are used to retrieve the vegetation indices NDVI, NDBI, NDWI, and SLAVI. The analysis of vegetation deterioration using remote sensing is the main topic of this work. The study region has been chosen, and additional materials and methods demonstrating the research design and outcomes demonstrating the total temporal analysis have been used. The main requirement for decision-makers interested in monitoring polluted mining regions to lessen the environmental impact is estimates of vegetation and land degradation.

2. Material and Methods

2.1. Description of Study Area

District Chakwal lies in the subtropical and rain-fed region owing to its elevation, in northwest Punjab Pakistan at 32° 55' 29.39" North Latitude and 72° 51' 11.99" East Longitudes. The Punjabi districts of Jhelum, Mianwali, Attock, Rawalpindi, and Khushab border it. The overall land area of the district is 1,652,441 acres (6,609 km2). The district has 138,146 residents overall and is 498 meters above sea level (PMD, 2017). The area is made up of the Salt Range, a mountain chain in the Pakistani province of Punjab that has large concentrations of rock salt that extend along the southern edge of the Potohar Plateau, is important for mining operations, and contains minerals such as coal and gypsum. The climate in District Chakwal is semi-arid and subtropical, with scorching summers and icy winters. The Chakwal district experiences summer temperatures between 15 and 40 degrees Celsius and winter temperatures between 4 and 25 degrees Celsius (Sajjad et al., 2021). The study region map is shown in Figure 1 for this investigation.

Figure 1: Location map of the Study Area District Chakwal

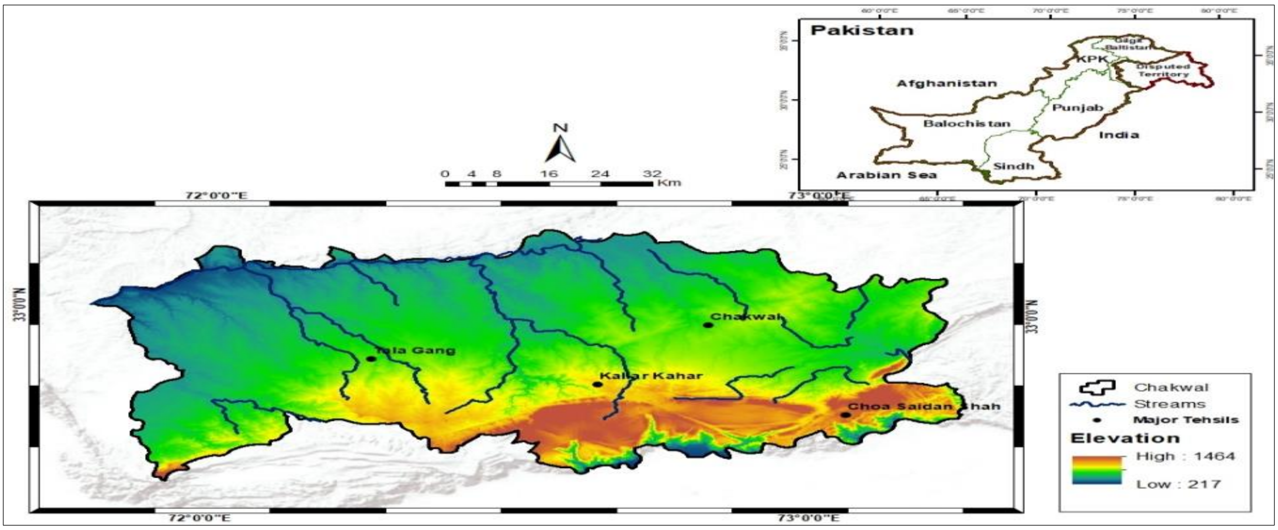
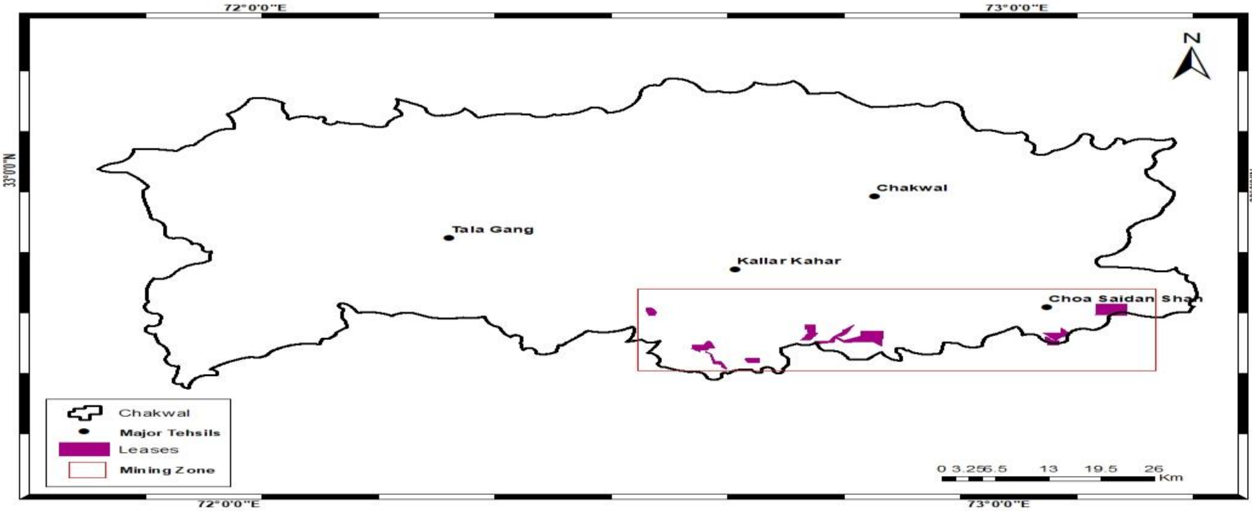


Figure 2: Lease data of Study area



2.2. Pre-processing and Data Acquisition

A subset of every Landsat digital image recorded over the region between June 1990 and 2020 was submitted to image processing and geometric rectification procedures to handle the digital data. The digitized images were geometrically and radio-metrically rectified to one another to ease assessment. Geometric rectification is necessary for the long-term production of spatially rectified maps. Correct per-pixel registration of multi-temporal remote sensing data is essential for change detection since there is a chance that registration errors could be interpreted as changes in land cover and land use, which would cause an overestimation of genuine change. In a GIS context, Landsat TM and Landsat ETM+ datasets covering the annual period 1990 to 2020 were processed, examined, and interpreted to determine the effects of land degradation on vegetation coverage. The datasets were selected so that, from May to September, the test site would not be covered by cloud formations and would match the vegetation stages and collapses of these years. In Landsat images obtained in June, the high-resolution radiometer that collected data in 11 bands with a spatial resolution of 30m improved the ability of vegetation and lithological separation between the rocks.

