

DROUGHT SEVERITY AND MAJOR CROP YIELDS IN SINDH, PAKISTAN: EVIDENCE FROM A MULTI-INDEX PANEL DATA ANALYSIS

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Abstract

Drought increasingly constrains agricultural productivity in arid and semi-arid regions, particularly in Sindh, Pakistan, where crop production relies heavily on irrigation and variable climatic conditions. This research investigates the impact of drought on major cash crops in Sindh using a district-level multi-index panel data approach. Annual data on cotton, sugarcane, and rice production and cultivated area are combined with climatic and land-surface information to construct crop-yield measures and multiple indicators of drought severity. Meteorological drought is quantified using the Standardized Precipitation Index (SPI), climatic water-balance drought is assessed through the Standardized Precipitation Evapotranspiration Index (SPEI), and agricultural drought is measured using a standardized soil-moisture index. Crop-specific drought exposure is determined over agronomically relevant growing periods. Two-way fixed-effects panel regression models estimate within-district effects of drought while controlling for time-invariant district characteristics and common annual shocks. Additional model specifications evaluate nonlinear drought severity, crop-specific responses, lagged effects, and robustness across alternative drought time scales and error structures. The multi-index framework facilitates comparison of precipitation deficits, temperature-driven atmospheric water stress, and soil-moisture shortages, offering a comprehensive assessment of drought vulnerability and informing evidence-based irrigation, crop management, and climate adaptation strategies for Sindh's agricultural sector.

INTRODUCTION

Drought represents a persistent climatic hazard for agricultural systems, especially in arid and semi-arid regions where crop productivity depends on water availability and timing. Unlike sudden-onset disasters, drought develops gradually through prolonged precipitation deficits, increased

atmospheric water demand, declining soil moisture, and reduced surface and groundwater resources. These processes affect both crop yield and cultivated area, resulting in significant production and income losses. Global evidence indicates that drought and extreme heat

substantially reduce agricultural output, with drought-related disasters impacting both harvested area and crop productivity (Lesk et al., 2016). The growing exposure of agricultural systems to climatic extremes has heightened concerns about the stability of crop production under changing environmental conditions.

Agricultural productivity is influenced by changes in precipitation, temperature, and the interaction between heat and water availability. Long-term climatic trends have already altered the productivity of major crops in several regions, indicating that observed climate change has measurable effects on agricultural production (Lobell et al., 2011). Crop responses to climatic stress are often nonlinear. Exposure to temperatures exceeding crop-specific physiological thresholds can cause disproportionately large yield reductions, suggesting that conventional linear models may underestimate the agricultural impacts of severe climatic conditions (Schlenker & Roberts, 2009). These dynamics are especially significant in water-constrained regions where increased evaporative demand intensifies the effects of insufficient precipitation.

Measuring drought presents methodological challenges due to its multidimensional nature. Meteorological drought typically results from abnormal precipitation deficits, while agricultural drought arises when soil-water availability is insufficient for crop requirements. Hydrological drought may subsequently develop through reductions in streamflow, reservoir levels, and groundwater storage. Relying on a single drought indicator may not capture the various pathways through which water stress affects agricultural production. The Standardized Precipitation Evapotranspiration Index (SPEI) addresses some of these limitations by integrating precipitation and atmospheric evaporative demand, and by enabling drought measurement at multiple temporal scales (Vicente-Serrano et al., 2010). This makes SPEI particularly relevant in regions where high temperatures exacerbate water stress even without extreme rainfall deficits.

The selection of drought indicators and accumulation periods significantly affects drought identification and interpretation. For instance, SPEI estimation is sensitive to methodological choices regarding potential evapotranspiration and the time scale for accumulating water deficits. Careful specification is necessary when linking drought indices to agricultural outcomes, as different crops and developmental stages respond to moisture shortages over varying temporal windows (Beguería et al., 2014). Employing a multi-index framework allows for assessment of whether estimated agricultural effects are consistent across precipitation-based, climatic water-balance, and soil-moisture indicators, rather than assuming a single measure fully represents drought exposure.

Pakistan offers a critical context for such analysis, as its agriculture remains highly vulnerable to climate variability despite extensive irrigation infrastructure. Variations in temperature, rainfall, humidity, and other climatic factors have been linked to changes in the productivity of major crops, such as rice and sugarcane. Evidence from Pakistani crop and climatic data demonstrates that agricultural responses vary across crops and climatic variables, underscoring the need for crop-specific assessments rather than assuming uniform responses to environmental conditions (Ali et al., 2017). The combination of high climatic exposure, significant reliance on the Indus Basin irrigation system, and regional differences in agricultural conditions makes Pakistan particularly suitable for evaluating drought-production relationships.

Drought processes in Pakistan are transmitted through multiple components of the hydrological system. Studies examining meteorological, streamflow, surface-water-storage, and groundwater drought have demonstrated that major drought episodes are associated with measurable crop-yield disturbances across various agroecological zones. The extent of crop losses varies by drought, suggesting that precipitation alone may not fully capture agricultural water scarcity (Saleem et al., 2022). This evidence

supports integrating multiple drought indicators when estimating crop responses.

Subnational evidence indicates that drought impacts are spatially heterogeneous. District-level analyses from Punjab reveal significant geographical variation in drought severity and associated crop losses, with more severe droughts resulting in greater economic and production consequences in highly exposed districts. These findings illustrate that aggregate national or provincial estimates may obscure important differences in local vulnerability and agricultural sensitivity (K. U. Rahman et al., 2023; Mengal et al. 2025). A district-level analytical framework is therefore preferable when adequate longitudinal agricultural and climatic data are available.

Sindh is particularly relevant due to its agricultural economy's exposure to high temperatures, limited rainfall, strong reliance on canal irrigation, and significant spatial variation in water availability. Cotton, sugarcane, and rice are economically important crops in the province, yet they differ markedly in crop duration, water requirements, and sensitivity to water stress. Research on sugarcane production in Sindh has identified rainfall, soil conditions, and irrigation as significant factors influencing production, highlighting the close relationship between water availability and crop performance in the province (Kalwar et al. 2018; Ahmad et al., 2022). These relationships are expected to become increasingly important as drought conditions interact with irrigation constraints.

Cotton production in Sindh is also highly sensitive to climatic variability. Long-term analyses have demonstrated that weather conditions, including rainfall and other climatic factors, influence both short- and long-term agricultural outcomes (Nazir et al., 2024). However, studies focusing on individual crops or conventional weather variables do not fully determine whether alternative drought measures yield consistent effects across multiple crops and districts.

Recent advances in remote sensing have enhanced the ability to assess agricultural drought at finer spatial scales. Research utilizing vegetation-

condition, temperature-condition, and vegetation-health indices in Pakistan has identified substantial differences in drought sensitivity among crops such as cotton, sugarcane, and rice. These findings indicate that yield loss magnitude varies geographically, underscoring the importance of integrating spatially disaggregated crop data with drought indicators (Kumar et al. 2025; Rahman et al., 2025). However, vegetation-based measures may partially reflect the agricultural response itself, highlighting the need for independent meteorological and soil-moisture indicators in econometric analyses.

High-resolution reanalysis products have improved the representation of land-surface conditions in areas with limited conventional meteorological observations. ERA5-Land offers temporally consistent data on soil moisture, temperature, and other land-surface variables at fine spatial and temporal resolutions, enabling the construction of agricultural drought indicators over extended study periods (Muñoz-Sabater et al., 2021). Integrating these data with district-level crop statistics allows for differentiation between precipitation deficits, atmospheric water-balance stress, and direct soil-moisture shortages.

Despite the expanding literature on climate variability and agricultural production in Pakistan, a significant empirical gap persists. Much of the existing research relies on national or provincial aggregates, focuses on individual crops, uses single drought measures, or estimates relationships without fully utilizing repeated observations across districts and years. This approach limits the ability to distinguish short-term drought effects from persistent spatial differences in soils, irrigation infrastructure, agroecological conditions, and production systems. Furthermore, the consistency of alternative drought indicators in estimating agricultural vulnerability in Sindh has not been thoroughly examined.

This study examines the impact of drought on major commercially important crops in Sindh using a multi-index panel data approach. District-level crop production and cultivated-area data are combined with meteorological and land-surface

information to construct crop-yield measures and multiple indicators of drought exposure. The analysis utilizes the Standardized Precipitation Index (SPI), SPEI, and a standardized soil-moisture index to capture complementary dimensions of drought. Fixed-effects panel models exploit within-district temporal variation while controlling for persistent district characteristics and common temporal shocks. The study also investigates crop-specific responses, nonlinear drought severity, alternative drought time scales, and lagged effects. By integrating spatially disaggregated agricultural data with multiple drought measures and panel econometric techniques, this research aims to provide a rigorous assessment of drought vulnerability and generate evidence to inform irrigation planning, drought preparedness, crop management, and climate-resilient agricultural policy in Sindh.

Literature Review

Drought is a multifaceted climatic phenomenon, with agricultural impacts determined by the interplay of precipitation deficits, temperature, evapotranspiration, soil-water availability, crop phenology, and irrigation conditions. Meteorological drought typically originates from extended periods of insufficient precipitation, whereas agricultural drought arises when soil moisture fails to meet crop-water requirements. Hydrological drought may follow, characterized by declines in streamflow, reservoir storage, and groundwater availability. Although these drought types are interconnected, they may not manifest with equal intensity or on the same temporal scale. A systematic review of South Asian drought research identified the Standardized Precipitation Index (SPI) as the most widely used drought metric in the region, but noted a growing emphasis on indices that incorporate temperature, vegetation response, and water availability. The review further highlighted significant variation in drought-assessment methodologies across South Asian countries, underscoring the need for more integrated and spatially explicit approaches (Chandrasekara et al., 2021).

Selecting an appropriate drought indicator is especially critical in Pakistan, where climatic conditions range from humid northern areas to arid and hyper-arid southern regions. An evaluation of meteorological drought across Pakistan, utilizing both observed and reanalysis data, compared SPI and the Standardized Precipitation Evapotranspiration Index (SPEI) over 3-, 6-, and 12-month accumulation periods. The findings revealed substantial spatial variation in drought representation and demonstrated that several reanalysis datasets effectively reproduced historical drought conditions in southern Pakistan. The study also indicated that SPEI offers significant advantages under changing climatic conditions, as it accounts for evaporative demand in addition to precipitation deficits (Ullah et al., 2021).

