APPRAISAL OF CLIMATE CHANGE DISASTER AND FOOD SECURITY IN KHYBER PAKHTUNKHAW PAKISTAN USING GEOSPATIAL TECHNOLOGIES

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ABSTRACT

Drought is one of the most severe natural disasters. It negatively influences the crop output considerably as water resources are inadequate across large geographic areas. Food insecurity, hunger, and poverty are widespread in three Pakistani provinces: Baluchistan, Khyber Pakhtunkhwa, and Sindh. Until March/April 2022, roughly 4.66 million people, or 25% of the population examined, were severely food insecure. Historically, the severity of a drought is evaluated using several different indicators, with the selection of indices depending on the data that is easily accessible. By multiple aspects, including potential evapotranspiration and rainfall data on a standard timescale and computing monthly, seasonal, or annual data, the Reconnaissance Drought Index (RDI) has a significant advantage over the other indices in determining drought severity. When rainfall in a region is significantly lower than the amount of potential evapotranspiration, drought situations can occur on the earth. Rainfall will often occur in locations with an increase in the relative humidity of the air. The reconnaissance drought index (RDI) for Khyber Pakhtaunkhawa province in Pakistan was calculated from 1981 to 2020 for 3-, 6-, and 12-month timeframes. This research employed rainfall, minimum and maximum temperature data from KPK province to describe drought using the DrinC program, the Man Kendall test, and Sen's slope calculator to determine drought patterns and variation. All regions had moderate, severe, and extreme droughts, with RDIs between -1.0 and -3.5. RDI 3-, 6-, and 12-month evaluations highlighted 1991, 1994, 2000, 2010, 2015, and 2017. These results indicate that productivity declines in dry and subsequent years due to seasonal rainfall and soil moisture retention.Wheat production averaged 1.7 tones ha-1 year-1, with significant variations. Between October and December, it is an essential to have favorable growing conditions to increase productivity. If droughts occur in this era, the yield will be substantially more negatively impacted than if they occur later in the growing cycle. The 3-month RDI values offer a more accurate description of this variation than the six-month and twelve-months RDI Values. Geospatial drought analysis indicates a considerable variance in drought patterns across the Kpk province over the last 4 decades. Because long-term droughts sometimes affect water quality, especially groundwater, a rise in the intensity of long-term droughts could pose a risk to the water management in the regions that have been examined. Analysis of the Landsat TM 30 m data took place. At the same time, Landsat imageries were utilized to generate the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) for drought evaluation. The findings of the NDWI indicate an increase in value from 0.58 to 0.7 for the KPK region.

1. INTRODUCTION

Pakistan, a country in Southeast Asia with 225.2 million inhabitants (PBS 2021), has serious water issues (Bacha et al., 2021). In Pakistan, where there is a 52% water deficit, the severe water crisis has affected even essential services. Global climate change cannot be avoided, and Pakistan is currently in a dangerous scenario (Kirby et al., 2016; P. Kumar et al., 2021). According to the Intergovernmental Panel on Climate Change (IPCC), the average global temperature of the Earth, oceans, and atmosphere increased by 0.85 degrees Celsius between 1880 and 2012. (J. A. Khan, 2011). According to Podger et al. (2021), drought is seen as an environmental calamity that has catastrophic effects on the agriculture sector and the ecosystem. It also has long-lasting effects on ecosystems, the atmosphere, water quality, and food production. Even without the faintest comprehension of the different types of droughts, agricultural droughts are an issue. It produces a harsh climate where food production needs insufficient moisture levels, resulting in crop failure and a food shortfall (Banerjee & Bera, 2021). (Mao et al., 2017). These consequences may be observed in those areas and agricultural systems that are most vulnerable to the destruction caused by drought (for example, rain-fed agriculture) (Yu et al., 2018; Qaiser et al., 2021). Due to its severe effects on ecosystems, the atmosphere, water quality, and food production, drought is a pervasive environmental disaster that has recently piqued the interest of many researchers from a variety of fields, including agriculture, ecosystems, earth sciences, climatology, hydrology, and geography (Surendran et al., 2017). Droughts may exacerbate the country's water dilemma, which already exists in normal years. Droughts are a type of meteorological disaster that can have significant social and economic repercussions. The drought that started in 1998 had a negative impact on agricultural output in 2000–2001, which was just 2.6%. The spatial-temporal inequalities in water distribution that create water shortages are expected to worsen as the climate changes. Drought is a reoccurring issue with effects on the environment and human existence in various ways. The impacts of drought on several facets of society are substantially more severe (Haile, 2019). Droughts were predominantly felt in northwestern mid-high latitudes due to an increase in worldwide ambient temperature and a decrease in rainfall; the impact of these temperatures will continue to increase (Jiang et al., 2022). In Pakistan, 42.3% of the nation's workforce—or 67 percent of the populace—is employed in agriculture, which is primarily practised in rural areas (Bhandari et al., 2020). Rainfall in Khyber Pakhtaunkhawa varies in frequency, amount, and distribution. In the KPK region over the previous 48 years, droughts have become more common, which has reduced the amount of water available for crops (Xu et al., 2021). In regions where arid climate causes droughts, evaluating rainfall and evapotranspiration variability is crucial (Ahmed et al., 2018; Liu et al., 2021). The DrinC (Drought Index Calculator) programme was used to calculate the drought indices. 2014 (Stagge et al.).Landsat images are used in indices like the Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), the Scaled Drought Condition Index (SDCI), the Soil Moisture Agricultural Drought Index (SMADI)(Sánchez et al., 2016), and the Empirical Standardized Soil Moisture Index (Carro et al., 2016) to evaluate the effects of drought on vegetative cover, while also Studies on agricultural drought have been undertaken using simpler markers that were initially intended for assessing meteorological drought (Zhang et al., 2017). KPK has turned into a hotspot for all hydrometeorological and geological disasters because of its more varied topography than other Pakistani provinces. Rural areas are where KPK is most prevalent. Only 17% of the population lives in urban areas. According to the national economic framework, agriculture accounts for 30% of the region's GDP (Abid et al., 2013).