3. Methodology

The reddish-brown soils, chernozem, cambric chernozem, pseudoglay, and alluvial soils found in the Chakwal salt mining region are among its constituents. Along with the occurrences of ravens and deforestation, the chernozem soils contributed to the degradation of the region. Remote sensing techniques can be used to monitor changes in vegetation cover using the normalized difference vegetation index (NDVI), which has a significant correlation with plant cover. Vegetation activity and dynamics have been efficiently measured using time series of Landsat NDVI data. The normalized difference vegetation index, which is defined as the difference between the spectral reflectance in the near-infrared (NIR) and red (R) bands over their total as Eq. 1, reduces multispectral observations to a single value.

$$\mathrm{NDVI} = \frac{(\boldsymbol{NIR-RED})}{(\boldsymbol{NIR+RED})} \tag{1}$$

Low NDVI values (0.1 or below) can be seen in salt fields, rocks, and sand. Grassland and dying crops are two examples of sparse vegetation with moderate NDVI values (between 0.2 and 0.5). High NDVI levels have been associated with thick vegetation, such as forests or crops that are at their height. Averaging the NDVI readings across time can reveal the state of the vegetation and the conditions under which it is developing in a given area. The NDVI temporal series analysis can show if the vegetation is flourishing or under stress in addition to variations brought on by anthropogenic activities, natural disturbances, or changes in the phonological stage of the plant. Inland degradation monitoring and change detection techniques are often used. It is possible to detect change by changing the percentages of environmental components as well as their number. This method combines map algebra and direct measurement with visual interpretation. Change vector analysis can be used to evaluate the degradation of the vegetation cover by comparing the size and direction of the change between two time periods. Recently, the focus of LAI research has shifted from an empirical and statistical stage to a stage that is process-based and uses remotely sensed datasets and the use of numerical models (Baret et al., 2001). The Normalized Difference Water Index (NDWI) is employed to characterise and remove water bodies from regions that were vulnerable to saturation. A band from the near-infrared spectrum and a band from the shortwave infrared spectrum, respectively, are used to determine the NDVI and NDWI.

$$\mathrm{NDWI} = \frac{NIR-G}{NIR+G}\ , NDWI \in [-1, 1] \tag{2}$$

Adjusted Difference Residential areas were subtracted from the built-up index calculation to determine the cause of vegetation degradation, which was determined as follows:

$$\mathrm{NDBI} = \frac{(\boldsymbol{SWIR - NIR})}{(\boldsymbol{SWIR + NIR})} \tag{3}$$

The temperature of the earth's surface, commonly expressed in degrees Celsius or Kelvin, is known as land surface temperature (LST). Additionally, several elements, such as vegetation, sun radiation, and air, which are determined by applying Eq 4. The following equation was used to convert the digital number (DN) of the Landsat ETM+ TIR band into spectral radiance.

$$L\lambda = 0.0370588 \times DN + 3.2 \tag{4}$$

The spectral radiance is then converted to blackbody temperature (TB) for satellites using the assumption of uniform emissivity (Landsat Project Science Office, 2002). The converting formula is TB 1/4 K2.

$$\text{TB} = \frac{K^2}{Ln(K1 + 1)} \tag{5}$$

Where Lk is spectral radiance, TB is the effective at-satellite temperature (in K), and K2 and K1 are the pre-launch calibration constants. K1 = 666.09 K and K2 = 1282.71 K for Landsat-7 ETM+. In terms of a black body, the temperature data from above are expressed. Due to the kind of land cover, modifications for spectral emissivity (e) were necessary. The following equation (Eq. 6) was used to calculate the emissivity-corrected land surface temperatures (St) (Artis & Carnahan, 1982).

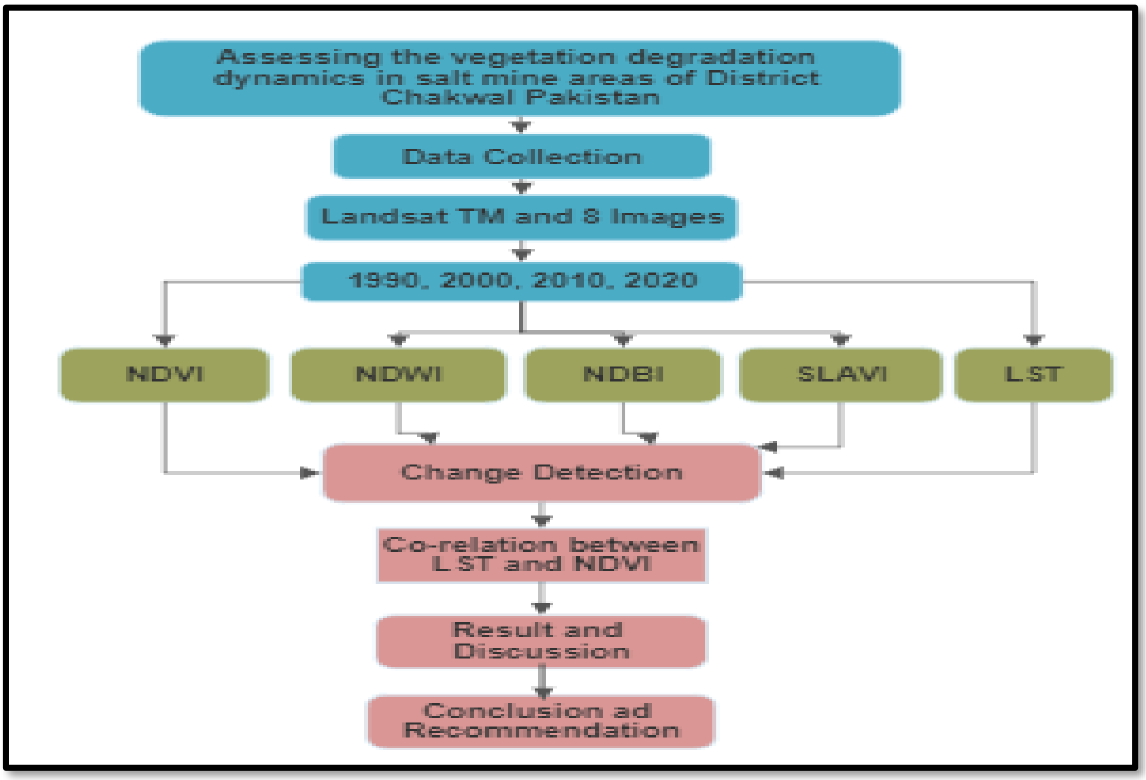
$$St = \frac{\boldsymbol{TB}}{\mathbf{1} + (\boldsymbol{\lambda} \times \boldsymbol{T\beta}\ \boldsymbol{\rho}) \ln \boldsymbol{\epsilon}} \tag{6}$$

