OPEN ACCESS

Kashf Journal of Multidisciplinary Research
Vol: 02 - Issue 1 (2025)
P-ISSN: 3007-1992 E-ISSN: 3007-200X
https://kjmr.com.pk

# QUANTIFYING THE INTERRELATIONSHIP OF SOIL MOISTURE VARIATIONS WITH AGRICULTURAL DROUGHT SEVERITY AND AGRICULTURE YIELD

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***DOI:*** https://doi.org/10.71146/kjmr219

## Article Info



**Abstract**

*This study investigates the impact of climate-induced soil moisture variation on agriculture in different districts of South Punjab. It analyzes changes in soil moisture, precipitation, and the Normalized Difference Vegetation Index (NDVI) over time. Additionally, it assesses agricultural drought using the Normalized Vegetation Supply Water Index (NVSWI) and Soil Moisture Agriculture Drought Index (SMADI). The study's statistical analysis measures the impact of agricultural drought fluctuations on crop yield spanning from 2007 to 2021. Based on trend analysis on average NDVI and Soil Moisture showed a decreasing trend at most of the stations except Lohdran and Vehari where a slightly increasing trend has been observed. The assessment of SMADI and NVSWI indicated that from 2007 to 2018, dry years had an average value of 2.89 and 35.24 at most stations, while 2019-2021 were spot as wet years, averaging 1.83 and 42.10 for SMADI and NVSWI, respectively. Moreover, the correlation analysis between soil moisture with SMADI, NVSWI, and yield showed that SM had a positive and negative correlation with yield, SMADI, and NVSWI. Based on analysis, it was noted that a decline in soil moisture has triggered the agricultural drought and ultimately has decreased agricultural land as well as yield in South Punjab. Therefore, it is crucial to give serious consideration to reassessing and correcting the factors that lead to soil moisture variation. This should be accompanied by the implementation of an effective irrigation system to ensure the sustainability of agricultural yield and address the issue of food insecurity in South Punjab, Pakistan.*

**Keywords:**
*Soil Moisture; NDVI; Climate Change; SMADI; NVSWI; Agricultural drought.*

**Introduction**

Agriculture is the cornerstone of global food and socio-economic development which plays an indispensable role in ensuring food security and driving economic progress worldwide (Pawlak & Kołodziejczak, 2020; Wijerathna-Yapa & Pathirana, 2022). Soil moisture (SM) is crucial in shaping the connection between the Earth's surface and the atmosphere, serving as a vital boundary condition that influences their interaction within the agricultural system, SM represents a critical parameter and refers to the water content present in the soil's active layer typically found in the top 1–2 meters. The factors influence the SM of climate change, including precipitation and temperature, (Feng et al., 2017). Precipitation serves as the primary input for water balance, directly impacting soil moisture (Sehler et al., 2019). On the other hand, temperature plays a role in controlling evapotranspiration and indirectly affecting soil moisture (Feng & Liu, 2015; Gripp et al., 2023; Lugo Kuzy, 2023; Verstraeten et al., 2008). Soil moisture (SM) is recognized as a crucial factor in meeting the water requirements of crops and can significantly impact on crop production by causing a decrease (AghaKouchak, 2015; Gines et al., 2018). Insufficient SM is directly relevant to agricultural drought (Cao et al., 2022) and indicates the reduction of crop yields due to less water availability in the soil. Therefore, comprehending and managing soil moisture levels are fundamental aspects of ensuring successful and sustainable agricultural practices.

In the past few years, there has been a noteworthy decline in soil moisture levels within the root zone layer specifically at depths ranging from 0 to 100 cm across the globe. Over the past 30 years, Pakistan has encountered numerous extreme events, particularly agricultural droughts, a significant shift in rainfall patterns, and a consistent increase in temperature years (Abbas, 2013; Khan et al., 2019; Nawaz et al., 2019; Zahid & Rasul, 2011). A notable example is the drought spanning from 1998 to 2002, regarded as one of the most severe in the last 50 years. This event impacted 1.2 million individuals, led to the demise million animals, and resulted in substantial agricultural losses. SM variations occur due to alterations in precipitation patterns, temperature shifts, and changes in land use/land cover(Cheng & Huang, 2016; Dai, 2013; Hirsch et al., 2014). The fluctuations in temperature and rainfall can be attributed to both human activities and climatic variations (Khoso et al.; Zohrabi et al., 2014). Previous studies also indicated that the Cambodian drought in 2004 (Gines et al., 2018) resulted in an 82% reduction in potential crop yield. Low soil moisture subjects to crop moisture stress affecting their productivity and increasing food insecurity (Kiboi et al., 2017). Consequently, the regions are reliant on agriculture but it is mostly affected by various factors such as dam development, food insecurity, and rapidly growing populations.

Globally in-situ measurement stations for monitoring soil moisture changes with high temporal resolution were lagged due to low gauge density (Holgate et al., 2016). Nevertheless, the installation of such devices poses a challenge in densely populated areas worldwide, including regions like Africa and northwest China. This difficulty arises from financial limitations, as highlighted in the research conducted by (Gu et al., 2019). Similarly, this challenge is also evident in areas such as Southern Punjab, Pakistan, where costly measurements become a hindrance As an alternative, satellite-based soil moisture products have been widely used to track soil moisture variations (Beck et al., 2021; Fan & Van Den Dool, 2004; Ying, 2010). Moreover, studies have utilized various soil moisture datasets like the Global Land Data Assimilation System (GLDAS) developed by (Rodell et al., 2004), the Soil Moisture Active Passive (SMAP) by (Das et al., 2018; Entekhabi et al., 2010) ERA-Interim and MERRA V2, highlighted (He et al., 2021; Luo et al., 2020; Peng et al., 2017). However, because of the low spatial resolution and low availability of the above-mentioned datasets have been rarely utilized. Comparatively, GLDAS 2.1 provided long-term soil moisture data and fulfilled the requirement of the research period. Moreover, various soil moisture-based agricultural drought indices have been developed such as Soil Moisture Condition Index by (Zhang & Jia, 2013), Soil Moisture Deficit Index by (Narasimhan & Srinivasan, 2005) and Soil Water Deficit Index by (Sánchez et al., 2016) . However, they have some limitations in assessing soil moisture changes and their impact on agriculture yield whereas, the vegetation supply water index (VSWI) (Chen et al., 2020) and soil moisture agriculture drought index (SMADI) (Martínez-Fernández et al., 2015;

Souza et al., 2021) perform better as compared to previous. It is very important to understand the soil moisture variations which is essential to improve the scientific recognition of regional and global agricultural processes. This study aimed to understand the impact of SM variation on crop yield has not been studied yet comprehensively in Pakistan, especially in the south Punjab region. The specific objectives are (i) spatiotemporal analysis of satellite-based soil moisture, precipitation, and NDVI data; (ii) to assess the soil moisture agriculture drought index (SMADI) and vegetation supply water index (VSWI); and (iii) to evaluate the impact of soil moisture variations on agricultural yield. Understanding the causes of SM variation (i.e., natural climate change) and its impact may shed new light on sustainable soil-moisture management and minimize alarming agriculture production challenges.

## 1. MATERIALS AND METHODS

The study follows a step-by-step process to investigate the relationship between soil moisture, agriculture drought and crop yield using remote sensing data and statistical tools as shown in Figure 1. The details are provided in next sections.