2. MATERIALS AND METHODS

2.1. Study area

The study area is the Pakistani province of Khyber Pakhtunkhawa, which is situated in the country's northwest. KPK is the smallest province in terms of territory and ranks third in terms of people behind Sindh and Punjab (Figure 1). Thecoordinates of this place are 34°57'9.44"N and 72°19'52.01"E. The Federally Administered Tribal Areas (FATA) cover 101,741 km2, or 12.8% of Pakistan's total land area, and are 27,220 km2 larger than Khyber Pakhtunkhawa (74,521 km2), (Rahman et al; 2019)

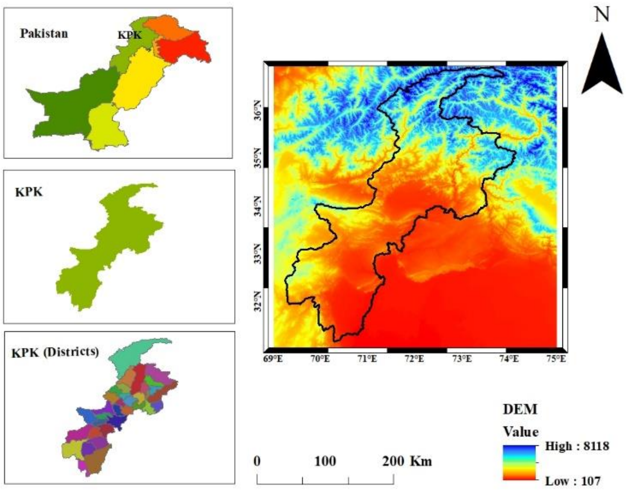

Figure 1. Map of Study Area

According to the agro-climatic classification, there is a predictable progression of climatic conditions from "dry regions" in the southern portion, through "dry semi-arid" and "wet semi-arid," to a transversal monsoon area in the middle of KPK, with a "sub-humid" and even "humid" climate in some places. (M. S. Khan, 2016) (Britannica 2012). In the province, agriculture provides a living for more than 85% of the inhabitants (Ashraf et al., 2014). The economies of agriculture and livestock are crucial to the development of the nation's economy.(Rahman et al., 2002).

3. DATA AQUISITION AND METHODOLOGY

Landsat photos from the Operational Land Imager (OLI), Enhanced Thematic Mapper Plus (ETM+), and Thematic Mapper (TM) have been extensively used in several remote sensing studies over the past three decades. According to the study area's calculations, USGS Earth Explorer's (http://earthexplorer.usgs.gov) high resolution reference data was matched. Data on temperature and precipitation from 1981 to 2020 was obtained from the TerraClimate website. Monthly rainfall statistics and the potential evapotranspiration (PET) based on minimum and maximum temperature were used to determine the annual precipitation parameters. The aridity index (AI) was determined using the UNEP approach, and the PET was calculated using Hargreave's method.