Several technologies are used in accurate farming. Crop development models, GPS, Geographical Information Systems (GIS), remote sensing, change detection, yield and vegetation monitoring, and variable rate application are a few of these (Al-Tamimi & Al-Bakri, 2005). Using the most up-to-date technology, remote sensing is used to identify changes, monitor agricultural conditions, and analyze land usage (Meera Krishna, Khan, & Khan, 2019). The emphasis of LAI research has lately evolved from an empirical and statistical phase to a stage focused on process, thanks to the utilization of remotely sensed data and the application of numerical models (Baret et al., 2001). The formula in Eq. 7 is used to calculate the specific leaf area vegetation index (SLAVI) created for Landsat images.

$$\boldsymbol{SLAVI} = \frac{\boldsymbol{NIR}}{\boldsymbol{RED} + \boldsymbol{MIR}} \tag{7}$$

The research design below shows the methodology of this study.

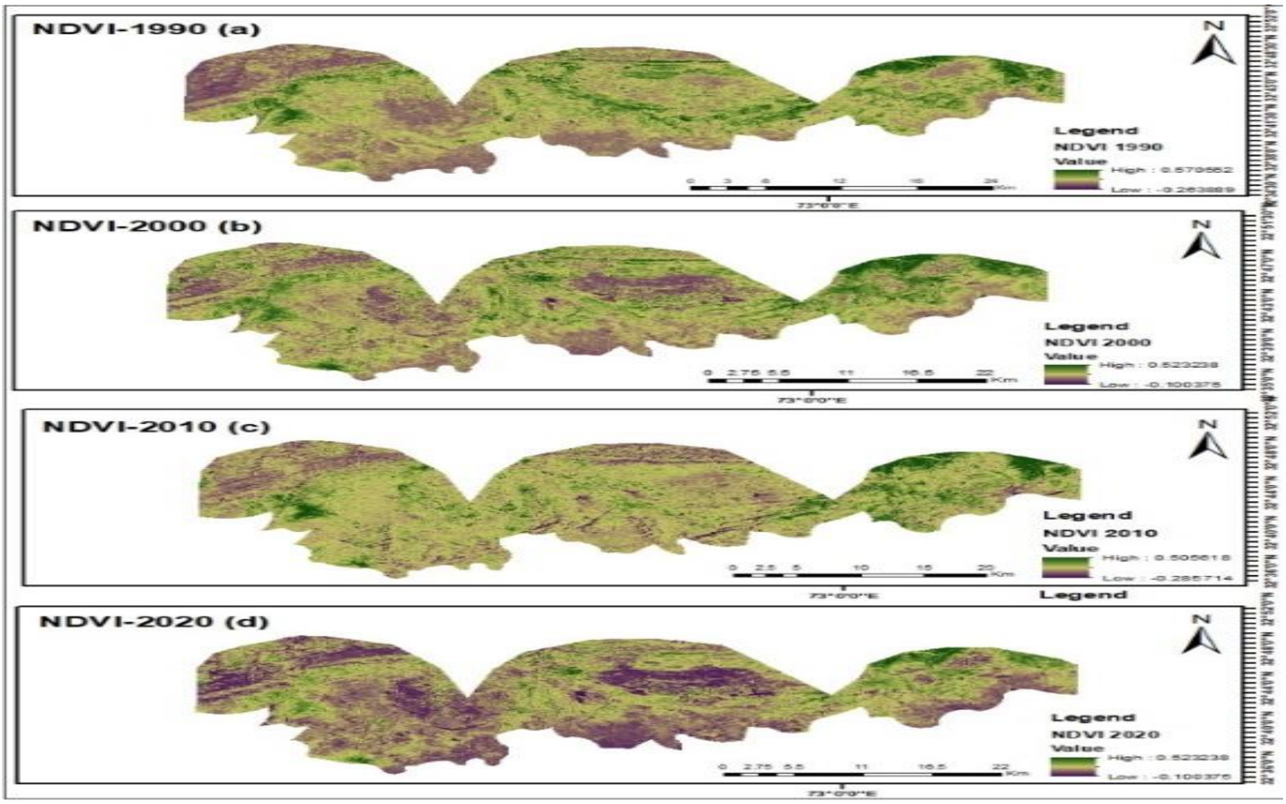
Figure 3: Flow chart of the Research Design



4. Results

Assessment of vegetation or land degradation is a challenging field of science. The definition of what constitutes degradation has been the subject of an open debate, which contributes to this complexity. Due to the interdisciplinary nature of desertification, which includes geographical, ecological, meteorological, and social perspectives, all of which have the potential for regionally specific interpretations, this confusion arises. Remote sensing data were effectively used to quantify the change in forest cover. However, monitoring of change was unaffected by two epochs. The change in vegetation and other parameters were measured using the Landsat data. These maps illustrate the land/water interface and different moisture content levels while differentiating between different vegetation kinds. As a result, there are many different colors of green in the plants. Orange hues are emitted by plants with a relatively low moisture content, while green hues show that vegetation reflects more in SWIR and less in NIR. Blue to grey shades are caused by urban environments and barren soil. The data are shown in Fig. 3 to show that plant cover has reduced as the mining activity has increased. The data gathered indicates a more severe degree of land degradation. As a result of this mining disaster, the vegetative indices (NDVI) are retrieved from Landsat data and merged into Arc Map for mapping. The maps that were acquired are shown in Fig. 4 (a, b, c, and d).