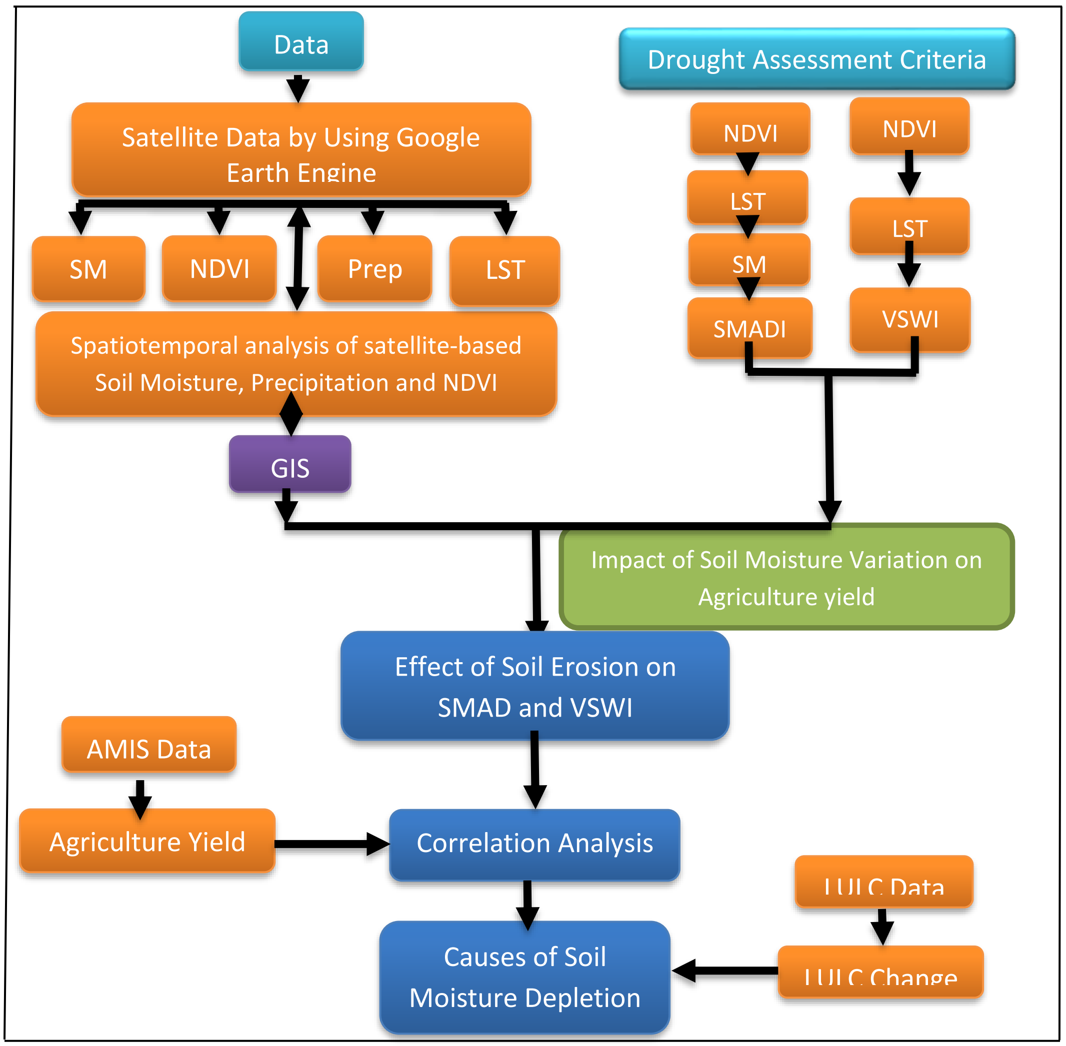


**Figure 1: Schematic methodology flowchart used in this study**

### 1.1. Study Area

South Punjab (SPP) is located geographically at 29.85° to 30.43°N and the longitude 71.5° to 72.47° E as shown in Figure 2. It covers an area of about 116,518 $Km^2$, accounts for 36% of the total Punjab population, and encompasses 45% of the state's land area. It serves as a significant agricultural region in the country, contributing substantially to agricultural output. The primary crops cultivated in SPP are cotton, sugarcane, sunflower, mustard, rice, and wheat. The region is known for its abundant production of fruits and vegetables. The temperature in the SPP region exhibits variation, ranging from 4°C to 46°C. However, during the summer, temperatures can exceed 50°C, while winter temperatures can drop to around 10°C. The average annual rainfall stands at 186 mm.

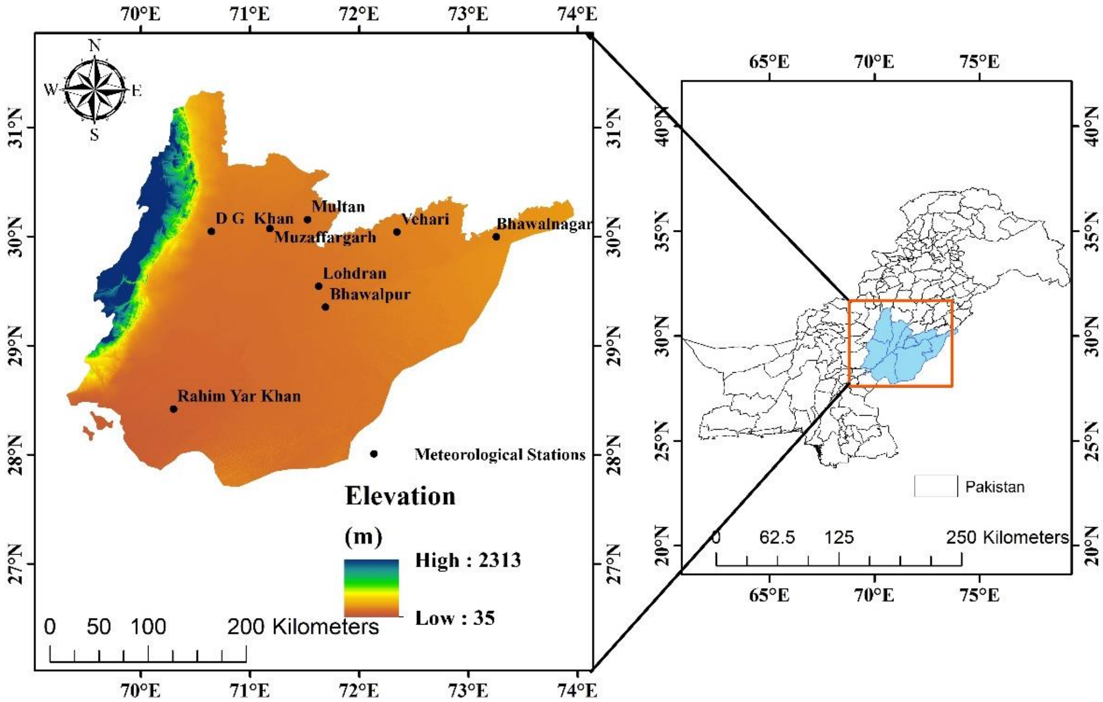


**Figure 2: Location of the study area along with elevation and meteorological stations**

The study utilized Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua products i.e., MYD09A1 and MYD11A2. MYD09A1 dataset was used to obtain NDVI data spanning from 2007 to 2021 which has a spatial resolution of 500 m and a temporal interval of 16 days. MYD11A2 product was utilized to acquire Land Surface Temperature (LST) with a spatial resolution of 1 km. Soil moisture data was acquired using the Global Land Data Assimilation System (GLDAS-2.1) product spanning from 2007 to 2021 spatial resolution of $0.25^0$ m and a temporal interval of 3 hourly. We used monthly precipitation data obtained through the utilization of the Global Precipitation Measurement (GPM) product from 2007 to 2021 with spatial resolutions $0.5^0$ and temporal resolutions monthly. Land use land cover images (2007- 2021) were collected from Earth explorer USGS (https://earthexplorer.usgs. gov/) having spatial resolution 30 m. Monthly crop production data (tons) was obtained from the Agricultural and Marketing Information Service (AMIS) for the extensive time frame of 2007 to 2021. Moreover, as part of the preprocessing and quality control phase, multi-source remote sensing and hydrological data were resampled to achieve a consistent spatial resolution, enhancing overall data quality. To maintain uniformity, spatial resampling to 0.25° × 0.25° was applied to soil moisture products.

**Table 1. Description of the datasets utilized in this study**

| Sr. | Datasets | Time Period | Temporal Resolution | Spatial Resolution |
|---|---|---|---|---|
| 1 | NDVI | 2007-2021 | 16-Day | 500 m |
| 2 | LST | 2007- 2021 | 8 days | 1000 m |
| 3 | Soil Moisture | 2007-2021 | 3-Hourly | 0.250 × 0.250 |
| 4 | Precipitation | 2007-2021 | Monthly | 0.50 × 0.50 |
| 5 | LULC | 2007-2021 | | 30 m |
| 6 | Agriculture Yield | 2007-2021 | Monthly | / |

### 1.2.Assessment of agriculture drought

In this study, two indices were utilized i.e. Vegetation Supply Water Index (VSWI) and Soil Moisture Agricultural Drought Index (SMADI). These standardized indices are used in this study based on robustness to detect drought conditions in arid-dominated regions such as SPP, and the drought severity status evaluated.