3.1. Reconnaissance Drought Index (RDI)

The standardized RDI used for our research is thought to be accurate and supported in the literature(Vangelis et al., 2013). It could be used during times when there is no rainfall. For dry and semi-arid environments, the Reconnaissance drought index is much more susceptible than the Standardized Precipitation Index (Asadi Zarch et al., 2017). The SPI has some flaws, one of which is that it ignores the impact of other variables connected to severe droughts. It is dependent on both total precipitation (P) and potential evapotranspiration (PET), which are two different factors, one measurable (P) and the other estimated (PET) (Angelidis et al., 2012). PET was estimated by applying Hargreave's approach (Equation 1) from maximum and minimum temperatures(Vangelis et al., 2013). Comparing the Thornthwaite and Blaney–Criddle is a preferable option for mountainous regions (Cai et al., 2015).

$$\mathbf{PET} = \mathbf{0.0023} \times \mathbf{Ra} \times (\mathbf{Tmean} + \mathbf{17.8}) \times \mathbf{TR}0.5 \quad (1)$$

Where,

Ra = Extra-terrestrial radiation

TR= Diurnal temperature variation (T min and T max)

Hargreave's approach is well-known for its efficiency (Lang et al., 2017), and it has been widely used in semi-arid and dry environments. For droughts assessment and management, the RDI can be utilize in three different ways: the initial value RDI (αk), the normalized RDI (nor), and the standardized RDI

RDI is computed using the equation 2 (assuming the log-normal distribution is used.)

$$\text{RDIst(i)} = \text{y(i)-y}/\boldsymbol{\sigma}\text{\^{}y} \quad (2)$$

Where

y(i) = is the ln (ak(i))
y = arithmetic mean
σˆ y = Standard deviation
(Asadi Zarch et al., 2017)

For estimating the specific frequency distributions of k, the gamma probability density function (pdf) was utilized (Khan et al., 2017). Compared to the normal conditions of the country, positive RDI value shows rainy seasons, and negative values show dry seasons. Drought severity is divided into four categories: extreme (2.0), severe (1.5 to 2.0), moderate (1.0 to 1.5) and mild (0.5 to 1.0).

3.2. Spatio-Temporal Analysis NDVI and NDWI

The Normalized Difference Vegetation Index, An indicator called NDVI was created to assess plant productivity using remote sensing methods (Hamrell, 2014). Due to the NDVI's

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accuracy as a measure of land plant productivity, it has been utilised as an indication of crop growth, land cover, crop productivity analysis, rainfall and droughts analysis, and warning systems for many years (Alhawiti & Mitsova, 2016). This technique can be used to track changes in flora, land use, and climate patterns. The NDWI is frequently used to identify changes in water body content. Water absorbs visible and infrared light, hence NDWI uses near-infrared and green electromagnetic bands to represent waterways.

$$\boldsymbol{NDVI} = NIR - \frac{RED}{NIR} + RED \qquad (3)$$

$$\boldsymbol{NDWI} = \quad NIR - Green/NIR + Green \qquad (4)$$

Red and near-infrared light (red reflectance) provides the basis for the NDVI (red reflectance plus near-infrared). Due to the significant chlorophyll absorption at 0.67 m, the near-IR band can detect up to eight leaf levels, but the red band can only detect one or frequently fewer (Mlenga et al., 2019). Two near-IR bands are included in the NDWI, one at 1.2 m and the other at 0.86 m. The NDWI is calculated using the Near-Infrared (NIR) and Green (G) bands. The amount of water in waterbodies is highlighted by this formula (Erban et al., 2022).

3.3 Aridity Index

The aridity index is used to gauge a region's climate patterns based on total rainfall and potential evapotranspiration (Li et al., 2017). By employing the equation, it is a powerful indication of the degree of dryness and drought identification (Qaisrani et al., 2022):

Aridity Index AI =P/PET (5)

Where,

'P' = "mean annual precipitation"

"PET" = "mean annual evapotranspiration."

PET was significant for the calculation of RDI.

4. REULTS AND DISCUSSIONS

4.1. Spatio-Temporal Analysis of Climatic variables (Interpolation by IDW Method)

Each climatic variable's interpolation performance was analysed separately. In order to estimate the values for the pixels in a raster, interpolation techniques require a minimal number of sample points (Berndt & Haberlandt, 2018). To estimate missing values, any geographic spatial information can be employed, including terrain, precipitation, pollutant levels, temperature, potential evapotranspiration, and others. IDW is an accurate interpolator, hence the maximum and minimum values in the interpolation area can only occur at specific places (Figure 2). Clusters and exceptions have an effect on the output region. IDW contends that the movement of the surfaces is caused by the neighborhood's local variability (Samanta et al., 2012).

