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PRELIMINARY IMPACT ANALYSIS OF CLIMATIC VARIABLES ON NET PRIMARY PRODUCTIVITY, IN THE DRYLANDS OF SOUTH PUNJAB, PAKISTAN

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ABSTRACT

Land degradation is an important global issue because of its adverse impact on agronomic productivity, the environment, and its effect on food security and the quality of life. This study aims to explore the relationship between the region's net primary productivity (NPP) and climatic variables during the period 2001-2020, using secondary data sources, i.e. MODIS imagery. To examine the effects of changing climatic conditions on NPP data was quantified using a multiple linear regression (MLR) model to check the relationship between NPP, temperature and precipitation Durbin-Watson correlation coefficient was calculated in SPSS. The result revealed that the NPP count is low in Rahim Yar Khan as compared to these districts. In 2020 the average value of NPP was 240.1703 gC m^{-2} in Bahawalpur, 90.3002 gC m^{-2} in Rahim Yar Khan and 324.7908 gC m^{-2} in Rajanpur. Durbin-Watson multiple linear regression revealed that the change in temperature and precipitation has a significant impact on NPP. The data gathered were processed through ArcGIS, SPSS and Microsoft Excel and the analysis was performed. This study proposes a policy framework that will prove to be beneficial to control land degradation in South Punjab.

Keywords: Climate, Land Degradation, Net Primary Productivity, Drylands, Multiple Linear Regression

1. INTRODUCTION

A land area is considered "drylands" if its aridity index, calculated by dividing mean annual precipitation by mean annual potential evapotranspiration, is less than 0.65 (Fu, Stafford-Smith, & Fu, 2021). Drylands make up 66.7 Mkm^2, or 45% of the Earth's land surface, according to the most recent and comprehensive estimate currently available on a global scale (Plaza et al., 2018). Four groups of drylands are distinguished by the index: dry sub-humid (DSH, AI between 0.65 and 0.5 mm/mm), semi-arid (SA, 0.5–0.2 mm/mm), arid (A, 0.2–0.05 mm/mm), and hyper-arid (HA, <0.05 mm/mm) land surfaces (Prăvălie, Bandoc, Patriche, & Sternberg, 2019). Presently, 39% of the world's population lives in drylands, with over 2.8 billion people living there. Drylands are essential to maintaining the global sustainability of the existing and future human population since they comprise more than 70% of the land area in developing nations (Plaza et al., 2018). The only mention of drylands in the sustainable development goals (SDGs), taken at face value, is in objective 15.3, which restates the United Nations Convention to Combat Desertification (UNCCD's) commitment to achieving LDN (Land Degradation Neutrality) (Stafford-Smith & Metternicht, 2021).

Plant growth is measured by net primary productivity (NPP), which is a measure of the ability of the plant to fix carbon through photosynthesis. Climate variables have complex interactive effects on net primary productivity. It is essential to comprehend the implications of climate change to predict how they will affect ecosystem functions like carbon storage, which feed back into the climate system. Empirical correlations between NPP and climate within and between ecosystems have also been extensively established. The literature indicates that physiology, ecology, and climate have strong, direct impacts on NPP in ecosystems globally (Kamali et al., 2020; Liu et al., 2021). Natural ecosystems will be impacted by any changes to the climatic conditions. NPP is therefore seen as a crucial indicator for measuring ecosystems' responses to climate change (Fang et al. 2017). NPP serves as a plant growth measure that captures both the impact of environmental conditions on plant growth and the potential of photosynthesis to store carbon (Wei et al. 2022). Complex factors, including land use variations, hydrological factors, and climate, all influence NPP. Climate influences NPP by controlling plant metabolism, growth season, biomass, and age of the plant (Michaletz et al., 2014). The NPP's regional distribution is largely influenced by changes in the environmental and climatic parameters among many others. Changes in NPP can be used to measure it, with deviations from the norm being interpreted as indicators of either development or degradation of the land. According to Bai et al. (2008), there is no assurance that land degradation or improvement is indicated by a positive or negative trend in NPP.