#### 1.2.1. Vegetation supply and water index (VSWI)

The normalized difference vegetation index is a widely used metric for quantifying the health and density of vegetation using sensor data. A higher NDVI value indicates the presence of robust and abundant vegetation, whereas lower NDVI values indicate a scarcity of vegetation, with values ranging between -1 and +1.

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad (1)$$

The measurements of reflectance in the near-infrared (*NIR*) and red spectra are collected from the regions of near-infrared and visible light, respectively. Following that, the Vegetation Supply Water Index (*VSWI*), is computed by combining the Normalized Difference Vegetation Index (*NDVI*) and land surface temperature (*LST*), used to assess the condition of plants. The Vegetation Condition Index (*VCI*) serves as an indicator of water shortage, indicating insufficient soil water storage to sustain plant growth.

$$\text{VSWI}= \frac{NDVI}{LST} \qquad (2)$$

$$\text{NVSWI}= \frac{(VSWI_i - VSWI_{\min})}{(VSWI_{\max} - VSWI_{\min})} \times 100 \qquad (3)$$

#### 1.2.2. Soil moisture agriculture drought index (SMADI)

The (*SMADI*) combines measurements of soil moisture, surface temperature, and vegetative vigor obtained through remote sensing(Sánchez et al., 2018; Sánchez et al., 2016). However, to highlight the inverse relationship, modifications have been made to the Temperature Condition Index (*TCI*) and Vegetation Condition Index (*VCI*) using Equations (4) and (5), resulting in the Modified TCI and VCI. A higher value of the Modified *TCI/VCI* indicates drier conditions (i.e., high MTCI and low VCI). The subscripts "min" and "max" indicate the minimum and maximum values, respectively, for standardizing the scale and representing wet and dry conditions in a comparable manner.

$$\text{VCI}=\frac{(NDVI_i - NDVI_{\min})}{(NDVI_{\max} - NDVI_{\min})} \quad (4)$$

$$\text{TCI}=\frac{(LST_i - LST_{\min})}{(LST_{\max} - LST_{\min})}\times 100 \quad (5)$$

$$\text{MTCI}=\frac{(LST_i - LST_{\min})}{(LST_{\max} - LST_{\min})} \quad (6)$$

The SMADI integrates soil moisture information by employing the Soil Moisture Condition Index (SMCI) (Eq. (7), with $SM_{min}$ and $SM_{max}$ denoting the lowest and highest soil moisture levels, respectively. This procedure standardizes the SM, resulting in a range from one to zero, indicating the progression from dry to wet conditions.

$$SMCI = \frac{(SM_{\max} - SM_i)}{(SM_{\max} - SM_{\min})} \quad (7)$$

The SMADI's integration of the VCI generated from the two extra indices, taking into account the lag between the vegetation response and the soil moisture situation, is a crucial part of the equation (11).

$$\text{SMADI}=\text{SMCI}\,\frac{MTCI_i}{VCI_{i+1}} \quad (8)$$

In the given context, the variable "*i*" corresponds to each monthly period, while "$VCI_i+_1$" refers to the subsequent time step.

**Table 2: Thresholds adopted to define the classes of drought for each index**

| Drought category | SMADI | NVSWI |
|---|---|---|
| Normal | 0 to 0.99 | 60 to 80 |
| Mild | 1 to 1.99 | 40 to 60 |
| Moderate | 2 to 2.99 | 20 to 40 |
| Severe | 3 to 3.99 | 10 to 20 |
| Extreme | >4 | >10 |

### 1.3.Modified Mann Kendall (MMK) for temporal variation analysis

Modified Mann Kendall (MMK) is a statistical method utilized to measure the trend of the linear relationship between two variables (Hu et al., 2020; Yue & Wang, 2004). It has been widely used to analyze the significance and magnitude of the hydrological and climatic time series data (Yue and Wang, 2004). In the present study, the MMK test was used to detect the historical trend of rainfall, temperature, and crop production in SPP from 2007 to 2021.

$$S = \sum_{i>j} \operatorname{sgn}(x_j - x_i) \quad (9)$$

where; the number of observations is denoted by n; while $x_i$ and $x_j$ are represented as the rank of *ith* ($i = 1, 2, 3. \ldots n - 1$) and *jth* ($j = i + 1, 2, 3. \ldots n$) observations (for detailed description, see Mann 1945; Kendall 1957; Praveen et al. 2020).

### 1.4. Inverse distance weighted (IDW) for spatial variation analysis

Inverse distance weighted (IDW) was used to predict the values for any unmeasured location, by measuring the surrounding values predicted location (Chen & Liu, 2012; Choi & Chong, 2022). It determines the cell values using a linearly weighted combination of a set of sample points. This method operates on the assumption that the variable being mapped diminishes its significance as the distance increases from its original sampled location. In this study, the interpolation technique was applied to map the spatial variation trend of annual soil moisture, precipitation, and NDVI data for the period of 2007 to 2021.

$$Z_p = \frac{\sum_{i=1}^{n}\left(\frac{z_i}{d^{p}{}_{i}}\right)}{\sum_{i=1}^{n}\left(\frac{1}{d^{p}{}_{i}}\right)} \tag{10}$$

where; $Z_i$ is the value of the known point; $d^{p}{}_{i}$ is the distance to a known point n is a user-selected exponent.

### 1.5. Pearson correlation analysis

Pearson correlation coefficient was used to measure the strength and direction of the relationship between two variables, it is denoted by the symbol "r" and has a range between -1 and 1. In this analysis, correlation was used to detect the relationship between soil moisture with different drought indices and agriculture yield in span of 2007-2021. Positive linear relationship indicates that when one variable increases, the other variable also increases proportionally. On the other hand, a Negative linear relationship means, that one variable decreases as the other variable increases.

$$r = \frac{\sum\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum\left(x_i - \bar{x}\right)^2 \sum\left(y_i - \bar{y}\right)^2}} \tag{11}$$

where; $r$ is Pearson correlation coefficient; $x_i$ is $x$ variable samples $x$ is mean of values in $x$ variable mean of values; in $y$ variable $y_i$ is $y$ variable sample.

## 2. RESULTS

### 2.1. Land use and land cover change analysis

The supervised LULC classification was performed on Landsat images for the years of 2007 and 2021 as depicted in Figure 3. The images were categorized into five classes: water, vegetation area, barren land, urban land, and agriculture. A significant change in the percentage areas of different LULC was observed in the study region. Results indicate that water, barren land, vegetation, and agriculture were decreased with -2.00%, -1.02%, -5.38%, and -11.66% respectively. While urban land notable rise of 18.91% as shown show that Urban land and vegetation cover were dominant; however, urbanization expanded in the grassland/Shrubland.in Figure 4

