Proceedings of the Pakistan Academy of Sciences: A Physical and Computational Sciences 62(3): 193-207 (2025)

ISSN (Print): 2518-4245; ISSN (Online): 2518-4253
http://doi.org/10.53560/PPASA(62-3)843

Pakistan Academy of Sciences

Research Article

Assessing Drought Vulnerability in Pakistan (2001-2022) Using EVI-Based Standardized Vegetation Index in Google Earth Engine

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Abstract: This study examines vegetation dynamics and drought risk in Pakistan from 2001 to 2022 using MODIS Enhanced Vegetation Index (EVI) and Standardized Vegetation Index (SVI) processed in Google Earth Engine. EVI highlights high greenness in the irrigated plains of Punjab and Sindh, while SVI exposes widespread stress in these same areas, revealing a "greening paradox" where apparent productivity masks underlying vulnerability. Monthly SVI patterns follow strong seasonal cycles, with positive anomalies peaking during the monsoon driven kharif season (June-October) and persistent deficits occurring in the rabi season (December–May). Spatially, high EVI values (>0.4) were concentrated along the Indus River corridor, while arid zones such as Balochistan and the Thar Desert exhibited low EVI (<0.2). Mean SVI maps contradicted these patterns, showing negative anomalies in high EVI regions. Long term analysis indicated stable EVI until 2018, followed by a modest upward trend, while SVI shifted from chronic negative anomalies in the early 2000s (mean = –0.21) to sustained positive values after 2020 (mean = +0.58). At the provincial scale, Punjab showed a post 2015 decline, Sindh demonstrated recovery after drought episodes in 2010-2012 and 2017-2018, Khyber Pakhtunkhwa displayed high variability without a clear trend, and Balochistan recorded the strongest improvement since 2005. Overall, EVI captured absolute greenness, while SVI provided anomaly based insights into drought conditions, detecting hidden stress in intensively irrigated areas and identifying genuine recovery in marginal regions. By integrating EVI and SVI, this study offers a robust framework for spatiotemporal drought monitoring in Pakistan. The results provide a scientific basis for climate smart agriculture, early warning systems, and sustainable land and water management strategies aimed at safeguarding food security in the face of rising drought frequency.

Keywords: Standardized Vegetation Index (SVI), Drought Vulnerability, Vegetation Stress, Remote Sensing, Google Earth Engine (GEE), Drought in Pakistan.

1. INTRODUCTION

Agriculture serves as the foundation for numerous businesses and provides millions of people with a means of subsistence [1]. However, unpredictable weather brought on by climate change has drastically decreased agricultural output. Drought disaster is one of the most frequent, severe natural disasters widespread on a year to year basis. As a result, climate smart agribusiness is now more important than ever. With this approach, agricultural productivity is intended to increase while mitigating and adjusting to the impacts of climate change [2-4]. Climate smart agriculture now requires the use of remote sensing and machine learning methods on cloud data [5]. In remote sensing, sensors are used to collect data on the earth's surface and atmosphere [6]. This technique makes it possible to get information on crucial agricultural characteristics including crop health and soil moisture. As a result, choices may be made about crop management, such as when to schedule irrigation, fertilize, and apply pesticides [7]. In addition, crop monitoring and forecasting are aided by remote sensing [8].

Received: November 2023; Revised: August 2025; Accepted: September 2025
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Unlike sudden onset disasters such as floods or earthquakes, drought is a slow onset hazard that is often difficult to define precisely due to its creeping nature, spatial variability, and delayed socio economic impacts. Drought occurrences are classified into four major categories based on the sectors they impact: meteorological, agricultural, hydrological, and socio economic drought. This study focuses primarily on agricultural drought defined as a period during which soil moisture falls below the level required for normal crop growth and development as it directly affects food production and rural livelihoods in Pakistan.

For agriculture, drought is characterized by a period of soil moisture being less than the amount required for normal plant growth and development [9]. Numerous methods for monitoring and quantitatively describing drought have been developed during the last few decades, including the development of drought indices used in meteorology, hydrology, and agriculture. Traditional drought monitoring techniques rely on indices derived from meteorological station data such as precipitation. A number of the most broadly utilized meteorological drought indexes based only on this parameter is the World Meteorological Organization's (WMO) proposed Standardized Precipitation Index (SPI).

However, other climatic factors, including as evapotranspiration and temperature, impact the occurrence and severity of droughts. Beguera *et al*. [10] introduced the Standardized Precipitation Evapotranspiration Index (SPEI), which is based on both precipitation and potential evapotranspiration (PET). SPEI, like SPI, may be calculated at time intervals ranging from one to forty eight months. According to several researches, a 3 month SPI and SPEI are preferable for monitoring the impacts of drought on plants [11]. Since traditional station based drought monitoring systems required continuous historical information, satellite based methods give rapid and realistic findings for close to real time acquisition, drought analysis, and extensive and continuous geographic coverage [12].

Tucker and Choudhury [13] applied the Normalized Vegetation Index (NDVI) as a satellite based drought monitoring tool. The greatest and widely used satellite based vegetation indicator 'NDVI' offers a useful indication of vegetation moisture conditions. In addition to NDVI, Land Surface Temperature (LST) derived from thermal satellite bands are used to improve drought measurements as temperature rises and soil moisture reduces.

