Drought Risk Assessment of Muzaffargarh District by Using Geospatial Techniques

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Abstract

Drought is a major natural hazard characterized by extended periods of insufficient precipitation, posing serious threats to both ecosystems and human livelihoods. This study evaluates drought risk in Muzaffargarh District, Pakistan, by combining geospatial techniques such as remote sensing (RS) and geographical information systems (GIS). Landsat ETM+ and OLI imagery from 2002, 2008, 2013, and 2018 were used to compute the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). The study found that LST increased from 38.77 °C in 2002 to 42.54 °C in 2018, while NDVI values decreased from 0.989 to 0.576. This inverse trend confirms declining vegetation cover and rising surface temperatures, which are important indicators of increasing meteorological and agricultural drought risk. Regression analysis confirms a negative correlation between LST and NDVI ($R^2 = 0.4167$), indicating the region's vulnerability to climatic stress. The supervised classification of LU/LC data reveals significant urban expansion and vegetation loss between 2002 and 2018. The resulting drought risk maps identify increasingly dry zones, providing critical spatial insights for policymakers and stakeholders as they develop targeted and proactive drought mitigation plans.

***Keywords**:* Drought, GIS, LST, meteorological drought, NDVI, remote sensing.

Introduction

Drought is one of the most complex and devastating natural hazards, affecting millions of people worldwide, particularly in arid and semi-arid areas. It is characterized by a prolonged deficiency in precipitation, resulting in water scarcity, crop failure, and socioeconomic distress. (WHO 2021). Climate change has increased the frequency, severity, and duration of droughts, posing significant challenges for water resource management and food security (IPCC et al. 2023). Pakistan, as a predominantly agrarian economy, is especially vulnerable to droughts. Southern Punjab's Muzaffargarh District is not an exception; it has experienced ongoing dry spells that have negatively impacted livelihoods and agricultural productivity (Ahmad et al. 2020).

Traditional drought monitoring approaches frequently deficiency spatial resolution and fail to deliver timely warnings at the local level. The integration of geospatial techniques, with remote sensing (RS) and geographic information systems (GIS), has been established as a reliable and cost-effective technique for drought risk assessment (Nepal et al., 2021). These technologies permit unceasing monitoring of vegetation health, land surface temperature, soil moisture, and rainfall anomalies, all of which are key gauges of drought. The Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), and the Standardized Precipitation Index (SPI) are broadly used indicators to measure drought vulnerability and spatial degree (Amarasingam et al. 2022). In Muzaffargarh, a comprehensive drought risk assessment is vital for making knowledgeable decisions and planning. The district's varied agro-climatic zones, reliance on seasonal rainfall, and growing demand for water resources necessitate the usage of advanced geospatial tools for real drought monitoring and mitigation. This study purposes to assess drought risk in Muzaffargarh District by investigating multitemporal satellite data and climatic variables through geospatial techniques. The consequences are anticipated to provision local authorities and stakeholders in developing targeted drought preparedness and resilience strategies.

Research objectives

This study aims to:

- To evaluate the underlying factors contributing to drought risk in the study area through geospatial analysis.
- To track changes in vegetation health and surface temperature over time.
- To investigate how land use and land cover changes contribute to drought risk.

Study area

Muzaffargarh District is located in south-central Punjab province, Pakistan, at latitude 30°4′10″N and longitude 71°11′39″E. The district covers 8,249 km² and borders the Chenab River to the east and the Indus River to the west. The region is divided into four tehsils: Muzaffargarh, Jatoi, Alipur, and Kot Addu, with 111 union councils in total.

- The districts of Khanewal and Multan are located on the eastern side of District Muza ffargarh, across the Chenab; the district of Layyah borders the district on the north; an d the districts of Bahawalpur and Rahimyar Khan Border to the south. The districts of Dera Ghazi Khan and Rajanpur are located on the western bank of the Indus River, w hile District Jhang is located in the northeast.