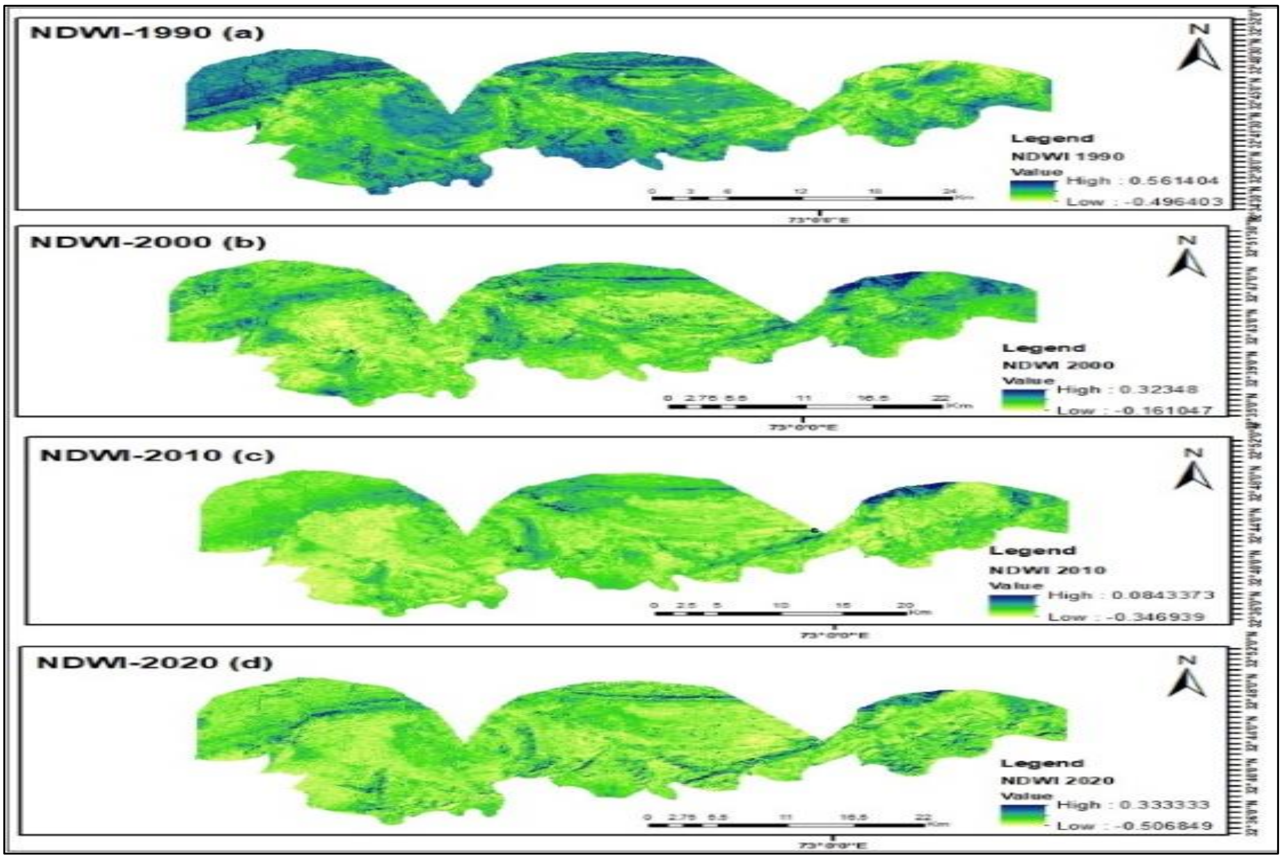
Figure 4: NDVI retrieved from Landsat 5 TM and 8 imageries from the years (1990-2020)



Analysis of the NDWI maps Figure 5 (a, b, c, and d) demonstrates why plants have a larger water content. It is observed that NDVI cannot distinguish minute variations in canopy density. Additionally, a discrepancy is found in the acquired NDVI dataset, which is examined using the specific leaf area vegetation index, potential evapotranspiration, the Water index, and the Built index. The built-up area is also affected by mining, as shown in Figure 4, which depicts how much of District Chakwal is built up. This is because mining disrupts residential areas, or because the growth of residential areas reduces the amount of vegetation cover in the area. The built-up extent underwent temporal changes, as shown in Figure 4. From 1990 onward, there will be an increase in built-up areas, which will cause the NDVI vegetation cover to drastically change.

Figure 6 (a, b, c, d) shows the calculated NDBI values which is showing an increasing trend of built-up in the study region from the year 1990 to 2020. The increasing built up cause temperature variation plus the new construction cause damage to vegetation as it results in deforestation. This is an alarming situation for the district because the growth of residential areas reduces the amount of vegetation cover which further causes the increase in surface temperature.

Figure 5: NDWI retrieved from Landsat 5 TM and 8 imageries from the years (1990-2020)



SLAVI calculated from Landsat 8 images showing the prominent decrease in vegetation from the years 1990 to 2020. The high values in Figure 6 (a, b, c, d) show increased vegetation or dense, whereas the low values show decreased vegetation values. The decrease in vegetation is the reason for mining in salt mine areas.

Figure 6: NDBI retrieved from Landsat 5 and 8 imageries from the years (1990-2020).

