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Environmental Influences on Rabi Crops using GIS and Remote Sensing: A Case Study of Mianwali District

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ABSTRACT

Current study aims at to analyze the environmental influence on Rabi crops and to analyze the rainfall pattern with the vegetation pattern. Despite a declining GDP contribution, agriculture remains a fundamental pillar of Pakistan's economy, supporting livelihoods, nutrition, and export earnings. Focused on Mianwali District, the research integrates data from Landsat satellites, MODIS LST, and rainfall records to untangle relationships between environmental factors and Rabi crop productivity. Analysis of the Normalized Difference Vegetation Index (NDVI) provides insights into crop health by revealing variations in vegetation cover. Land Surface Temperature (LST) data offers perspectives on thermal conditions during the Rabi season, crucial for understanding water stress. Rainfall data assists in assessing water availability and its impact on crop yield. Correlation analysis highlights the direct impact of environmental conditions on agricultural productivity. Temporal trends show diversification in crop types, with "High Crops" on an upward trajectory, while the overall crop area in Mianwali District consistently decreases, possibly linked to changing environmental patterns. Land Surface Temperature conditions suggest potential environmental adaptations, supported by a decrease in LST values from 2000 to 2022, indicating improved thermal conditions or adaptive strategies. Rainfall analysis underscores the significance of understanding climatic patterns for sustainable agriculture. The correlation between NDVI and LST emphasizes vegetation sensitivity to thermal conditions, providing valuable insights for ecological studies and precision agriculture. The positive correlation between Rainfall and NDVI highlights the crucial role of water availability in fostering vegetation health and guiding sustainable agricultural practices.

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1. Introduction

The agricultural which has four important aspects like plants, livestock, soil and related technology plays important role in financial gains but also serves as a crucial catalyst for the overall development of the nation (Naiyer & Md, 2015). Since the attainment of independence, agriculture has steadfastly remained the primary source of income, offering livelihoods to more than 60% of the Pakistan's masses and supporting a staggering 115.5 million families depending upon agriculture (Arjun, 2013). Despite its declining contribution to the economy, from 55.1% in 1950–1951 to 17% in 2008–2009 H. Gupta (2013); S. Gupta (2014), agriculture persists as a linchpin due to multifaceted reasons. Firstly, while Pakistan has achieved macro-level self-sufficiency in food production, it grapples with micro-level challenges, particularly the pervasive issue of malnutrition among children. Secondly, despite the diminishing fiscal shares in a countries development, the rural workforce's reliance on farming for engaging people (H. Gupta, 2013). Thirdly, agriculture contributes significantly to total export earnings, accounting for about 14.7% through the export of agricultural commodities, with agricultural raw materials comprising 20% of Pakistan's total exports (Mallika, 2012). In the present scenario, Pakistan’s agriculture faces the formidable challenge of catering to the needs of a rapidly growing population, underscoring the paramount importance of food crop production for farmers. As a result, most of the area are reserved for food crops (Sharma, 2007). The mid-1960s marked a pivotal period with a chanin of interventions, encompassing an upgraded farming package, advanced technologies, access to modern inputs and a conducive environmental sector. These initiatives culminated in the Green Revolution, a transformative phase in cereal production that shifted Pakistan from a food-deficient nation to one achieving self-sufficiency (Malik & Singh, 2010). The resilience witnessed in wheat and rice production in Pakistan can be attributed to the changes of new seed and technologies associated with the Green Revolution. The surge in crop production is not merely a result of expanded cultivation areas but is equally attributable to enhanced productivity due to technological advancements (Naik, 1999). Consequently, grain produced skyrocketed from over 50 million tons (MT) in 1950–1951 to an impressive 250 MT during 2011–2012 (Arjun, 2013).

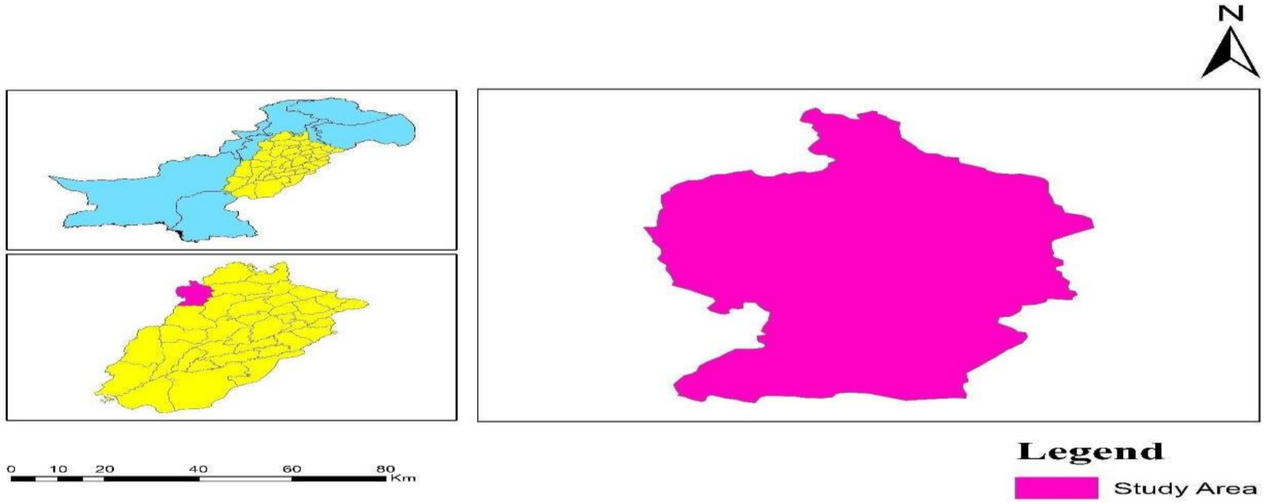
Turning to Pakistan, where the cropping months are Kharif which are in summar and Rabi which are in winter, the agricultural landscape is characterized by a diverse array of crops. The significance of precipitation in Rabi crop cultivation cannot be overstated, as it not only supplements crop with essential moisture but also maintains low temperatures crucial for their optimal development (Chhabra & Haris, 2014; Nageswararao, Dhekale, & Mohanty, 2018; Nageswararao, Mohanty, Osuri, & Ramakrishna, 2016; R. Pal, Murty, & Rao, 2012; R. Pal, Rao, Nain, & Sumanan, 2012; S. Pal, Chowdhury, Talukdar, & Sarda, 2022). Winter precipitation, combined with summer season rainfall, exerts a profound influence on Rabi crops by ensuring water and soil moisture availability across various regions in Pakistan. Production of Kharif and Rabi crops has been extensively explored in numerous research studies (Al Mamun et al., 2022; Bibi et al., 2021; Charjan et al., 2023; Chhabra & Haris, 2014; Gadakh, Dalvi, Nirmal, & Dudhade, 2021; Krishna Kumar, Rupa Kumar, Ashrit, Deshpande, & Hansen, 2004; Kumar, KaurSidana, & Thakur, 2023; Mujtaba et al., 2022; Nageswararao et al., 2018; S. Pal et al., 2022; Selvaraju, 2003; Shinde, Jadhav, Patil, Bavadekar, & Pawar, 2021). The objective of the study is: (1) To prepare NDVI, LST, and Rainfall map of the study region (2) To analyze the connection between NDVI and LST (3) To analyze the relation between the NDVI and Rainfall. This study uniquely endeavors to scrutinize the environmental impact on Rabi crops in the designated area, delving into the shifts in climatic patterns and their profound repercussions on cropland. Leveraging NDVI, LST, and Rainfall Data, the study seeks to comprehensively assess the environmental dynamics influencing Rabi crop cultivation.