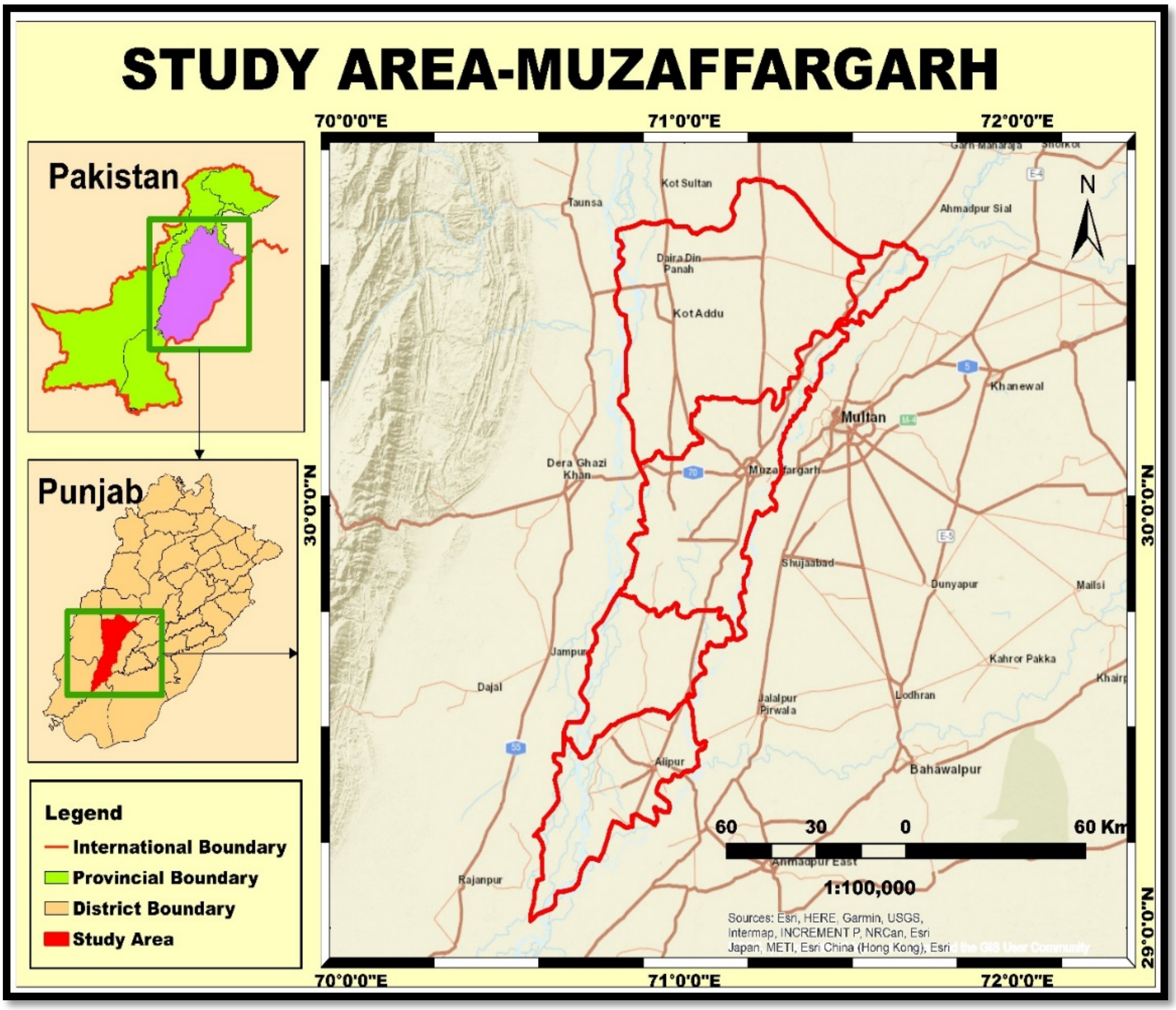

Figure 1: *Study Area Map*

(Source: USGS Earth Explorer)

Climate

Mostly the area of Muzaffargarh is dry and also consists of the barren lands and sand dunes known as the thal area, but the other portion of the area, whether flooded from the river or irrigated by inundation canals, is less dry.

- The climate of Muzaffargarh is arid, with scorching summers and moderate winters. The city has seen among Pakistan's most severe weather. The months of May through Septem ber are hot, but between mid-August and mid-September, a cool breeze might begin to bl ow, which would lower the temperature. In December and January, there are cold nights with heavy frost, which seriously damages vegetables, cotton, mangoes, and sugarcane.
- The temperature that was recorded was roughly 1°C at the lowest point and 54°C at the m

aximum.

- The maximum temperature graph displays how many days per month reach certain tempe ratures. Figure 2 shows that the maximum temperature that is of 40°C the Muzaffargarh is in June to July, the whole month in 2018.

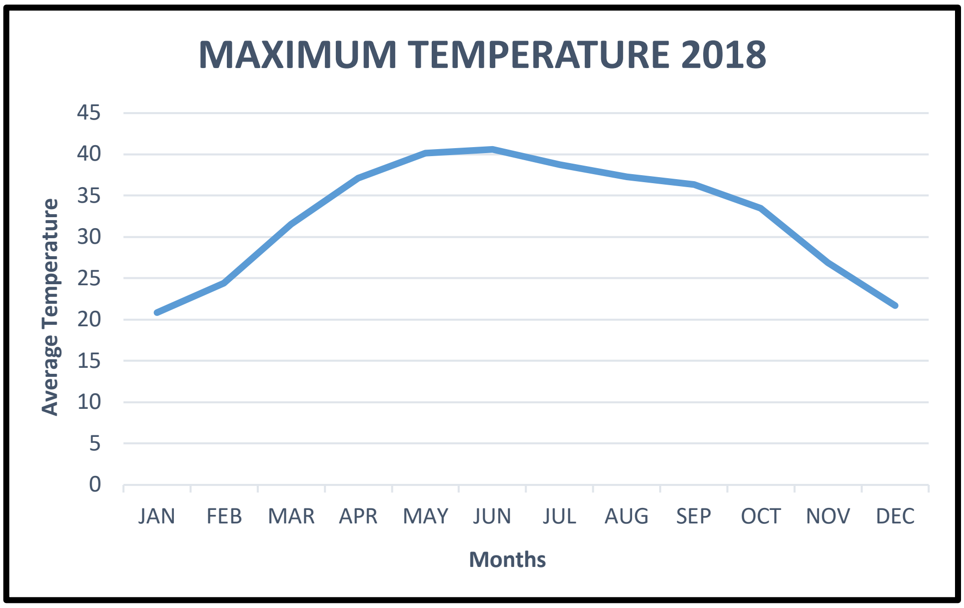

Figure 2: *Graphical representation of the maximum temperature in Muzaffargarh (2018)*

Material and Methods

The overview of used methodology used to work out the proposed research. Reliable indices to distinguish the spatial and temporal dimensions of drought existence and its concentration are necessary to evaluate the impact, and also for decision-making and crop research priorities for improvement. The methodological framework is illustrated in Figure 2.

