

Article

Regionalizing Meteorological-to-Agricultural Drought Propagation for Agricultural Risk Management Using Event Metrics and Explainable Machine Learning

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Abstract

Developing context-specific drought regionalization is crucial for targeted risk management, as drought evolves as a cascading hazard driven by complex land–atmosphere interactions rather than isolated climatic anomalies. However, conventional regionalization frameworks remain largely static and fail to capture the dynamic propagation from meteorological forcing to agricultural impacts. To address this limitation, we developed a framework that links continuous drought dynamics to discrete drought events, enabling identification of propagation patterns and their associated environmental mechanisms across the Loess Plateau, China. By integrating run theory, dimensionality reduction, clustering, and explainable machine learning, we identified three distinct drought propagation regimes: Propagation Blocked, Disaster Amplified, and Response Desensitized zones. At the regional scale, eco-hydrological factors, particularly vegetation productivity and soil moisture dynamics, showed the strongest attribution signals for differentiating drought propagation regimes. However, regime-specific environmental associations differed substantially: (i) propagation blockage was associated with terrain–vegetation interactions; (ii) disaster amplification was associated with low ecological productivity and declining soil moisture; and (iii) response desensitization was associated with intensive agricultural activities and relatively favorable soil moisture conditions, which may partly buffer vegetation responses to thermal and meteorological stress and create apparent resilience that may mask underlying hydrological vulnerability. SHAP analysis further indicated that topography and thermal conditions were strongly associated with broad-scale differentiation, while eco-hydrological conditions showed stronger associations with local regime-specific responses. Anthropogenic activities may also be associated with altered drought propagation pathways and potential risks of unsustainable water use. These findings highlight drought as a dynamic propagation process rather than a static hazard and provide a basis for targeted drought management strategies.

Keywords: agricultural drought; drought propagation; agricultural risk zoning; event metrics; remote sensing; explainable machine learning; Loess Plateau



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1. Introduction

As a pervasive natural hazard intensified by global warming [1,2], drought causes substantial socio-economic losses worldwide and poses a critical threat to agricultural production and food security [3,4]. Future climate change may further alter crop yield, phenology, and irrigation water requirements, especially in water-limited agricultural systems [5–9]. Consequently, enhancing drought resilience is essential for safeguarding livelihoods and supporting sustainable development [10–12]. To support effective mitigation, drought regionalization has been widely adopted as a key framework for spatial management. However, traditional regionalization approaches predominantly rely on a static perspective, focusing on the independent delineation of isolated drought types or static hydroclimate variables without adequately considering their cascading evolution [13–15]. In reality, drought is a dynamic propagation process that spreads from the atmospheric system to the terrestrial system. Regionalization methods that neglect this propagation perspective inevitably fail to accurately capture the spatio-temporal evolution and amplification of drought impacts. This limitation is particularly evident in the Loess Plateau, where drought vulnerability exhibits strong spatial variability, with significantly higher sensitivity observed in the arid western margins compared to ecologically restored regions [16,17].

Recent drought research has shifted from single-type analyses toward cross-type propagation mechanisms [18–21]. To characterize drought across multiple dimensions, researchers increasingly integrate several drought and eco-hydrological indices. With the continuous refinement of eco-hydrological observation systems, foundational indicators have expanded into multidimensional spaces. Beyond combining traditional indices like the Standardized Precipitation Evapotranspiration Index (SPEI) and Vegetation Health Index (VHI) [22,23], Gross Primary Productivity (GPP) [24] and soil moisture datasets are frequently used to evaluate ecosystem productivity impairment and subsurface moisture dynamics. Soil moisture–vegetation feedback also varies across climatic regions, suggesting that vegetation drought responses are jointly shaped by water availability and ecosystem conditions [25]. This multi-index framework allows for a more granular characterization of the transition from atmospheric water deficits to ecological and agricultural stress. Notably, vegetation responses to drought over the Loess Plateau exhibit pronounced spatial heterogeneity and are jointly regulated by climatic variability and large-scale ecological restoration processes [26,27]. Existing studies have widely employed these indices in conjunction with run theory to effectively quantify critical propagation metrics, such as the drought onset time (DOT), onset speed (DOS), and the lag time between different drought types.

Nevertheless, the current academic focus remains largely concentrated on the long-term temporal trend evolution of these propagation characteristics [28], with few attempts to systematically translate this dynamic propagation process into spatial management metrics for regionalization. While some studies have successfully delineated drought zones by clustering the evolutionary features of indices like SPEI or VHI [29], or have performed climate regionalization based on traditional hydroclimatic variables such as precipitation and temperature using clustering approaches [30], they often overlook the process-based spatial heterogeneity, specifically, how the efficiency and speed of drought propagation vary across different landscapes.

Furthermore, while drought event characteristics (e.g., duration, severity) and propagation metrics can jointly describe the dynamic evolution of the drought system, existing studies often overlook the highly non-linear coupling and information redundancy among these variables when directly applying them to spatial clustering. For instance, a prolonged drought duration is typically accompanied by a greater

cumulative severity, and propagation time and rate may partially reflect similar response processes. Such uncritical superimposition of multiple variables not only increases interpretational complexity but also obscures the true mechanisms dominating drought evolution.