2. Material and Methodology

2.1. Study Area

The Mianwali District is characterized by its strategic location and diverse geographical features. It shares borders with several significant districts. This positioning not only underscores its regional importance but also contributes to the district's cultural and economic interchange with neighboring areas. The district's central hub, Mianwali (Miānwāli), serves as the administrative seat. Located at a latitude of 32°35'7.48"N and a longitude of 71°32'37.02"E or 32.585411 and 71.543617, respectively, Mianwali is strategically positioned for both local and regional connectivity. This geographical centrality has historical significance, as the district has been a crossroads for trade, cultural exchange, and communal interactions over the years. The diverse topography of Mianwali, characterized by plains and the presence of the Indus River, not only adds to the scenic beauty but also provides a rich foundation for various economic activities. Agriculture, influenced by the fertility of the plains and the availability of water from the Indus River, plays a pivotal role in the district's economy. Beyond its geographical attributes, Mianwali boasts a cultural tapestry woven with the threads of tradition and history. The district has been witnessing the rise and fall of civilizations, leaving behind landmarks and heritage that invite exploration and study. Its cultural amalgamation, influenced by the neighboring districts, contributes to a unique identity that is both rooted in tradition and open to modernity. As a focal point in the Punjab province, Mianwali District offers an intriguing blend of natural beauty, historical significance, and economic vitality. Researchers, historians, and those interested in regional studies can delve into the district's multifaceted characteristics to gain a comprehensive understanding of its past, present, and future trajectory.

Figure 1: Shows the Study Area



Source (Author)

2.2. Data Source

The dataset utilized for this study was sourced from reputable and widely recognized platforms, providing a comprehensive and multi-temporal perspective on environmental variables. Specifically, the information was collected from the United States Geological Survey (USGS) website for Landsat 4, 5, 7, and 8, spanning the years 1990, 2000, 2010, and 2022. These Landsat satellites have been pivotal in Earth observation, offering high-resolution imagery crucial for discerning changes in land cover and vegetation over time. For the analysis of vegetation dynamics, the Near-Infrared (NIR) and Red bands from Landsat 4, 5, 7, and 8 were employed. These spectral bands are instrumental in calculating vegetation indices, providing insights into the health and density of vegetation in Mianwali. The utilization of multiple Landsat satellites over different temporal periods enables a longitudinal assessment of vegetation changes, offering a nuanced understanding of the ecosystem's evolution. Additionally, Land Surface Temperature (LST) data were acquired from the NASA Earth data website, specifically from the Moderate Resolution Imaging Spectroradiometer (MODIS) LST product. This dataset spans the same temporal intervals 1990, 2000, 2010, and 2022 and offers invaluable information on the thermal properties of the study area. Understanding variations in land surface temperature is essential for discerning climatic patterns, urban heat island effects, and potential impacts on vegetation health. To complement the remote sensing data, rainfall data were sourced from the Pakistan Meteorological Department website, covering the identical years of interest 1990, 2000, 2010, and 2022. Rainfall is a pivotal climatic variable that profoundly influences ecosystem dynamics, including vegetation growth and land surface temperature patterns. The incorporation of meteorological data enhances the study's robustness by considering the climatic context in which vegetation and land surface temperature changes occur.

3. Data Analysis

3.1. NDVI Calculation

The NDVI serves as a pivotal metric for gauging area under vegetation health in remote sensing utilization. NDVI is calculated by utilizing the Near-Infrared (NIR) and Red bands from satellite imagery. In the case of Landsat 4, 5, and 7 Band 3 is designated as the Red Band, while Landsat 8 designates Band 4 for this purpose. Correspondingly, Landsat 7's Band 4 and Landsat 8's Band 5 serve as the Near-Infrared (NIR) bands, as outlined by (Bustos & Meza, 2015; Tenreiro, García-Vila, Gómez, Jiménez-Berni, & Fereres, 2021; Waseem et al., 2023; Yang et al., 2019). The NDVI formula, a widely employed vegetation index, is expressed as follows:

$$NDVI = (NIR - RED) / (NIR + RED) \qquad (1)$$

This formula quantifies the normalized difference between the Near-Infrared and Red spectral reflectance values. A resulting NDVI value ranges from -1 to +1, where higher values typically signify healthier and more abundant vegetation (Bustos & Meza, 2015; Tenreiro et al., 2021; Waseem et al., 2023). The utilization of Landsat 4, 5, 7 and Landsat 8 data, with their distinct spectral bands, enhances the accuracy and consistency of NDVI calculations over time. This index is invaluable for monitoring changes in vegetation cover, assessing land degradation, and contributing to a comprehensive understanding of ecosystem dynamics (Tenreiro et al., 2021; Waseem et al., 2023). The NDVI formula's simplicity belies its significance in providing actionable insights for environmental management, agriculture, and ecological studies.