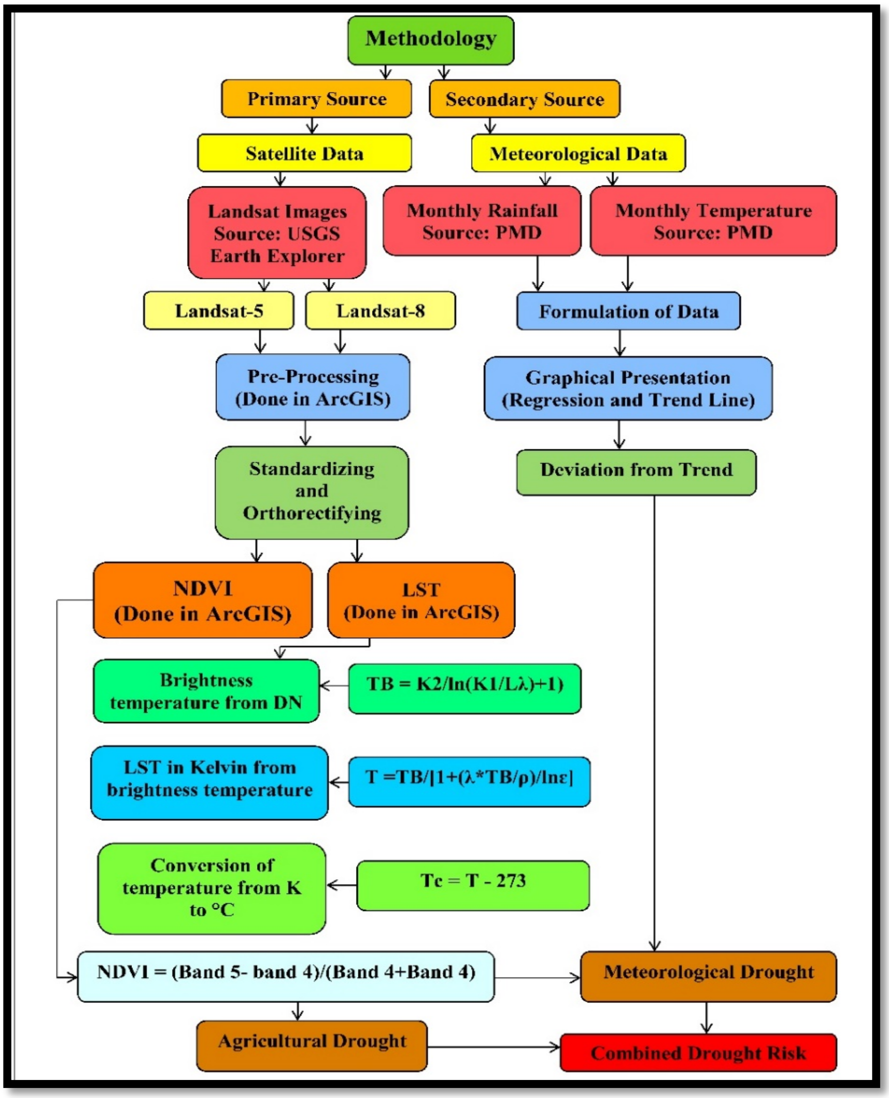

Figure 3: *Methodological Framework*

Dataset used

The satellite data, that has been taken from the United States Geological Survey (USGS) (http://earthexplorer.usgs.gov), Landsat 5 and 8 Enhanced Thermal Mapper (ETM+) and Operational Land Imager (OLI), images (path 150 rows 39, path 151 rows 39 and path 151 row 40) with the 30 m resolution, of July, for the years 2002, 2008, 2013 and 2018 as mentioned in Table 1 used for applying the analysis by using the Remote Sensing and Geographical Information System techniques. In this study, the secondary data source, as Pakistan Meteorological Department (PMD), brings meteorological data on monthly rainfall and monthly temperature, which has been collected for the period 16 years, ranging from 2002-2018.

Table 1. Detailed Information about satellite imagery. (Source: USGS Earth Explorer)

Satellite	Dates of Images	Resolution	Reference system/Path/Row
Landsat 5	14/07/2002	30m	WRS/150/39
Landsat 5	21/07/2002	30m	WRS/151/39
Landsat 5	21/07/2002	30m	WRS/151/40
Landsat 5	14/07/2008	30m	WRS/150/39
Landsat 5	05/07/2008	30m	WRS/151/39
Landsat 5	21/07/2008	30m	WRS/151/40
Landsat 8	12/07/2013	30m	WRS/150/39
Landsat 8	19/07/2013	30m	WRS/151/39
Landsat 8	19/01/2013	30m	WRS/151/40
Landsat 8	10/07/2018	30m	WRS/150/39
Landsat 8	01/07/2018	30m	WRS/151/39
Landsat 8	01/07/2018	30m	WRS/151/40

Data analysis

Satellite imagery was analyzed using key drought indices such as the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use and Land Cover (LU/LC). The Pakistan Meteorological

Department (PMD) provided secondary climatic data in addition to satellite data. Microsoft Excel was used to establish and examine the mean temperature and precipitation averages for the year. The line graphs were formed by applying regression analysis to these variables, which assisted in influential and identifying the study area's drought risk. A vigorous measure of the Earth's surface energy balance, land surface temperature (LST) is extensively recognised as a vital variable in the investigation of land-surface processes at both regional and global scales (Yadav et al. 2024). In this study, LST was performed by means of satellite thermal bands—Band 6 for Landsat 5, and Bands 10 and 11 for Landsat 8. The satellite imagery for Muzaffargarh, Pakistan, experienced knowledgeable preprocessing, which comprised mosaic generation and geometric correction.