Subsequently, numerous vegetation indices (VIs) like the Vegetation Condition Index (VCI) were developed to better the research of vegetation states without weathering, particularly in non homogeneous areas. Because of its amplified sensitivity to water stress, temperature was also employed to develop drought indices such as the Temperature Condition Index (TCI) [14]. Drought indices including VCI and TCI can efficiently identify drought conditions since the combination of NDVI and LST provides statistics on both vegetation and moisture. Finally, scientists created the Vegetation Health Index (VHI) based on a numerical combination of VCI and TCI [15]. Using machine learning on cloud data, like Google Earth Engine (GEE), makes it possible to examine remote sensing information, more quickly and affordably [16]. Machine learning algorithms can be trained on large datasets in order to find trends and forecast future crop yields or other crucial agricultural parameters. These forecasts can be used to improve crop management techniques, lower input costs, and boost total productivity [17].

The standardized vegetation index (SVI) is one of the most important instruments for climate smart agriculture [18]. SVI, a measurement of plant development and cover, is created using satellite data. Since drought conditions may significantly affect agricultural productivity, the indicator is especially helpful for keeping track of them. The Enhanced Vegetation Index (EVI), a gauge of vegetation greenness, may be used to determine the SVI. The EVI is then normalized to produce an index that may be utilized to contrast various places and periods [19]. SVI may be used as a drought mitigation tool and to detect water stress early on by tracking plant growth and cover [20].

This study operationalizes the SVI via Google Earth Engine (GEE) to deliver scalable, near real time drought intelligence for Pakistan. As country is a climate vulnerable region increasingly beset by intensifying water scarcity, prolonged dry spells, and more frequent and severe extreme weather events, thus enabling proactive, data driven responses to agricultural stress. With employing SVI to enhance climate smart farming decision making is especially critical during periods of drought as early detection allows farmers and government agencies to implement timely interventions for adjusting irrigation schedules, shifting planting dates, or selecting drought resilient crop varieties. This can significantly mitigate yield losses and reduce systemic vulnerability to water shortages, ultimately supporting food security and rural livelihoods [21, 22].

The utility of SVI extends beyond mere drought assessment, as it provides a robust, spatially explicit indicator that can inform adaptive land management strategies, optimize resource allocation, improve crop yield forecasts, and help buffer agricultural systems against the escalating impacts of climate change, including rising temperatures, erratic rainfall patterns, and accelerated soil degradation. This study is good to leverage the power of cloud based remote sensing and Google Earth Engine to compute, monitor, and map SVI across Pakistan's diverse agro ecological zones, where recurrent droughts, declining groundwater tables, and extreme climatic variability have rendered traditional monitoring approaches inadequate. Pakistan needs an integrated, high resolution, and operationally feasible drought early warning system to safeguard national agricultural resilience in an era of accelerating environmental uncertainty.

This study aims to establish a satellite based, cloud computing framework for agricultural drought monitoring in Pakistan using the Standardized Vegetation Index (SVI). Specifically, it seeks to:

(1) To generate multi decadal (2001-2022) SVI and EVI time series for Pakistani provinces using MODIS data within Google Earth Engine;
(2) To characterize mean, monthly, and inter annual patterns of vegetation stress to identify regional drought vulnerabilities and seasonal dynamics;
(3) To evaluate SVI's performance in capturing agriculturally relevant drought signals compared to traditional metrics; and
(4) To make the foundation for integrating SVI analytics into national early warning systems and climate smart agricultural policies for supporting targeted interventions in irrigation, crop selection.

2. MATERIALS AND METHODS

2.1. Study Area

Pakistan is a South Asian nation bordered to the east by India, to the northwest by Afghanistan, to the west by Iran, and to the northeast by China (Figure 1). It has a total land size of approximately 881,913 km² and a diverse topography of mountains, plateaus, and plains. Agriculture industry contributes significantly to the country's economy and employing approximately 42% of the labour force and accounts for more than one fifth of GDP share. The farming is heavily dependent on irrigation, as around 90% of its agricultural land needs irrigation water. The main crops are wheat, rice, cotton, sugarcane, and maize, these are among Pakistan's for food and export items,also significant production of fruits and vegetables such as mangoes, citrus, apples, and potatoes. The agriculture industry in Pakistan is confronted with a number of issues, including water scarcity, soil degradation, and climate change [23]. Pakistan has experienced severe droughts in recent years and affecting its agriculture. The agriculture sector is also vulnerable to floods that can cause extensive damage to crops and infrastructure [24, 25]. The Pakistani government has launched a number of initiatives in response to these challenges, including irrigation techniques and new methods, to support climate smart agriculture practices. These initiatives aim to increase agricultural productivity while mitigating the negative impacts of climate change [23]. The government is also investing in the study and creation of new technologies and practices to improve the efficiency and sustainability of

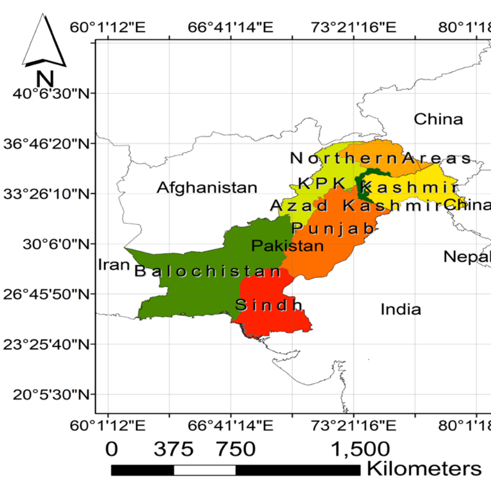

Fig. 1. Study area Pakistan.

agriculture, as country geography and topography make it ideal for agriculture which is a significant contributor to the country's economy [26]. Though, country still faces a number of challenges, such as water scarcity, soil degradation, and climate change, necessitating the creation of novel solutions and practices [27].