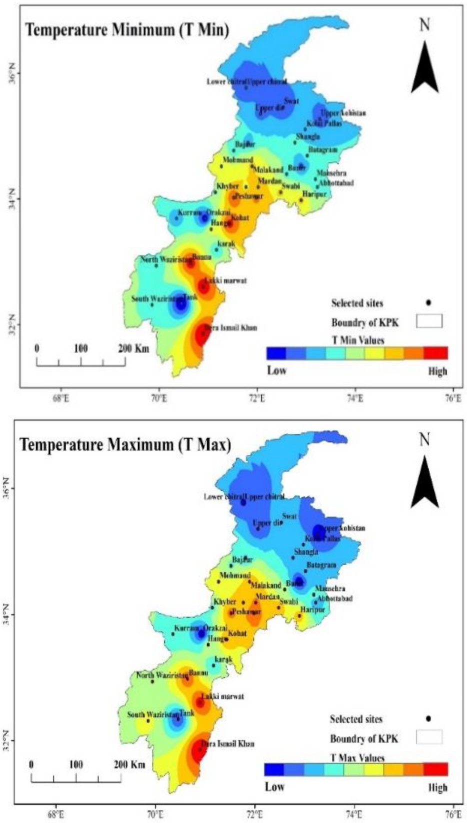

Figure 2. Interpolated Maps With Minimum/Maximum Temperatures From 1981-2020.

Recently, researchers found that temperature during droughts have been increasing more than in normal conditions in and, they relate this increase to water vapours in the atmosphere. This figure illustrates the lowest and highest minimum temperature. are 8.11, the lowest value, and 17.5 is the highest.Figure 7 displays the KPK maximum temperature, with 18.9 representing the minimum and 32 representing the maximum. This graph demonstrates that while some districts experience high temperatures, nearly 20 had low to moderate temperatures. Rainfall and PET (Figure 3) have an impact on agricultural water access in the soil, which has a clear and strong link to droughts.Using data from a 40-year average, we show the spatial-temporal variations in precipitation and PET. Changes in the drought may be influenced by a variety of causes, but changes in rainfall and ET are the most important ones (which can be reflected by PET). The spatial variance of PET generally shows a gradient lowering from south to north. The greatest and lowest values of PET are 122.1 and 88.42, respectively. When the amount of precipitation falls significantly short of the amount of potential evapotranspiration, causing the area to dry out, drought conditions arise on land. In general, rain will fall where the humidity is higher. PPT also ranges from 22.92 to 120, with 120 being the highest value. Swat and Mansehra in KPK have an increase in precipitation, whereas D.I. Khan, Bannu, and Karak experience declines. The soil will dry out if PET is higher than PPT until conditions are steady or water is supplied.

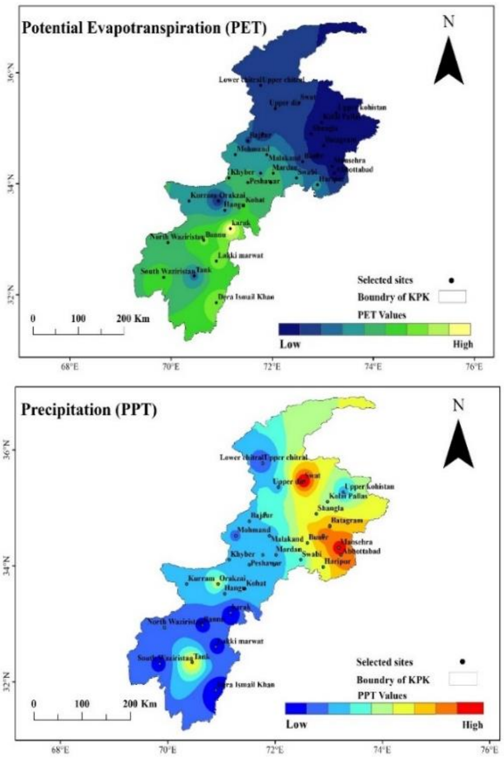

Figure 3. Maps Showing PET (Left) And PPT (Right) Variations During 1981-2020

4.2. Aridity Index Analysis

For characterising the climatic characteristics of a region, the aridity index (AI) is crucial. RDI was calculated using the UNEP method in the DrinC programme for specified locations. You may view the AI for each region and the pertinent meteorological data at each location in (Figure 5). This diagram illustrates how the aridity index is divided into categories for each of the KPK's regions. The lowest value in this case is 0.29, which occurs in a hyper-arid location, while the greatest value, 1.27, occurs in a very humid zone.