Satellite data was transformed into real-world spatial coordinates during image processing by applying the WGS 1984 datum and the Universal Transverse Mercator (UTM) projection system. Table 2 shows the full sequence of image processing and analytical procedures used in this LST:

Step no. 1: Conversion of DN values to the spectral radiance by using the equation

$$\mathbf{L\lambda = ML*Qcal + Al}$$

Lλ is the cell value as radiance (Ebaid 2016). ML is the radiance multi-band value, Al is the radiance add band value, and Qcal is the thermal band used in it.

Step no.2: Radiance values from the TM 5 / L8 thermal band were then changed to radiant surface temperature, that is, top-of-atmosphere brightness temperature, using thermal calibration constants (Ebaid 2016) by the given equation:

$$\mathbf{TB = K2/ln(K1/L\lambda)+1)}$$

Step no.3: In the very last step in we got the outcomes that are the temperature, which was in kelvin, converted into Celsius (Cº) through this equation:

$$\mathbf{T= T(K)-273.15}$$

Table 2. Processing steps, as well as the conversion of DN numbers to LST

Processing Steps	Formulas	Explanation
Conversion of DN (Digital Number) to At-Satellite Brightness	TB = K2/ln(K1/Lλ)+1)	• K1 Band specific thermal conversion constant (in watts/meter squared *ster*µm) • K2 = Band-specific thermal conversion consta nt (in kelvin) • Lλ =spectral radiance at sensor aperture meas ures (in watts/ meter squared *star*µm) • λ =wavelength of emitted radiance • ρ =h*c/σ (1.438*10^-²m-K)

Temperature.		• h=Plank's Constant (6.62*10^-34 j-s) • σ = Boltzmann Constant (1.38*10^-23 j/K) • c =velocity of light (2.998*10^8 m/s) • ε =emissivity, which is given at: ε = 1.009+0. 047 ln(NDVI)
Calculation of Land Surface Temperature in Kelvin	T=TB/[1+(λ*TB/ρ)/lnε]	• T = land surface temperature in Kelvin • Tc = land surface temperature in Celsius.
Conversion from Kelvin to Celsius	Tc = T – 273	

The Normalized Difference Vegetation Index (NDVI) is one of the most extensively used and reliable vegetation indices for monitoring plant health and assessing drought conditions (Whig et al. 2024). Tucker and Choudhury applied it to drought monitoring for the first time in 1987. In this study, vegetation-related features were extracted from the Muzaffargarh district 3-band satellite imagery using the NDVI technique.

NDVI = (NIR- RED)/(NIR+RED)

Or

NDVI = (Band 5 – Band 4)/(Band 4 + Band 5)

NIR signifies near-infrared reflectance, and RED characterizes red reflectance. This ratio demonstrates the difference between healthy vegetation, which strongly reflects NIR and absorbs RED, and stressed or non-vegetated surfaces, which do not exhibit this spectral behavior. Using this index on Landsat satellite imagery, variations in vegetation cover across space and time were successfully identified, allowing for a detailed assessment of vegetative stress and potential drought conditions in the region.

Variations in land use and land cover (LU/LC) pose a threat to our comprehension of environmental change on a global scale. In this study, supervised classification of LU/LC dynamics in the Muzaffargarh district was carried out using ArcGIS 10.5.

- The process began with the satellite images being organized. For each tile, multispectral images were formed by combining Landsat 5 bands 1–6 and Landsat 8 bands 1–11. After extracting the study area from the larger dataset, a mosaic process was carried out using a reliable spatial reference system.

- To confirm the land features in the study area, ground truthing was carried out by superimposing a base map in ArcGIS. Initiating the pertinent tool and generating training samples in polygonal form over the removed image tiles was the first step in supervised classification. Water, vegetation, and built-up areas were the three main LU/LC categories into which these samples were detached. After that, a GCS (Geographic Coordinate System) signature file encompassing the training data was saved.
- Importing the GCS signature file into the ArcGIS workspace was the last step by step. Applying the symbology of the layer, each land cover class was given a distinct color: brown for built-up areas, green for vegetation, and blue for water bodies. The inclusive distribution of land cover and its variations over time were accurately and clearly represented by this classification.

Results

Abundant geospatial analyses, such as the Index of Normalized Difference Vegetation (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use/Land Cover (LU/LC) mapping, were performed using the Landsat satellite sequence. To confirm outstanding spatial resolution, all maps were made at a scale of 1:10,000. Agricultural and meteorological drought risks have been mixed to generate a composite risk map, which demonstrates that the study area is likely to knowledge compounded hazards due to the convergence of these drought categories.

Land cover change

In this study, LU/LC variations were analyzed using a supervised classification method, chiefly applying the Maximum Likelihood Classification (MLC) technique. The land cover was classified into three major groups: water, vegetation, and built-up areas, by normal remote sensing classification practices. The investigation of the Muzaffargarh district over 16 years (2002-2018) exposes a significant change in land use patterns.

The most notable change is rapid urbanization, which has resulted in a significant increase in built-up areas. This trend coincides with both population growth and the arrival of refugees in the region. As urbanization has increased, vegetative cover has decreased, indicating a significant shift in land use. These spatial changes are displayed by LU/LC maps created with ArcGIS 10.5. Although the built-up area has grown, vegetation still occupies a larger portion of the district. However, the consistent decline in vegetation suggests a possible change in local climatic conditions, particularly an increase in land surface temperature. This pattern demonstrates a direct relationship between land use changes and the risk of meteorological drought, which can lead to agricultural drought. The temporal LU/LC maps for 2002 and 2018 show in Figure 4 visual evidence of these changes, emphasizing the importance of sustainable land management in mitigating environmental risks.