2.2. Correlation Analysis

Linear correlation, a widely recognized similarity measure between two random variables, is instrumental in quantifying the degree of dependence between them. The Pearson correlation coefficient (ρ), a specific type of linear correlation coefficient, serves as a key metric for assessing the strength and direction of the linear relationship between two variables (Gong et al., 2020; Karim, 2021; Press, 1992). Expressed mathematically, the Pearson correlation coefficient (ρ) for a pair of variables X and Y, each with values xi and yi, is determined by the following equation (Gong et al., 2020; Karim, 2021; Press, 1992):

$$\rho = cov(X,Y) \,/\, \sqrt{\sigma 2(X) \cdot \sigma 2(Y)} \tag{2}$$

Here, cov(X,Y) represents the covariance between variables X and Y, while $\sigma 2(X)$ and $\sigma 2(Y)$ denote the variances of X and Y, respectively. In essence, the Pearson correlation coefficient provides a standardized measure of how much X and Y vary together relative to their individual variances. The coefficient ranges from -1 to +1, where:

ρ=+1: Indicates a perfect positive linear relationship—variables move in the same direction.
ρ=−1: Reflects a perfect negative linear relationship—variables move in opposite directions.
ρ=0: Signifies no linear correlation—there is no systematic linear relationship between the variables.

The numerator of the equation, the covariance, captures the joint variability of X and Y, while the denominator normalizes the coefficient by dividing by the square root of the product of their individual variances (Gong et al., 2020; Press, 1992).

3. Results and Discussion

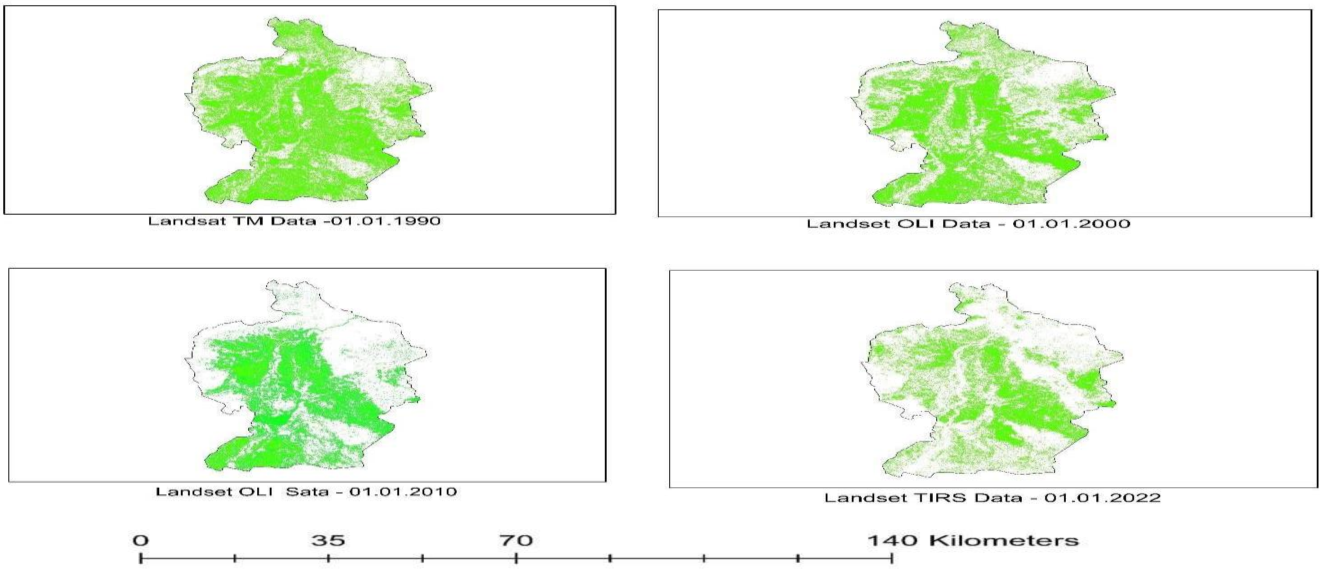
The investigation into the environmental influences on Rabi crops in Mianwali District, leveraging Geographic Information Systems (GIS) and Remote Sensing technologies, represents a pioneering effort in advancing precision agriculture. The integration of these cutting-edge tools enables a nuanced exploration of the intricate relationships between environmental factors and agricultural productivity, particularly during the Rabi season. This approach not only provided a dynamic visualization of the health and distribution of Rabi crops but also served as a valuable indicator of the overall ecological vigor of the agricultural landscape. Areas exhibiting flourishing growth were juxtaposed with those facing potential stress, offering actionable insights for targeted interventions. The examination of Land Surface Temperature data obtained through MODIS LST added a critical layer to the analysis, offering a detailed perspective on the thermal conditions prevailing during the Rabi season. Variations in LST were interpreted as potential indicators of water stress, soil moisture levels, and broader environmental conditions impacting crop performance. This thermal insight facilitates a more comprehensive assessment of temperature-related stresses on crops, aiding in the identification of areas susceptible to thermal challenges. The inclusion of rainfall data sourced from the Pakistan Meteorological Department enriched the study by facilitating a detailed examination of precipitation patterns during the Rabi season. This information proved instrumental in understanding water availability, drought conditions, and their consequential influence on crop yield. Correlations between rainfall patterns and spatial variations in crop health highlighted the intricate connection between water availability and agricultural productivity in Mianwali District. A robust statistical correlation analysis was employed to quantitatively assess the relationships between key environmental variables NDVI, LST, and rainfall and Rabi crop yield. The results yielded significant correlations, providing empirical evidence of the direct impact of environmental conditions on agricultural productivity in the district. This quantitative approach not only validated qualitative observations but also laid the groundwork for predictive modeling and precision agriculture strategies.