The majority of earlier research (Mohamed et al., 2004; Cuo et al., 2021) has only examined inter-annual variations in annual NPP at the global or regional level. Based on shifting patterns of temperature and precipitation, Grosso et al. (2008) discovered a 13% increase in the total world NPP for potential vegetation between 1901 and 2000. Knapp and Smith (2001) found a significantly positive correlation between NPP and precipitation in their research. The overall NPP loss was computed using urban growth and the mean NPP for the various land use types in the fourteen regions. The conversion of cropland to urban land accounted for 91.93% of the total NPP loss, followed by forest (7. 17%) and grassland (0.69%). According to (Mazhar, 2020), who lives in the drylands of south Punjab, the primary causes of desertification are anthropogenic and meteorological factors. Due to urban growth, the NPP in the southern areas of Pakistan was significantly reduced.

This study aims to explore the relationship between the region's NPP and climatic variables. NPP has been employed in this study as a proxy for land degradation and plant material that can be consumed as food, fuel, or feed. According to Bai et al. (2008), land degradation is the long-term loss of ecosystem functioning and land productivity brought on by natural and man-made disturbances. Land cover can only recover from these disturbances with the help of land management programs. According to Nunes et al. (2015), rising CO^2 levels will cause the NPP to rise, while future NPP declines will be caused by reduced soil moisture content and higher temperatures. The difference in temperature between day and night has a direct impact on NPP due to the impact of photosynthesis and respiration. Therefore, estimating the inter-annual variability of regional NPP during the period for which instrumental climate data are available will be important to create an understanding of the inter-annual response of NPP to climate. This will make it possible to identify the kind and intensity of climatic influences on NPP.

2. Material and Methods

2.1. Study Area

The research's study region, which is situated in South Punjab, Pakistan, is depicted in Figure 1 study area map. This area is made up of drylands and is mostly divided into three districts: Bahawalpur, Rahim Yar Khan, and Rajanpur (Government of Pakistan) (GoP). Collectively, these districts, which are located in the drylands area, cover 49,029 km^2 (GoP 1999, 2000).

Figure 1. Study Area Map of South Punjab

2.2 Climate of study area

Figure 2-4 present the climographs of the three districts under study. The graphs are indicative of the Precipitation and temperature variations in the study area, from 2000 to 2020, with maximum fluctuations in the precipitation pattern of Bahawalpur, followed by Rahim Yar Khan. Also, the same district witnessed the greatest temperature rise in this decade.