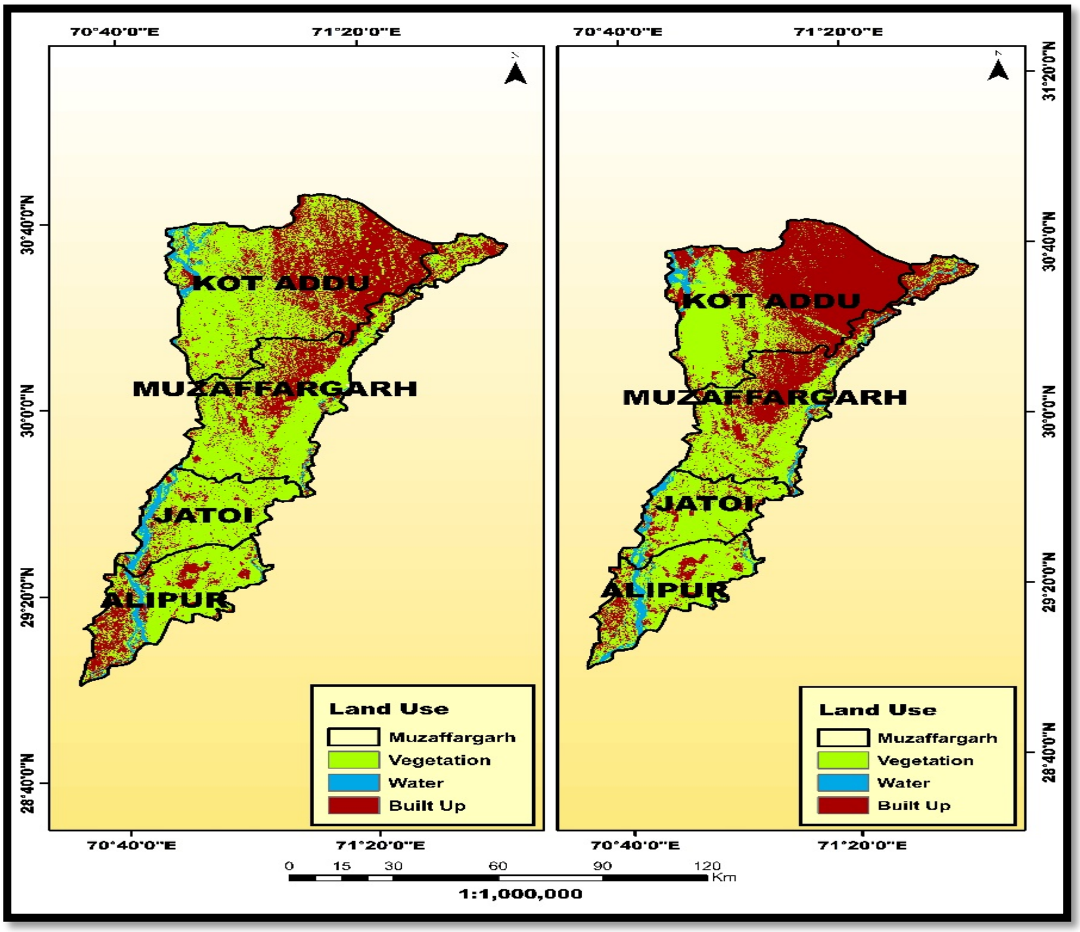

Figure 4: *Temporal Variation in Land Use Mapping (2002-2018)*

Land surface temperature (LST)

Globally, urban temperatures have been steadily increasing (Patel and Patel 2024). Several studies have used satellite-based measurements to accurately calculate Land Surface Temperature (LST) (Mustaquim 2024). The present analysis shows in Figure 5 a significant increase in maximum temperature from 38.77 °C in 2002 to 42.54 °C in 2018. The line Graph 1 and 2 depicts the trend in average maximum and minimum land surface temperature (MMaxT and mminT) for the years 2002, 2008, 2013, and 2018. This consistent temperature rise indicates an increasing risk of meteorological drought. Furthermore, the rise in LST has had a direct impact on vegetation health and coverage, accelerating the onset of agricultural drought.

Over the 18-year study period, the maximum Normalized Difference Vegetation Index (NDVI) value decreased significantly, from 0.989 in 2002 to 0.576 in 2018. This decrease reflects the declining vigor and extent of vegetative cover, particularly cropland, which is extremely vulnerable to climatic stress. A comparison of NDVI and LST maps reveals that the study area experienced increasingly dry conditions in 2018. The spatial correlation between rising surface temperatures and declining vegetation highlights throughout Table 3 the region's increased vulnerability to drought, emphasizing the importance of proactive mitigation strategies and sustainable land management practices.