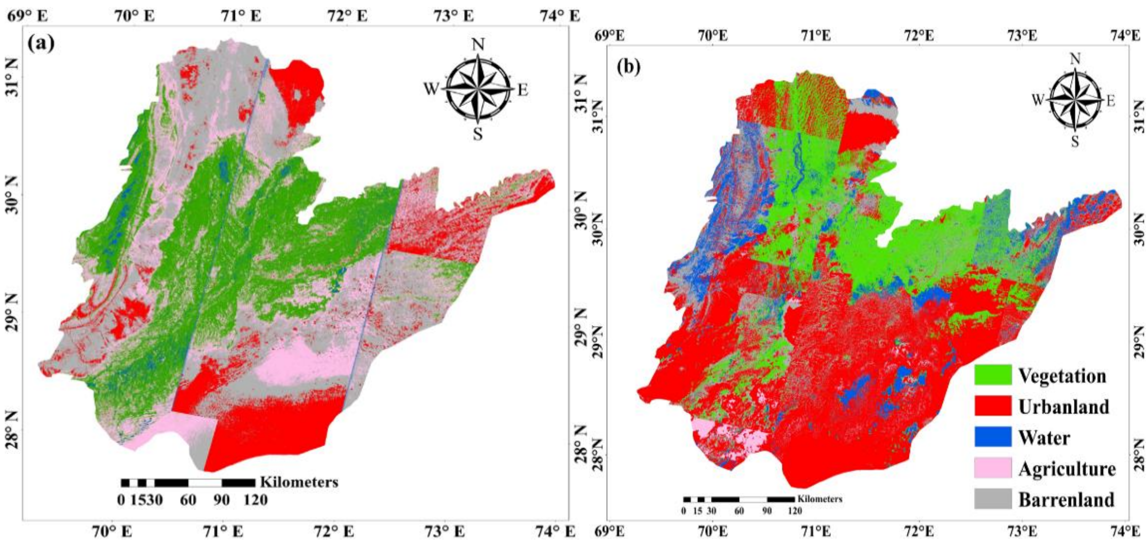


**Figure 3 Map of land cover and land use classification for a years a) 2007 and b) 2021**

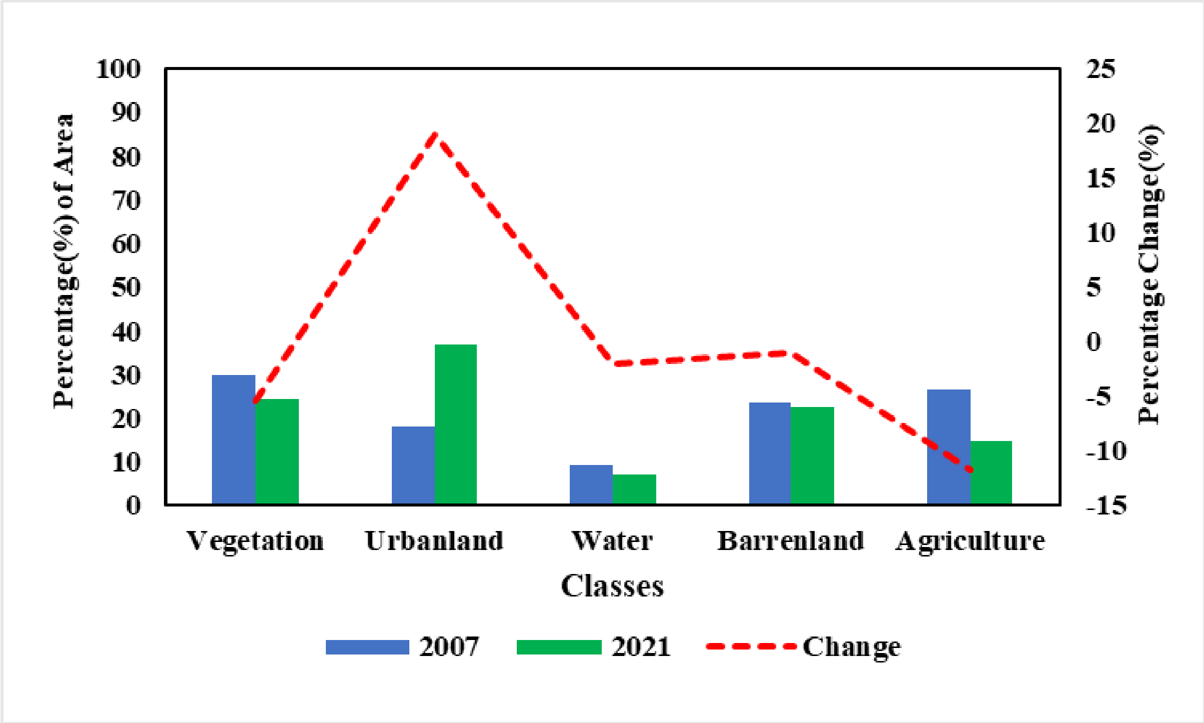


**Figure 4 Percentage change in the area of different LULC classes**

**2.2.Temporal variation of climatic factors**

The average annual temperature and precipitation trends were analyzed for the study period of 2007 to 2021 as represented in Figure 5. Temperature displayed a slight upward trend with a rate of an average of 0.027/year, whereas precipitation exhibited a decreasing trend with an average value of -0.232mm/year with fluctuations due to interannual variability and drought conditions. Thus, the strictly increasing temperature and slightly decreasing precipitation pattern mainly caused SM variation.

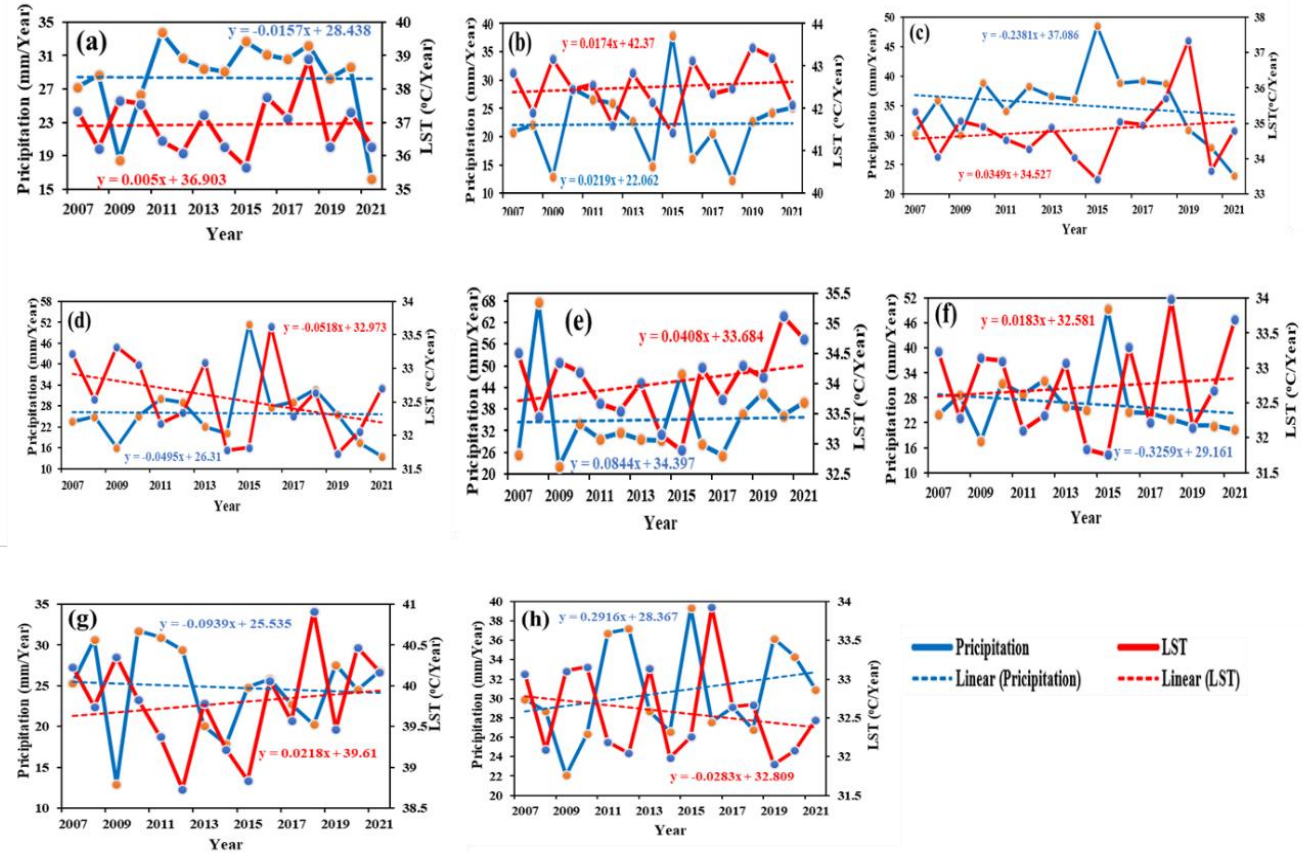


**Figure 5 Temporal variations of precipitation and land surface temperature: (a) Bahawalnagar (b)Bahawalpur (c) D G Khan (d) Lohdran (e) Muzaffargarh (f) Multan (g) Rahim Yar Khan (h) Vehari**