2.2. MODIS Data Product (MOD13Q1)

The MOD13Q1 is a product of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard NASA's Terra and Aqua satellites. It is a vegetation index dataset, global data is available that provides information on vegetation health and productivity at a spatial resolution of 250 meters. This MOD13Q1 data is using in many applications such as crop monitoring, land cover classification, and climate change studies [28, 29]. MOD13Q1 provides both the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) data products. However, in this study only MODIS derived EVI product has been used.

2.3. Enhanced Vegetation Index (EVI)

MODIS is an excellent sensor system, this is one of NASA's most extensively used in scientific studies. MODIS product/vegetation datasets is the MOD13Q1, this global level product provides reliable and high quality measures of vegetation health and productivity. This has a spatial resolution of 250 meters with biweekly temporal coverage, and is widely used in the scientific and operational areas. The MOD13Q1 data is useful for applications such as crop monitoring, land cover categorization, drought assessment, phenological analysis, and long term climate change studies. Its uniform processing, substantial archive since 2000 and multi sensor continuity make it a must have resource for understanding terrestrial ecosystem processes at regional and global scales [28-31].

The EVI equation includes blue and red bands, as well as the near infrared band. The equation is:

$$EVI = 2.5 \times \frac{(NIR - Red)}{NIR + 6 \times Red - 7.5 \times Blue + L} \quad (1)$$

Where, NIR is the reflectance in the near infrared band, Red is the reflectance in the red band, and Blue is the reflectance in the blue band.

In an attempt to provide a more accurate measurement of vegetation canopy, the factors in the equation are employed to lessen the impact of the aerosol component of the atmosphere on the vegetation signal. Higher numbers denote more plant density and good growth, and the resulting EVI values range from -1 to +1.

2.4. Standardized Vegetation Index (SVI)

The SVI is a standardised measure that may be used to assess the productivity and health of vegetation in various places and throughout various time periods, particularly during extreme weather. This index offers information on the length and severity of droughts as well as how they affect vegetation [32]. SVI is derived from EVI by standardizing the EVI values across time and space:

$$\mathrm{SVI} = \frac{(\mathrm{EVI} - \mathrm{mean}\,(\mathrm{EVI}))}{\mathrm{standard\ deviation}\,(\mathrm{EVI})} \quad (2)$$

Where, mean(EVI) is the average EVI value across a specified time period and area, and standard deviation (EVI) is the standard deviation of EVI across the same time period and area.

SVI evaluation applying MODIS EVI data in Google Earth Engine (GEE) involves a number of processes. The accuracy of the study is increased by first filtering the data from MODIS EVI by date and area of interest (AOI). The EVI range is then scaled to -1 to +1 after the filters have been applied to the data. Each image has statistics computed for it, such as mean values and standard deviation [33]. The rescaled EVI data, mean, and standard deviation numbers are then factored into a formula to determine the SVI. The mean EVI, and SVI image are used for visualization. The rescaled EVI data, mean, and standard deviation numbers are then factored into a formula to determine the SVI. The mean EVI, most recent EVI and SVI image are all included in the data display process using GEE. This method offers a quick and precise means to evaluate SVI using MODIS EVI data using GEE [34]. Provincial wise time series data were retrieved on monthly SVI data from 2001 to 2022, finally, mean SVI for whole Pakistan was calculated.

3. RESULTS AND DISCUSSION

The EVI was calculated for the entire Pakistan region. The mean EVI map shows high vegetation productivity (>0.4) along the Indus River corridor in Punjab and Sindh, driven by irrigation and agriculture. Lower values (<0.2) dominate arid regions like Balochistan and the Thar Desert, reflecting limited biomass. Negative values in mountainous and urban areas suggest bare soil (Figure 2). Monthly SVI datasets were used to obtain the mean SVI index for Pakistan indicating significant deviations from long term climatological norms. Negative SVI values (yellow to red) dominate central and southern regions, reflecting persistent drought conditions in irrigated and rainfed agricultural zones. In contrast, positive SVI values (green) are localized in northern mountainous areas and in many parts of Balochistan, suggesting above average vegetation health during the study period (Figure 3).

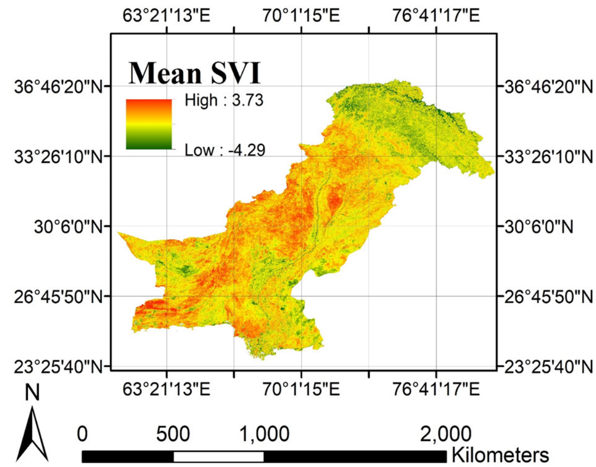

Fig. 3. Mean SVI index values in Pakistan.

3.1. Mean Monthly EVI and SVI Dynamics in Pakistan (2001 2022)

Figure 4 shows mean monthly EVI and SVI dynamics in Pakistan during the study period. This monthly averaged EVI and SVI reveal distinct seasonal patterns that closely align with the region's dual cropping agricultural system. EVI, which serves as a robust proxy for vegetation density and photosynthetic activity, exhibits a bimodal distribution with two pronounced peaks: one in February (0.153) and another in August (0.164). These peaks correspond to the growth phases of the rabi (winter) and kharif (monsoon) cropping seasons, respectively. The February peak reflects the vigorous development of rabi crops such as wheat and mustard, which benefit from winter precipitation and irrigation. The August peak, the highest of the year, coincides with the monsoon season, during which kharif crops like rice and maize achieve full canopy closure under favorable moisture conditions. The subsequent decline in EVI during September and October indicates crop maturation and harvest, leading to reduced green vegetation cover.