4. Results

4.1. NDVI

The provided data presents information on the types and areas of crops in three different years: 1990, 2000, and 2010. Additionally, projections for the year 2022 are included. The crops are categorized into two types: Low Crops and High Crops. Let's analyze the trends and changes in crop types and areas over the specified years. Only one type of crop, labeled as "Low Crops," was recorded in 1990. The total area under cultivation in 1990 was 317 square kilometers. Two types of crops were reported in 2000: "High Crops" and "Low Crops". "High Crops" covered a substantial area of 821 square kilometers, indicating a notable increase in agricultural land dedicated to this crop type. "Low Crops" still contributed significantly, with an area of 263 square kilometers.

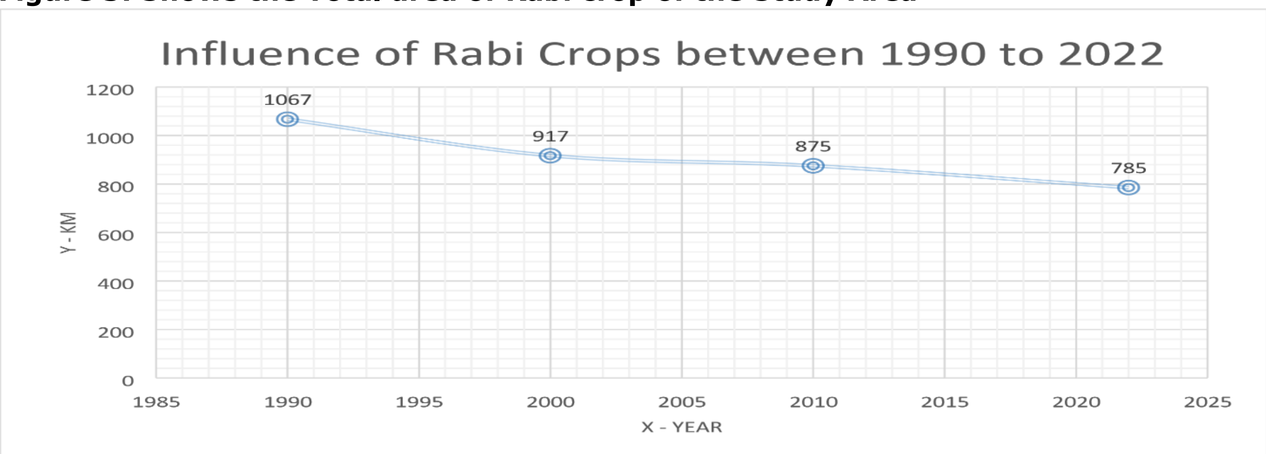
Figure 2: Shows the NDVI maps of the Study Area



Source (Author)

The crop types observed in 2010 were consistent with those in 2000. The area under "High Crops" decreased to 654 square kilometers, showing a slight reduction from 2000. "Low Crops" maintained a substantial area of 203 square kilometers. Like 2010, both "High Crops" and "Low Crops" were cultivated in 2022. The area dedicated to "High Crops" witnessed a slight increase to 672 square kilometers, surpassing the 2010 figure. "Low Crops" continued to contribute significantly, covering an area of 235 square kilometers. The data indicates a diversification of crop types over the years, with the introduction of "High Crops" alongside "Low Crops". While "High Crops" experienced fluctuations in area across the years, there is an overall upward trend from 1990 to 2022. "Low Crops" consistently maintained a substantial area, showcasing the persistence of this category in agricultural practices.

Figure 3: Shows the Total area of Rabi crop of the Study Area



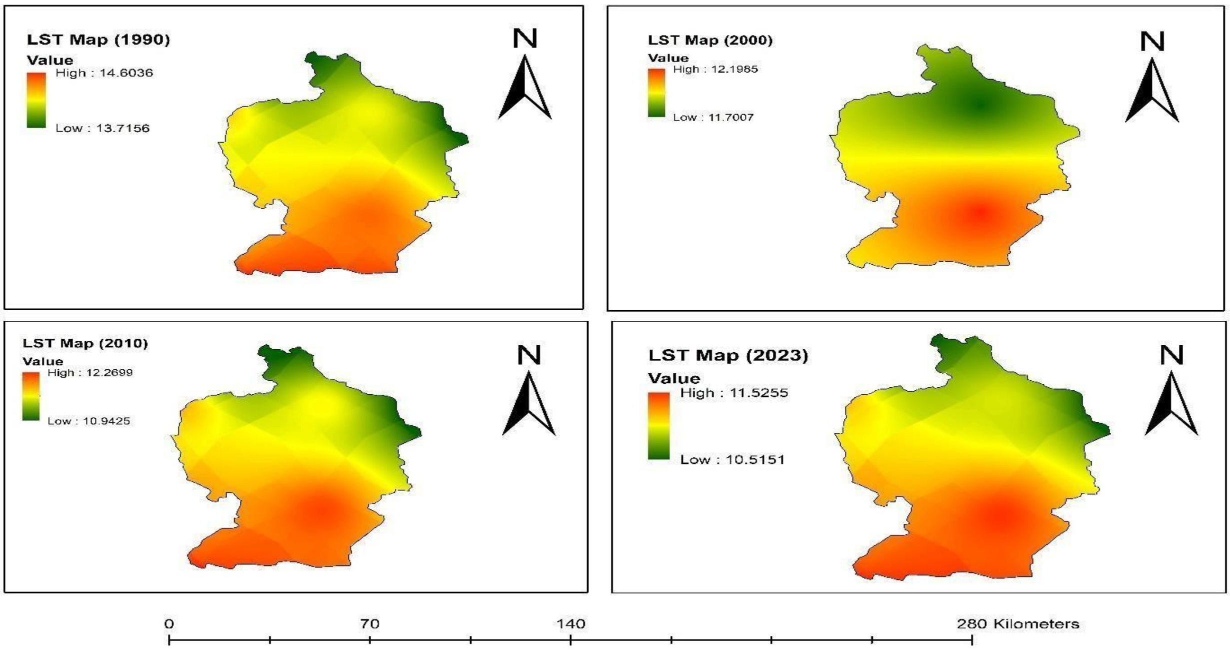
Source (Author)