### 2.3. Temporal variation in soil moisture, precipitation and NDVI

Temporal analysis of annual average SM and NDVI was performed over fifteen years as demonstrated in Figure 6. This study investigation such as Bahawalnagar, Bahawalpur, Dera Ghazi Khan, Multan, Muzaffargarh, and Rahim Yar Khan exhibit lower trends within the range of -0.11 to -0.24 to,_however, Vehari and Lohdran demonstrate an increasing trend in Soil Moisture. The South Punjab Pakistan (SPP) Observed a positive inconsistency that displayed a slight decrease in soil moisture (SM) pattern from 2007 to 2021, as depicted in Figure 6 Since 2021, SM has predominantly remained below the long-term average. The variation in soil moisture (negative anomaly) underscores the potential for increased evapotranspiration (ET), thus indirectly intensifying the regional hydrologic cycle. It should be noted that global warming may not be the sole cause of soil moisture variation, as it may not follow a consistent trend. The declining soil moisture (SM) patterns observed across the (SPP) over the past 15 years could have multiple contributing factors, primarily climate change activities This decline is likely attributed to land use and land cover changes (LULC), particularly the dynamic reduction of vegetation/water and agriculture, accompanied by an alarming expansion of built areas, bare land, and other factors aggravated by climate change. On the other hand, the NDVI analysis reveals a significant decreasing trend ranging from -0.0083 to -0.0018 in Bahawalnagar, Bahawalpur, Dera Ghazi Khan, Multan, Muzaffargarh and Rahim Yar Khan. In contrast, Vehari and Lohdran exhibits an increasing trend in NDVI.

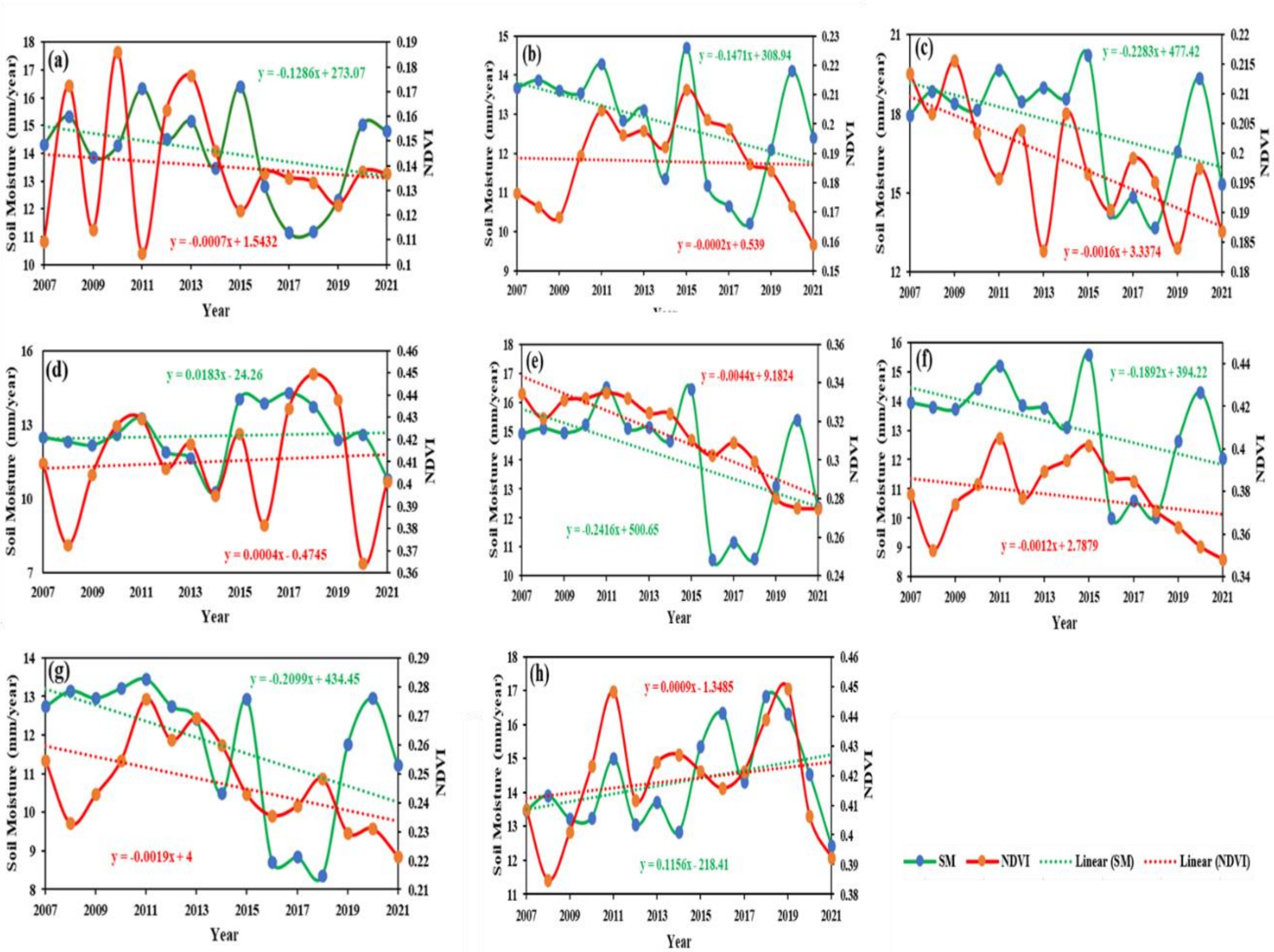


**Figure 6 Temporal variations of soil moisture and Normalized difference vegetation index in: (a) Bahawalnagar (b)Bahawalpur (c) D G Khan (d) Lohdran (e) Muzaffargarh (f) Multan (g) Rahim Yar Khan (h) Vehari**

### 2.4.Spatial variation of soil moisture, precipitation and NDVI

Figure 7 represents spatial trend distributions of annual soil moisture, precipitation, and NDVI for the period of 2007-2021. The analysis revealed a downward trend in average soil moisture having a Z value is -0.19 in the entire study area. Conversely, Vehari and Lohdran exhibited an increasing trend in Soil Moisture. While examining Precipitation, an average Z value of -0.28 indicated a decreasing trend in most of the stations, while Vehari showed an increasing trend. In terms of NDVI, an average Z value of -0.0037 indicated a decreasing trend in all stations. These findings emphasize the spatial variability of trends in South Punjab, with different areas displaying both increasing and decreasing patterns.