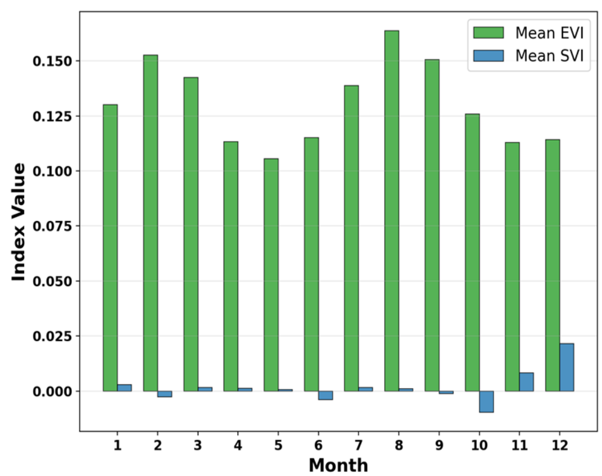

Fig. 4. Mean monthly EVI and SVI dynamics in Pakistan (2001-2022).

In contrast, the SVI remains largely neutral (≈0.00) across most months, suggesting relatively stable. Notably, SVI registers a slight negative value in October (-0.01), likely reflecting post monsoon soil drying following the kharif harvest. However, a modest but meaningful positive shift occurs in November (0.01) and peaks in December (0.02), indicating improved soil moisture conditions coinciding with the sowing and early establishment of rabi crops. This late year rise in SVI may be

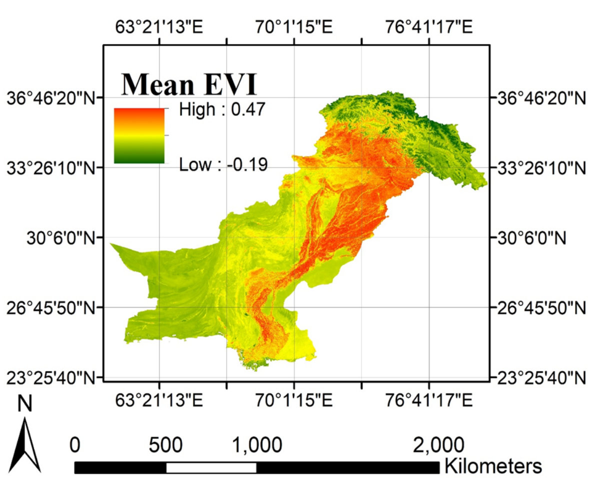

Fig. 2. Mean EVI index values in Pakistan.

attributed to winter rainfall, residual soil moisture retention, or supplemental irrigation, all critical for supporting the rabi cropping cycle in this semi-arid agro climatic zone.

The near zero SVI values observed during the peak EVI months (February and August) suggest that while vegetation is thriving, the soil moisture signal is either masked by dense canopy cover or remains within a balanced range that does not trigger strong positive or negative SVI responses. This underscores the complementary nature of EVI and SVI: while EVI effectively captures vegetation phenology, SVI provides nuanced insights into underlying conditions that support or constrain vegetation growth. Together, these indices confirm the resilience and productivity of Pakistan's agricultural system, which leverages both monsoon rains and winter moisture (natural or managed) to sustain year-round cultivation. The 2001-2022 data thus encapsulate a typical, well-functioning agricultural calendar in Pakistan, characterized by timely transitions between cropping seasons and effective moisture management.

3.2. Temporal Dynamics of Vegetation and Soil Conditions in Pakistan (2001–2022): Insights from EVI and SVI Time Series

The SVI and EVI derived long term monthly time series for Pakistan from 2001 to 2022 provide crucial data on vegetation phenology and soil vegetation interactions (Figure 5). This reflects the region's dominant double cropping system, the EVI time series shows consistent seasonal trends with recurring peaks during the kharif (monsoon) season, particularly in August, and secondary peaks during the rabi (winter) season, primarily in February and March. The primary forces behind these bimodal cycles are monsoon rains (June-September), which support kharif crops like rice and maize, and winter irrigation and rainfall, which support rabi crops like wheat and mustard. It's interesting to note that while EVI values fluctuate from year to year, noteworthy increases have been observed recently (e.g., 2019-2022), suggesting higher vegetation production possibly linked to improved irrigation practices, crop management, or favorable climatic conditions.

In contrast, the SVI time series displays more dynamic and variable behavior, indicating significant fluctuations over time (Figure 6). The early years (2001-2005) show predominantly negative SVI values (down to –1.18), suggesting dry soil conditions or sparse vegetation cover, a marked shift occurs post 2007, with increasing frequency and magnitude of positive SVI anomalies. The most notable surge occurs around 2020-2022, where SVI reaches values exceeding 1.0, indicating exceptionally favorable soil moisture and vegetation conditions. This upward trend may reflect changes in land use, increased groundwater utilization, climate variability (e.g., higher winter precipitation), or improvements in agricultural infrastructure. However, the high volatility in SVI suggests sensitivity to short term weather events, such as droughts or heavy rainfall, which can rapidly alter soil moisture dynamics and impact crop health.