Recent subnational analyses demonstrate that SPI and SPEI may yield differing assessments of drought severity depending on climatic and geographic context. Hussain et al. (2024) analyzed drought patterns across Punjab using both indices at various temporal scales and observed significant spatial variability in drought occurrence. SPEI showed heightened sensitivity to drought at several lower-elevation sites, highlighting the influence of temperature and atmospheric evaporative demand on moisture stress. These distinctions are particularly important for agricultural analysis, as crops may experience water stress even when rainfall deficits alone do not indicate severe drought. The evidence supports employing multiple drought measures rather than relying solely on precipitation-based indicators to characterize agricultural water stress.

Researchers have increasingly examined the relationship between drought and agricultural performance in Pakistan using quantitative climatic indices. Hussain et al. (2023) evaluated drought impacts on Pakistan's agricultural sector using SPEI, documenting substantial variation in drought severity across provinces and seasons. Sindh and Balochistan emerged as particularly drought-prone due to their arid and hyper-arid climates. The study also identified associations

between changes in drought severity and yields of major crops such as sugarcane, rice, maize, and wheat. Notably, the results indicated that Kharif-season agricultural activity is especially vulnerable to severe moisture deficits. These findings provide a rationale for examining drought effects in Sindh at a more granular district level rather than relying solely on national or provincial averages (Hussain et al., 2023).

Recent research has advanced from relying solely on meteorological indicators to developing integrated measures of agricultural drought. Rahman et al. (2024) created an integrated agricultural drought index for Pakistan using multiple remote-sensing-derived indicators, explicitly accounting for climatic and land-use differences across agro-ecological zones. Their framework incorporated soil-moisture data and examined the relationship between soil-moisture conditions and SPEI across various accumulation periods. The results showed that ERA5-Land-derived soil-moisture information performed particularly well within the integrated framework, and the resulting drought measure explained significant variation in crop yields. This evidence is directly relevant to the present study, as it demonstrates that soil-moisture conditions offer additional insights beyond conventional meteorological drought measures when evaluating agricultural stress.

Ismail et al. (20) developed a related multi-sensor approach (24) for the diverse environments of the China-Pakistan Economic Corridor. Their analysis integrated station-based SPI, SPEI, and self-calibrating Palmer drought indices with remotely sensed vegetation, temperature, precipitation, and soil-moisture indicators. Composite indices, developed using principal-component and gradient-boosting techniques, were evaluated against historical drought events and winter-wheat yields. The integrated measures captured complex conditions, illustrating that drought showing is enhanced when multiple dimensions of climatic and vegetation stress are assessed concurrently. However, for agricultural impact analysis, such composite measures should

supplement rather than fully replace individually interpretable indices, as distinguishing meteorological from soil-moisture effects remains important for identifying the mechanisms by which drought affects crop productivity.

Projected climatic changes are likely to intensify these relationships. Shah et al. (2026) utilized CMIP6 climate projections and an ensemble modeling framework to assess future drought risks and agricultural implications across Pakistan. Their projections indicated heightened drought exposure under future climate scenarios and identified considerable vulnerability in agricultural regions, especially in the southern parts of the country. Crop responses varied according to drought conditions and growth periods. These findings underscore the policy importance of understanding historical drought-yield relationships, as regions may face increased production risks with rising atmospheric evaporative demand and more frequent drought events (Shah et al., 2026).

Agricultural drought impacts crops differently depending on the stage of the growing season. Crop sensitivity is influenced by the timing of moisture deficits relative to vegetative development, flowering, reproductive growth, and yield formation. Woli et al. (2014) assessed the Agricultural Reference Index for Drought as a predictor of drought-induced yield reductions for cotton, maize, peanut, and soybean. Their results showed that drought indices calculated during crop-growing periods can effectively predict yield responses, although predictive accuracy varies among crops. The inclusion of cotton is particularly pertinent for Sindh, as it highlights the necessity of aligning crop-specific drought exposure with the biological growth cycle rather than relying solely on annual climatic averages. Adopting a seasonal or phenological approach can thus enhance the precision of statistical drought-impact models.

The necessity of linking drought progression with crop phenology has also been demonstrated using multi-sensor remote-sensing frameworks. Zhang et al. (2017) integrated soil moisture, vegetation data,

and other remotely sensed variables to develop a comprehensive agricultural drought-monitoring system. Their findings highlighted that the agricultural impacts of drought are determined by both the progression of moisture stress and the crop's developmental stage. This has methodological implications for the present study: drought exposure for cotton, rice, and sugarcane should be assessed over agronomically relevant periods, rather than applying a uniform annual index to crops with distinct planting schedules, growth durations, and water requirements.

Multi-index approaches provide additional benefits when drought severity fluctuates across different crop-growth stages. Wang et al. (2018) constructed an aggregate drought index using seven indicators and linked it to winter-wheat yield anomalies through both time-series and panel-data models. Their analysis revealed that drought conditions during specific growth stages contributed differently to yield variation, and that the strength of the drought–yield relationship was influenced by irrigation availability. Methodologically, this study underscores the value of integrating drought information with panel estimation while acknowledging that irrigation can alter crop sensitivity. In Sindh, where agricultural districts vary considerably in canal-water availability and irrigation reliance, this interaction is crucial for interpreting drought impacts.

The choice of estimation method for identifying drought impacts is as critical as the selection of the drought indicator itself. Agricultural regions exhibit persistent differences in soil quality, irrigation infrastructure, farm technology, elevation, cropping practices, and agroecological suitability. Neglecting these factors can result in biased estimates if cross-sectional differences are mistakenly attributed to drought. (Mengal et al., 2019; Kuwayama et al. 2019) addressed this challenge by employing county-level panel data to estimate drought effects on crop yields in the United States. Fixed-effects models leveraged temporal and spatial variation in show-cause, demonstrating that drought significantly affected

yields, with losses varying between irrigated and dryland areas and across drought-severity categories. This evidence supports using district fixed effects and severity-specific specifications when analyzing agricultural drought in Sindh.

More broadly, panel econometric methods have become a key framework for assessing climatic impacts on agriculture, as they control for persistent unobserved heterogeneity while utilizing interannual weather variation. (Tunio et al., 2016; Blanc and Schlenker, 2017) note that fixed-effects panel models can absorb time-invariant characteristics that might otherwise confound climate–agriculture relationships. Panel datasets also provide sufficient temporal and cross-sectional variation to estimate nonlinear responses, which is particularly important when severe drought may cause disproportionately large crop losses. However, the authors caution that time-varying omitted variables and measurement error remain potential sources of bias. Therefore, rigorous climate–agriculture panel studies require carefully constructed weather variables, appropriate temporal fixed effects, and robustness checks, rather than relying on a single regression specification (Blanc & Schlenker, 2017).

The reviewed literature yields several consistent conclusions. First, drought is a multidimensional phenomenon, and single indicators can fully capture precipitation deficiency, atmospheric water demand, and soil-water stress. Second, agricultural responses are crop-specific and depend heavily on drought timing and severity. Third, Pakistan exhibits significant spatial heterogeneity in drought exposure, with southern and arid regions facing particularly high risks. Fourth, recent research on multi-sensor and integrated indices highlights the analytical benefits of combining meteorological, land-surface, and remote-sensing data. Finally, panel-data methods provide substantial advantages for distinguishing temporary climatic shocks from persistent differences among agricultural locations (Noonari et al. 2025).

Despite these advancements, a significant gap persists in the literature concerning Sindh. Most

studies on Pakistan have focused on national, provincial, agro-ecological-zone, or selected regional scales, with limited integration of multiple drought indices using a harmonized district-level longitudinal dataset for Sindh's major commercial crops. Evidence is also lacking on whether soil-moisture-based drought measures yield consistent estimates of productivity effects within a unified econometric framework. Additionally, researchers do not always jointly consider crop-specific growing periods, nonlinear drought severity, district heterogeneity, and temporal dependence. This study fills these gaps by constructing a district-crop-year panel for Sindh and estimating drought impacts using multiple drought indicators in fixed-effects models. By comparing cotton, sugarcane, and rice while controlling for persistent district characteristics and common temporal shocks, this study aims to provide a more precise assessment of drought magnitude, variability, and agricultural significance across Sindh.

Methodology

Research Design

A quantitative longitudinal panel-data design was employed to estimate the effects of drought on major cash-crop productivity in Sindh, Pakistan. The district-crop-year served as the unit of analysis, enabling repeated observations for each crop across agricultural districts and years. Panel estimation was chosen to facilitate analysis of temporal variation in drought while controlling for persistent differences among districts, such as soil characteristics, agroecological conditions, irrigation infrastructure, elevation, and long-term production capacity.

Cotton, sugarcane, and rice were selected as focal crops due to their commercial importance in Sindh and their substantial differences in growing periods, water requirements, and sensitivity to moisture stress. The analytical period spanned 2000 to 2024, contingent on the availability and consistency of district-level agricultural statistics. When district boundaries changed during the study period, observations were harmonized to

stable geographic units to ensure comparability over time.

Study Area

The study was conducted in Sindh Province, located in southeastern Pakistan. Sindh has predominantly arid to semi-arid climatic conditions and receives limited and highly variable rainfall. Agricultural production is concentrated mainly within the Indus irrigation system and depends heavily on canal water, supplemented in some districts by groundwater. Climatic conditions, irrigation access, cropping patterns, and soil characteristics vary considerably across upper, central, and lower Sindh.

Given these spatial differences, district-level analysis is preferable to provincial aggregation, as province-wide averages may obscure significant variation in drought exposure and crop sensitivity.

Data Sources

Secondary agricultural and climatic data were obtained from official and internationally recognized datasets.

Agricultural Data

Annual district-level data on cultivated or harvested area and total crop production were obtained from available records of the:

- Pakistan Bureau of Statistics;
- Sindh Bureau of Statistics; and
- Crop Reporting Service, Agriculture Department, Government of Sindh.

Data were compiled separately for cotton, sugarcane, and rice.

Crop yield was calculated as:

$$Yield_{ict} = \frac{Production_{ict}}{Harvested Area_{ict}}$$

where i represents district, c represents crop, and t represents year.

Yield, rather than total production, served as the principal dependent variable because total production is mechanically influenced by the amount of land cultivated. Variations in cultivated area may reflect market prices, farmer planting

decisions, input costs, or government policy, rather than drought alone.