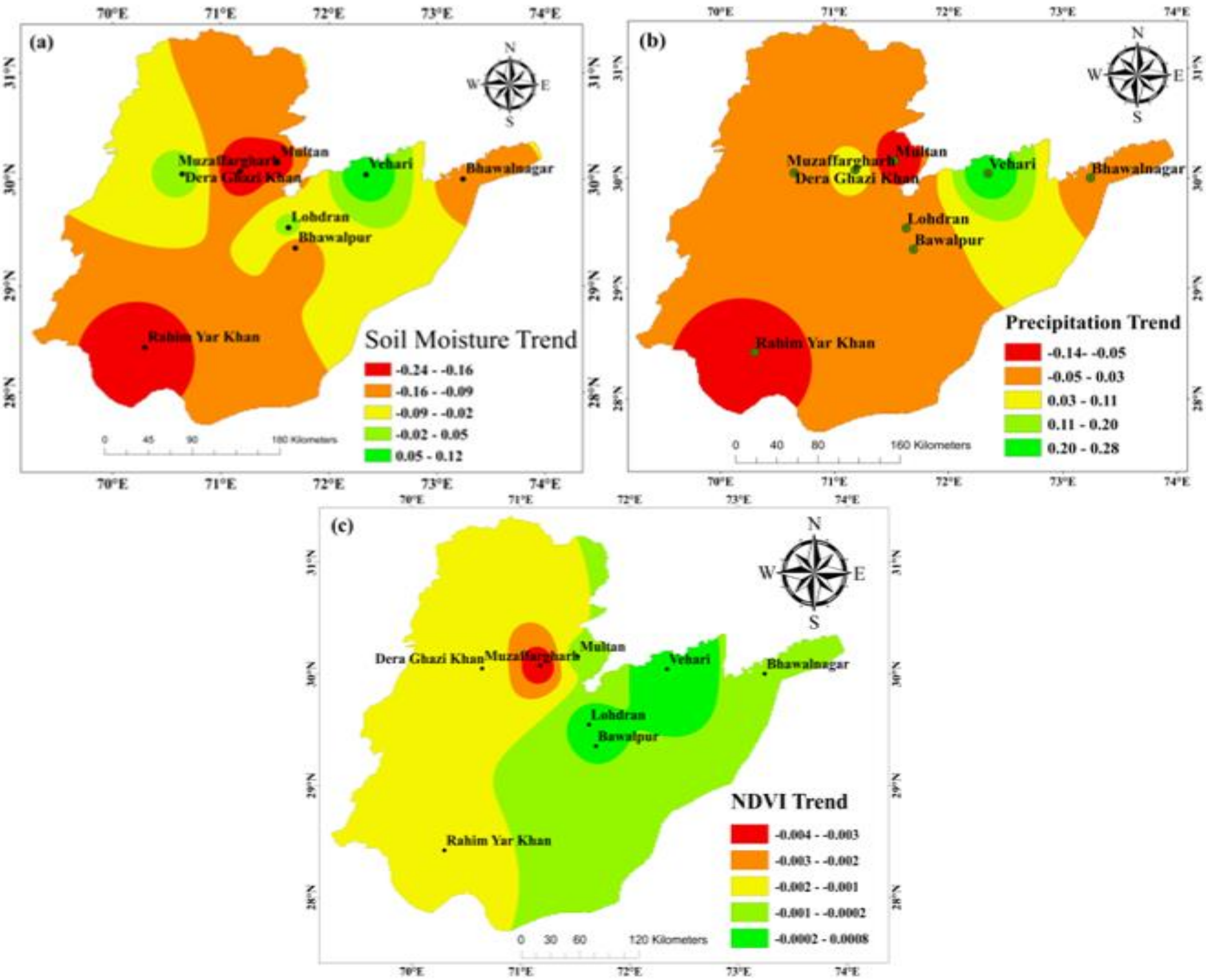


**Figure 7 Spatial variability of soil moisture, precipitation and NDVI**

### 2.5. Relationship between soil moisture, agriculture drought index (SMADI) and normalized vegetation supply water index (NVSWI)

The Soil Moisture Agriculture Drought Index (SMADI) and the Normalized Vegetation Supply Water Index (NVSWI) were assessed temporally from 2007 to 2021 as shown in Figure 8. Results demonstrated that the average SMADI showed a decreasing trend ranging from -0.004 to -0.083 in Bahawalnagar, Bahawalpur, D G Khan, Multan, Muzaffargarh, Rahim Yar Khan, on the other hand, Lohdran and Vehari observed increasing trend 0.016 and 0.025 respectively. Decreasing SMADI suggests worsening soil moisture conditions and potential drought stress on crops. Conversely, the NVSWI also demonstrated a notably declining trend ranging from -0.02 to 0.078 in Bahawalnagar, Bahawalpur, Dera Ghazi Khan, Multan, Muzaffargarh, Rahim Yar Khan but the increasing trend in Lohdran and vehari 0.16 to 0.19. declining in NVSWI persists, it could lead to a reduction in crop yields. Water stress during critical growth stages can result in smaller crop sizes, lower-quality produce, and, in extreme cases, crop failure.

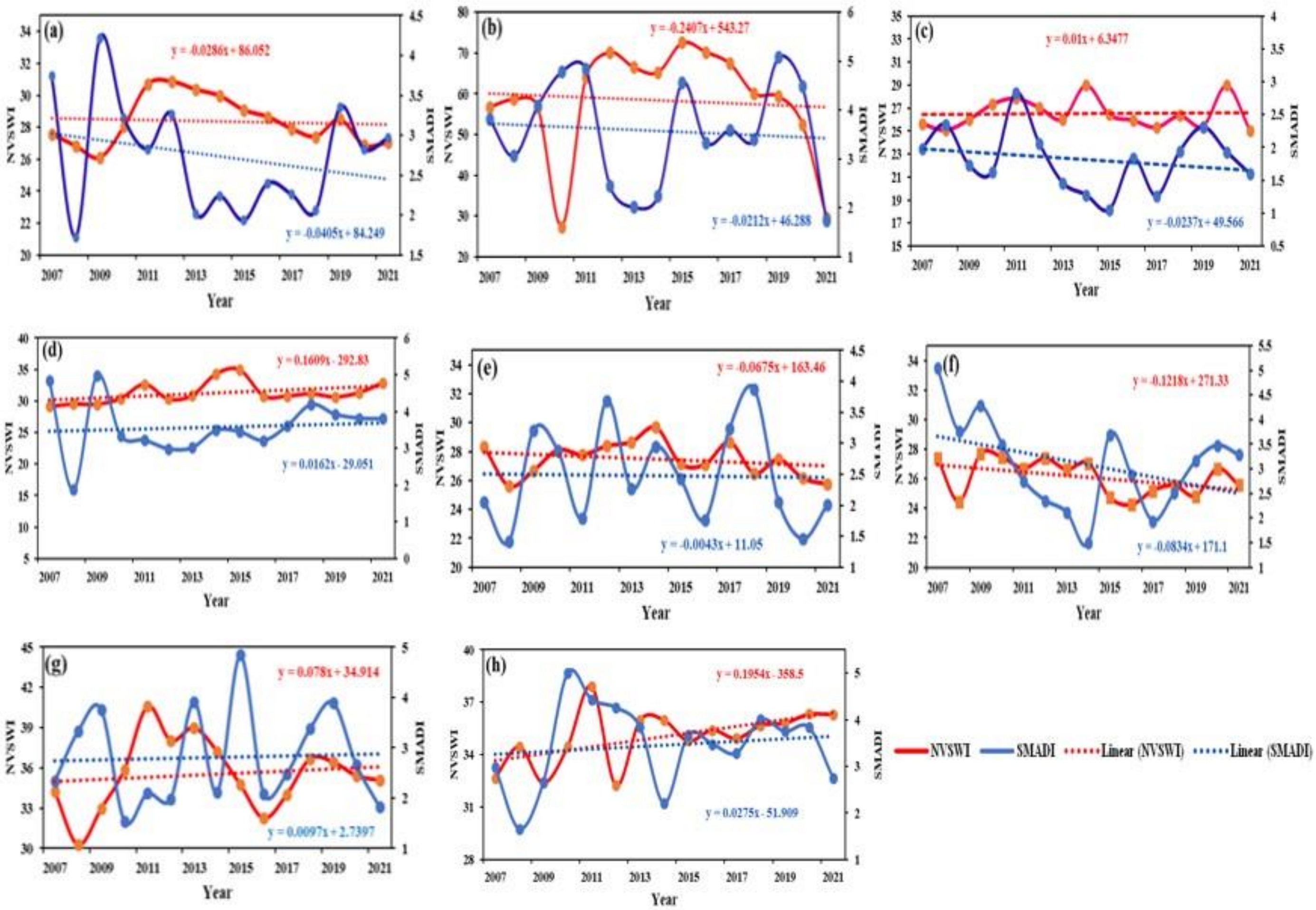


**Figure 8 Relationship of soil moisture with agriculture drought index and Normalized vegetation supply water index in: (a) Bahawalnagar (b)Bahawalpur (c)D G Khan (d)Lohdran (e)Muzaffargarh (f)Multan (g)Rahim Yar Khan (h)Vehari**

The SMADI and NVSWI were utilized to demonstrate a significant prevalence of drought events in the entire study area as depicted in Figure 9. There were notable fluctuations of severe drought events in the years of 2007, 2009, 2010, 2016, 2017, and 2018, while moderate drought events were observed in 2008, 2011, 2012, 2013, 2014, and 2015. Mild drought events occurred in 2019, 2020, and 2021. Similarly, the analysis of the NVSWI results indicated the occurrence of drought events, ranging from mild to extreme, during the same period. There were significant fluctuations of moderate drought events in the years 2007 to 2018 as well as in 2021, while mild drought events were observed in 2019 and 2020. These findings highlight the varying intensity and frequency of drought events in South Punjab, Pakistan, as captured by both the SMADI and NVSWI indices throughout the analyzed period.