The mean monthly SVI index values were estimated for Pakistan (Figure 7), This shows

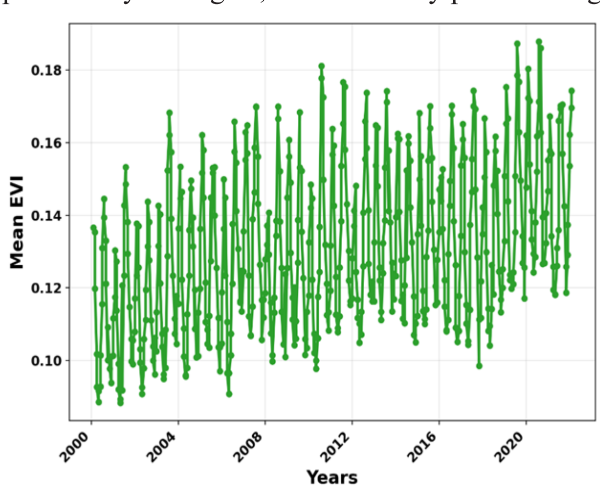

Fig. 5. Monthly time series of EVI.

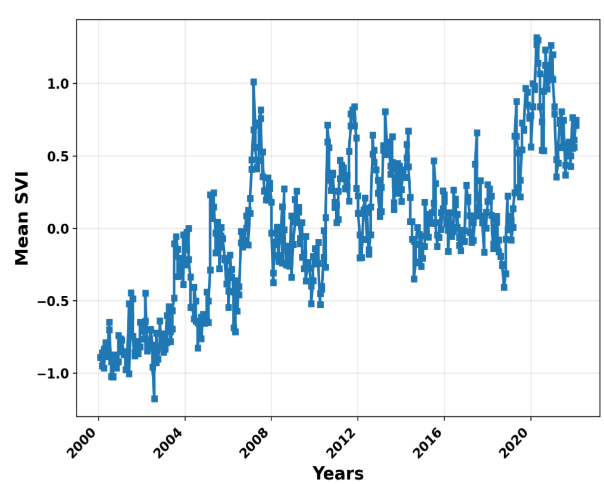

Fig. 6. Monthly time series of SVI.

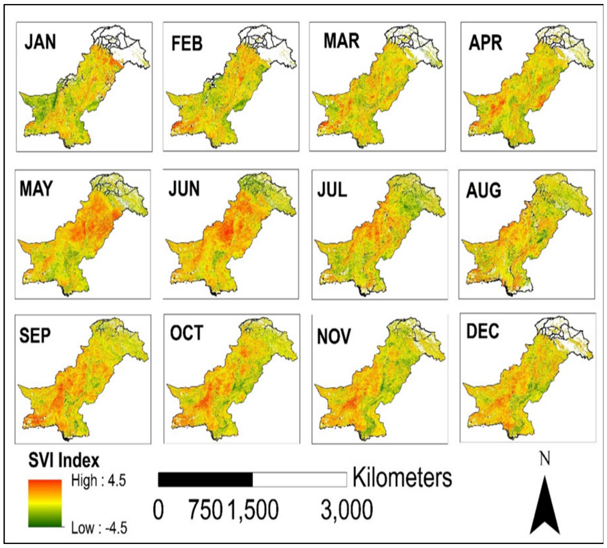

Fig. 7. Mean monthly SVI index values in Pakistan.

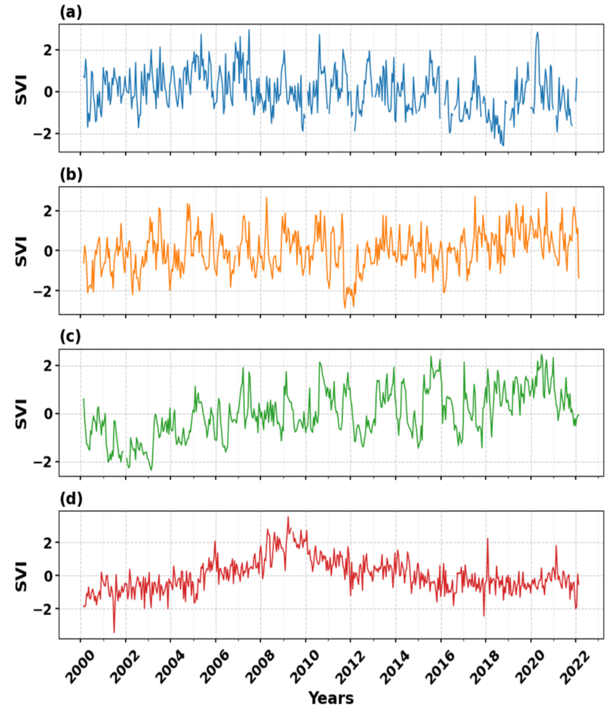

Fig. 8. Time series SVI in provinces of Pakistan: (a) Punjab, (b) Sindh, (c) Khyber Pakhtunkhwa, and (d) Balochistan.

the monthly variation in vegetation stress across Pakistan from January to December. The highest SVI values occur during June–October, corresponding with the monsoon season and peak crop growth, particularly in Punjab and Sindh. In contrast, negative SVI values dominate during the dry winter months (December-February), indicating below average vegetation conditions. This seasonal pattern reflects strong dependence on monsoon rains and agricultural phenology, with central and southern regions showing greater variability due to irrigation and rainfall fluctuations.