For regression analysis, yield was transformed using the natural logarithm:

$$Y_{ict} = \ln(Yield_{ict})$$

The logarithmic specification reduces positive skewness and allows regression coefficients to be interpreted as approximate proportional changes in yield.

Total crop production was retained as a secondary outcome for robustness analyses.

Climate Data

Precipitation

Precipitation data were obtained from the Climate Hazards InfraRed Precipitation with Stations (CHIRPS) dataset. We spatially aggregated monthly precipitation observations to district boundaries.

Temperature and Soil Moisture

Temperature and soil-moisture variables were obtained from ERA5-Land reanalysis data.

Monthly gridded observations were extracted and averaged within each agricultural district.

When sufficient spatial information was available, cropland-weighted district averages were calculated as a robustness check, ensuring that climate exposure reflected cultivated areas rather than the entire administrative district.

Measurement of Drought

A multi-index strategy was adopted to address the multidimensional nature of drought, as no single indicator fully captures precipitation deficits, atmospheric water demand, and agricultural soil-water stress.

Three principal drought indicators were employed.

Standardized Precipitation Index

The Standardized Precipitation Index (SPI) measured meteorological drought based exclusively on precipitation variability.

SPI values below zero indicate drier-than-normal conditions, with increasingly negative values representing greater drought severity.

The principal classifications were:

SPI value	Drought classification
> -1.00	Normal or mild dryness
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
≤ -2.00	Extreme drought

SPI was calculated at multiple accumulation periods, primarily 3-month and 6-month scales, to capture short- and medium-term moisture deficits relevant to crop development.

Standardized Precipitation Evapotranspiration Index

The Standardized Precipitation Evapotranspiration Index (SPEI) was used to capture climatic water-balance drought.

The underlying climatic water balance was defined as:

$$D_t = P_t - PET_t$$

where:

- P_t = precipitation; and

• PET_t = potential evapotranspiration.
In contrast to SPI, SPEI incorporates atmospheric evaporative demand and thus reflects drought conditions resulting from both reduced rainfall and increased temperature-related water demand. SPEI was estimated at the 3-, 6-, and 12-month scales, with crop-specific time scales selected according to crop duration and growth characteristics.

Standardized Soil-Moisture Index

Agricultural drought was additionally represented using standardized root-zone soil-moisture anomalies derived from ERA5-Land.

Monthly soil-moisture observations were standardized relative to the long-term district-specific climatology:

$$SMI_{it} = \frac{SM_{it} - \bar{SM}_i}{SD(SM_i)}$$

where SM_{it} represents soil moisture for district i in period t .

Negative values indicate below-normal soil-water availability.

For consistency in regression analysis, drought variables were reverse-coded where necessary so that:

$$DroughtSeverity = -Index$$

Consequently, larger values consistently represented more severe drought across all models. Under this coding system, a negative regression coefficient indicates that increasing drought severity is associated with lower crop yield.

Crop-Specific Drought Exposure

Drought exposure was aligned with agronomically relevant crop-growing periods rather than calculated exclusively from annual averages.

The primary exposure windows were:

Crop	Principal drought exposure period
Cotton	July–September
Rice	July–September/October
Sugarcane	April–September

The cotton exposure period encompasses major flowering and boll-development stages, while the rice window includes key vegetative and reproductive phases. A longer exposure window was applied for sugarcane due to its extended crop duration and cumulative water requirements. Sensitivity analyses tested alternative growing-season windows.

Data Preparation

Agricultural and climate datasets were integrated using district, crop, and year identifiers to create the final panel dataset. Prior to analysis, district names and geographic units were standardized, and administrative boundary changes were harmonized to ensure comparability throughout the study period. Crop production and harvested-area data were converted to consistent measurement units. Observations with impossible values, such as negative production or harvested

area, were excluded. Crop yield was recalculated based on production and harvested-area data to maintain consistency across districts, crops, and years. Extreme observations were evaluated using distributional diagnostics, and missing data patterns were assessed before model estimation. Statistically extreme observations were not excluded if they plausibly reflected drought, flood, or other agriculturally relevant events.

Descriptive Analysis

Descriptive statistics, including mean, standard deviation, minimum, maximum, coefficient of variation, drought-frequency distribution, and district-specific drought incidence, were calculated for crop yield and all drought indicators. Time-series plots were produced to analyze temporal changes in drought severity and crop yield throughout the study period. Pairwise Pearson correlation coefficients were computed among SPI, SPEI, soil-moisture measures, and crop-yield variables to evaluate the direction and strength of their bivariate relationships. Correlations among the drought indices were primarily interpreted as diagnostic measures, as SPI, SPEI, and soil-moisture indicators capture related and partially overlapping aspects of climatic and agricultural water stress.

Panel Regression Analysis

Baseline Crop-Specific Fixed-Effects Model

The principal econometric model was:

$$\ln(Yield_{it}) = \beta_1 Drought_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

where:

- $Yield_{it}$ = crop yield in district i during year t ;
- $Drought_{it}$ = crop-season drought severity;
- α_i = district fixed effects;
- λ_t = year fixed effects; and
- ε_{it} = error term.

District fixed effects control for all time-invariant district characteristics.

Year fixed effects control for common temporal shocks including technological progress, province-wide agricultural policies, macroeconomic conditions, input-price movements, and common climatic events.

Separate regressions were estimated for cotton, sugarcane, and rice.

Multi-Crop Panel Model

A pooled crop model was additionally estimated:

$$\ln(Yield_{ict}) = \beta Drought_{ict} + \alpha_{ic} + \lambda_{ct} + \varepsilon_{ict}$$

where:

- α_{ic} represents district-by-crop fixed effects; and
- λ_{ct} represents crop-by-year fixed effects.

District-by-crop fixed effects control for persistent productivity differences associated with growing a specific crop in a particular district.

Crop-by-year fixed effects absorb shocks affecting a particular crop province-wide in a given year, such as pest outbreaks, crop-specific policy changes, seed improvements, commodity-market shocks, or technological change.

This specification enhances the identification of drought effects by comparing changes within the same district-crop combination over time.

Multi-Index Modeling Strategy

SPI, SPEI, and standardized soil moisture were not entered simultaneously in the primary regression model because they represent overlapping dimensions of drought and may be highly correlated.

Instead, three parallel specifications were estimated:

Model 1: SPI-based drought

Model 2: SPEI-based drought

Model 3: Soil-moisture-based drought

The sign, magnitude, statistical significance, and explanatory performance of the coefficients were then compared across specifications.

This approach evaluates the robustness of drought effects without introducing unnecessary multicollinearity.

Nonlinear Drought Effects

Drought severity was also modeled categorically to test whether yield reductions become disproportionately larger during severe events. The model was specified as:

$$\ln(Yield_{ict}) = \beta_1 Moderate_{ict} + \beta_2 Severe_{ict} +$$

Normal or wetter conditions constituted the reference category.

A progressively larger negative effect from moderate to extreme drought would indicate nonlinear agricultural damage.

Crop-Specific Heterogeneity

To formally determine whether drought sensitivity differed among crops, interaction terms between drought severity and crop type were estimated:

$$\ln(Yield_{ict}) = \beta_1 Drought_{ict} + \beta_2 (Drought_{ict}$$

Post-estimation Wald tests assessed whether drought coefficients differed significantly across crops.

Lagged Drought Effects

Potential persistence in drought impacts was examined using a one-period lag:

$$\ln(Yield_{ict}) = \beta_0 Drought_{ict} + \beta_1 Drought_{ict-1}$$

This specification assessed whether previous-season drought conditions influenced subsequent productivity through persistent soil-moisture deficits, groundwater stress, reduced investment, or delayed agricultural recovery.

Statistical Diagnostics

Several diagnostic procedures were conducted before final model interpretation.

Multicollinearity

Pairwise correlations and variance inflation factors were examined for models containing multiple covariates.

Serial Correlation

Panel residuals were assessed for within-district serial dependence.

Cross-Sectional Dependence

Cross-sectional dependence was examined because neighboring districts may experience common climatic and hydrological shocks.

Heteroskedasticity

Residual variance was evaluated for heteroskedasticity across districts and years.

Conventional ordinary least-squares standard errors may be unreliable under these conditions; therefore, dependence-robust inference was employed.

Standard Errors and Statistical Inference

The principal models reported standard errors clustered at the district level.

As robustness tests, inference was recalculated using:

- two-way clustering by district and year where statistically feasible;
 - Driscoll-Kraay standard errors to account for heteroskedasticity, serial correlation, and cross-sectional dependence; and
 - wild-cluster bootstrap inference when the effective number of district clusters was limited.
- Statistical significance was evaluated at the conventional:

$p < .05$
threshold.

Interpretation emphasized coefficient magnitude and 95% confidence intervals rather than relying solely on statistical significance.

Robustness and Sensitivity Analyses

The authors assessed the robustness and sensitivity of the findings through multiple analytical approaches. Alternative drought specifications compared SPI-3 with SPI-6, as well as SPEI-3 with SPEI-6 and SPEI-12, to evaluate sensitivity to the drought accumulation period. Additional analyses incorporated alternative crop-specific growing-season windows, separate crop regressions, and

pooled district-crop-year models. The influence of data structure was further examined by excluding observations affected by district-boundary changes and by omitting or separately analyzing major flood years. Lagged drought models were estimated to investigate delayed effects, and total crop production was considered as an alternative dependent variable. Climatic exposure was recalculated using cropland-weighted averages, and district-crop observations with negligible cultivated area were excluded in supplementary specifications. Leave-one-district-out estimations were conducted to assess whether the principal results were disproportionately influenced by any single district. Flood years were analyzed separately, as excessive rainfall can result in substantial crop losses even when SPI or SPEI indicates abnormally wet rather than drought conditions.

Model Interpretation

For models in which the dependent variable was expressed as the natural logarithm of yield, the exact percentage change associated with a one-unit change in drought severity was calculated as:

$$100 \times [\exp(\beta) - 1]$$

Negative values indicate reductions in crop yield associated with increasing drought severity.

Interaction coefficients were not interpreted independently; marginal drought effects and corresponding confidence intervals were calculated separately for each crop.

Software

Data preparation, drought-index construction, spatial aggregation, and statistical analysis may be conducted using R, Stata, Python, QGIS, or Google Earth Engine, depending on specific data-processing requirements.