Table 3. Summary of Land Surface Temperature (LST)

Year	**LST Value (C°)**	
	Maximum	**Minimum**
2002	38.77419	21.012
2008	38.7097	21.324
2013	39.4871	21.42
2018	42.5432	21.54

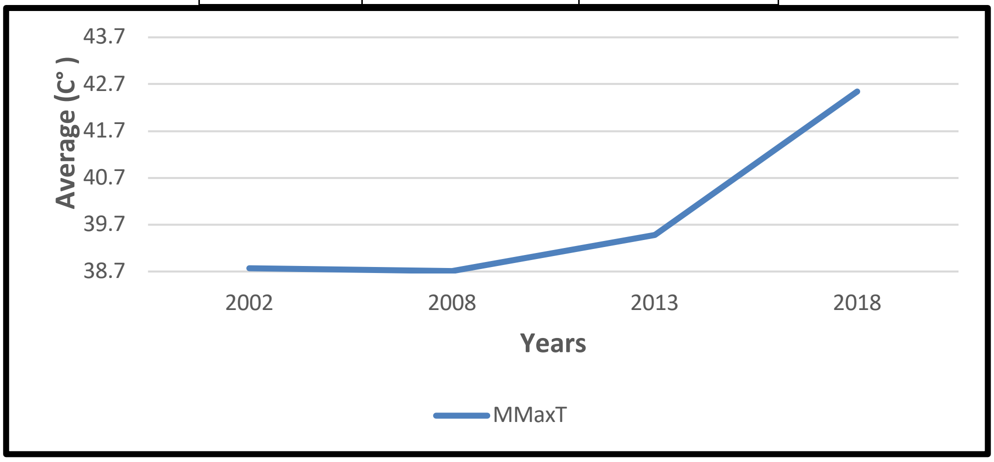

Figure 5: Temporal variation in maximum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

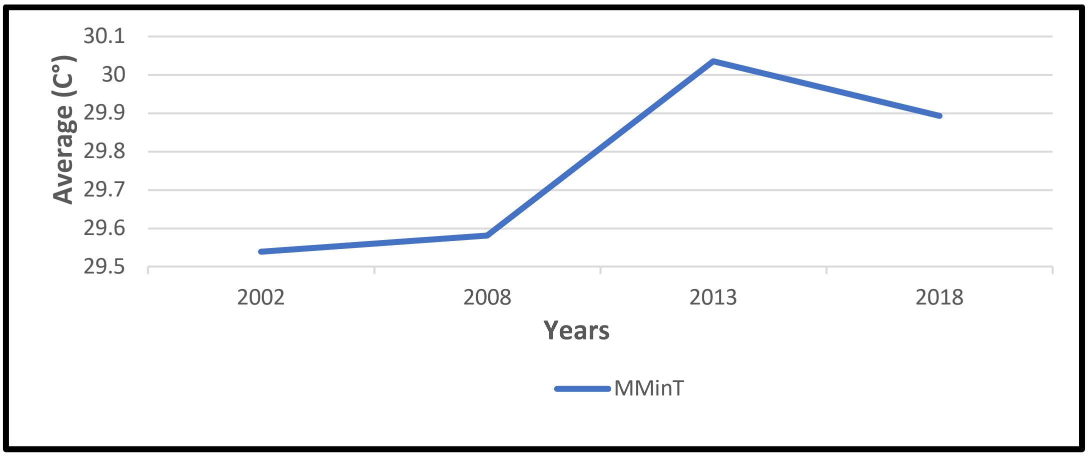

Figure 6: Temporal variation in minimum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