To address feature redundancy and the limitations of subjective threshold-based regionalization, previous studies have increasingly adopted data-driven approaches to reconstruct multi-dimensional drought feature spaces. In particular, dimensionality reduction techniques such as Principal Component Analysis (PCA) have been widely used to transform correlated variables into orthogonal components, thereby capturing the dominant modes of variability while mitigating multicollinearity [31]. Building upon these reduced feature representations, clustering algorithms—most notably K-means and its variants—have been widely applied to objectively delineate spatial patterns in hydro-climatic and ecological systems [32]. For instance, K-means clustering has been successfully employed to identify ecosystem service bundles and delineate eco-functional zones on the Loess Plateau, providing a data-driven basis for regional management. However, existing applications have largely focused on static ecological indicators, without explicitly incorporating the dynamic propagation processes linking different drought types [33].

Feature-based regionalization identifies spatial outcomes but does not explain their environmental controls. To further elucidate the underlying environmental drivers, introducing external variables for attribution analysis has become increasingly important [20]. Recent evidence suggests that while climate provides the fundamental forcing, local factors such as Land Use/Land Cover (LULC) and topographic characteristics significantly reshape the secondary control mechanisms of drought propagation [34]. When exploring these mechanisms, traditional statistical methods often struggle to capture complex non-linearities. To address this, the SHapley Additive exPlanations (SHAP) framework combined with eXtreme Gradient Boosting (XGBoost) has recently gained traction. For example, SHAP has been successfully applied to evaluate ecological thresholds in agro-pastoral zones [35] and to interpret the non-linear driver contributions of multi-type drought propagation chains at a global scale [36]. However, its potential for disentangling the relative contributions of environmental drivers behind regionalized drought propagation patterns remains under-explored.

Accordingly, this study examines drought propagation and its eco-hydrological controls across the Loess Plateau. Specifically, it aims to decode the spatial heterogeneity of drought propagation and its underlying eco-hydrological control mechanisms. To this end, the multi-source feature space of drought propagation is first reconstructed using Principal Component Analysis (PCA), enabling the extraction of orthogonal components that capture the dominant propagation characteristics while reducing redundancy. Based on these reconstructed features, a K-means clustering framework is subsequently applied to objectively identify distinct drought propagation typologies across the region. Specifically, this study aims to: (1) track the cascading sequence from meteorological water deficits to agricultural impacts at the pixel scale; (2) identify and regionalize distinct drought propagation regimes based on their intrinsic dynamic characteristics; and (3) employ the XGBoost-SHAP framework to quantify the relative contributions and non-linear dependencies of climatic, topographic, ecological, and anthropogenic predictors associated with these regimes. Ultimately, this study provides a process-oriented and data-driven basis for understanding drought evolution and supports the development of spatially targeted drought mitigation and adaptive management strategies.

2. Materials and Methods

2.1. Study Area

The Loess Plateau is located in northern China, approximately between 34–41° N and 100–115° E, covering an area of about 640,000 km² (Figure 1). Elevation varies substantially across the region, with high terrain in the west and lower terrain in the east. The Loess Plateau has a temperate semi-arid to semi-humid climate, with an average annual temperature of 6–14 °C and an average annual precipitation of 300–700 mm, mostly concentrated from July to September. The main land use types are farmland and grassland, with wheat, maize, and other crops being the primary cultivated species.