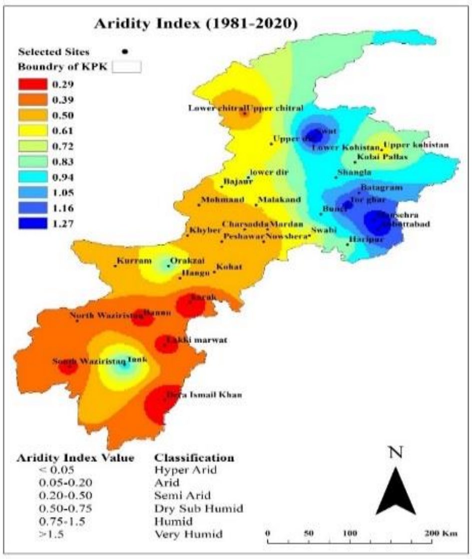

Figure 4. Spatial-Temporal Patterns of Aridity Index showing Classification for Khyber Pakhtaunkhawa.

4.3. Statistical Analysis of Climatic variables (Mann-Kendall Test)

The Mann–Kendall (M–K) technique is a nonparametric statistical test method developed by Mann and Kendall. The World Meteorological Organization (WMO) says this is the best way to study water and weather (Li et al., 2019). Drought patterns were analyzed using the nonparametric Mann-Kendall tests (Bandyopadhyay et al., 2016). Hydro-climatic time series data were analyzed using the Mann-Kendall test to look for any distinctive trends (Pablos et al., 2017). Sen presented a nonparametric method in 1968 that can determine the slopes of observed values if it has a linear trend line(Kousari et al., 2014; Yacoub & Tayfur, 2020). The most commonly used nonparametric method for analysing the trend in the time series is the Mann-Kendall (MK) test (Mann 1945, Kendall 1975). Researchers have extensively used this method for different hydro-meteorological parameters (Hirsch 1984, Aziz and Burn 2006, Mondal et al. 2012). Mann-Kendall test is an important tool for analysing the trend of climatic parameters, evaporation, reference evapotranspiration, stream flows and groundwater fluctuations (Bandyopadhyay et al. 2009, Ramazanipour and Roshani 2011). HO is a hypothesis, X1. Xn is series data, and n is the number of samples. S is calculated as(Gocic & Trajkovic, 2013);(Yue et al., 2002):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i),$$

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} 1 & (x_j - x_i) > 0 \\ 0 & (x_j - x_i) = 0 \\ -1 & (x_j - x_i) < 0 \end{cases}$$

Where S is a 0 mean and variance of

$$\operatorname{Var}(S) = \frac{n(n-1)(2n+5)}{18}, \tag{7}$$

Z of S formula:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\operatorname{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \dfrac{S+1}{\sqrt{\operatorname{Var}(S)}} & S < 0 \end{cases} \tag{8}$$

If Z has a positive number, the trend is heading higher, and vice versa.

For a rank sequence:

$$S_k = \sum_{i=1}^{k} r_i \ (k = 1,2,\dots,n) \tag{9}$$

$$r_i = \begin{cases} 1, & x_i > x_j \\ 0, & x_i < x_j \end{cases} 1 \le j \le i \tag{10}$$

The UF_k statistic is defined as follows if the time series in question is genuinely random and uncorrelated:

$$UF_k = \frac{[S_k - E(S_k)]}{\sqrt{\mathrm{Var}(S_k)}} \tag{11}$$

$\mathrm{Var}(S_k)$ Indicate variance and $E(S_k)$ Indicate mean. These could be calculated as:

$$E(S_k) = \frac{k(k-1)}{4}, \mathrm{Var}(S_k) = \frac{k(k-1)(2k+5)}{72} \tag{12}$$

UF_K= Standard distribution normal. $UF_K > UF_{\alpha/2}$ is indicating trend change. $UF_K>0$ shows a positive upward trend and vice versa.

For the lowest temperature, The time series data of minimum temperature revealed an increasing trend, as indicated by the positive values of Kendall's tau and S statistics. Zc statistics showed that the trend was statistically significant between 1981 and 2020. Positive Kendall's tau and S statistics for maximum temperatures demonstrate the upward trend in maximum temperature time series. Using time series data of climatic parameters, the effect of climate variability and its implications on potential evapotranspiration were assessed. Results revealed a decreasing trend for PET for Banuu, but an increasing trend for minimum temperature, maximum temperature, and precipitation (Figure 5). Figures 6--9 display the full graphs and their trend. The results of the analysis showed that the variability of climatic parameters can be described by the Mann-Kendall test with Sen's slope estimator. Based on the findings, it can be inferred that all climatic factors must be taken into account when assessing how climate change would affect crop water needs. be conducted in other regions of the nation.