The temporal analysis of crop areas in Mianwali District from 1990 to 2022 reveals a consistent pattern of decrease, signaling a noteworthy shift in the region's agricultural landscape. The total crop area, which stood at 1067 square kilometers in 1990, experienced a gradual decline over the subsequent decades. In the year 2000, the total crop area decreased to 917 square kilometers, marking a noticeable reduction. This decline persisted, and by 2010, the crop area further contracted to 875 square kilometers. The trend continued in 2022, with the crop area reaching its lowest recorded value of 785 square kilometers. The observed decline in crops raises questions about the underlying factors influencing this shift. A notable factor contributing to this trend is the changing environmental patterns in the study area. Environmental variables such as climate, temperature, and precipitation play a crucial role in shaping agricultural productivity. The shifting environmental patterns could encompass alterations in rainfall distribution, temperature regimes, or other climatic factors that directly impact crop growth and yield.

4.2. Land Surface Temperature

Figures on Land Surface Temperature (LST) conditions in the study area offer a temporal glimpse into the thermal dynamics of the region. LST is a critical parameter that reflects the heat emitted from the Earth's surface, providing insights into climatic patterns and potential impacts on the environment. Let's delve into the nuances of the LST values over the specified years. The illustration depicts a high LST value of 14.6°C, suggesting relatively warm surface temperatures. The low LST value for this year is 13.72°C, indicating a range of temperature variations within the study area. These values may be indicative of prevailing climatic conditions, land cover characteristics, or potential heat islands within the region. A noticeable shift is observed in 2000, where the high LST value increases to 12.2°C. Conversely, the low LST value decreases to 11.7°C, signifying a potential variation in thermal conditions within the study area. Changes in land use, urbanization, or alterations in vegetation cover could contribute to these temperature dynamics.

Figure 4: Shows the LST Maps of the Study Area



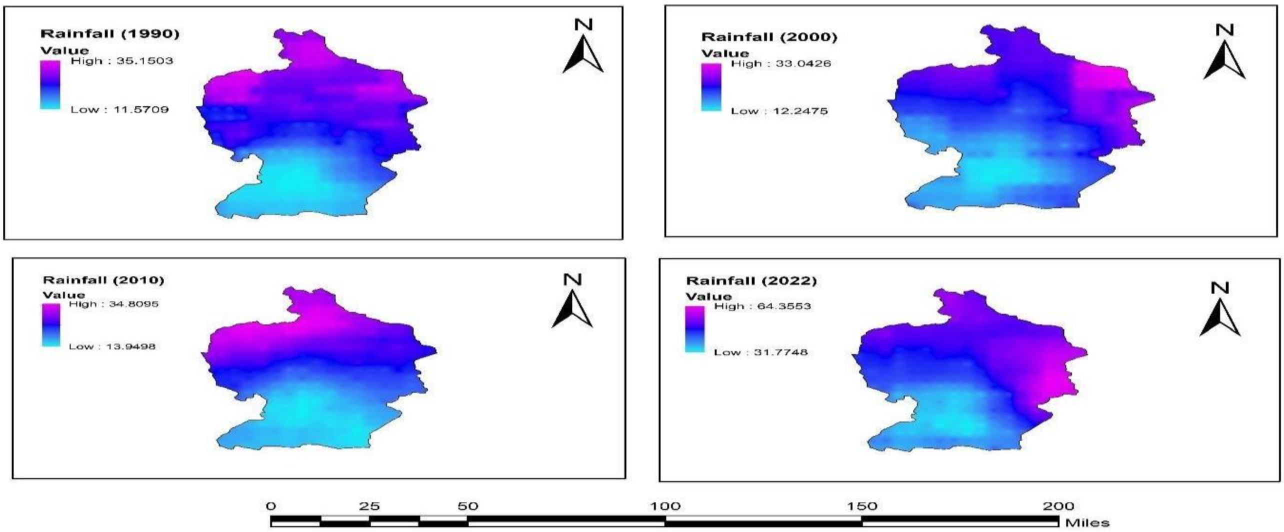
Source (Author)

The high LST value decreases to 12.3°C in 2010, suggesting a moderation in surface temperatures compared to 2000. The low LST value also shows a decrease to 10.92°C, indicating a potential range of temperatures conducive to diverse land cover and land use characteristics. In 2022, the trend continues with a further decrease in both high and low LST values. The high LST value stands at 11.53°C, while the low LST value drops to 10.52°C. These values suggest a potential amelioration in thermal conditions, possibly influenced by environmental changes, land management practices, or other factors affecting the local microclimate. The observed variations in LST values over the years might be linked to factors such as climate change, land use alterations, or modifications in vegetation cover. Understanding these temperature dynamics is crucial for assessing the impact of environmental changes on the study area's ecology, agriculture, and overall sustainability. The decreasing trend in LST values from 2000 to 2022 could imply potential environmental amelioration or adaptation strategies in response to changing conditions.

4.3. Rainfall

The rainfall data for January 1990 serves as a baseline, indicating the precipitation levels during that month. A comprehensive understanding of historical data aids in establishing climatic norms and identifying deviations in subsequent years. Comparing the rainfall in January 2000 with the baseline provides insights into short-term variations. An increase or decrease in precipitation during this period could be indicative of climatic fluctuations or trends. By 2010, analyzing the rainfall data for January offers an opportunity to observe changes over a decade.