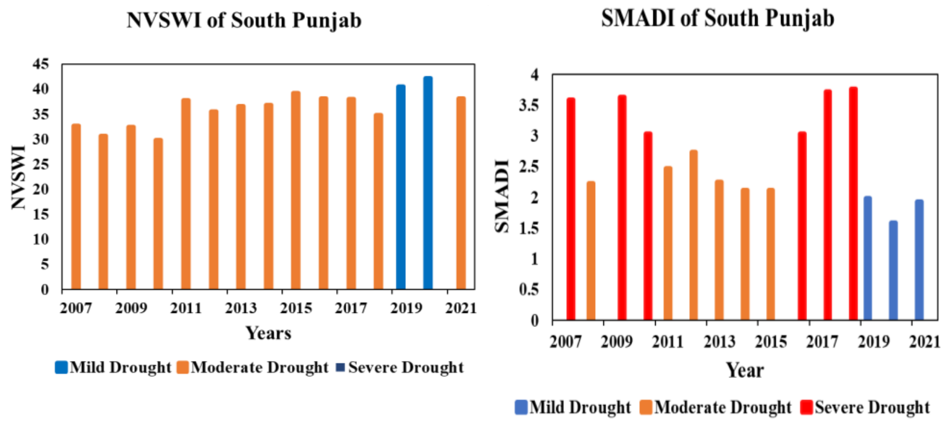


**Figure 9 Temporal variation of drought severity events based on SMADI and NVSWI index**

### 2.6. Correlation of soil moisture with agriculture yield, agriculture area, SMADI and NVSWI for different crops

Figure 10 presented the soil moisture relationship with different agriculture crops, areas and agricultural drought indices at the regional scale from 2007-2021. This study indicated that cotton and maize crops display a positive weak correlation, whereas rice and sugarcane crops indicate a weak negative correlation with soil moisture. However, NVSWI exhibits a strong positive correlation, while SMADI shows a weak negative relationship with soil moisture endorsing the insufficient nexus of SM owing to their dependence on irrigation. This dependence is aggravated by a lack of enough rainfall and inadequate vegetation coverage

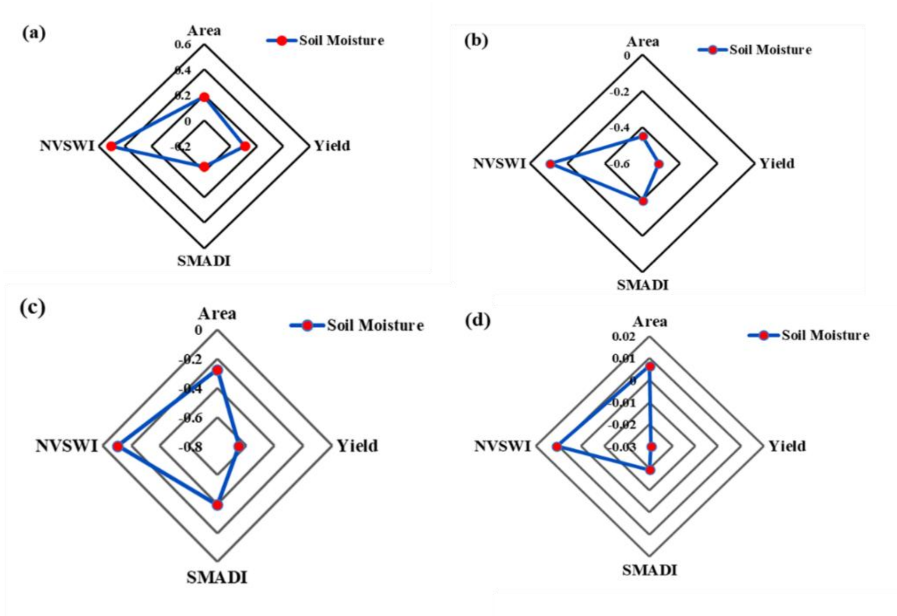


**Figure 10 Relationship of soil moisture with agriculture drought index, normalized vegetation supply water index, Crop area and agriculture yield for different Crops: (a) Cotton (b) Maize (c) Rice (d) Sugarcane**

### 2.7. Correlation of soil moisture with different crop growth stages and crop yield

The correlation analysis was performed between soil moisture of agricultural crop stages and crop yield as illustrated in Figure 11. A negative correlation was observed during the growth stage in some regions which indicates inadequate soil moisture during this period. The existence of a negative correlation during the growth stage implies that soil moisture deficit during this critical period may adversely impact agriculture productivity. Conversely, the positive correlation during the sowing and harvesting stages implies that variations in soil moisture levels during these stages align with changes in crop yield. Conversely, a positive correlation was observed during the sowing and harvesting stages of the crop. The correlation between soil moisture at different crop stages and crop yield is complex and multifaceted, with numerous factors influencing the relationship.

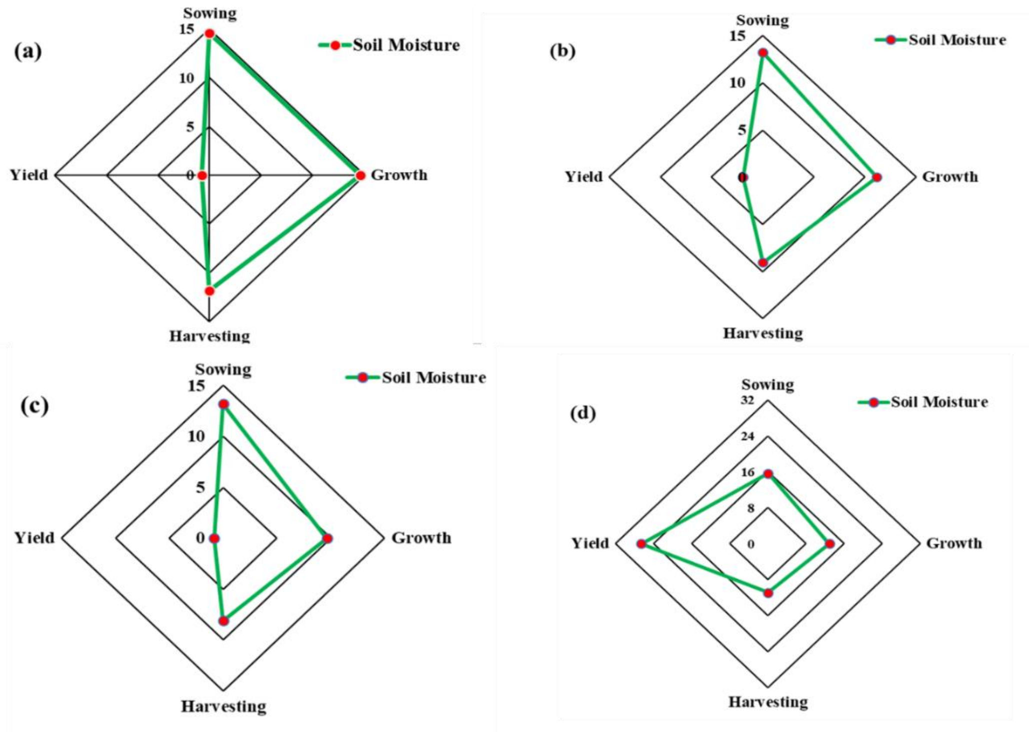


**Figure 11 Relationship of soil moisture with different growth stages of crop and crop yield: (a) Cotton (b) Maize (c) Rice (d) Sugarcane**