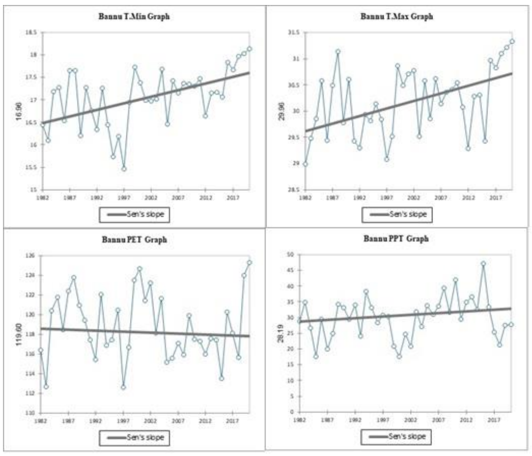

Figure 5. Sen’s linear estimates of minimum, temperature, maximum temperature, PET and Precipitation for Bannu District of Khyber Pakhtaunkhawa.

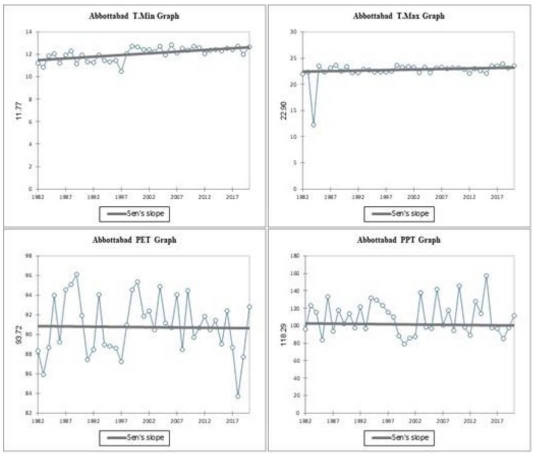

Figure 6. Sen’s linear estimates of minimum, temperature, maximum temperature, PET and Precipitation for Abottabad Ditrict of Khyber Pakhtaunkhawa.

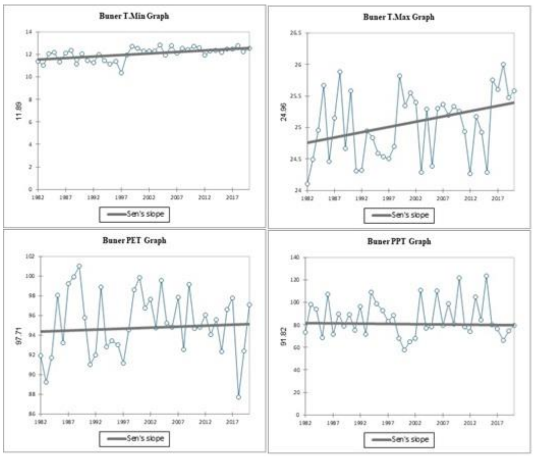

Figure 7. Sen’s linear estimates of minimum, temperature, maximum temperature, PET and Precipitation for Bunner Ditrict of Khyber Pakhtaunkhawa.

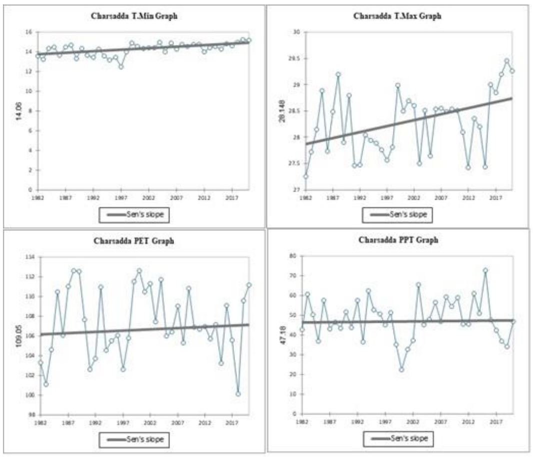

Figure 8. Sen’s linear estimates of minimum, temperature, maximum temperature, PET and Precipitation for Charsadda Ditrict of Khyber Pakhtaunkhawa.