Figure 5: Shows Rainfall Maps of the Study Area



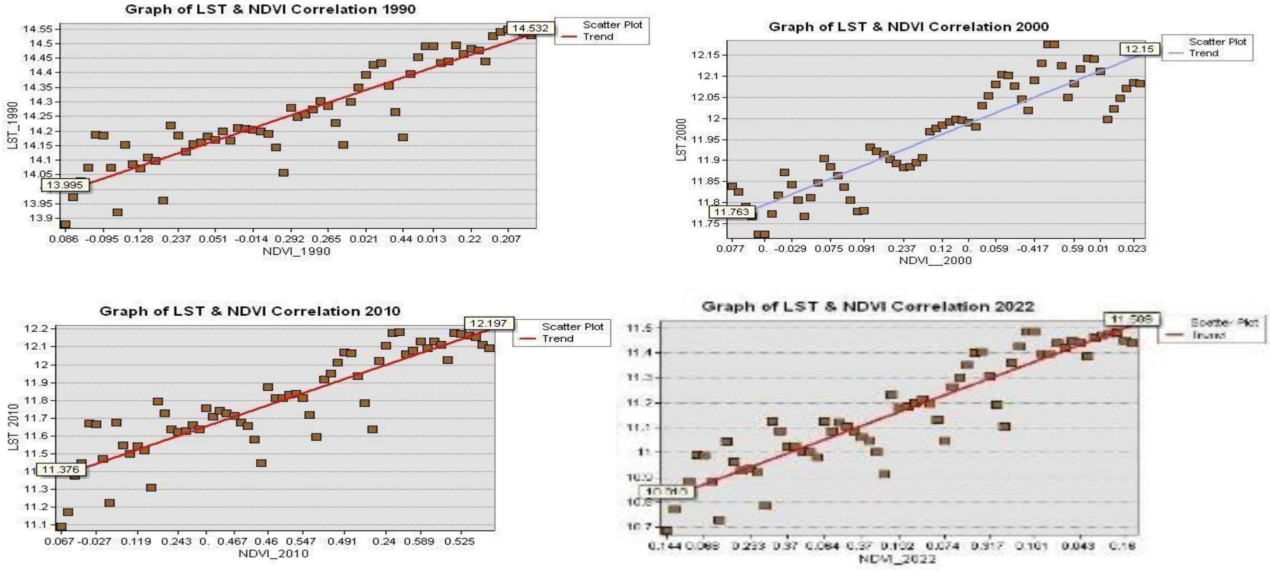
Source (Author)

Understanding long-term trends is essential for assessing climate resilience, agricultural planning, and potential impacts on water resources. The most recent data for January 2022 completes the temporal sequence, allowing for an evaluation of recent climatic conditions. Comparing this data with the baseline and intermediate years helps identify potential shifts or patterns in precipitation.

4.4. Correlation between NDVI and LST

The figure presented unveils a positive correlation between NDVI and LST, shedding light on the intricate relationship between vegetation health and thermal conditions. This correlation, vividly portrayed in the figure, suggests a compelling connection wherein higher NDVI values align with elevated Land Surface Temperatures, providing a nuanced perspective on ecosystem dynamics. The observed positive correlation implies that an increase in vegetation health, as measured by NDVI, is associated with a rise in Land Surface Temperatures. This relationship reflects the complexity of environmental interactions. The scenario illustrated in the figure hints at a dynamic where healthier and more robust vegetation tends to exhibit higher temperatures, presenting a captivating insight into the thermoregulation of ecosystems. Positive correlations between NDVI and LST, as depicted, are subject to the influence of various factors, including climate conditions, soil moisture levels, and the composition of land cover within the studied area. The figure highlights that warmer temperatures may stimulate heightened vegetation activity, consequently leading to an elevation in NDVI values. This dynamic relationship underscores the sensitivity of vegetation to thermal conditions. The presented correlation is instrumental in ecological studies, aiding researchers in understanding how temperature variations impact vegetation health and providing a foundation for climate resilience assessments.

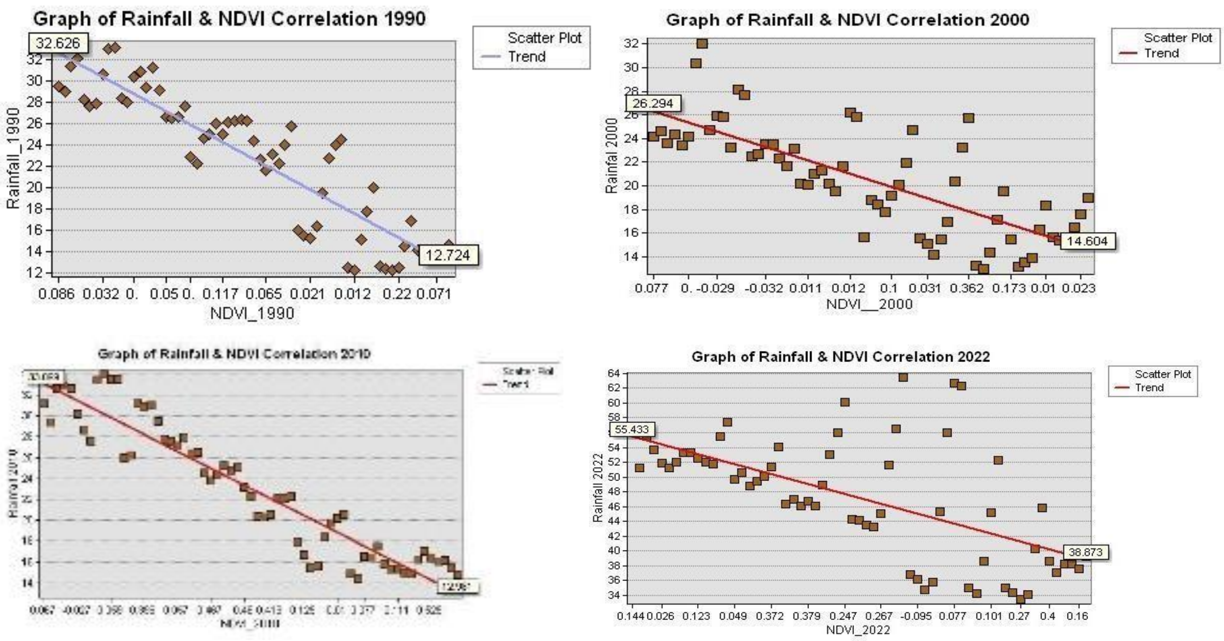
Figure 6: Shows the correlation between LST and NDVI