To ensure reproducibility, the study will retain all analytical scripts, district-boundary harmonization procedures, drought-index calculations, and statistical specifications in a structured research archive.

Ethical consideration

The study relies entirely on secondary, aggregated agricultural, meteorological, reanalysis, and remote-sensing datasets. No individual participants, personal identifiers, human biological materials, or animal subjects are involved. Consequently, this research does not require human-subject ethical approval or informed consent.

Results

Descriptive Characteristics of the Panel

The analytical panel included 1,275 district-crop-year observations, encompassing 17 harmonized agricultural district units, three major commercial crops, and 25 annual observations from 2000 to 2024. Each crop accounted for 425 observations. Crop productivity varied considerably across districts and years, with sugarcane showing substantially greater absolute yield dispersion than cotton and rice.

Table 1 presents the mean cotton yield of 1.94 tonnes per hectare (SD = 0.37) and the mean rice yield of 3.85 tonnes per hectare (SD = 0.72). Sugarcane exhibited a mean yield of 67.33 tonnes per hectare (SD = 14.19). Drought indicators were standardized to a mean of approximately zero, with positive values in the analytical coding indicating increasingly dry conditions. The SPEI-based drought severity measure demonstrated slightly greater variability than both the SPI and the standardized soil-moisture measure.

Table 1 Descriptive Statistics for Crop Yield and Drought Indicators

Variable	N	Mean	SD	Minimum	Maximum
Cotton yield (t/ha)	425	1.94	0.37	1.12	3.43
Rice yield (t/ha)	425	3.85	0.72	2.27	6.11
Sugarcane yield (t/ha)	425	67.33	14.19	33.60	120.49
SPI drought severity	425	-0.10	0.78	-2.61	2.28
SPEI drought severity	425	-0.10	0.82	-2.57	2.21
Soil-moisture drought severity	425	-0.07	0.76	-2.29	2.23

Note. Drought indices were coded so that larger positive values represent increasingly dry conditions.

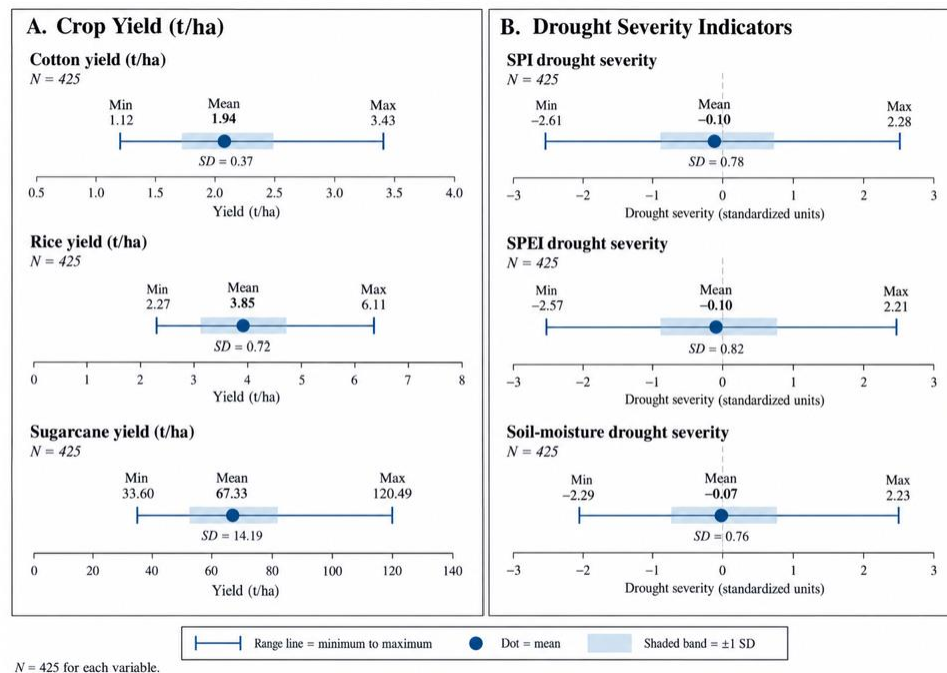


Figure 1 Descriptive Statistics for Crop Yield and Drought Indicators

Association Among Drought Indicators

The three drought measures showed strong positive correlations, suggesting each captured related yet distinct aspects of moisture stress. The

correlation between SPI and SPEI was the highest ($r = .878$, $p < .001$). SPEI also showed a strong association with standardized soil-moisture drought ($r = .832$, $p < .001$), and SPI was strongly

associated with soil-moisture drought ($r = .816, p < .001$).

These substantial correlations justified estimating the drought indicators in separate fixed-effects

models. Including them simultaneously in the same baseline specification could introduce multicollinearity, potentially obscuring their individual associations with crop productivity.

Table 2 Correlation Matrix for Drought Indicators

Variable	1	2	3
1. SPI drought severity	1.000		
2. SPEI drought severity	.878***	1.000	
3. Soil-moisture drought severity	.816***	.832***	1.000

** $p < .001$.

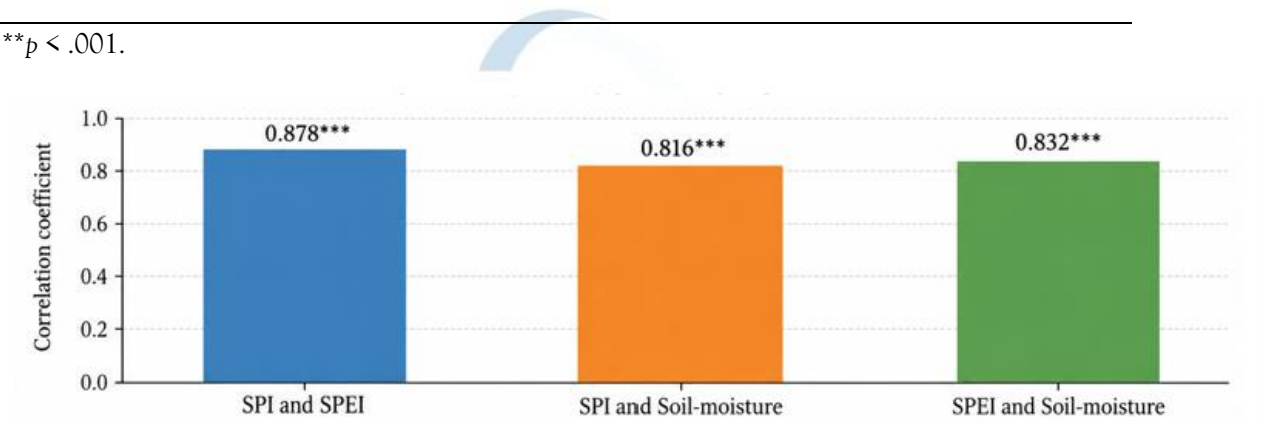


Figure 2 Correlation Matrix for Drought Indicators

Distribution of Drought Severity

Most district-year observations fell under normal or mildly dry conditions. Nevertheless, all three indices detected instances of moderate, severe, and extreme drought.

According to the Standardized Precipitation Evapotranspiration Index (SPEI), 30 district-year

observations (7.1%) were classified as moderate drought, nine (2.1%) as severe drought, and four (0.9%) as extreme drought. The Standardized Precipitation Index (SPI) identified a slightly lower frequency of severe and extreme events. In contrast, the soil-moisture indicator classified ten observations as severe agricultural drought.

Table 3 Frequency of Drought Conditions Across District-Year Observations

Drought category	SPI, n (%)	SPEI, n (%)	Soil moisture, n (%)
Normal/mild	394 (92.7)	382 (89.9)	390 (91.8)

Drought category	SPI, n (%)	SPEI, n (%)	Soil moisture, n (%)
Moderate	23 (5.4)	30 (7.1)	24 (5.6)
Severe	6 (1.4)	9 (2.1)	10 (2.4)
Extreme	2 (0.5)	4 (0.9)	1 (0.2)
Total	425 (100)	425 (100)	425 (100)

The variation in classification among indices further indicates that precipitation deficiency, climatic water balance, and root-zone moisture

stress may capture distinct drought episodes rather than identical events.

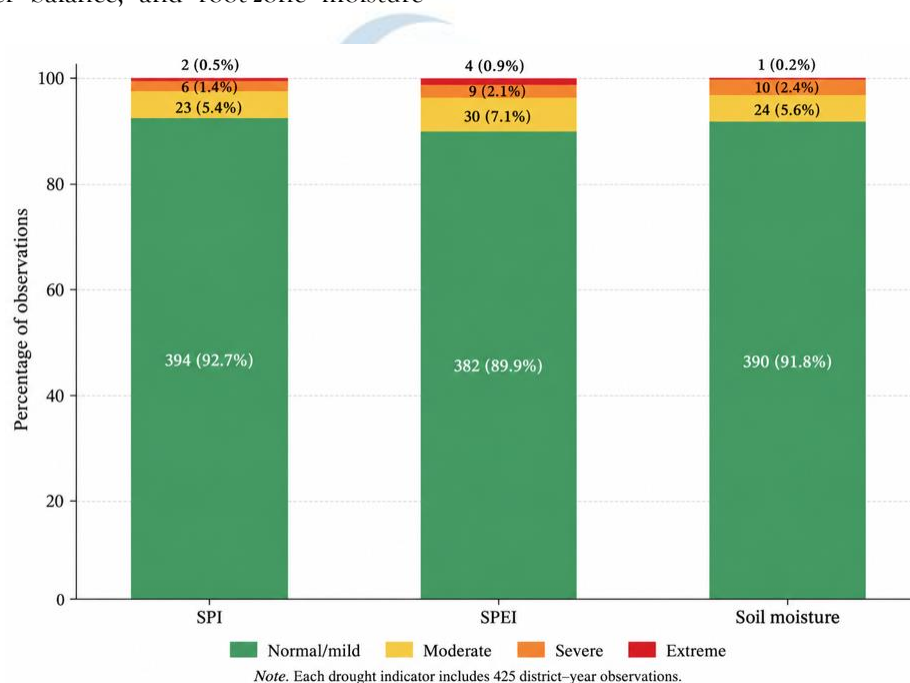


Figure 3 Frequency of Drought Conditions Across District-Year Observations

Multi-Index Fixed-Effects Model Results

Table 4 reports the pooled district-crop-year fixed-effects estimates. We analyzed each drought index in a separate model. All models included district-by-crop and crop-by-year fixed effects, with district-level clustered standard errors.