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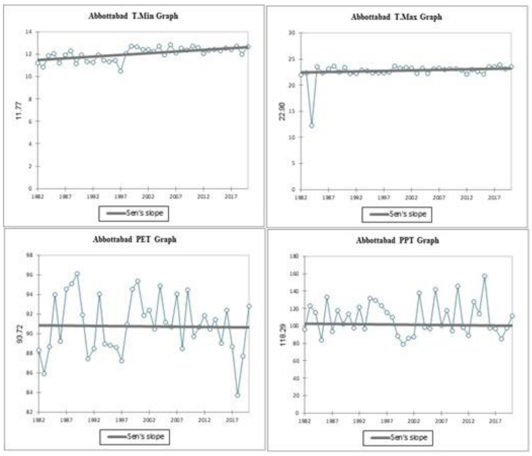
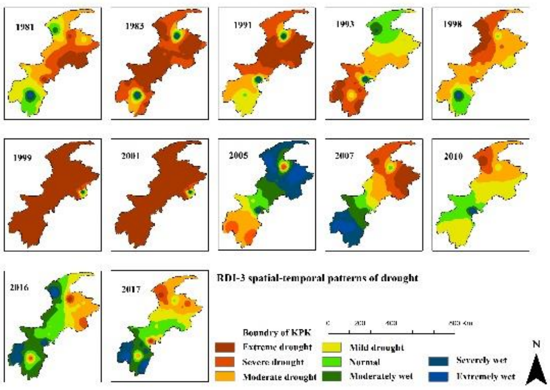


Figure 9. Sen's linear estimates of minimum, temperature, maximum temperature, PET and Precipitation D.I.Khan Ditrict of Khyber Pakhtaunkhawa

The geographical classification of droughts was developed using the inverse distance weighting (IDW) interpolation technique and 3 distinct RDI periods (3, 6, and 12 months) (Ben Abdelmalek & Nouiri, 2020). Because the data is created for a specific area, autocorrelation is not considered in the IDW technique, making it a deterministic approach that relies on calculated information (Amini et al., 2019; Cavus and Aksoy, 2019). The geographic display pictures with RDI values produced by Arc GIS 10.8 highlight the droughts season (Figure 9-11). Years that have RDI values were taken into account for the spatial analyses. The only dataset for the area that was at the time accessible was used to create the interpolation maps. These results demonstrate that the three drought classes' affected regions vary among the three RDI values. Extreme droughts were observed throughout the whole study region in 1999 and 2001. Large-scale severe droughts occurred in 1991, and severe and moderate droughts were frequent in 1981, 1998, 2010, and 2017. The other periods covered a range of geographic conditions, from mild drought to typical conditions.



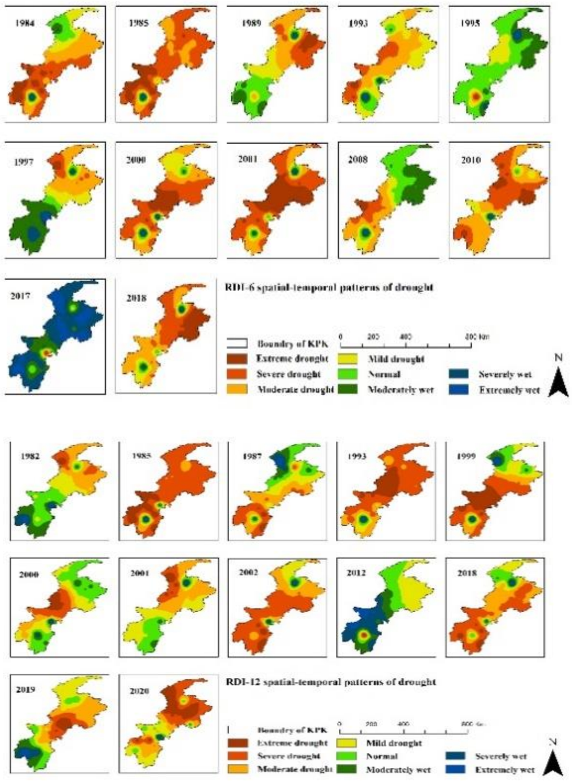


Figure 10. RDI for 3-6-12 Months showing Spatio-temporal patterns of drought in Khyber Pakhtaunkhawa for1981-2020.

4.4. NDVI and NDWI Variations

The growth phase is between October and March, when NDVI values are high, according to the average Landsat NDVI readings for KPK. The peak vegetative season lasts from January through March, and during this time, NDVI values between 0.58 and 1 indicate dense vegetation. The range of NDVI readings is typically between -1.0 and 1.0, with negative values signifying clouds and precipitation, positive values of 0 denoting dry ground, and higher positive values ranging from thin vegetation (0.1 to 0.5) to dense greenery (0.6 and above).