Source (Author)

In agricultural contexts, the positive correlation offers valuable information for precision farming, allowing farmers to make informed decisions about crop health, water management, and potential heat stress. Resource management strategies can be enhanced by leveraging the insights from this correlation, guiding sustainable land-use practices, and contributing to the mitigation of temperature-induced stress on vegetation. This correlation analysis provides a valuable framework for further exploration, encouraging in-depth studies that consider temporal variations, spatial dynamics, and additional environmental parameters to enrich our understanding of the complex interplay between NDVI and LST.

Figure 7: Shows the correlation between Rainfall and NDVI



Source (Author)

The figures presented vividly showcase a positive relationship between Rainfall and the Normalized Difference Vegetation Index (NDVI), offering valuable insights into the interconnected dynamics of precipitation and vegetation health. The observed positive correlation indicates that as rainfall increases, there is a concurrent rise in the proportion of vegetation in the study area, highlighting the close association between water availability and plant growth. The figures suggest that higher levels of rainfall contribute to the overall health of vegetation, fostering conditions conducive to robust growth and development. This positive relation underscores the crucial role of rainfall in influencing the NDVI, serving as a pivotal factor in determining the vitality and extent of vegetation cover. As the figures imply, increased rainfall leads to a proportional enhancement in the NDVI, signaling improved vegetation health and potentially indicating areas with flourishing ecosystems. The dynamic showcased in the figures aligns with ecological principles, where water availability is a fundamental driver of vegetation vitality, affecting biodiversity and ecosystem functioning. Farmers and land managers can leverage this correlation to anticipate and respond to changes in vegetation dynamics based on rainfall patterns, aiding in sustainable agricultural practices. The positive relationship between rainfall and NDVI holds significance for environmental monitoring, providing valuable data for assessing the impact of changing climate conditions on vegetation cover. The figures illustrate a compelling narrative where optimal rainfall fosters a healthier vegetation landscape, influencing land-use decisions and ecological conservation efforts. Understanding the positive correlation between rainfall and NDVI is crucial for regions dependent on agriculture, as it informs strategies for crop management, irrigation planning, and drought resilience. These figures offer a visual representation of the intricate balance between precipitation and vegetation, emphasizing the need for holistic approaches in environmental studies and resource management. The positive relation highlighted in the figures serves as a foundation for further research, encouraging investigations into the specific plant species, land cover types, and microclimatic factors that contribute to the observed patterns in the study area.

5. Conclusion

In conclusion, this study extensively investigates the environmental impacts on Rabi crops in Mianwali District, Pakistan, leveraging advanced Geographic Information Systems (GIS) and Remote Sensing technologies. Despite a diminishing contribution to the GDP, agriculture remains pivotal to Pakistan's economy, supporting livelihoods, nutrition, and export earnings. Focused on the strategically significant Mianwali District, the research integrates data from Landsat satellites, MODIS LST, and rainfall records to explore intricate relationships between environmental factors and Rabi crop productivity. The analysis of the Normalized Difference Vegetation Index (NDVI) reveals spatial and temporal variations in vegetation cover, offering crucial insights into crop health and distribution. Land Surface Temperature (LST) data provides perspectives on thermal conditions during the Rabi season, crucial for understanding water stress and environmental impacts. Rainfall data aids in assessing water availability and its impact on crop yield. Correlation analysis uncovers significant relationships, emphasizing the direct influence of environmental conditions on agricultural productivity. Temporal trends in crop types indicate diversification, particularly with "High Crops" showing an upward trajectory. However, the overall crop area in Mianwali District consistently decreases, possibly linked to changing environmental patterns. Land Surface Temperature conditions suggest potential environmental adaptations, supported by a decrease in LST values from 2000 to 2022, indicating improved thermal conditions or adaptive strategies. Rainfall analysis underscores the importance of comprehending climatic patterns for sustainable agriculture. The correlation between NDVI and LST highlights vegetation sensitivity to thermal conditions, offering valuable insights for ecological studies and precision agriculture. The positive correlation between Rainfall and NDVI emphasizes the crucial role of water availability in fostering vegetation health, guiding sustainable agricultural practices.

References

Al Mamun, M. A., Rahman, A. S., Shabee, M. S. S. A., Das, J., Alam, G. M., Rahman, M. M., & Kamruzzaman, M. (2022). Effects of climatic hazards on agriculture in the teesta basin of Bangladesh. In *Monitoring and Managing Multi-hazards: A Multidisciplinary Approach* (pp. 81-96): Springer.

Arjun, K. M. (2013). Indian agriculture-status, importance and role in Indian economy. *International Journal of Agriculture and Food Science Technology, 4*(4), 343-346.

Bibi, S., Ali, N., Nazneen, S., Rehman, S., Yousaf, R., & Khan, S. (2021). Climate change impacts on the cropping pattern in the foothills of the Himalayas, Pakistan. *Arabian Journal of Geosciences, 14*(24), 2732. doi:https://doi.org/10.1007/s12517-021-08999-9

Bustos, E., & Meza, F. J. (2015). A method to estimate maximum and minimum air temperature using MODIS surface temperature and vegetation data: application to the Maipo Basin, Chile. *Theoretical and Applied Climatology, 120*, 211-226. doi:https://doi.org/10.1007/s00704-014-1167-2

Charjan, Y., Wankhade, R., Paslawar, A., Nage, S., Lawhale, A., & Magare, P. (2023). Evaluation of suitable crop for limited irrigated condition under rabi cropping. doi:https://doi.org/10.22271/tpi.2023.v12.i2d.18441

Chhabra, V., & Haris, A. (2014). Temperature Trends and their impact on rabi crops in changing climatic scenario of Bihar. *Scholars Journal of Agricultural and Veterinary Sciences, 1*(4A), 230-234.