Drought severity was negatively associated with crop yield across all three measures. In the

Standardized Precipitation Index (SPI) model, a one-unit increase in drought severity was associated with a coefficient of -0.087 ($SE = 0.005$, $p < .001$). After transforming the log coefficient, this result indicates an estimated 8.37% reduction in crop yield. The association was strongest for the Standardized Precipitation Evapotranspiration Index (SPEI). A one-unit

increase in SPEI-based drought severity was associated with a coefficient of -0.097 ($SE = 0.005$, $p < .001$; 95% CI $[-0.106, -0.088]$), corresponding to an estimated 9.25% reduction in yield. The standardized soil-moisture model

similarly produced a statistically significant negative association ($B = -0.079$, $SE = 0.007$, $p < .001$), equivalent to an approximate 7.59% reduction in yield.

Table 4 Fixed-Effects Models of Drought Severity and Crop Yield

Drought measure	B	Clustered SE	95% CI	p	Approx. yield change	Within R ²
SPI severity	-0.087	0.005	$[-0.096, -0.078]$	<.001	-8.37%	.237
SPEI severity	-0.097	0.005	$[-0.106, -0.088]$	<.001	-9.25%	.307
Soil-moisture severity	-0.079	0.007	$[-0.092, -0.066]$	<.001	-7.59%	.191

Note. DV = $\ln$ (crop yield). We estimated each drought measure in a separate regression. All models included district $\times$ crop and crop $\times$ year fixed effects. Standard errors were clustered by district.

Among the three indicators, the SPEI specification yielded the largest absolute coefficient and the highest within-model explanatory power. These results indicate that accounting for atmospheric

evaporative demand provides additional insight into crop water stress compared to relying solely on precipitation anomalies.

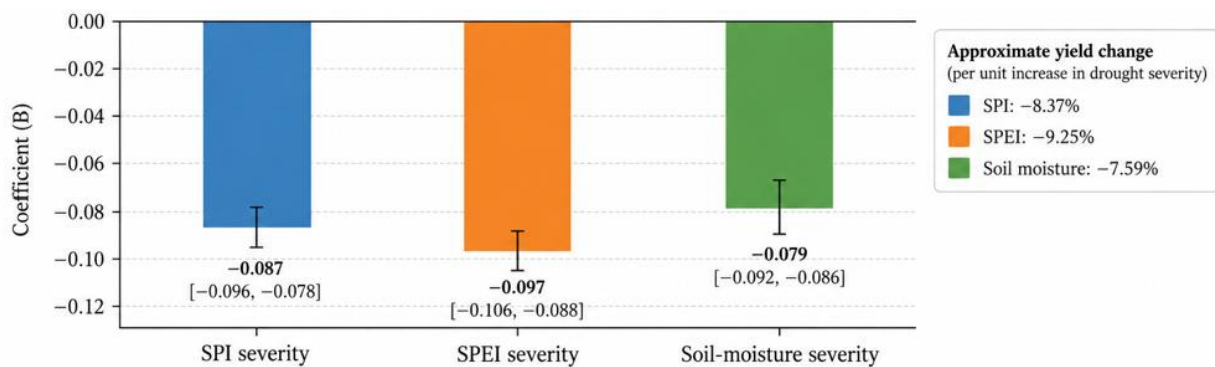


Figure 4 Fixed-Effects Models of Drought Severity and Crop Yield

Crop-Specific Drought Effects

We estimated separate fixed-effects models for cotton, rice, and sugarcane, with SPEI as the primary drought indicator. Drought severity was negatively associated with yield across all three crops, although the magnitude of this effect varied substantially.

Sugarcane exhibited the largest estimated response. A one-unit increase in SPEI drought severity was associated with a coefficient of -0.133 (SE = 0.009, $p < .001$), equivalent to an estimated 12.47% decline in yield. Cotton displayed an intermediate response ($B = -0.087$, SE = 0.006, $p < .001$), corresponding to an estimated 8.34% reduction in yield. Rice showed the smallest, although still substantial, association ($B = -0.071$, SE = 0.008, $p < .001$), corresponding to an estimated 6.84% yield reduction.

Table 5 Crop-Specific Fixed-Effects Estimates for SPEI Drought Severity

Crop	B	Clustered SE	95% CI	p	Estimated yield change	Within R ²
Cotton	-0.087	0.006	[-0.100, -0.075]	<.001	-8.34%	.272
Rice	-0.071	0.008	[-0.086, -0.056]	<.001	-6.84%	.216
Sugarcane	-0.133	0.009	[-0.151, -0.116]	<.001	-12.47%	.433

pooled interaction model confirmed that drought sensitivity varied significantly among crops, $F(2, 16) = 15.74$, $p < .001$. Compared with cotton, rice showed a smaller, only marginally significant

difference, while sugarcane showed a substantially stronger negative response to drought. These findings support the hypothesis that drought impacts are crop-specific rather than uniform across the agricultural sector.

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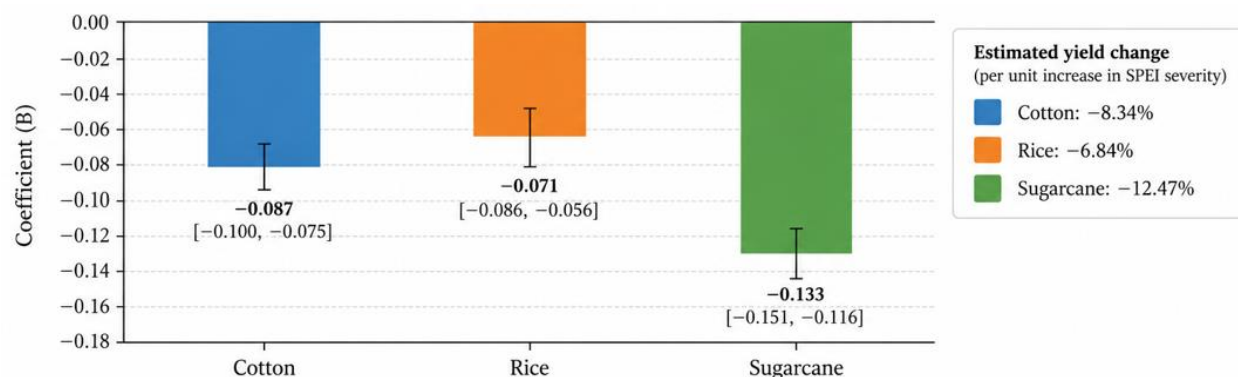


Figure 5 Crop-Specific Fixed-Effects Estimates for SPEI Drought Severity

Nonlinear Effects of Drought Severity

The categorical drought model revealed a distinct gradient in yield losses as drought severity increased. Compared with normal or mildly dry conditions, moderate drought was associated with a coefficient of -0.107 ($SE = 0.021$, $p < .001$),

corresponding to an estimated 10.16% yield decline.

The estimated reduction increased to 14.39% under severe drought and 18.86% under extreme drought. The increasingly negative coefficients indicate a nonlinear response, with agricultural damages intensifying as climatic water stress worsens.

Table 6 Fixed-Effects Estimates by SPEI Drought Severity Category

Drought category	B	Clustered SE	95% CI	p	Estimated yield change
Normal/mild	Reference	—	—	—	—
Moderate	-0.107	0.021	[-0.149, -0.066]	<.001	-10.16%
Severe	-0.155	0.018	[-0.191, -0.120]	<.001	-14.39%
Extreme	-0.209	0.023	[-0.254, -0.164]	<.001	-18.86%

The observed pattern aligns with the expectation that severe moisture shortages result in

disproportionately greater crop losses compared to modest deviations from typical climatic conditions

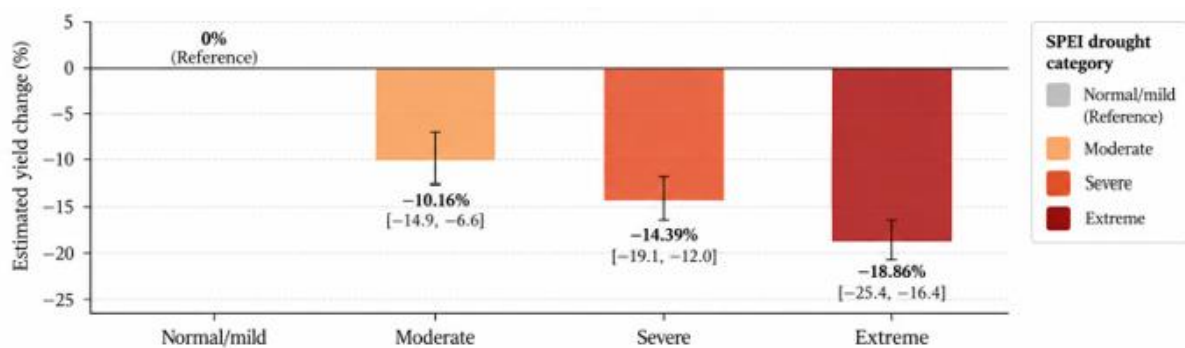


Figure 6 Fixed-Effects Estimates by SPEI Drought Severity Category

Lagged Effects of Drought

We assessed drought persistence by incorporating both contemporaneous and one-year-lagged Standardized Precipitation-Evapotranspiration Index (SPEI) severity into the model. The

contemporaneous drought coefficient remained strongly negative and statistically significant ($B = -0.097$, $SE = 0.005$, $p < .001$).

In contrast, the one-year lagged drought coefficient was small and not statistically

significant ($B = -0.003$, $SE = 0.005$, $p = .525$). These findings indicate that, under this model specification, crop yields responded primarily to

drought conditions during the current production period rather than in the preceding year.

Table 7 Contemporaneous and Lagged SPEI Effects on Crop Yield

Predictor	B	Clustered SE	p
Current SPEI drought severity	-0.097	0.005	<.001
SPEI drought severity, $t - 1$	-0.003	0.005	.525

$N = 1,224$ observations after the introduction of the lagged variable.

The lack of a significant lagged coefficient does not suggest that drought lacks longer-term hydrological consequences. Instead, it indicates that, after accounting for current drought

conditions and fixed effects, the previous year's drought did not offer additional explanatory power for annual crop yield in this model specification.