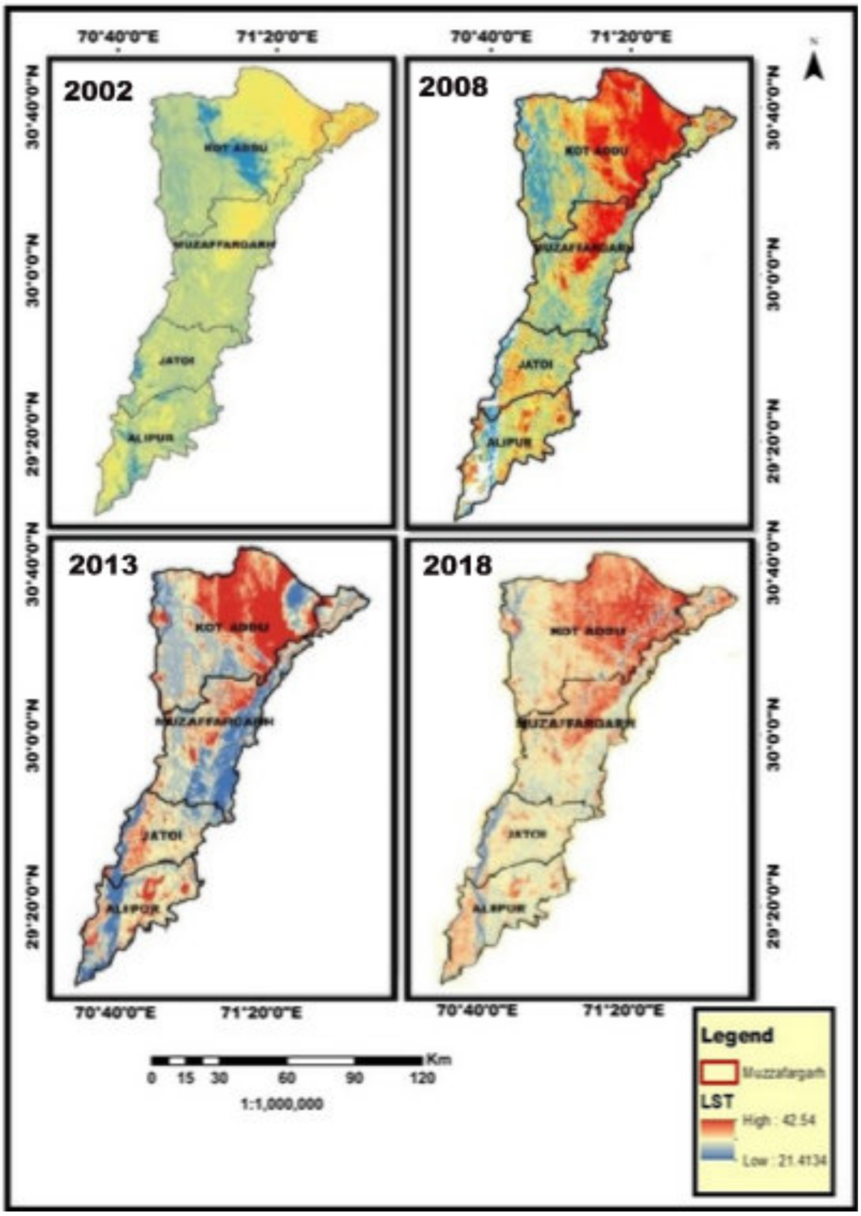

Figure7: *Temporal Map of Land Surface Temperature (LST) (2002-2018*)

Normalized difference vegetation index (NDVI)

NDVI was used to derive vegetation cover classes, allowing for the identification of spatial and temporal variations between 2002 and 2018. NDVI values fell dramatically during this time, from a high of 0.989 in 2002 to 0.576 in 2018, indicating, through Figure 6, a significant decline in vegetation health and density. This decline is primarily due to climate change, specifically rising atmospheric and land surface temperatures. According to international classification standards, much of the study area has shifted from moderate vegetation to increasingly dry conditions, as shown in Table 4. This shift indicates an increased risk of agricultural drought, which could harm crop productivity and local livelihoods. The observed trend emphasizes the critical need for climate-resilient agricultural practices and sustainable land use planning.

Table 4. Classification of NDVI

NDVI Ranges	Drought
<0	Extreme Drought
0-0.2	Dry
0.2-0.4	Moderate
0.4-0.6	Wet
>0.6	Extreme Wet

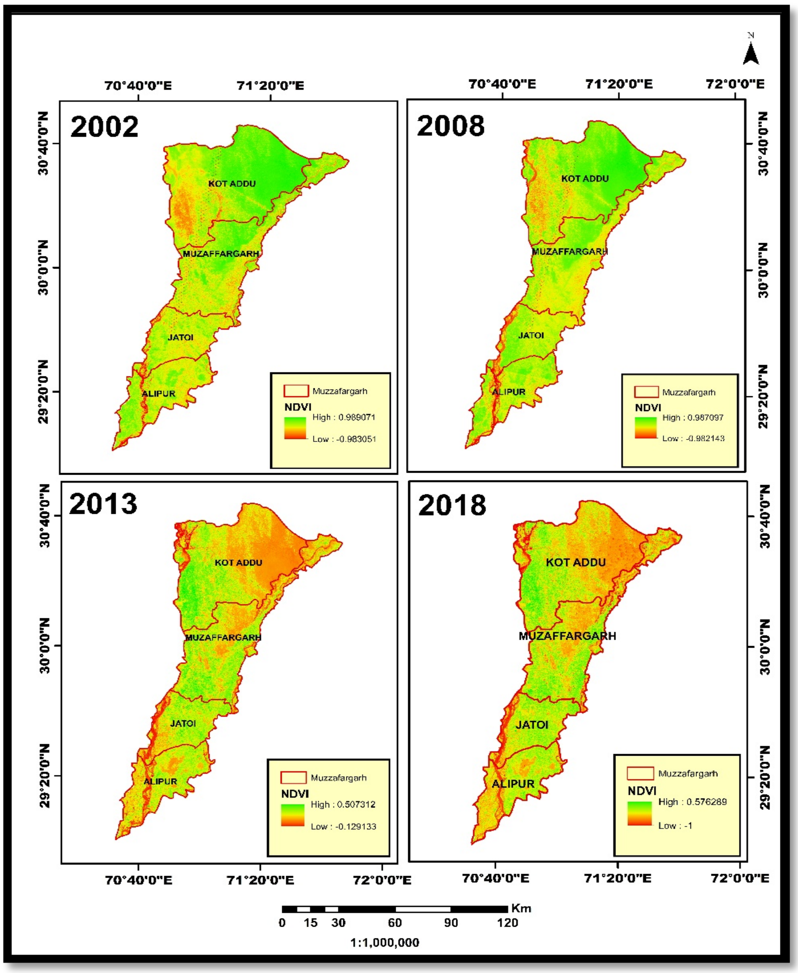

Figure 8: *Temporal Variation in Normalized Difference Vegetation Index (NDVI)*

The NDVI values in Muzaffargarh District indicate as well in Table 8, a clear decline i n vegetation health over time. The maximum NDVI values for 2002 and 2008 were relatively high (0.989 and 0.987, respectively), indicating dense and healthy vegetation cover. However, by 2013, the maximum value had fallen significantly to 0.507, with only a slight recovery to 0 .576 in 2018. Similarly, minimum NDVI values indicate increased vegetation stress, with the lowest value recorded in 2018 (-1.0). These trends indicate a consistent degradation of vegetat ion cover, most likely due to rising temperatures, urban expansion, and climatic stress, implyi ng an increased risk of agricultural droughts.