## 3. DISCUSSION

The intricate interplays among soil, climate, and plants govern the soil moisture (SM) response, a pivotal indicator for assessing agriculture (Feng et al., 2023). Hence, an in-depth exploration of the spatiotemporal dynamics of SM and NDVI would augment our current understanding of agricultural evaluation. Despite an overall diminishing trend of SM with an average rate of -0.19mm/year and -0.0019/year for NDVI (Figure 6). This declining pattern is likely attributed to climate change, LULC, droughts particularly dynamically diminishing trends of forest and alarmingly expanding built-up area, bare land. Certain areas within SPP exhibit a rising pattern of SM. For instance, the global spatiotemporal trajectory of satellite-based soil moisture has generally decreased (-10mm/year), primarily influenced by the drying trend in the southern hemisphere (Peng et al., 2023). Similarly, NDVI displays a declining trend in the western Ordos Plateau's desert, Longzhong Loess Plateau, and built-up and adjacent areas (He et al., 2021), characterized by changes in land use, land cover, and climate patterns (Rahman et al., 2023). This includes variations in temperature with increasing trends and precipitation with decreasing trends in the region, significantly impacting soil moisture fluctuations and highlighting the potential for increased evapotranspiration (ET) and indirect intensification of the regional hydrologic cycle(Huntington, 2006). It's noteworthy that global warming may not be the sole cause of soil moisture variation (Sheffield & Wood, 2008). Conversely, Vehari and Lohdran regions exhibit significantly increasing trends in SM and NDVI, attributed to rising precipitation trends and declining temperature patterns. A positive trend in soil moisture and NDVI in agricultural production typically signals favorable conditions for crop growth.

The problematic situation of agricultural production faces even more severe challenges under the evolving climate, particularly in developing nations like Pakistan. Pakistan holds the 8th position on the list of countries most adversely affected by climate change (Rahman et al., 2023; Syed et al., 2022). The ongoing climate change scenario has hastened hydrological extremes, particularly drought events in Pakistan, where the increase in temperature surpasses the global average (Waseem et al., 2022). This study explores the variations in soil moisture (SM) during severe drought events in the years 2007, 2009, 2010, 2016, 2017, and 2018, with moderate drought events observed in 2008, 2011, 2012, 2013, 2014, and 2015. Mild drought events occurred in 2019, 2020, and 2021 in SPP (Figure 9). NVSWI results indicate the occurrence of drought events, ranging from mild to extreme, during the same period. Significant fluctuations in moderate drought events were noted from 2007 to 2018 and in 2021, while mild drought events were observed in 2019 and 2020. The drought events in the SPP are linked to teleconnections, such as the SM variation related to moderate and severe drought events in 2000–2003, 2006–2008, 2013, 2017, and 2018 from northern Punjab to southern Punjab (Rahman et al., 2023). This region is characterized by more frequent extreme events, such as droughts, due to severe climate changes in Pakistan. Historical severe drought events (e.g., 2000–2002) have led to a significant decline in agricultural production in the SPP. This current study contributes to the existing literature by emphasizing key factors, including precipitation, temperature, and drought computation, in understanding yield losses.

Moreover, aside from climate teleconnections, the soil moisture (SM) in South Punjab is also influenced by local vegetation coverage and various other factors. To illustrate, examining SPP as a whole (see Figure 11), there exists a robust negative correlation between SMADI and cotton, maize, rice, and sugarcane. In contrast, NVSWI exhibits a weak correlation in maize and sugarcane due to insufficient vegetation coverage (Figure 10). This notable positive/negative correlation arises from variations in vegetation coverage and expansion of rainfed or irrigated agricultural land across SPP stations. In Vehari and Lohdran, NVSWI and SMADI display a negative relationship with SM ($r = -0.14$ to $-0.15$) (refer to Figure 11), attributed to prevalent bare land and irrigation. Conversely, a positive relationship is observed in Bahawalnagar, Bahawalpur, Dera Ghazi Khan, Multan, Muzaffargarh, and Rahim Yar Khan. Therefore, the positive/negative correlation between NVSWI and SMADI is primarily linked to Land Use and Land Cover (LULC) changes (Zhang et al., 2016), human activities (Gu et al., 2019), agricultural development associated with rainfed or irrigated farmland (Ambika & Mishra, 2019; Borrelli et al., 2017), farmer behaviors, and various other contributing factors. Consequently, SMADI and NVSWI can serve as ideal indices for monitoring or assessing agricultural yield security in areas with vegetation cover or rainfed agricultural practices.

During variations in soil moisture (SM), inadequate moisture levels fail to meet crop water requirements, resulting in a decline or failure in crop production (Gines et al., 2018). This, in turn, leads to agricultural drought (AghaKouchak, 2015), commonly causing insecurity in agricultural yields. Consequently, agricultural drought is closely linked to SM, a significant factor contributing to yield insecurity (Baik et al., 2019). The reduced availability of water in the soil for crop growth in rainfed agriculture, particularly in regions like SPP, leads to diminished crop yields and production (Baig et al., 2013). However, in irrigated areas, the risk of crop production failure can be mitigated by compensating for soil moisture deficits.

The variation in SM has a direct impact on food security by diminishing agriculture yield per capita. In SPP, where agricultural yield is the primary source of food supply, we consider agricultural yield as an indicators of production security, especially during drought years. This is attributed to insufficient moisture to meet crop water requirements, leading to a decline or failure in crop production (Gines et al., 2018). Understanding the SM response is crucial for assessing agricultural yield given the complex interplay among soil, climate, and plant control processes.

## 4. CONCLUSIONS

GLDAS 2.1 datasets was provided high resolution soil moisture (SM) data for the long period of time in this study. Statistical Approaches included Modified Mann Kendall and Pearson Correlation was utilized to investigate the causes and effects of SM variation on precipitation, temperature and normalized difference vegetation index (NDVI). Additionally, to evaluate the water stress impact of soil moisture on different drought indices i.e. (SMADI & NVSWI) and agricultural yield. The following are main conclusions of this study:

1. The changes in different LULC classes shown that vegetation, barren land, water and agriculture land was decreased to -5.39%, -1.09%, -2.00% and -11.66% decrease respectively while, urban land was increased to +18.9% during 2007 to 2021.
2. Based on trend analysis, it was resulted that average NDVI and soil moisture showed a decreasing trend at most of the stations.
3. The drought severity assessment based on SMADI and NVSWI showed that 2007-2018 were the dry year had an average value of 2.89 and 35.24 and 2019-2021 was found a wet year with an average value of 1.83 and 42.10 at most of the stations respectively.
4. Correlation analysis was indicated that SM having a negative correlation with agriculture yield, SMADI and NVSWI drought indices.
5. Based on the overall analysis, it was noted that a decline in soil moisture has triggered down the agricultural drought and ultimately has decreased agricultural land as well as yield in South Punjab.

Therefore, in South Punjab Pakistan, it is strongly advised to reconsider and address the causes of SM depletion while installing a reliable irrigation system to provide agricultural productivity security impacted by agricultural drought.

## ACKNOWLEDGMENTS

The research work was made possible through the support of Agricultural and Marketing Information Service (AMIS) which generously provided agriculture yield data for conducting this research.

## FUNDING

There is no funding for this research work

## AUTHOR CONTRIBUTIONS

Khawar Abbas: Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft. Muhammad Waseem: Formal analysis; methodology; writing – review and editing; supervision. Mudassar Iqbal: Conceptualization; formal analysis; methodology; resources. Muhammad Mujahid: Data curation; formal analysis; writing – review and software. Umar Sultan: Data curation; formal analysis; editing. Muhammad Laraib: Formal analysis; writing – review and editing. Abu Bakar Arshed: Formal analysis; writing – review and editing. Muhammad Ayub Shah: Formal analysis; writing – review and editing. Mohsin Raza: Formal analysis; writing – review and editing.

## DATA AVAILABILITY

The data used in this study, including agriculture yield data is the property of the Agricultural and Marketing Information Service (AMIS), Pakistan which can be requested via official channels. However, geospatial data which is freely available and can be accessed from the websites given in the datasets section of the manuscript.

**CONFLICT OF INTEREST**

The authors collectively state that they do not possess any conflicts of interest.

**SUPPLEMENTARY MATERIAL**

There is no supplementary material.

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