Inter annual SVI conditions were observed using time series SVI in Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan provinces respectively in Figures 8(a to d). The SVI for Punjab shows strong seasonal fluctuations with distinct peaks during the summer months, indicating healthy vegetation growth driven by monsoon rains and agricultural activity (Figures 8(a)). However, the index displays no significant long-term trend and even suggests a slight decline after 2015, potentially reflecting increasing water stress, overuse of resources, or environmental degradation despite high agricultural productivity. In Sindh, the SVI exhibits moderate seasonality and a notable upward trend starting around 2015, signaling improved vegetation conditions over time (Figures 8(b)). This positive shift may be attributed to better irrigation infrastructure, climate variability, or agricultural development, suggesting a recovery from earlier periods of drought and land degradation, particularly observed during 2010-2012 and 2017-2018. Khyber Pakhtunkhwa experiences high variability in SVI, with sharp peaks and frequent negative values, reflecting its mountainous terrain and dependence on seasonal rainfall (Figures 8(c)). The lack of a consistent long-term trend indicates ongoing ecological instability, with vegetation remaining vulnerable to climate extremes and land degradation, highlighting the need for sustainable land and water management practices. Balochistan stands out with a remarkable upward trend in SVI beginning around 2005, transitioning from very low vegetation levels to near normal conditions by 2015 (Figures 8(d)). This significant improvement suggests successful rangeland restoration, afforestation efforts, or increased rainfall, marking one of the most positive environmental developments across Pakistan's provinces in the past two decades.

The SVI provides a powerful metric for assessing vegetation stress and productivity by quantifying deviations of current vegetation conditions from long term climatological norms. Low or negative SVI values typically indicate below average vegetation performance, often linked to water stress, drought, or poor soil moisture availability, while positive values signify above average vigor, suggesting favorable growing conditions. The magnitude of these anomalies offers insight into the severity of stress or the degree of productivity enhancement. However, interpretation must be contextualized: a negative SVI may reflect natural aridity in rangelands but signal critical stress in irrigated croplands, where even minor moisture deficits can compromise yield. Thus, SVI should not be interpreted in isolation but integrated with land use, crop type, and hydrological data to avoid misclassification of ecological states.

Drought is a pervasive and escalating global phenomenon, characterized by prolonged deficiencies in atmospheric, surface, or subsurface water supplies that persist for months or years [35]. Driven by climate change, population growth, and intensified land use, droughts have become more frequent, severe, and widespread particularly in tropical and subtropical regions such as South Asia. Their impacts include soil retrogression, desertification, reduced agricultural output, ecosystem degradation, increased frequency of wildfires and sandstorms, and heightened socio-economic vulnerabilities [36-38]. As one of the most dangerous climate related hazards, drought directly threatens food security, economic stability, and rural livelihoods [39], making timely monitoring and assessment essential for proactive adaptation and resource allocation [40]. In this context, remote sensing-based drought monitoring has emerged as a scalable and cost-effective tool for tracking spatiotemporal dynamics across vast, data scarce regions like Pakistan.

This study leverages MODIS derived Enhanced Vegetation Index (EVI) and Standardized Vegetation Index (SVI), processed via Google Earth Engine (GEE), to investigate the evolution of vegetation stress and resilience over a 22-year period (2001-2022). GEE enables efficient access to decades of satellite data, facilitates large scale analysis, and supports visualization of spatial trends through maps and time series critical for collaboration among researchers and decision makers [41-43]. Drought assessment is critically important in Pakistan, where arid and semi-arid climates heighten vulnerability to water scarcity, threatening agricultural productivity, economic stability, and social wellbeing [44, 45]. Timely monitoring enables proactive interventions such as deploying drought resistant crops [46], optimizing irrigation, and activating early warning systems to mitigate impacts on vulnerable communities. Integrating remote sensing and machine learning enhances the accuracy and scalability of drought detection, supporting data driven policy and resource allocation [47]. Ultimately, robust drought assessment strengthens climate resilience, safeguards food security, and contributes to poverty reduction and sustainable development across Pakistan's agricultural landscapes. By analyzing EVI and SVI jointly, we move beyond passive observation toward diagnostic assessment: EVI captures absolute biomass and canopy greenness, while SVI reveals whether current vegetation performance deviates significantly positively or negatively from historical baselines [48, 49].

Pakistan's agro ecosystem, dominated by the Indus Basin irrigation network, is particularly vulnerable due to its arid and semi-arid climate, heavy reliance on groundwater, and exposure to monsoon variability. The consistent bimodal pattern in EVI peaking in February-March (rabi season) and August (kharif season) confirms the enduring stability of Pakistan's dual cropping system, sustained by canal irrigation and extensive groundwater extraction [50]. The modest upward trend in EVI since 2018 aligns with documented increases in cropping intensity, adoption of high yielding varieties, and expansion of double cropping into marginal lands, driven by government subsidies, mechanization, and improved seed distribution [51, 52].

However, EVI alone cannot distinguish between sustainable intensification and ecologically unsustainable practices. Here, SVI provides critical diagnostic clarity. The emergence of sustained positive SVI anomalies (> +1.0) after 2007, and their culmination in record high values during 2020-2022 indicates that vegetation performance has consistently exceeded historical expectations over the past 15 years. This shift is not merely recovery from earlier droughts (evident in persistent negative SVI during 2000-2006) [53]. It reflects a systemic transformation in the drivers of vegetation productivity. Three interrelated factors underpin this transition: First, intensified water management driven by proliferation of subsidized tubewells post 2005 has enabled farmers in Punjab (where >90% of irrigation is groundwater dependent) to advance rabi sowing and extend kharif seasons beyond natural rainfall limits [54, 55]. Yet this intensification comes at the cost of severe aquifer depletion, with the Indus Basin now recognized as one of the world's most overstressed groundwater systems, where extraction exceeds recharge by 100-120% in key districts [56].