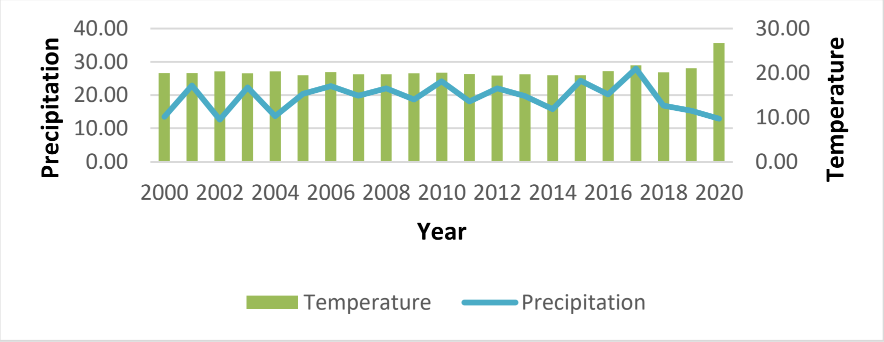

Figure 2. Climograph of Rajanpur

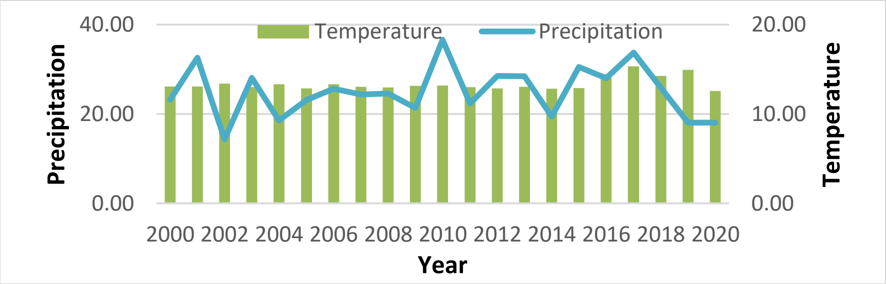

Figure 3. Climograph of Rahim Yar Khan

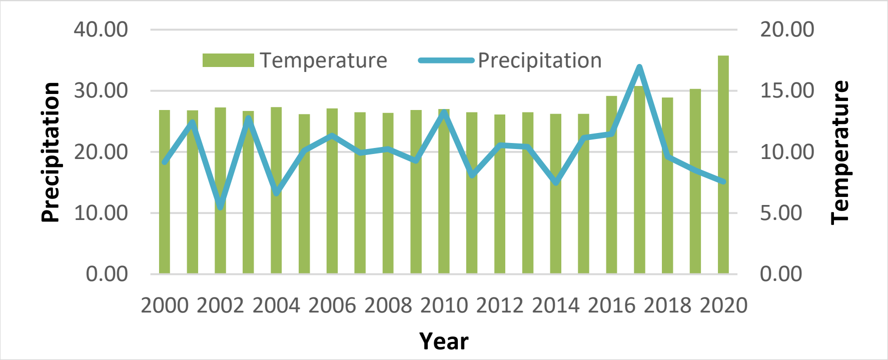

Figure 4. Climograph of Bahawalpur

2.3. METHODOLOGY

The datasets used as secondary data to evaluate land degradation in South Punjab are listed in Table 1. The gathered datasets are essential for fulfilling the goals of this research, which is to assess land degradation in the area.

Table 1. Datasets used in the study from secondary sources

Sr.no	Data sets	Organization Name	Period
1	MODIS 500m and 250m resolution images of the study area, sensor MOD17A3HGF, MOD17A3HGF, MOD17A3HGF	Google Earth Engine	2001, 2010, 2020
2	Temperature	Aphrodite	2000-2020
3	Rainfall	CHIRPS	2000-2020

2.3.1 Multiple Linear Regression Analysis

MLR is performed for the analysis of climatic variables' impact on NPP. This helps to assess the relationship between the climatic variables and NPP.

2.3.1.1 Assumptions of MLR for Rajanpur

The analysis presented in Fig. 5 supports the MLR assumption by showing a linear connection between the independent variables, Temperature and Precipitation, and the dependent variable, NPP, as shown by straight-line scatterplots. A VIF value of 1.097 and a tolerance of 0.912, both below the criteria, support the lack of multicollinearity. The Durbin-Watson test, however, reveals positive autocorrelation (1.851) between the variables. The distribution shown in scatterplots is random, the residuals show constant variance, and the P-P plot shows a distribution that is close to normal. The significant F statistic indicates a regression association between variables even though the ANOVA test yielded a non-significant p-value (0.13). The unimodal symmetric pattern in the histogram clearly shows consistency in the distribution of the data.