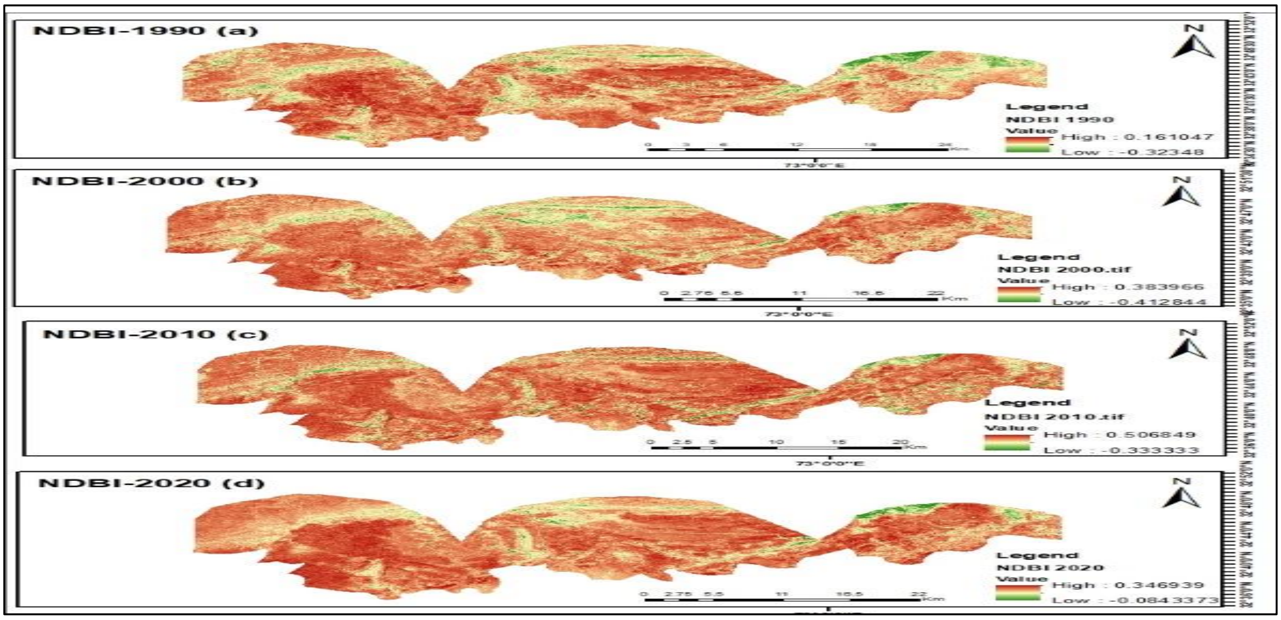
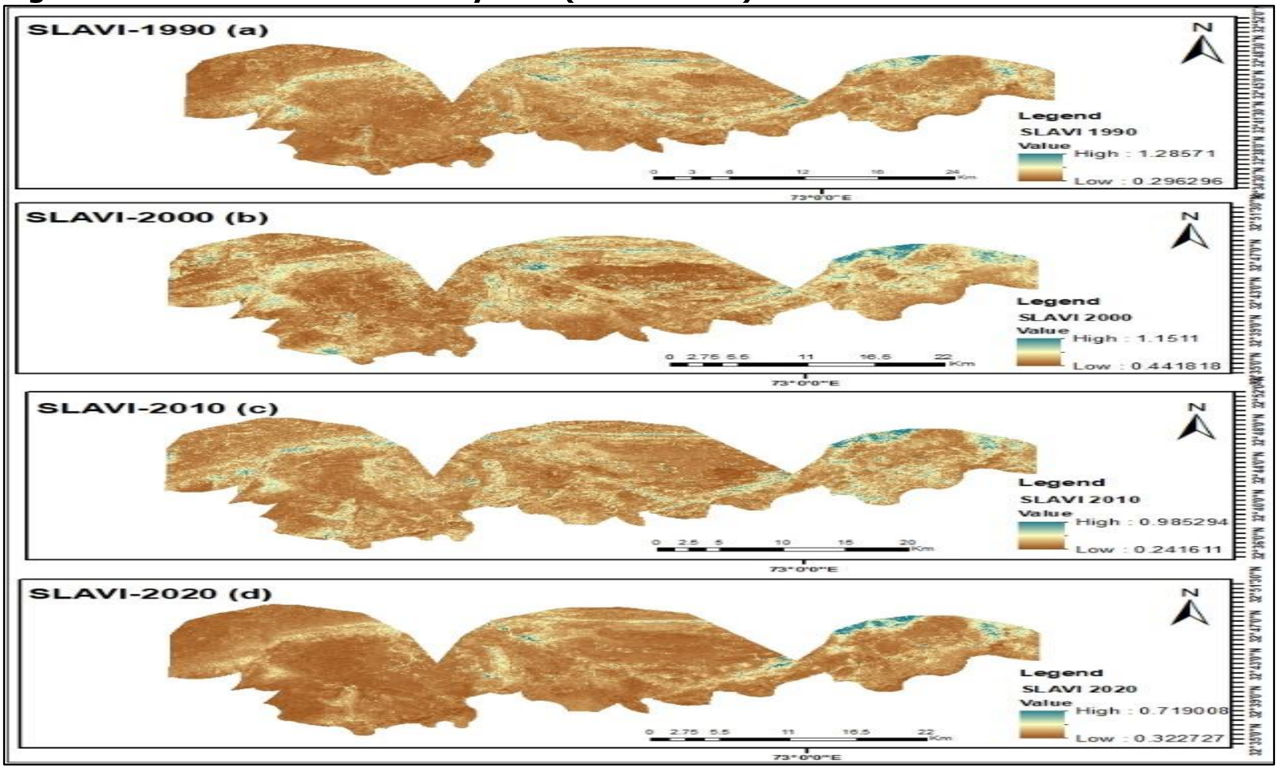


Figure 7: SLAVI retrieved from years (1990-2020)



The leaf area index (LAI), which measures the ratio of leaf surface area to unit ground-level area, indicates the potential surface area accessible for leaf exchange of gases between the earth's atmosphere and biosphere (Bréda, 2003). Controlling it is essential for several biological and physical activities that occur in plants, including transpiration, photosynthesis, autotrophic respiration, carbon and nutrient cycling, light attenuation via the canopy, and absorption of light and water (rain and fog). It is vital for modeling ecosystems because it connects the carbon and water cycles of plants and helps to measure their physiological activities. Functional diversity evaluation depends heavily on it. The vegetation degradation in the Chakwal salt mine area is confirmed by the results shown above.

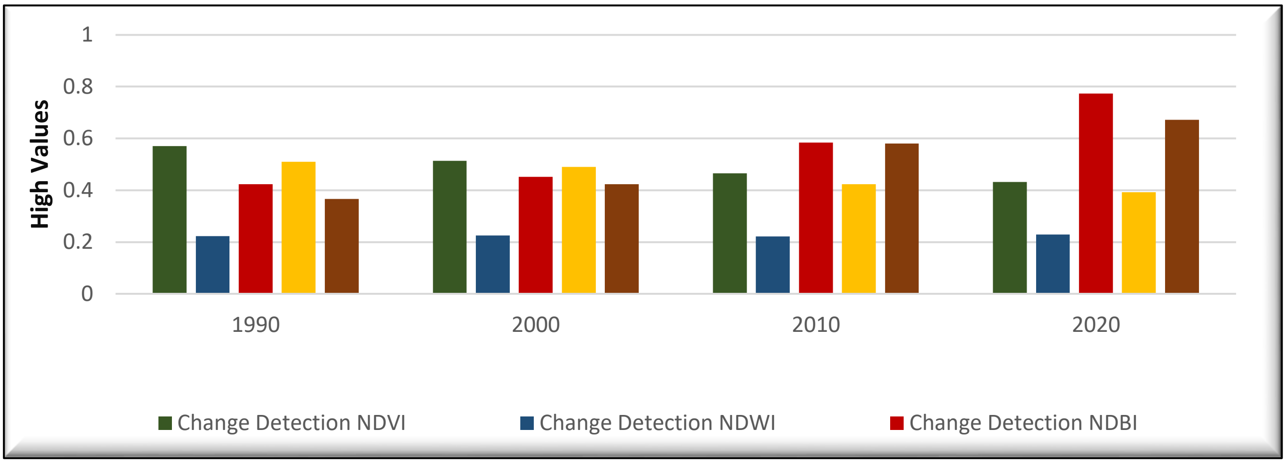
Mining activities are the cause of the vegetation rate's decline from 0.597 to 0.4321. The "difference image," which was utilised to carry out the NDVI change detection, is based on the idea that the values of the pixels connected with vegetation change exhibit values that are considerably different from those of the pixels related to unchanging areas. The altered image is then scrutinized (thresh held) to look for any modifications. Using Landsat imagery acquired in June (1990-2020), modifications in the NDVI data and all other metrics shown in Figure 8 were found. The comparison research showed that there was less vegetation cover and more built-up area.