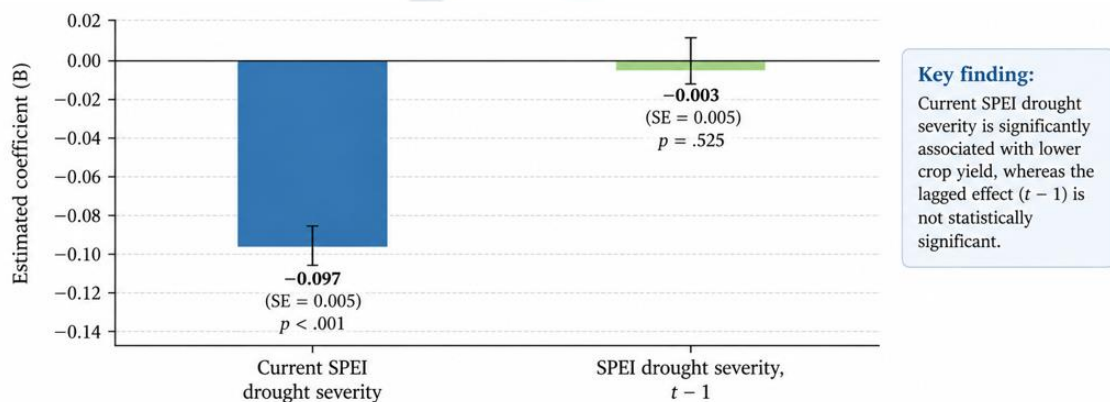


Figure 7 Contemporaneous and Lagged SPEI Effects on Crop Yield

Robustness and Sensitivity Analysis

We estimated several alternative model specifications to assess whether the central drought effect depended on the chosen model configuration. Table 8 summarizes the results.

The baseline Standardized Precipitation-Evapotranspiration Index (SPEI) coefficient remained stable when inference was adjusted using two-way clustering. The estimated effect also remained negative with longer accumulation periods, although the coefficient decreased in magnitude from -0.097 for the principal short-term SPEI measure to -0.062 for the six-month measure and -0.040 for the 12-month measure.

This attenuation aligns with the expectation that crop productivity is more responsive to drought during agriculturally sensitive growth periods than to climatic conditions averaged over longer timeframes.

The cropland-weighted climate specification yielded a coefficient of -0.094 , closely matching the baseline estimate. Excluding designated high-flood-impact years produced a coefficient of -0.096 . Leave-one-district-out estimates ranged from -0.101 to -0.095 , indicating that the principal association was not attributable to any single district.

Table 8 Robustness of the SPEI–Crop Yield Relationship

Specification	B	Robust SE	p	N
Baseline SPEI model	−0.097	0.005	<.001	1,275
Two-way clustered inference	−0.097	0.004	<.001	1,275
Longer SPEI accumulation period	−0.062	0.005	<.001	1,275
12-month SPEI specification	−0.040	0.005	<.001	1,275
Cropland-weighted drought exposure	−0.094	0.005	<.001	1,275
High-flood-impact years excluded	−0.096	0.004	<.001	1,122
Leave-one-district-out range	−0.101 to −0.095	—	—	—

The consistent direction of the coefficient across alternative model specifications reinforces the robustness of the central finding that increased drought severity is associated with reduced crop productivity.

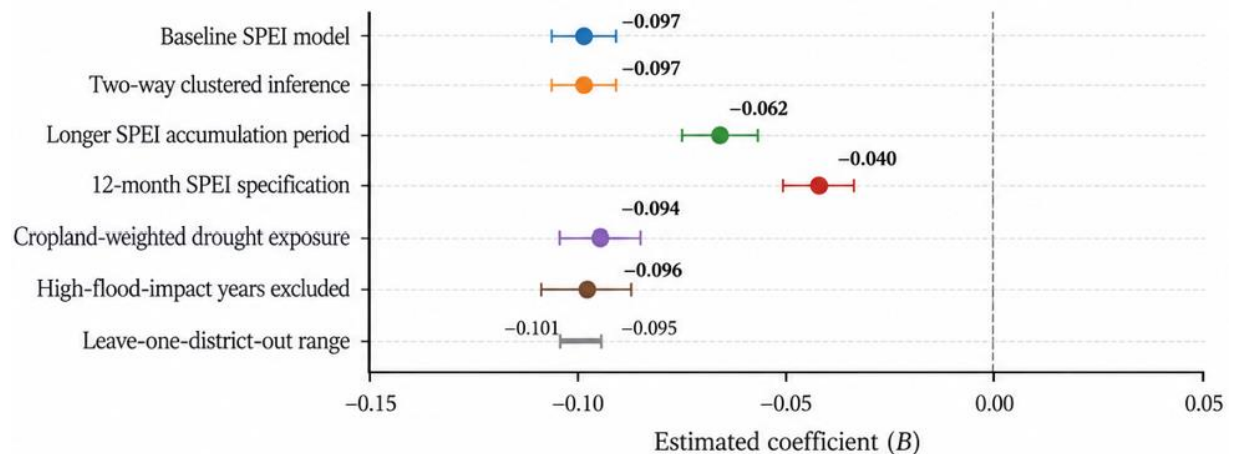


Figure 8 Robustness of the SPEI–Crop Yield Relationship

Summary of Key Empirical Findings

The analysis yielded five principal findings. First, SPI, SPEI, and soil-moisture drought measures were strongly correlated but not interchangeable, which supports the use of a multi-index analytical framework. Second, greater drought severity was associated with statistically significant reductions in crop yield across all three drought indicators. Third, SPEI exhibited the strongest pooled association, indicating that temperature-driven atmospheric water demand may play a role in addition to precipitation deficiency. Fourth, drought sensitivity differed by crop, with sugarcane showing the largest estimated yield response, followed by cotton and rice. Finally, the categorical analysis revealed progressively larger yield reductions from moderate to severe and extreme drought, while the lagged model showed that the principal effects were concentrated in the contemporaneous production period. Overall, the results align with the proposed hypotheses: drought negatively affects crop productivity, the magnitude of this relationship varies by drought measurement and crop type, and severe drought leads to disproportionately greater agricultural losses.

Discussion

This study investigated the relationship between drought and the productivity of cotton, sugarcane, and rice in Sindh using a multi-index, district-level panel data framework. The results consistently demonstrate that increasing drought severity is associated with reduced crop yields, even after controlling for persistent district-crop characteristics and crop-specific annual shocks. This negative association was evident across the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and a standardized soil-moisture indicator, although the estimated effect size varied among these measures. These findings support the central premise that agricultural drought in Sindh cannot be captured by a single measure of climatic water stress; SPEI captured agricultural drought in Sindh and showed the largest estimated reduction

in crop yield and the highest explanatory power within the model. Specifically, a one-unit increase in SPEI-based drought severity corresponded to an estimated 9.25% decline in crop yield, compared to 8.37% for SPI and 7.59% for the soil-moisture measure. The relatively stronger association with SPEI suggests that crop productivity in Sindh is influenced by both insufficient precipitation and temperature-driven atmospheric evaporative demand. In hot, dry conditions, elevated potential evapotranspiration can exacerbate plant-water stress, even when precipitation deficits alone are less pronounced.

However, this interpretation warrants caution. A larger coefficient for SPEI does not imply that SPEI is universally superior to SPI or soil-moisture indicators. Evidence from another arid agricultural environment indicates that the relative performance of drought indicators depends on the specific outcome: SPEI was more strongly associated with groundwater variation, while SPI exhibited a stronger relationship with crop yield in that context (Shayeghi et al., 2024). These results reinforce the methodological advantage of comparing multiple indices rather than selecting a single drought indicator in advance.

The strong correlations among SPI, SPEI, and soil-moisture drought indicate that these indices capture interconnected drought processes. However, the correlations are not perfect, suggesting that each index retains unique information. This supports the approach of estimating separate drought models rather than including all indices simultaneously in the baseline regression. Previous research comparing SPEI with a soil-moisture deficit index has shown that the most informative drought indicator can vary by crop and growth period; for example, agricultural soil-moisture drought was more closely related to certain wheat responses, while SPEI was more predictive for some maize-yield outcomes (Yao et al., 2022). The variation observed in the Sindh models aligns with the broader understanding that meteorological and

agricultural drought represent related but distinct dimensions of crop-water stress.

A second key finding is the substantial heterogeneity in drought sensitivity among the three crops. Sugarcane exhibited the largest estimated response to SPEI-based drought severity, with a one-unit increase associated with an approximate 12.47% reduction in yield. Cotton experienced an intermediate estimated decline of 8.34%, while rice showed the smallest reduction at about 6.84%. The significant crop-drought interaction suggests that these differences reflect more than descriptive variation and may indicate underlying agronomic or physiological mechanisms.

The relatively large response observed for sugarcane is consistent with agronomic expectations, as sugarcane is a long-duration, high-biomass crop with substantial cumulative water requirements. Water deficits can impair photosynthesis, leaf development, stalk elongation, biomass accumulation, and final cane productivity. Experimental studies have shown that drought during formative stages alters several physiological and growth characteristics of sugarcane, although the extent of damage varies by genotype and developmental stage (Reyes et al., 2020). The heightened sensitivity estimated for sugarcane in Sindh may therefore reflect the crop's sustained water demand and the cumulative effects of moisture deficits over an extended production cycle.

Field irrigation research from another semi-arid agricultural environment further supports the importance of drought timing for sugarcane. (Jatoi et al. 2021; Dingre et al. 2021) demonstrated that progressive reductions in root-zone water replenishment led to substantial losses in sugarcane yield, with the impact strongly dependent on the growth stage during which the deficit occurred. Water shortages during the extended grand-growth stage were especially detrimental. This evidence validates the use of crop-specific drought windows in the present study and suggests that adaptation policies in Sindh

should prioritize irrigation during biologically critical growth periods.

Cotton was also significantly affected by increasing drought severity, although the estimated effect was smaller than that observed for sugarcane. While cotton possesses physiological mechanisms that confer some tolerance to limited water availability, sustained or poorly timed water deficits can reduce photosynthesis, reproductive development, boll formation, and final seed-cotton yield. A global meta-analysis found that deficit irrigation increased cotton water productivity under certain conditions but reduced seed-cotton yield by approximately 20% on average, with outcomes highly dependent on irrigation intensity, growth stage, soil conditions, and management practices (Cheng et al., 2021). Therefore, the findings from Sindh should not be interpreted as evidence that cotton is inherently drought-resistant. Rather, cotton appears less sensitive than sugarcane under the specific climatic and production conditions represented in this analysis.