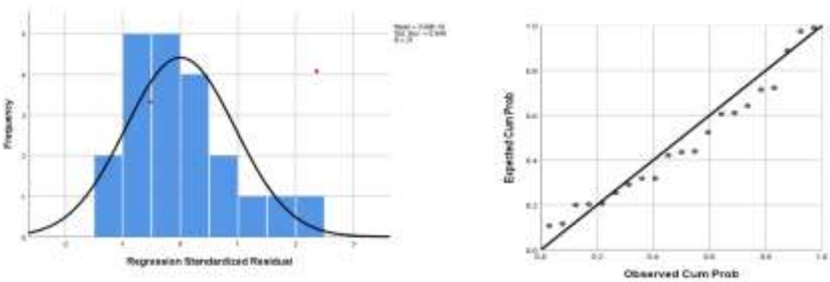

Figure 5. Histogram and P-P Plot of Rajanpur

2.3.1.2 Assumptions of MLR for Bahawalpur

Figure 6 demonstrates a linear relationship between the independent and dependent variables, supported by straight-line scatterplots. Multicollinearity is not evident, with a VIF score of 1.017 and a tolerance of 0.983, both much below the standards. The Durbin-Watson test, however, indicates that there is positive autocorrelation (0.966) between the variables. Scatterplots show a random array, a near-normal distribution in the P-P plot, and constant variance in the residuals. The significant F statistic indicates a regression link even if the ANOVA test yielded a non-significant p-value (0.273). The data reliability is strengthened by the histogram's consistent unimodal symmetric pattern.

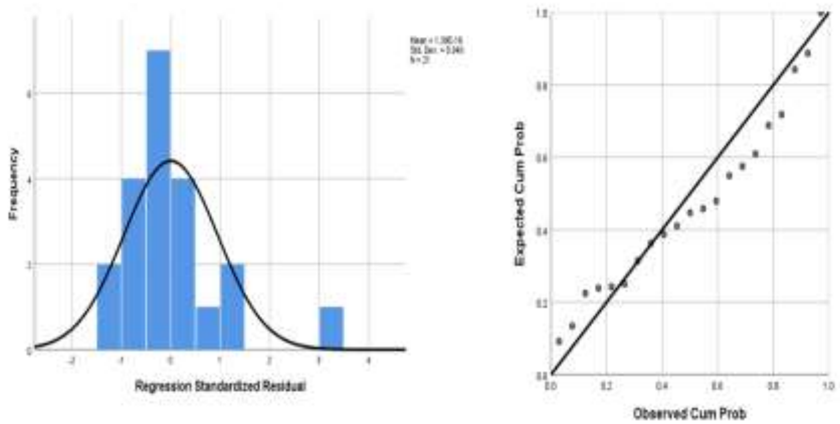

Figure 6. Histogram and P-P Plot of Bahawalpur

2.3.1.3 Assumptions of MLR for Rahim Yar Khan

Figure 7 illustrates the linear relationship between the independent and dependent variables, supported by straight-line scatterplots. Data integrity is demonstrated by the analysis, with both the VIF and Tolerance values at 1.00, suggesting no multicollinearity. Positive autocorrelation between the variables is indicated by the Durbin-Watson value of 1.973. Whereas residuals show a near-normal distribution and constant variance in the P-P plot, scatterplots show a random array. The significant F statistic indicates a regression link even though the ANOVA test yielded a non-significant p-value (0.42). The data's dependability is strengthened by the histogram's consistent unimodal symmetric pattern.

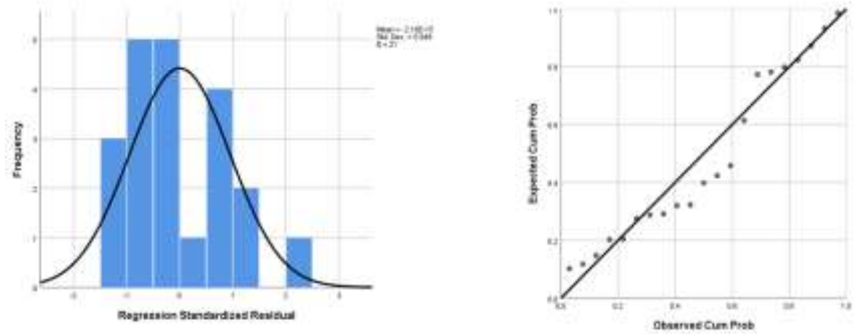

Figure 7. Histogram and P-P Plot of Rahim Yar Khan

4. RESULTS AND DISCUSSIONS

From 2000 to 2020, the annual NPP in the South Punjab shows significant spatial heterogeneity. High NPP areas are mainly located in the southern tip of Rajanpur district. Median NPP areas are mainly in the high-altitude cropland and grassland of Bahawalpur district. Low NPP areas are in the district of Rahim Yar Khan.