Table 1: Comparative Analysis (Change Detection) of NDVI, NDWI, NDBI

Year	Change Detection				
	NDVI	NDWI	NDBI	SLAVI	LST
1990	0.5705	0.223	0.424	0.51	0.367
2000	0.5132	0.225	0.452	0.49	0.423
2010	0.4656	0.222	0.584	0.423	0.581
2020	0.4321	0.229	0.773	0.393	0.672

Table 1 shows the temporal change of NDVI, NDWI, NDBI, SLAVI, and LST. Vegetation has decreased from 1990 to 2020, on the other hand, NDBI built-up ratio has increased. Mining has devastatingly affected the District. The area is affected by vegetation degradation, which has a direct impact on vegetation coverage.

Figure: 8 Graphic Representation of change Detection from the Years (1990-2020)



4.1. Relationship Between LST and Vegetation Abundance

For each correlation analysis (pixel by pixel), the link between LST and NDVI was examined. At various levels of resolution, the two variables' Pearson's correlation coefficients. A one-tail Student's t-test was used to examine the significance of each correlation coefficient. Figure 9 (a, b, c, d) shows the 1990_2020 LST conditions.

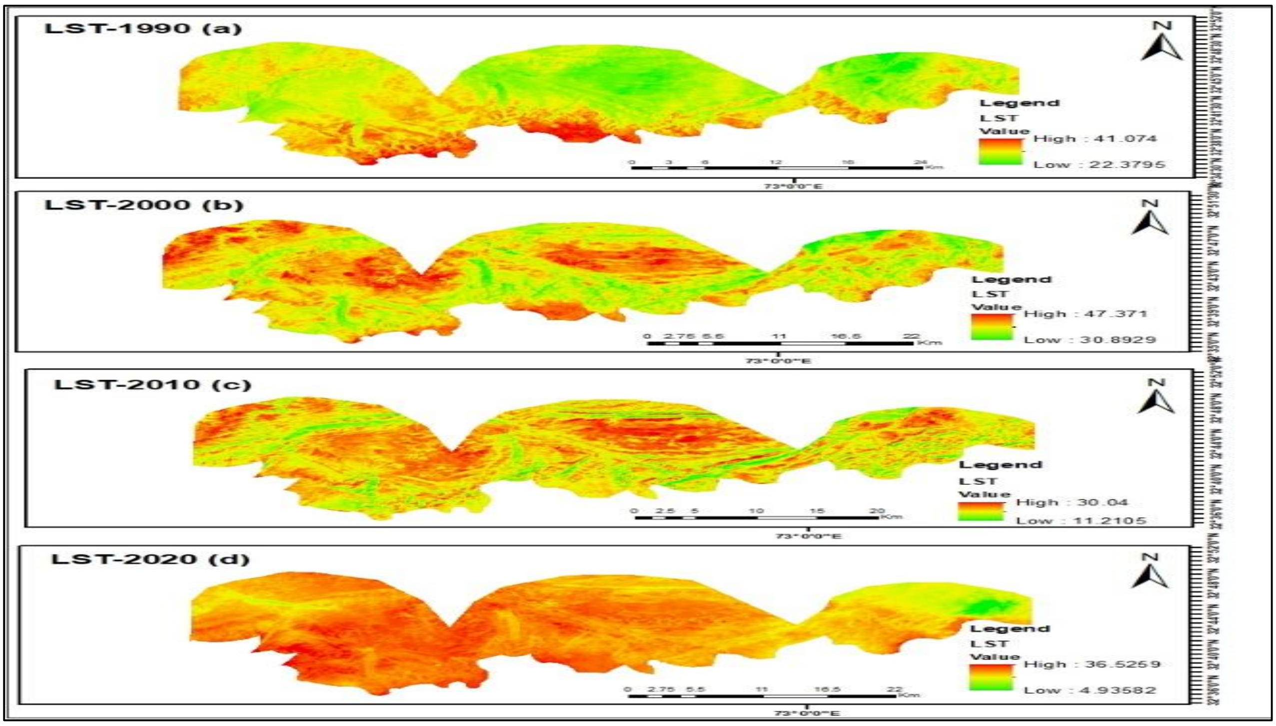
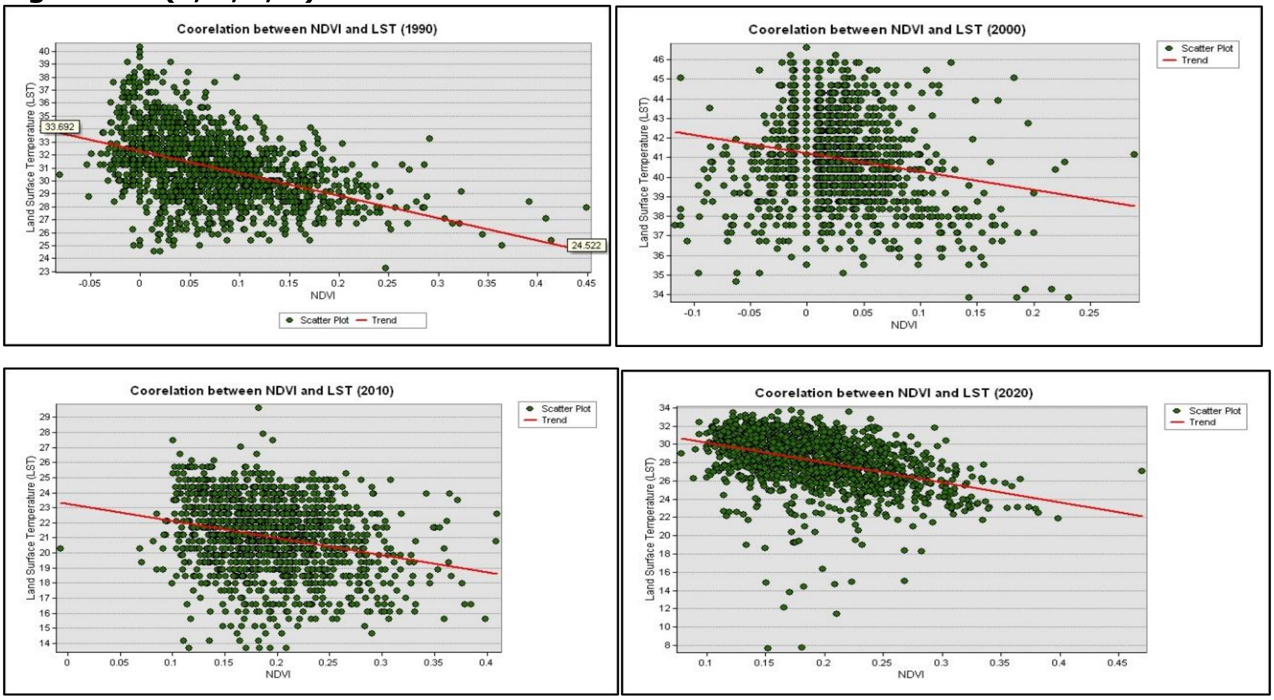