Second, improved agronomic practices including zero till drilling, residue retention, and precision fertilizer application have gained traction since 2010 under Climate Smart Agriculture initiatives, enhancing soil moisture retention and reducing evaporation, thereby boosting SVI even under suboptimal rainfall [57]. Third, climatic amelioration has contributed: recent analyses confirm an increase in winter precipitation events linked to shifting mid latitude cyclones and enhanced moisture transport from the Mediterranean and Caspian Sea [58]. Though episodic, their heightened frequency since 2007 has provided critical supplemental recharge during key sowing windows, synergizing with managed irrigation and conservation practices.

Provincial level analysis (Figures 8(a-d)) reveals stark regional contrasts. In Punjab, rising EVI and increasingly positive SVI since 2015 mask alarming groundwater decline and a temporary boost in productivity fueled by non-renewable aquifer drawdown [59]. In Sindh, moderate EVI gains coupled with a clear, accelerating SVI rise since 2015 suggest improved resilience through infrastructure investments canal lining, floodwater harvesting, and distributary rehabilitation reducing conveyance losses without excessive groundwater dependence [60]. Khyber Pakhtunkhwa exhibits high SVI volatility with no long-term trend, reflecting its rain fed, mountainous terrain and vulnerability to erratic precipitation; however, the province's Billion Tree Tsunami afforestation project (2014-2017) the world's largest single region reforestation initiative has significantly restored upland ecosystems, indirectly supporting microclimatic stability and groundwater recharge, though its impact on lowland cropland SVI remains limited [61, 62]. Most notably, Balochistan demonstrates the most dramatic transformation: transitioning from among the lowest SVI values nationally (pre-2005) to consistently positive anomalies by 2015. This recovery correlates strongly with community-based rangeland restoration programs led by the Balochistan Forest and Range Department, supported by FAO, UNDP, and ICARDA, which promoted native species (Prosopis cineraria, Acacia nilotica, Ziziphus mauritiana), contour bunding, water harvesting, and regulated grazing resulting in improved soil moisture, reduced erosion, and increased biomass all achieved without significant groundwater extraction [63]. Balochistan thus offers a replicable model of ecological resilience grounded in ecosystem-based adaptation rather than resource exploitation.

The central insight of this study is that a positive SVI does not equate to sustainability. This reflects relative performance against historical norms, not absolute ecological health. In Pakistan the rising SVI may signal genuine improvement through better water delivery, conservation agriculture, or restoration but it may also mask dangerous tradeoffs as unsustainable groundwater mining, land degradation, chemical overuse, and biodiversity loss.

Punjab and parts of Sindh also experience a more severe self-reinforcing feedback loop: higher SVI → increased farmer confidence → increased tubewell pumping → rapid aquifer depletion → eventual system collapse. Similar patterns have been observed in other areas where satellite derived greening concealed a disastrous groundwater decrease until wells dried up and farming ceased to be profitable [64].

Pakistan now stands at a point, where short term productivity gains are being purchased at the expense of long-term hydrological capital. Relying on SVI alone as a success indicator risks incentivizing practices that maximize yield today at the cost of ruin tomorrow. A farmer achieving an SVI of +1.5 through 50% more groundwater abstraction may reap bumper harvests now but face poverty when the aquifer collapses. Therefore, policy must evolve beyond measuring "performance" to evaluating true resilience: the capacity of the agro ecosystem to maintain productivity under future stress without depleting its natural capital.

While our analysis leverages robust MODIS derived EVI and SVI data processed via Google Earth Engine, several methodological limitations must be acknowledged. First, the 500 m spatial resolution of MODIS aggregates heterogeneous land covers including irrigated fields, fallow land, urban patches, and degraded rangelands potentially smoothing local anomalies and obscuring field scale dynamics; future studies should integrate higher resolution sensors such as Sentinel 2 or Landsat 8/9 to resolve fine grained heterogeneity [65].

Second, SVI is sensitive to atmospheric aerosols, cloud contamination, and sensor calibration drift, particularly during the monsoon months (July-September), introducing noise and data gaps in peak season estimates; rigorous quality control and temporal gap filling techniques (e.g., harmonic regression) are essential [66]. Third, the absence of a nationwide network of in situ validation sites measuring soil moisture, groundwater levels, and crop yields severely limits causal inference; urgent collaboration between remote sensing teams, universities (e.g., University of Agriculture Faisalabad, National Defence University), and institutions like FAO is needed to establish ground truth stations across agro climatic zones. Fourth, SVI captures vegetation response to moisture with lags of weeks to months, especially for deep rooted crops such as sugarcane or cotton; integrating thermal indices (e.g., Land Surface Temperature, LST; Thermal Condition Index, TCI) could improve detection of immediate soil moisture stress. Fifth, SVI cannot distinguish between cultivated crops, weeds, invasive species, or fallow land a high SVI value in non-agricultural areas may falsely suggest "improvement"; coupling SVI with high resolution land cover classifications (e.g., GlobeLand30) would enhance interpretability. Finally, while we correlate SVI trends with policy interventions (e.g., canal lining, afforestation), we cannot quantify their individual contributions without econometric modeling or farm level surveys; future research must combine remote sensing with participatory rural appraisals and household level water use data to disentangle climate, management, and policy drivers.

This study provides actionable intelligence for designing climate resilient agricultural policies in Pakistan, proposing five evidence-based priorities. First, energy and fertilizer subsidies must be reoriented away from water intensive crops such as rice and sugarcane toward drought tolerant alternatives including millets, sorghum, and chickpeas and scaled up investments in precision irrigation technologies like drip and sprinkler systems, as well as solar powered tubewells to reduce fossil fuel dependence. Evidence from pilot programs in Punjab demonstrates that drip irrigation on wheat can achieve 30-40% water savings without yield loss, yet adoption remains below 5% due to upfront cost barriers [67].