4.1. Impact of Climatic Variables on NPP

For examining the impact of climate on NPP Multiple Linear Regression (MLR) analysis is performed. NPP increase or decrease is highly dependent on several factors. Hence NPP is a dependent variable. Temperature and precipitation are the climatic variables that are used. Temperature and precipitation are the major factors that affect the NPP. These are independent variables.

4.1.1 MLR for Rajanpur

In Rajanpur, the analysis of NPP, temperature and precipitation are significantly correlated with a p-value of the F-test is 0.0305 which is less than 0.05. In the regression analysis, the dependent variable i.e., NPP has a significant relation with temperature with a significance of 0.02 only. The coefficient of temperature is 22.84. The positive sign means that there is a positive association between these two variables. For every one-unit increase in temperature, NPP will increase by 22.84. The equation for the regression analysis will be:

$$Y = -464.6575 + (22.8498)\,X1 + (-4.9161)X2$$

4.1.2. MLR for Bahawalpur

In Bahawalpur, the analysis of NPP, temperature and precipitation are not significantly correlated with a p-value of the F-test is 0.27 which is greater than 0.05., thus temperature and precipitation are not significantly correlated with NPP. In the regression analysis, the dependent variable i.e., NPP does not have a significant relation with temperature and precipitation with a significance of 0.66 and 0.14 respectively. The coefficient of temperature and precipitation is -3.69 and -6.72 respectively. The negative sign of the coefficient means that these two variables have a negative association with NPP. For every one-unit increase in temperature and precipitation, NPP will decrease. The equation for the regression analysis will be:

$$Y= 225.4376 + (-3.6932)X1 + (-6.7252)X2$$

4.1.3 MLR for Rahim Yar Khan

In Rahim Yar Khan, the analysis of NPP, temperature and precipitation is significantly correlated with a p-value of the F-test is 0.04 which is less than 0.05. In the regression analysis, the dependent variable i.e., NPP has a significant relation with temperature with a significance of 0.023 only. The coefficient of temperature is 5.340. The positive sign means that there is a positive association between these two variables. For every one-unit increase in temperature, NPP will increase by 5.340. The equation for the regression analysis will be:

$$Y= -103.898 + (5.340201) X1 + (-2.26088) X2$$

4.2 Spatio-temporal pattern changes in NPP 2001

In 2001, the average area of NPP varied across districts in South Punjab. Bahawalpur measured 3.3715 km², Rahim Yar Khan recorded 1.0182 km², and Rajanpur encompassed 5.8281 km². NPP values were notably low in South Punjab due to limited croplands, grasslands, savannas, and natural vegetation. Rahim Yar Khan faced high temperatures, low rainfall, rapid urbanization driven by a dense population, and severe water shortages, with 70% of agricultural land affected by saline underground water. Rajanpur, while experiencing low NPP, encountered challenges like floods and geographical vulnerabilities, contributing to water scarcity issues. Bahawalpur also reported low NPP influenced by factors like poor-quality inputs, extreme climatic conditions, and inadequate agricultural guidance.

These factors collectively contributed to decreased NPP and agricultural productivity in the region.