Figure 9: (a, b, c, d) LST (1990-2020)

4.2. Correlation Between NDVI and LST

Although remote sensing can measure land surface temperatures (LST) in a city, its ability to measure vegetation canopy temperatures is constrained by LST variability brought on by differences in the proportion of vegetation and non-vegetation, as well as the coarse resolution of thermal imagery that is currently available. The relation between NDVI and LST has been calculated in the study region to estimate the values of vegetation plus how the decrease or increase in vegetation affects the land surface temperature. The results in Figure 10 show the temporal change in temperature from 1990-2020. It showing the decrease in vegetation cause the increase in temperature. 1990 was the year of healthy vegetation so the temperature is low whereas, 2020 is the year having low values of NDVI but the temperature is showing high range values. Vegetation affects the climate of a particular region. The above graph shows the values of Higher NDVI and Lowest LST values whereas the Lowest NDVI and higher LST values, which is an alarming situation for the salt mines. Vegetation degradation or mining affects the vegetation and then it affects the surface temperature.

Figure 10. (a, b, c, d) shows the relation between NDVI and LST



5. Discussion

The scientific community places a high value on monitoring vegetation degradation. Numerous researchers use a variety of methods to do this, including measuring changes in species diversity, conducting repeated field surveys, and concentrating on small-scale and long-term vegetation changes (Zucca et al., 2011). The methodologies and strategies for evaluating the degradation of the land and vegetation in the Chakwal Salt Range mining area are discussed, including their theoretical and experimental aspects. Changes in vegetation cover, a primary indication of environmental conditions, assist us in understanding the phenomena that have led to changes in other environmental parameters. These elements consist of land use, vegetation cover, geomorphology, and water extent. Vegetation indices are used for the quantitative risk assessment of land degradation, the identification of plant biomass, and the investigation of environmental changes in places impacted by drought or floods. According to the data, there has been a significant shift in vegetation cover between 1990 and 2022, which supports the hypothesis that increasing mining activity has led to a drop-in vegetation cover, which in turn has increased the Land Surface Temperature. Monitoring mining activity and predicting future patterns in vegetation change can both be done using several time series analyses of remote sensing data.

Similar temperature connections between turfgrass and urban trees have been found in other investigations. Using a high-resolution aerial sensor over Salt Lake City, Utah, Quattrochi and Ridd (1998) discovered that residential lawns had a midday thermal response of less than 70 W/m2, whereas urban trees had a response of more than 80 W/m2. The microbial populations, biogeochemical processes, and soil hydrology of the soil are all altered by permafrost degradation, which increases the soil's nutrient availability and has an impact on plants. Additionally, when the temperature rises, vegetation may change in one of two successional directions, initially moving towards a wet or dry ecology over time, but eventually moving towards a less moist ecosystem due to the melting of permafrost in areas with permeable and well-drained soils. Therefore, it is important to timely and more effectively track, evaluate, and simulate terrestrial or integrated ecosystem models at desired spatiotemporal scales and resolutions. Such models are rapidly developing as a result of remote sensing, other space-, ground-, and airborne observing networks, as well as numerical predictive models (Jin et al., 2021). Using situ measurements of LST, Crum and Jenerette (2017) found that over the bulk of the daily cycle in Los Angeles, tree canopies had higher LST than turfgrass. This finding is consistent with our data. Finally, while comparing Las Vegas and Phoenix, USA, Myint and Firoozabadi (2015) discovered similar turfgrass LST-cover curves but noticeably different tree LST cover curves, demonstrating that changes in plant functional type LST may be affected by additional factors such as spatial arrangement. Trees can affect the environment's temperature both negatively (through shading and ET) and positively (by lowering wind, releasing less longwave energy, and raising ET of neighboring plants), claim (Litvak, Bijoor, & Pataki, 2014; Zhang et al., 2019). In our study area, the equilibrium of these conflicting impacts led to a decrease in vegetation that led to a rise in temperature. Using the change detection technique in a graphical manner applied to NDVI and all other factor data, the region impacted by land degradation, which directly affects vegetation covering, is determined. As a consequence, an analysis of the NDVI for vegetation shows that between 1990 and 2020, there was a sharp fall from 0.5973 to 0.4321, and the temperature changes are the whole proof that the decrease in vegetation is what is causing the temperature rise. Therefore, the government must act swiftly to implement several reasonable policies that will position it in the best possible way when the current environmental crisis inevitably passes.

6. Conclusion

Through trend analysis of several indices, this study tried to monitor vegetation degradation and the linkage between the land surface temperature due to increasing and decreasing trends of vegetation. Additionally, patterns that were seen were examined. The objective was to access the Chakwal District's vegetation dynamics from 1990 to 2020. The results of this study show that a pattern of vegetation disturbances may be captured using time series analysis of specific vegetation along with temperature and water indices (NDVI, NDWI, SLAVI, NDBI, LST). The changes could still be seen even if they were gradual. NDVI and all other factor data are applied to the change detection technique graphically to identify the area impacted by land degradation, which has a direct impact on vegetation covering. As a result, an analysis of the NDVI for vegetation shows that there has been a sharp reduction from 0.5973 to 0.4321 between 1990 and 2020. This, along with the temperature changes, provide conclusive proof that the declining vegetation is what is causing the temperature to rise. Additionally, thorough and frequent field trips to evaluate the state of salt mine sites' stands could also aid in validating the trends found. These results could be applied to develop suitable management strategies for the preservation and restoration of the vegetation ratio in Chakwal District, Pakistan, to regulate the surface temperature.

5.1. Recommendation

The analysis supports reports that the Chakwal Region Salt Range's plant cover has been eliminated. Land management takes local factors into account as it attempts to resolve problems between people and the land. The assessment model serves as a foundation for sensible management strategies and decision-making for stopping land degradation. The advancement of this methodology is crucial for scaling up deterioration evaluation. The results of the study implore the government, governmental organizations, and the populace as a whole to act immediately and address the problem. The best technique to plan the city is also required because the problem here goes beyond the vegetation cover. If not, both current and future generations' lives are in danger. By putting the offered solutions into practice, together with any others that may be suitable, the existing situation on our agricultural land is likely to improve.