Second, ecosystem-based adaptation (EbA) strategies proven successful in Balochistan such as community managed afforestation using native, drought tolerant species (Prosopis cineraria, Acacia nilotica), contour bunding, check dams, and micro watershed restoration must be replicated nationwide, particularly in Khyber Pakhtunkhwa and southern Punjab. These approaches have demonstrably improved soil organic matter by 22%, reduced runoff by 40%, and increased forage biomass by 60% over five years in Balochistan, offering a low input, high resilience model distinct from groundwater dependent intensification. Third, Pakistan must establish a National Vegetation Anomaly Monitoring System (PVAMS), operationalized through the National Disaster Management Authority (NDMA) and the Ministry of Climate Change, featuring real time dashboards displaying monthly SVI anomalies at the district level, automated alerts triggered when SVI falls below -1.0 for three consecutive months, and linkage to parametric drought insurance schemes that disburse payouts based on index thresholds rather than costly and delayed yield assessments models successfully deployed in India's Agromet Advisory System and Kenya's index based livestock insurance [68].

Fourth, groundwater governance must be modernized using remote sensing as an enforcement tool: areas exhibiting high EVI coupled with rapidly increasing SVI and declining groundwater tables should be designated "critical overdraft zones", where mandatory metering of tubewells and progressive pricing for excessive extraction are enforced mirroring the 35% reduction in groundwater use achieved in Gujarat, India, through satellite guided zoning [69, 70].

Fifth, national investment in data infrastructure and human capacity is critical: training for number of experts, agricultural extension officers to interpret EVI/SVI maps, launching mobile applications delivering localized SVI advisories in Urdu, Pashto, and Balochi, and establishing a centralized, open access national repository of in situ soil moisture, yield, and groundwater data all integrated with Google Earth Engine would empower farmers and policymakers alike with timely, actionable intelligence. Pakistan's agricultural system is not failing it is adapting, innovating, and, in many places, thriving. The sustained rise in EVI and the dramatic surge in SVI since 2007 stand as testament to the ingenuity of millions of smallholder farmers and decades of public investment in irrigation infrastructure and extension services. But we must ask: at what cost? The most alarming finding of this study is not the absence of progress, but the dangerous illusion of progress. Rising SVI values in Punjab and Sindh may reflect short term gains achieved through the liquidation of Pakistan's most vital natural asset: its groundwater. The same SVI signal that tells us "vegetation is doing better than ever" may also be screaming: "the aquifer is dying". True resilience is not measured by how well crops grow in a good year it is measured by how well the system survives in a bad one. Balochistan teaches us that ecological restoration can build resilience without exploitation. Sindh shows that infrastructure efficiency can decouple productivity from groundwater dependence. Punjab demonstrates the peril of intensification without regulation.

We urge policymakers to shift from reactive crisis response to proactive, data driven governance. The tools exist: MODIS, Google Earth Engine, SVI, and emerging ground networks. The future of Pakistan's food security does not lie in pumping more water it lies in managing less, smarter, and fairer. Continued monitoring of EVI and SVI is not optional, it is foundational. This can be good in management.

4. CONCLUSIONS

This study presents the first long term (2001-2022), province scale assessment of agricultural drought across Pakistan using the Standardized Vegetation Index (SVI) derived from MODIS EVI data processed in Google Earth Engine (GEE). Our analysis reveals distinct regional trajectories: Punjab shows a concerning post 2015 decline in SVI, indicative of mounting water stress despite intensive irrigation; Sindh and Balochistan exhibit significant recovery, likely attributable to improved water infrastructure and large scale afforestation efforts; while Khyber Pakhtunkhwa remains highly volatile, reflecting its rainfall dependent ecosystems. This work advances drought monitoring in semi arid, data scarce regions by introducing an open source, reproducible GEE workflow for operational SVI computation and statistically robust drought classification, the spatiotemporal behavior of SVI corresponds closely with documented drought events and regional patterns of agricultural water stress across Pakistan particularly in major cropping zones such as Punjab and Sindh. This alignment suggests that SVI, derived from satellite based vegetation dynamics, captures signals relevant to agricultural drought conditions beyond purely meteorological indicators like precipitation based indices. The SVI outputs offer practical utility for operational drought monitoring and can inform climate smart agriculture (CSA) decision making including strategic crop planning, irrigation prioritization, and early warning dissemination empowering provincial and national agencies to target interventions, allocate resources efficiently, and strengthen resilience in Pakistan's increasingly climate vulnerable farming systems.

5. ACKNOWLEDGEMENT

We gratefully acknowledge the use of MODIS MOD13Q1 vegetation index data (NASA LP DAAC) and the Google Earth Engine (GEE) platform in this study. The 250 meter resolution satellite observations and GEE's cloud based computational infrastructure were indispensable to our analysis. We extend our sincere appreciation to the developers and maintainers of both MODIS and GEE for providing open, high quality geospatial resources that enabled and enriched this research.

6. CONFLICT OF INTEREST

The authors have declared no conflict of interest.

7. DATA AND CODE AVAILABILITY

All data used are publicly available via Google Earth Engine: MODIS (MOD13Q1 V006) This study follows FAIR (Findable, Accessible, Interoperable, Reusable) principles; code for SVI computation and analysis will be made available upon request to ensure reproducibility and regional adaptation.

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