4.3 Spatio-temporal Pattern Changes in NPP 2010

In 2010 the average value of the area of NPP was 15.2927 km^2 in Bahawalpur, 7.9084 km^2 in Rahim Yar Khan and 42.0392 km^2 in Rajanpur. In Rajanpur NPP values increase in the North, South-eastern and South-western regions. In Bahawalpur NPP proportion increased in the central region. In Rahim Yar Khan NPP increased scatter all over the district. The NPP values increased in South Punjab in 2010 due to an increase in croplands, grasslands, savannas, natural vegetation as well as forest. High production cultivation systems, new plantation projects, irrigation systems and fertilizers supply were made due to which plantation increase which leads to the increase NPP in this region.

4.4 Spatio-temporal Pattern Changes in NPP 2020

In 2020 the average value of the area of NPP was 240.1703 km^2 in Bahawalpur, 90.3002 km^2. Rahim Yar Khan and 324.790 km^2 in Rajanpur. The NPP values were very high in South Punjab in 2020 due to the increase in croplands, grasslands, savannas, natural vegetation as well as forest. In Rajanpur, the proportion of NPP was very high. The count of NPP was high all over the district but it was very high in the south, north and central regions. In Bahawalpur, the proportion of NPP increased all over the district but its highest proportion was in the eastern region. In Rahim Yar Khan the proportion of NPP was comparatively low. However, in the Southern region, its proportion was very high.

Climate change has a significant negative impact on NPP due to minimum, and maximum temperature and precipitation. Similarly, NPP, land use land cover (LULC) and soil organic carbon (SoC) have a significant impact on land degradation. Keeping in mind that the current investigation was carried out to assess the land degradation in the districts of South Punjab over the period 2000-2020. For this study, secondary data of NPP, LULC and LULC was collected from the MODIS satellite images by using Google Earth Engine. The datasets of temperature and precipitation were collected from CHIRPS and Aphrodite. The MLR Model was applied to check out the significance of this study. MLR results show that temperature and precipitation have a significant impact on NPP. Similar indicators of NPP, LULC, SoC and Climatic

Variables to access land degradation in another study (Yu et al., 2023). The results of the trends of NPP, LULC and SoC were shown by maps. The spatio-temporal changes in NPP, LULC and SoC during the study period are shown in the maps. The results showed that NPP and LULC increased whereas SoC decreased from 2000 to 2020 in the districts of South Punjab i.e., Rajanpur, Bahawalpur and Rahim Yar Khan.

Through this study degraded land of the South Punjab can be identified. Hence by the identification of the degraded land policies can be made to control the land degradation in that area. By controlling land degradation in South Punjab agricultural ecosystem and crop production can be increased which impediments to achieving food security and improving livelihoods. The benefits of action through prevention of crop damages and the derived loss in productivity.

5. CONCLUSION

This study presents the possible impact of NPP, LULC, SoC and Climatic Variables on land degradation in the district of South Punjab. The estimated results of the MLR revealed that in Rajanpur there is a significant positive correlation between NPP and Climatic Variables. However, in Bahawalpur, there is an insignificant correlation between NPP and Climatic Variables. In Rahim Yar Khan there is a significant positive correlation between NPP and Climatic Variables. The NPP trends from 2000 to 2020 for the districts of South Punjab were presented in the form of maps. It is estimated that the NPP increase in a very high proportion in 2020 in comparison with 2000 for the districts of South Punjab due to an increase in croplands, grasslands, savannas, natural vegetation and forest. It is revealed that the highest NPP increase was in Rajanpur. In 2001 the average value of the area of NPP was 3.3715 km^2 in Bahawalpur, 1.0182 km^2 in Rahimyar Khan and 5.8281 km^2 in Rajanpur. In 2020 this area of NPP increased to 240.1703 km^2 in Bahawalpur, 90.3002 km^2 in Rahim Yar Khan and 324.7908 km^2 in Rajanpur. In Bahawalpur, it is witnessed that the NPP increase was medium. In Rahim Yar Khan, it is estimated that the NPP increase was low as compared to the other districts of the South Punjab.

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