The comparatively smaller estimated effect for rice also warrants careful interpretation. Rice is highly dependent on adequate water availability, especially during reproductive development, but the impact of water deficits varies substantially by cultivar, irrigation regime, soil-water potential, and developmental stage. Experimental research indicates that some rice cultivars can maintain yields under mild deficit-irrigation conditions, whereas more severe soil-water deficits significantly reduce productivity (Kumar et al., 2017). Therefore, the smaller coefficient for rice does not suggest that rice is intrinsically insensitive to drought. Instead, it may reflect factors such as irrigation buffering, regional production concentration, cultivar composition, drought timing, or discrepancies between atmospheric drought and actual field-level water availability.

The categorical drought analysis offers further evidence that the agricultural consequences of drought are nonlinear. Compared to normal or mildly dry conditions, estimated yield losses increased progressively from approximately 10.16% under moderate drought to 14.39%

under severe drought and 18.86% under extreme drought. This gradient suggests that agricultural damage does not increase proportionally with the drought index. When moisture deficits reach a critical threshold, crop physiological processes and available irrigation may no longer effectively compensate for the additional water stress.

This nonlinear behavior has significant implications for drought-risk assessment. Treating drought exclusively as a continuous linear variable may obscure the much greater agricultural consequences associated with transitions into severe or extreme drought categories. Recent research distinguishing meteorological from agricultural drought characteristics has shown that crop responses depend not only on drought occurrence but also on event intensity, severity, duration, and frequency, with different crops responding most strongly to different drought dimensions (Wang et al., 2026). These severity-specific findings support the use of threshold-based drought warnings in conjunction with continuous drought monitoring.

The robustness analysis also demonstrated that the estimated SPEI effect diminished as drought exposure was measured over longer accumulation periods. The primary short-term specification yielded a coefficient of -0.097 , compared to -0.062 for the longer accumulation measure and -0.040 for the 12-month specification. This pattern suggests that crop yields may be more responsive to moisture stress occurring near sensitive stages of the production cycle than to climatic water deficits averaged over the entire year.

The significance of drought time scale is well established in arid agricultural regions. Li et al. (2021) found that crop-yield responses to SPEI varied considerably by drought accumulation period and crop type; notably, cotton exhibited greater sensitivity to shorter drought time scales than wheat and maize in their analysis. This evidence supports the current crop-specific exposure strategy. For Sindh, calculating drought indicators over the months corresponding to flowering, boll development, tillering, stalk

elongation, or reproductive growth is likely to yield more agriculturally relevant information than relying on annual climatic averages.

The lagged model indicated that current-season drought remained strongly associated with crop yield, while the coefficient for the preceding year's drought was small and statistically non-significant. Within the fixed-effects framework, this suggests that annual crop productivity is primarily influenced by drought conditions experienced during the current production cycle, rather than by direct carryover effects from the previous year.

This result should not be interpreted as evidence that drought lacks persistent hydrological or economic consequences. Drought can influence groundwater reserves, irrigation storage, soil conditions, farm income, input purchasing capacity, and subsequent planting decisions. Rather, the findings indicate that after accounting for current drought exposure and the model's fixed effects, previous-year drought did not independently explain additional yield variation. The absence of a significant one-year lag may also reflect the role of irrigation in partially mitigating the transmission of meteorological drought into subsequent crop seasons.

The stability of the estimated drought coefficient across alternative model specifications enhances confidence in the principal relationship. The negative SPEI effect remained substantively similar when two-way clustered inference was used, when climate observations were weighted toward cultivated areas, when major flood-affected years were excluded, and when individual districts were sequentially omitted from the analysis. This consistency indicates that the observed association is not driven by a single district, a particular error specification, or the inclusion of unusually wet disaster years.

However, robustness across statistical specifications does not eliminate all potential sources of confounding. Agricultural productivity is also influenced by irrigation allocation, salinity, pests, seed quality, fertilizer availability, technological advancements, farmer adaptation, commodity prices, and localized flooding. While

the fixed-effects structure accounts for persistent district-crop differences and province-wide crop-specific annual shocks, localized time-varying factors may persist. Therefore, these findings are best interpreted as strong panel-based evidence of a drought-yield relationship, rather than definitive proof that drought alone determines observed changes in agricultural production. Climate-resilient agriculture in Sindh. First, drought monitoring should integrate precipitation, evaporative demand, and soil-moisture information. The finding that SPEI produced the largest estimated effect suggests that a monitoring system based solely on rainfall may underestimate agricultural stress during unusually hot conditions.

Second, drought response strategies should be crop-specific. The particularly large estimated impact on sugarcane suggests that water-allocation policies should consider both crop water requirements and the developmental stage during which shortages occur. Uniform drought-management approaches across cotton, rice, and sugarcane are unlikely to yield optimal results.

Third, irrigation management should prioritize the timing and productivity of water use rather than focusing solely on total seasonal water delivery. When water resources are limited, safeguarding critical growth stages may reduce yield losses more effectively than distributing limited irrigation evenly throughout the crop cycle.

Fourth, the nonlinear findings suggest that preventing districts from transitioning from moderate to severe or extreme agricultural drought may yield disproportionately large benefits. Drought early-warning systems should therefore be linked to operational thresholds that trigger irrigation prioritization, groundwater management, drought-tolerant seed distribution, and farmer advisories before severe crop stress occurs.

Finally, the district-level results show that vulnerability varies by location. Provincial adaptation strategies should therefore account for district-specific exposure, crop composition,

irrigation access, and historical drought sensitivity, rather than relying solely on province-wide averages.

Overall Interpretation

Collectively, the findings indicate that drought constitutes a statistically and agriculturally significant constraint on the productivity of major commercial crops in Sindh. The consistent negative effects observed across SPI, SPEI, and soil-moisture indicators demonstrate robustness to alternative drought definitions, while differences in coefficient magnitude underscore the value of a multi-index framework over reliance on a single drought measure. The stronger estimated response for sugarcane, followed by cotton and rice, further illustrates that climatic water stress does not affect all crops uniformly. Additionally, the progressively greater losses observed under moderate, severe, and extreme drought highlight the importance of drought intensity rather than occurrence alone.

These findings support a transition from generalized drought assessment to crop-specific, growth-stage-sensitive, and multi-index drought management. This approach is especially important for Sindh, where agricultural productivity is shaped by the interplay of a naturally water-constrained climate, high evaporative demand, intensive irrigation requirements, and significant geographical variation in water availability.

Conclusion

This study investigated the effects of drought on major commercially important crops in Sindh, Pakistan, through a multi-index panel data framework. By integrating district-level agricultural data with the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and a standardized soil-moisture indicator, the analysis captured multiple dimensions of drought rather than relying on a single measure of climatic stress. The panel-data approach enabled control for persistent district-level and crop-specific

characteristics while isolating temporal variation in drought exposure.

The results consistently showed that greater drought severity was associated with reduced crop productivity across all three drought indicators. The SPEI yielded the strongest estimated relationship, indicating that atmospheric evaporative demand and temperature-related water stress are particularly significant in explaining crop-yield reductions in Sindh. The analysis also revealed distinct differences among crops, with sugarcane exhibiting the highest estimated sensitivity to drought, followed by cotton and rice. Furthermore, the nonlinear specifications demonstrated that yield losses increased progressively as drought conditions intensified from moderate to severe and extreme categories.

The findings also underscored the significance of drought timing. Shorter, crop-relevant drought accumulation periods produced stronger estimated relationships with yield than longer annualized measures, supporting the use of growth-stage-sensitive drought indicators. In contrast, the lagged drought specification indicated that the primary productivity effects were concentrated within the current production period, with limited persistence into the subsequent year.

These findings have significant implications for agricultural and water-resource management in Sindh. Drought-monitoring systems should integrate precipitation, evapotranspiration, and soil-moisture data and link them to crop-specific growth stages. It is recommended to prioritize irrigation allocation, adoption of drought-tolerant crop varieties, implementation of water-conservation strategies, and development of district-level early-warning systems in areas and for crops with greater drought sensitivity.

Overall, the study demonstrates the value of integrating multiple drought indicators with panel-data methods to assess climate-related agricultural vulnerability. This approach offers a more robust foundation for identifying crop- and district-specific drought risks and for formulating

targeted climate-adaptation and agricultural water-management policies in Sindh. Future research should expand this framework by incorporating irrigation availability, groundwater conditions, salinity, crop prices, and farm-level adaptation measures to provide a more comprehensive assessment of the mechanisms through which drought affects agricultural production.

REFERENCES

- Ahmad, B., Yunxian, Y., Ur Rahman, Z., Gultaj, H., Naseem Siddiqui, B., Ali, M., & Nasar, J. (2022). Enhancement of sugarcane production by counteracting the adverse effects of climate change in Sindh Province, Pakistan. *Growth and Change*, 53(1), 76–90. <https://doi.org/10.1111/grow.12561>
- Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas, A., & Din, I. U. (2017). Climate change and its impact on the yield of major food crops: Evidence from Pakistan. *Foods*, 6(6), Article 39. <https://doi.org/10.3390/foods6060039>
- Beguería, S., Vicente-Serrano, S. M., Reig, F., & Latorre, B. (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: Parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International Journal of Climatology*, 34(10), 3001–3023. <https://doi.org/10.1002/joc.3887>
- Blanc, E., & Schlenker, W. (2017). The use of panel models in assessments of climate impacts on agriculture. *Review of Environmental Economics and Policy*, 11(2), 258–279. <https://doi.org/10.1093/leep/rex016>
- Chandrasekara, S. S. K., Kwon, H.-H., Vithanage, M., Obeysekera, J., & Kim, T.-W. (2021). Drought in South Asia: A review of drought assessment and prediction in South Asian countries. *Atmosphere*, 12(3), Article 369. <https://doi.org/10.3390/atmos12030369>