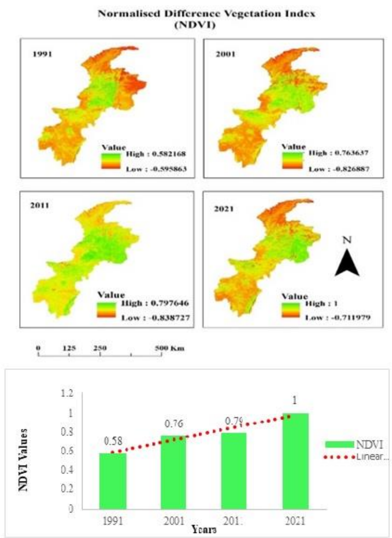


Figure 4.11. Comparative Analysis of NDVI for KPK region between 1991-2021

In 1991, there was more vegetation in the centre of KPK, such as Peshawar, Malakand, Mardan, and Swabi, than in some of the northern and southern regions. A very low NDVI value (below 0.1) this year indicates bleak terrain, snow, etc., while a very high NDVI value in 2021 indicates lush vegetation. This year's vegetation is lush, healthy, and green. Data that was gathered from a Landsat picture using the NDWI index is used to create graphs and maps that show how results vary over time as a curve. Except when the research region is a non-aqueous surface, the negative values to -1 are the apparent signs of water shortages. The positive values that reach +1 on a map usually have a bluish appearance and refer to either a high water content or a water level. The NDWI result has no dimensions and ranges from -1 to +1 depending on the type and amount of vegetation present. High NDWI readings are correlated with high vegetative cover percentage and water content (in blue). Lower NDWI values are associated with low vegetation water and low vegetation percent cover (in white).

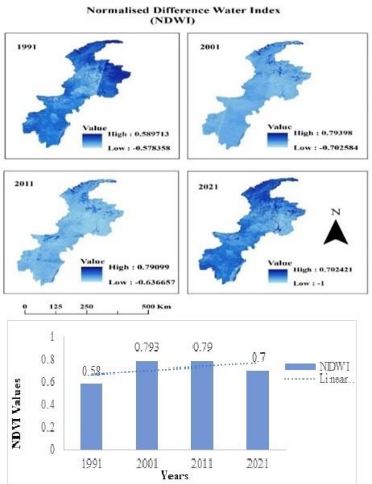


Figure **4.12.** Comparative Analysis of NDWI for KPK region between 1991-2021

NDWI levels will drop during a severe drought. The near-infrared bands increase the strong reflectance of terrestrial land use and soil properties while decreasing the low reflectivity of aquatic features. The NDWI algorithm yields positive results fo rivers while yielding negative numbers (or 0) for soils and dry vegetation.

5. CONCLUSION AND RECOMMENDATIONS

The most frequent natural calamity that has a large negative influence on crop output is drought, which occurs when there are insufficient water resources available across vast geographic areas. Depending on the data's availability, many drought indices are used to measure the intensity of the drought. This study evaluated general drought aspects in the Khyber Pakhtaunkhawa province from 1981 to 2020 using the reconnaissance drought index (RDI), which combines PPT and PET data. The area has a significant degree of rainfall variability and is located on the edge of the annual precipitation needed for wheat production. An increase in long-term drought severity could endanger the management of water resources in the studied areas because long-term droughts typically affect water quality, especially groundwater. The results indicate that these methods could contribute to the development of a calculated plan to combat the effects of droughts.Given that long-term water shortages have a significantly greater impact on water supply than short-term ones, particularly groundwater, According to the NDWI results, the value for the KPK region rises from 0.58 to 0.7. From January through March is when the vegetation is at its height; during this time, dense vegetation is reflected by NDVI values between 0.79 and 1. Examining the study month of September reveals that low NDVI values correspond to the years of drought forecast for the KPK region. The research focuses on climate-induced variability, which is crucial for understanding how the deficiency in the state of KPK emerged. These results provide national planners with references that they can use to create future policies and decisions to lessen the consequences of drought.River-based farming is prevalent due to the effective irrigation system in the nation. Water must be conserved and used judiciously for home and agricultural uses, though. To keep track of climate changes and their effects on droughts and floods, more data collection stations are needed in KPK because there aren't as many metrological stations there. As water shortage is a real-time and sustainable issue, the building of tube wells should be prioritised in drought-prone areas.

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