Gadakh, S., Dalvi, U., Nirmal, S., & Dudhade, D. (2021). Effect of temperature and rainfall regimes on growth phases and biological yield in rabi sorghum. *Journal of Progressive Agriculture, 12*(1), 58-65.

Gong, J., Dong, H., Xia, Q.-S., Huang, Z.-y., Wang, D.-k., Zhao, Y., . . . Wang, Q. (2020). Correlation analysis between disease severity and inflammation-related parameters in patients with COVID-19: a retrospective study. *BMC infectious diseases, 20*, 1-7. doi:https://doi.org/10.1186/s12879-020-05681-5

Gupta, H. (2013). Agricultural diversification in India. *International Journal of Advanced Research in Management and Social Sciences, 2*(5), 221-231.

Gupta, S. (2014). A comparative study of Indian economy in pre and post reform period: an econometric analysis. *Global Journal for Research Analysis, 3*(2), 51-56.

Karim, I. N. (2021). CORRELATION ANALYSIS: Are Religious Scavengers More Motivated? *AKADEMIK: Jurnal Mahasiswa Humanis, 1*(2), 59-67. doi:https://doi.org/10.37481/jmh.v1i2.229

Krishna Kumar, K., Rupa Kumar, K., Ashrit, R., Deshpande, N., & Hansen, J. W. (2004). Climate impacts on Indian agriculture. *International Journal of Climatology: A Journal of the Royal Meteorological Society, 24*(11), 1375-1393. doi:https://doi.org/10.1002/joc.1081

Kumar, S., KaurSidana, B., & Thakur, S. (2023). Climate change and its impact on productivity of major kharif and rabi crops in Punjab. *MAUSAM, 74*(1), 151-160.

Malik, D., & Singh, D. (2010). Dynamics of production, processing and export of wheat in India. *Journal of Food Security, 1*(1), 8-18.

Mallika, V. (2012). Agrarian crisis in India: its impact on production and export. *Socio-economic voices*, 1-8.

Mujtaba, A., Nabi, G., Masood, M., Iqbal, M., Asfahan, H. M., Sultan, M., . . . Nasirahmadi, A. (2022). Impact of cropping pattern and climatic parameters in lower Chenab Canal system—Case study from Punjab Pakistan. *Agriculture, 12*(5), 708. doi:https://doi.org/10.3390/agriculture12050708

Nageswararao, M., Dhekale, B., & Mohanty, U. (2018). Impact of climate variability on various Rabi crops over Northwest India. *Theoretical and Applied Climatology, 131*, 503-521. doi:https://doi.org/10.1007/s00704-016-1991-7

Nageswararao, M., Mohanty, U., Osuri, K. K., & Ramakrishna, S. (2016). Prediction of winter precipitation over northwest India using ocean heat fluxes. *Climate Dynamics, 47*, 2253-2271. doi:https://doi.org/10.1007/s00382-015-2962-x

Naik, G. (1999). Procurement and marketing of wheat and wheat products.

Naiyer, A., & Md, S. U. H. (2015). Agriculture play crucial role in the life of Indian economy. *International Journal of Scientific Research and Management, 3*(3), 2239-2245.

Pal, R., Murty, N., & Rao, M. (2012). Response of wheat to temperatures as simulated with CERES-wheat model in Tarai region. *Journal of Agrometeorology, 14*(2), 163-166. doi:https://doi.org/10.54386/jam.v14i2.1417

Pal, R., Rao, M., Nain, A., & Sumanan, R. (2012). Temperature effect on wheat (cv WH-542) as simulated with CERES-wheat model for different sowing environments. *J Environ Ecol, 30*(4A), 1541-1545.

Pal, S., Chowdhury, P., Talukdar, S., & Sarda, R. (2022). Modelling rabi crop health in flood plain region of India using time-series Landsat data. *Geocarto International, 37*(13), 3761-3790. doi:https://doi.org/10.1080/10106049.2020.1869328

Press, W. H. (1992). *The art of scientific computing*: Cambridge university press.

Selvaraju, R. (2003). Impact of El Niño–southern oscillation on Indian foodgrain production. *International Journal of Climatology: A Journal of the Royal Meteorological Society, 23*(2), 187-206. doi:https://doi.org/10.1002/joc.869

Sharma, P. (2007). *Human geography: the economy*: Discovery Publishing House.

Shinde, V., Jadhav, J., Patil, J., Bavadekar, V., & Pawar, P. (2021). Effect of Climate Change on Production of Major Rabi Cereals in Western Maharashtra: Consequences on Food Security. *Journal of Agriculture Research and Technology, 46*(1), 23.

Tenreiro, T. R., García-Vila, M., Gómez, J. A., Jiménez-Berni, J. A., & Fereres, E. (2021). Using NDVI for the assessment of canopy cover in agricultural crops within modelling research. *Computers and Electronics in Agriculture, 182*, 106038. doi:https://doi.org/10.1016/j.compag.2021.106038

Waseem, L. A., Shafiq, H., Maqbool, M. S., Rehaman, M. W. U., Ahmad, M., & Zahra, A. (2023). Spatiotemporal dynamics of agricultural drought and food insecurity in Asia. *Journal of Positive School Psychology, 7*(2), 89-103.

Yang, Y., Wang, S., Bai, X., Tan, Q., Li, Q., Wu, L., . . . Deng, Y. (2019). Factors affecting long-term trends in global NDVI. *Forests, 10*(5), 372. doi:https://doi.org/10.3390/f10050372