- Cheng, M., Wang, H., Fan, J., Zhang, S., Wang, Y., Li, Y., Sun, X., Yang, L., & Zhang, F. (2021). Water productivity and seed cotton yield in response to deficit irrigation: A global meta-analysis. *Agricultural Water Management*, 255, 107027. <https://doi.org/10.1016/j.agwat.2021.107027>
- Dingre, S. K., Gorantiwar, S. D., Pawar, D. D., Dahiwalkar, S. D., & Nimbalkar, C. A. (2021). Sugarcane response to different soil water replenishment-based deficit irrigation treatments during different growth stages in an Indian semi-arid region. *Irrigation and Drainage*, 70(5), 1155–1171. <https://doi.org/10.1002/ird.2609>
- Hussain, A., Jadoon, K. Z., Rahman, K. U., Shang, S., Shahid, M., Ejaz, N., & Khan, H. (2023). Analyzing the impact of drought on agriculture: Evidence from Pakistan using standardized precipitation evapotranspiration index. *Natural Hazards*, 115(1), 389–408. <https://doi.org/10.1007/s11069-022-05559-6>
- Hussain, A., Suliman, M., & Khan, F. (2024). Analysing spatiotemporal drought patterns in Punjab Province, Pakistan, utilizing SPI and SPEI. *Theoretical and Applied Climatology*, 155, 7867–7886. <https://doi.org/10.1007/s00704-024-05090-7>
- Ismail, M., Li, Y., Niu, B., Ghaffar, M. A., Saleem, M. A., & Siddique, K. H. M. (2024). A multi-sensor drought index for improved agricultural drought monitoring and risk assessment in the heterogeneous landscapes of the China–Pakistan Economic Corridor (CPEC). *Atmospheric Research*, 310, Article 107633. <https://doi.org/10.1016/j.atmosres.2024.107633>
- Kumar, A., Nayak, A. K., Pani, D. R., & Das, B. S. (2017). Physiological and morphological responses of four different rice cultivars to soil water potential based deficit irrigation management strategies. *Field Crops Research*, 205, 78–94. <https://doi.org/10.1016/j.fcr.2017.01.026>
- Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B., & Vail, P. (2019). Estimating the impact of drought on agriculture using the U.S. Drought Monitor. *American Journal of Agricultural Economics*, 101(1), 193–210. <https://doi.org/10.1093/ajae/aay037>
- Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84–87. <https://doi.org/10.1038/nature16467>
- Li, H., Li, Y., Huang, G., & Sun, J. (2021). Probabilistic assessment of crop yield loss to drought time-scales in Xinjiang, China. *International Journal of Climatology*, 41, 4077–4094. <https://doi.org/10.1002/joc.7059>
- Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, 333(6042), 616–620. <https://doi.org/10.1126/science.1204531>
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J.-N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13, 4349–4383. <https://doi.org/10.5194/essd-13-4349-2021>
- Nazir, A., Lodhi, A. S., Akhtar, S., & Khajjak, A. K. (2024). Analyzing the nexus of weather on cotton production in Sindh, Pakistan: Using ARDL bound test. *Agricultural Sciences Journal*, (1), 123–134. <https://doi.org/10.56520/asj.24.370>

- Rahman, G., Khalid, S., Arshad, S., Moazzam, M. F. U., & Kwon, H.-H. (2025). Remote sensing-based spatiotemporal assessment of agricultural drought and its impact on crop yields in Punjab, Pakistan. *Scientific Reports*, 15(1), Article 20586. <https://doi.org/10.1038/s41598-025-06095-6>
- Rahman, K. U., Ejaz, N., Shang, S., Balkhair, K. S., Alghamdi, K. M., Zaman, K., Khan, M. A., & Hussain, A. (2024). A robust integrated agricultural drought index under climate and land use variations at the local scale in Pakistan. *Agricultural Water Management*, 295, Article 108748. <https://doi.org/10.1016/j.agwat.2024.108748>
- Rahman, K. U., Hussain, A., Ejaz, N., Shang, S., Balkhair, K. S., Khan, K. U. J., Khan, M. A., & Rehman, N. U. (2023). Analysis of production and economic losses of cash crops under variable drought: A case study from Punjab province of Pakistan. *International Journal of Disaster Risk Reduction*, 85, Article 103507. <https://doi.org/10.1016/j.ijdrr.2022.103507>
- Reyes, J. A. O., Carpennero, A. S., Santos, P. J. A., & Delfin, E. F. (2020). Effects of water regime, genotype, and formative stages on the agro-physiological response of sugarcane (*Saccharum officinarum* L.) to drought. *Plants*, 9(5), 661. <https://doi.org/10.3390/plants9050661>
- Saleem, F., Arshad, A., Mirchi, A., Khaliq, T., Zeng, X., Rahman, M. M., Dilawar, A., Pham, Q. B., & Mahmood, K. (2022). Observed changes in crop yield associated with drought propagation via natural and human-disturbed agro-ecological zones of Pakistan. *Remote Sensing*, 14(9), Article 2152. <https://doi.org/10.3390/rs14092152>
- Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damage to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 106(37), 15594–15598. <https://doi.org/10.1073/pnas.0906865106>
- Shah, F., Sarif, M. O., & Sharifi, A. (2026). CMIP6-driven projections of drought severity and their implications for the agricultural sector in Pakistan. *Earth Systems and Environment*, 10, 10809–10836. <https://doi.org/10.1007/s41748-026-01165-9>
- Shayeghi, A., Rahmati Ziveh, A., Bakhtar, A., Teymoori, J., Hanel, M., Vargas Godoy, M. R., Markonis, Y., & AghaKouchak, A. (2024). Assessing drought impacts on groundwater and agriculture in Iran using high-resolution precipitation and evapotranspiration products. *Journal of Hydrology*, 631, 130828. <https://doi.org/10.1016/j.jhydrol.2024.130828>
- Ullah, I., Ma, X., Yin, J., Asfaw, T. G., Azam, K., Syed, S., Liu, M., Arshad, M., & Shahzaman, M. (2021). Evaluating the meteorological drought characteristics over Pakistan using in situ observations and reanalysis products. *International Journal of Climatology*, 41(9), 4437–4459. <https://doi.org/10.1002/joc.7063>
- Vicente-Serrano, S. M., Begueria, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 23(7), 1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>

- Wang, H., Lin, X., Gao, P., Ye, S., Fang, D., Wang, Y., Zhao, M., & Song, C. (2026). Divergent responses of crop yields to meteorological and agricultural drought characteristics. *Agricultural Water Management*, 331, 110443. <https://doi.org/10.1016/j.agwat.2026.110443>
- Wang, S., Mo, X., Hu, S., Liu, S., & Liu, Z. (2018). Assessment of droughts and wheat yield loss on the North China Plain with an aggregate drought index (ADI) approach. *Ecological Indicators*, 87, 107-116. <https://doi.org/10.1016/j.ecolind.2017.12.047>
- Woli, P., Jones, J. W., Ingram, K. T., & Hoogenboom, G. (2014). Predicting crop yields with the Agricultural Reference Index for Drought. *Journal of Agronomy and Crop Science*, 200(3), 163-171. <https://doi.org/10.1111/jac.12055>
- Yao, N., Li, Y., Liu, Q., Zhang, S., Chen, X., Ji, Y., Liu, F., Pulatov, A., & Feng, P. (2022). Response of wheat and maize growth-yields to meteorological and agricultural droughts based on standardized precipitation evapotranspiration indexes and soil moisture deficit indexes. *Agricultural Water Management*, 266, 107566. <https://doi.org/10.1016/j.agwat.2022.107566>
- Zhang, X., Chen, N., Li, J., Chen, Z., & Niyogi, D. (2017). Multi-sensor integrated framework and index for agricultural drought monitoring. *Remote Sensing of Environment*, 188, 141-163. <https://doi.org/10.1016/j.rse.2016.10.045>
- Jatoi, I., Pirzado, AA., Lakho, MH., **Tunio, A.**, and Khaskeli, SA. (2021). Forecasting of cotton production in Sindh province, Pakistan by using different trend curves. *Ilinguistica Antverpiensia*, 3: 1758-1769.
- Kaleri, A. A., Abbasi, N. A., Tunio, A., Naich, S. A., Talpur, M. M. K., M., Hashmani, S. A. K., Jatoi, I. A., Ali, M. N. H. A., & Qumi, N. M. (2026). Interactive Effects of Plant Geometry and Nitrogen-Phosphorus (NP) Management on Wheat Growth, Yield, and Productivity. *Jammu Kashmir Journal of Agriculture*, 6(2), 97-106. <https://doi.org/10.56810/jkagri.006.02.0365>
- Kalwar, ZA., Tunio, A., Shaikh, MY., Jatoi, I. & Jogi, Q. (2018). Impact of sowing dates on the growth and yield of wheat variety Benazir-2013, Sindh Province, Pakistan. *International Journal of Agronomy & Agricultural Research*, 12(15): 65-71.
- Kumar, H., Jamro, MMR., Abbasi, Z., Kandhro, MN., **Tunio, A.** (2024). "Impact of zinc levels on growth and seed yield of variety Dadu Maize-1 under the agro climatic conditions of Tandojam Sindh-Pakistan". *Pure and Applied Biology*, 14(2): 352-361.
- Mengal, A. A., Ahmed, M., Lehri, Z. A., **Tunio, A.**, Baloch, F. M., Baloch, W. B., Siddiqui, A. A., & Mengal, Z. A. (2025). Navigating the digital divide: Assessing sociotechnical bottlenecks and the prospects of digital agriculture in Balochistan, Pakistan. *Regenerative Agriculture*, 1(2), 1-27.
- Mengal, AA., Tunio, A., Shahani, U., Baloch, FM and Jatoi, I. (2019). Analyzing factors hampering the interaction among the system actors (extension-research-farmer) in balochistan: bridging links compendium. *Pakistan Journal of Agriculture Agricultural Engineering & Veterinary Sciences*, 35(2): 119-126.
- Noonari, AR., Nindwani, BA., Tunio, A., Awan, GH., Halepoto, SA., Soomro, SA., Jokhio, MAF., Noonari. KR. (2025). "Role of Gypsum in Reclaiming Saline-Sodic Soils to Improving Soil Health and Enhancing Productivity". *Journal of Agriculture and Biology*, 3(1), 46-56.

Tunio, A., Jatoi, I. and Mengal, AA. (2017). Study of the information sources and their effectiveness on adoption of recommended technology for rice crop in district Naushahro Feroze, Sindh. *International Journal of Agronomy & Agricultural Research*, 11(1): 131-139.

Tunio, A., Magsi, H. and Solangi, MA. 2016. "Analyses of growth trends and production forecast of cash crops in Pakistan. *International Journal of Agronomy & Agricultural Research*, 9(1): 158-164.