Table 5. Summary of Normalized Difference Vegetation Index (NDVI)

Year	**NDVI**	
	High	**Low**
2002	0.989071	-0.98305
2008	0.987097	-0.98214
2013	0.507312	-0.12913
2018	0.576289	-1

Correlation and linear regression analysis were performed between NDVI and LST anomaly. Graph 3 displays a clear view that there is an inverse correlation between land surface temperature (LST) and normalized vegetation index (NDVI). This directly indicates the risk of drought in this research target area. The graph demonstrates a negative linear relationship between temperature and NDVI, represented by the regression equation:

$$y = -0.0924x + 4.4492$$

This means that for every 1°C increase in temperature, the NDVI drops by about 0.0924 units, indicating a decline in vegetation health.

- The coefficient of determination ($R^2 = 0.4167$) indicates a moderate negative correlation. Temperature changes account for approximately 41.67% of the variation in NDVI.
- The NDVI values decrease as the temperature rises from 38.77°C (2002) to 42.54°C (2018), indicating that vegetation cover and surface temperature are inversely correlated.
- This tendency supports the theory of increased drought risk, which holds that vegetation stress, a decline of greenness, and possible agricultural drought are caused by increasing temperatures.

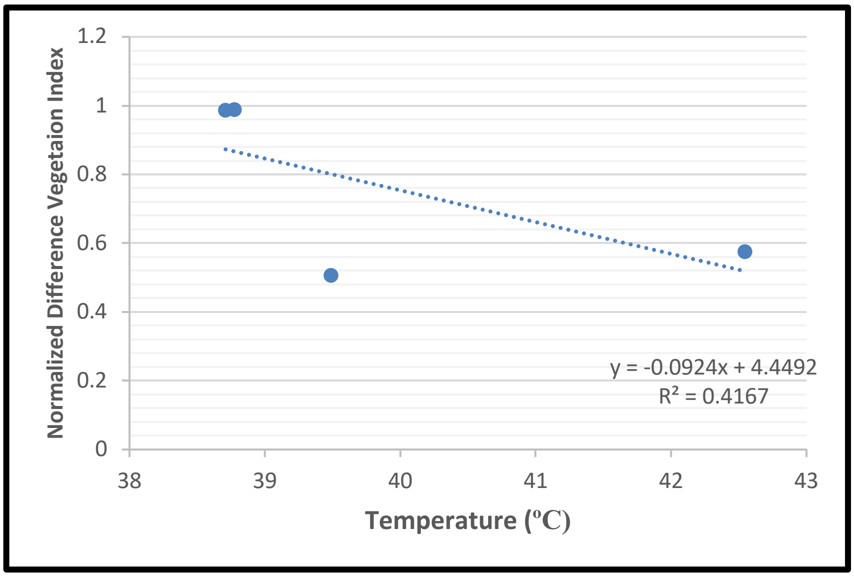

Figure 9: *Correlation between Land Surface Temperature and Normalized Difference Vegetation Index*
(Source: PMD)

Discussion

This study's objective was to measure the Muzaffargarh district's risk of agricultural and meteorological drought using geospatial methods. A mutual occurrence worldwide, droughts have distressing belongings on agriculture, ecosystems, and socioeconomic systems (WHO 2021). The absence of long-term, high-resolution rainfall data for the target area was a component of the study's restrictions. Nevertheless, this limit was addressed by using satellite-derived indices like the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and Land Use/Land Cover (LULC) classification. To professionally map and track situations of drought, a amount of studies have employed NDVI and LULC analysis (Mahajan and Dodamani 2015). Forest and shrubland areas have progressively decreased over time, according to historical trends in land cover shifts, while agricultural land, built-up areas, and water bodies have improved (Gandhi et al. 2015). In this study, a alike trend was detected, with supervised classification of LULC data and NDVI analysis revealing a gradual decline in vegetation cover from 2002 to 2018, representing increased agricultural drought vulnerability.

LST has been widely used in prior studies as a proxy for surface moisture circumstances and drought risk (Latha 2021). Our analysis reveals a rising trend in surface temperatures across the district, typically in recent years, which further supports the presence of meteorological drought. The inverse relationship between NDVI and LST, also engrained in earlier studies (Mahajan and Dodamani 2015; Sun and Kafatos 2007), was validated settled regression analysis in this research. The negative correlation experiential through the summer season strengthens the notion that improved surface temperatures contribute to vegetation stress and decline. Overall, the integration of NDVI, LST, and LULC data brings a comprehensive thoughtful of drought dynamics in Muzaffargarh. This approach not only enables spatial identification of drought-prone areas but also offers a scientific basis for developing risk mitigation strategies. Such multi-source geospatial analyses are energetic for effective drought monitoring, early warning systems, and adaptive land management planning under changing climatic circumstances (IPCC, 2023).

Conclusion

Prolonged precipitation deficiencies, or drought, pose thoughtful problems for agriculture and the situation. By pursuing agricultural and meteorological droughts using geospatial tools like the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), this study measures the risk of drought in the Muzaffargarh District. It has been demonstrated that declining rainfall lowers NDVI values, suggesting the beginning of drought and vegetation stress. From 2002 to 2018, research was led in Muzaffargarh, which is situated between the Chenab and Indus rivers. In accumulation to notable land use moves from vegetation to built-up areas, the results validate a steady rise in surface temperatures and a consistent decline in vegetation cover. This trend designates which drought vulnerability is increasing. Regression analysis demonstrates that LST and NDVI have an inverse relationship, highlighting surface temperature rise as a key factor influencing the risk of agricultural and meteorological drought.

Acknowledgement

I express my reflective gratitude to my honorable parents, and my technical supporter, Ms. Hira Shahbaz, who stimulated me to do my work with full confidence.

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Received: 19 March 2025
Revision Received: 27 May 2025