References

AbdelRahman, M. A., Natarajan, A., Hegde, R., & Prakash, S. (2019). Assessment of land degradation using comprehensive geostatistical approach and remote sensing data in GIS-model builder. *The Egyptian Journal of Remote Sensing and Space Science, 22*(3), 323-334. doi:https://doi.org/10.1016/j.ejrs.2018.03.002

Al-Tamimi, S., & Al-Bakri, J. T. (2005). Comparison Between Supervised and Unsupervised Classifications for Mapping Land Use/Cover in Ajloun Area. *Jordan Journal of Agricultural Sciences, 1*(1).

Anyamba, A., & Tucker, C. J. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981–2003. *Journal of arid environments, 63*(3), 596-614. doi:https://doi.org/10.1016/j.jaridenv.2005.03.007

Artis, D. A., & Carnahan, W. H. (1982). Survey of emissivity variability in thermography of urban areas. *Remote sensing of Environment, 12*(4), 313-329. doi:https://doi.org/10.1016/0034-4257(82)90043-8

Baret, F., Vintila, R., Lazar, C., Rochdi, N., Prévot, L., Favard, J., . . . Petcu, G. (2001). The ADAM database and its potential to investigate high temporal sampling acquisition at high spatial resolution for the monitoring of agricultural crops. *Romanian Agricultural Research, 16*, 69-80.

Bréda, N. J. (2003). Ground-based measurements of leaf area index: a review of methods, instruments and current controversies. *Journal of experimental botany, 54*(392), 2403-2417. doi:https://doi.org/10.1093/jxb/erg263

Chen, L., Zhang, H., Zhang, X., Liu, P., Zhang, W., & Ma, X. (2022). Vegetation changes in coal mining areas: Naturally or anthropogenically Driven? *Catena, 208*, 105712. doi:https://doi.org/10.1016/j.catena.2021.105712

Crum, S. M., & Jenerette, G. D. (2017). Microclimate variation among urban land covers: The importance of vertical and horizontal structure in air and land surface temperature relationships. *Journal of Applied Meteorology and Climatology, 56*(9), 2531-2543.

Dejun, Y., Zhengfu, B., & Shaogang, L. (2016). Impact on soil physical qualities by the subsidence of coal mining: a case study in Western China. *Environmental Earth Sciences, 75*, 1-14. doi:https://doi.org/10.1007/s12665-016-5439-2

Jin, X.-Y., Jin, H.-J., Iwahana, G., Marchenko, S. S., Luo, D.-L., Li, X.-Y., & Liang, S.-H. (2021). Impacts of climate-induced permafrost degradation on vegetation: A review. *Advances in Climate Change Research, 12*(1), 29-47. doi:https://doi.org/10.1016/j.accre.2020.07.002

Kumar, B. P., Babu, K. R., Rajasekhar, M., & Ramachandra, M. (2020). Identification of land degradation hotspots in semiarid region of Anantapur district, Southern India, using geospatial modeling approaches. *Modeling Earth Systems and Environment, 6*, 1841-1852. doi:https://doi.org/10.1007/s40808-020-00794-x

Kusimi, J. M. (2008). Assessing land use and land cover change in the Wassa West District of Ghana using remote sensing. *GeoJournal, 71*(4), 249-259. doi:https://doi.org/10.1007/s10708-008-9172-6

Li, X., Lei, S., Cheng, W., Liu, F., & Wang, W. (2019). Spatio-temporal dynamics of vegetation in Jungar Banner of China during 2000–2017. *Journal of Arid Land, 11*, 837-854. doi:https://doi.org/10.1007/s40333-019-0067-9

Litvak, E., Bijoor, N. S., & Pataki, D. E. (2014). Adding trees to irrigated turfgrass lawns may be a water-saving measure in semi-arid environments. *Ecohydrology, 7*(5), 1314-1330. doi:https://doi.org/10.1002/eco.1458

Meera Krishna, B., Khan, M. A., & Khan, S. T. (2019). Next-generation sequencing (NGS) platforms: an exciting era of genome sequence analysis. *Microbial Genomics in Sustainable Agroecosystems: Volume 2*, 89-109. doi:https://doi.org/10.1007/978-981-32-9860-6_6

Myint, P. C., & Firoozabadi, A. (2015). Thin liquid films in improved oil recovery from low-salinity brine. *Current Opinion in Colloid & Interface Science, 20*(2), 105-114. doi:https://doi.org/10.1016/j.cocis.2015.03.002

Quattrochi, D. A., & Ridd, M. K. (1998). Analysis of vegetation within a semi-arid urban environment using high spatial resolution airborne thermal infrared remote sensing data. *Atmospheric Environment, 32*(1), 19-33. doi:https://doi.org/10.1016/S1352-2310(97)00179-9

Sajjad, M. R., Rizvi, S. A., Rafique, R., Naseem, W., Khan, A., Muhammad, G., . . . Javid, S. (2021). Characterization of cowpea to harvest rainwater for wheat in semiarid conditions. *Spanish Journal of Agricultural Research, 19*(3), e1201-e1201.

Sandeep, P., Reddy, G. O., Jegankumar, R., & Arun Kumar, K. (2021). Modeling and assessment of land degradation vulnerability in semi-arid ecosystem of Southern India using temporal satellite data, AHP and GIS. *Environmental Modeling & Assessment, 26*, 143-154. doi:https://doi.org/10.1007/s10666-020-09739-1

Zhang, M., Wang, J., & Li, S. (2019). Tempo-spatial changes and main anthropogenic influence factors of vegetation fractional coverage in a large-scale opencast coal mine area from 1992 to 2015. *Journal of Cleaner Production, 232*, 940-952. doi:https://doi.org/10.1016/j.jclepro.2019.05.334

Zhengfu, B., Inyang, H. I., Daniels, J. L., Frank, O., & Struthers, S. (2010). Environmental issues from coal mining and their solutions. *Mining Science and Technology (China), 20*(2), 215-223. doi:https://doi.org/10.1016/S1674-5264(09)60187-3

Zucca, C., Julitta, F., & Previtali, F. (2011). Land restoration by fodder shrubs in a semi-arid agro-pastoral area of Morocco. Effects on soils. *Catena, 87*(3), 306-312. doi:https://doi.org/10.1016/j.catena.2011.06.017