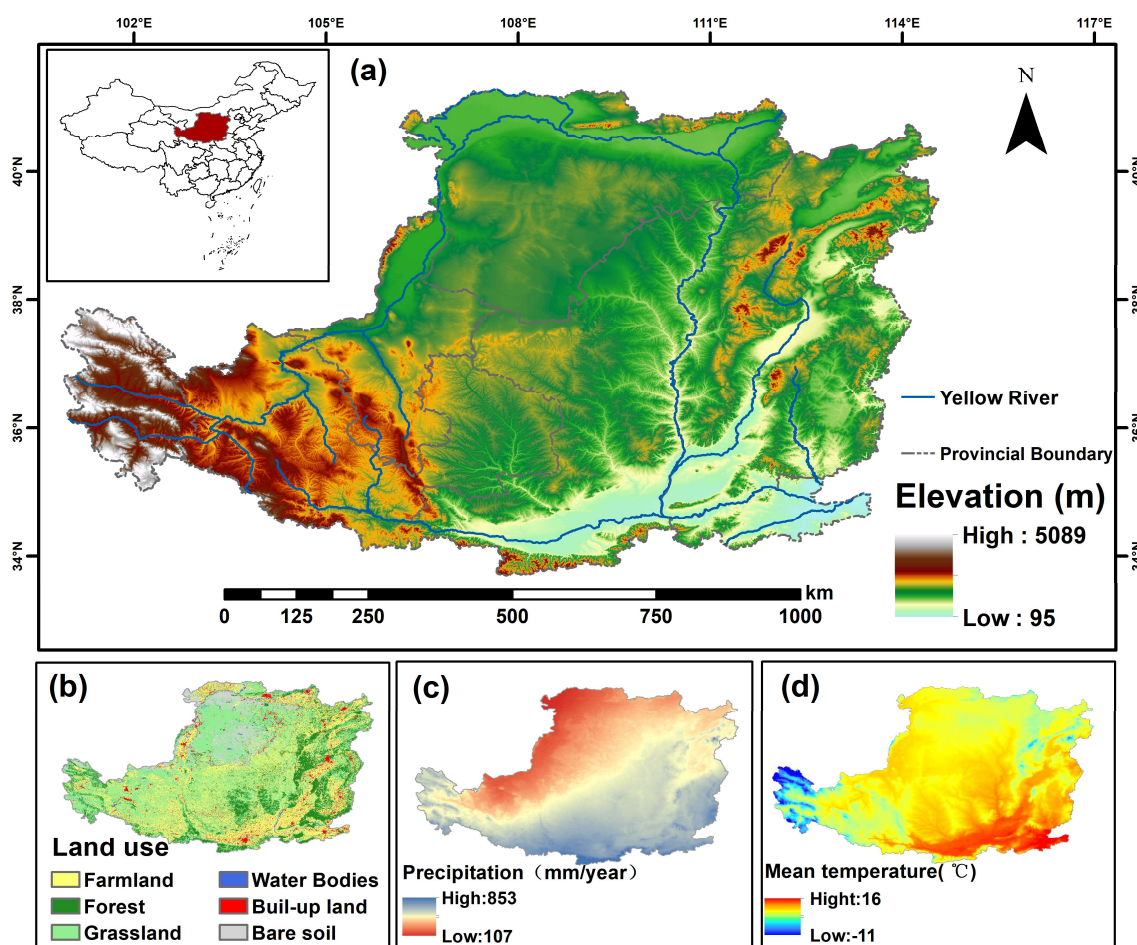


Figure 1. Overview of the study area. (a) Geographical location and elevation of the Loess Plateau; (b) land-use distribution; (c) mean annual precipitation; and (d) mean annual temperature.

2.2. Data

To characterize drought propagation across the Loess Plateau, a multi-source spatiotemporal dataset covering the main study period of 1982–2020 was constructed where possible (Table 1). Given the substantial differences in spatial resolution among datasets (ranging from 30 m to 9 km), all gridded variables were spatially harmonized before pixel-level event analysis and county-level attribution analysis.

Table 1. Summary of multi-source remote sensing datasets and environmental variables used in this study.

Data	Period	Temporal Resolution	Spatial Resolution	Source
Precipitation	1982–2020	monthly	4 km	TerraClimate [37]
Potential Evapotranspiration	1982–2020	monthly	4 km	TerraClimate [37]
Temperature	1982–2020	monthly	9 km	ERA5-Land [38]
Vegetation Health Index (VHI)	1982–2020	weekly	4 km	NOAA VHI [39]
Soil Moisture	1982–2020	monthly	0.1°	ESA CCI Soil Moisture [40], gap-filled following [41]
Gross Primary Productivity (GPP)	1982–2018	yearly	0.05°	GLASS GPP [42]
Land Use	1985–2022	yearly	30 m	CLCD [43]
Elevation (DEM)	Static	—	30 m	NASADEM [44]

Meteorological drought conditions were characterized using monthly precipitation and potential evapotranspiration (PET) from the TerraClimate dataset (4 km), from which the Standardized Precipitation Evapotranspiration Index (SPEI) was derived. Vegetation responses were represented by the Vegetation Health Index (VHI) obtained from NOAA STAR. Since the original VHI product is provided at a weekly resolution, weekly VHI data were aggregated to monthly values using monthly averaging to match the temporal resolution of SPEI and the event-based analysis. For the attribution analysis, environmental and anthropogenic variables were compiled from multiple sources. Thermal conditions (mean and trend of temperature) were derived from ERA5-Land (9 km). Vegetation productivity (mean and trend of Gross Primary Productivity, GPP) was obtained from the GLASS GPP dataset (0.05°), while soil moisture data were acquired from the ESA CCI dataset. Topographic variables, including elevation and slope, were derived from the NASADEM dataset (30 m). Anthropogenic influence was represented by the cropland ratio calculated from the China Land Cover Dataset (CLCD, 30 m).

To harmonize the attribution variables over the study period (1982–2020) for the subsequent XGBoost–SHAP modeling, the minor data gaps in the GPP dataset (2019–2020) were gap-filled using linear trend extrapolation based on its historical observation period (1982–2018).

2.3. Characterization of Drought Events and Propagation Dynamics

2.3.1. Drought Event Identification Based on Run Theory

To characterize the drought propagation process, we utilized the Standardized Precipitation Evapotranspiration Index (SPEI) and the Vegetation Health Index (VHI) to represent meteorological and agricultural droughts, respectively [39,45]. Specifically, the 1-month SPEI (SPEI-1) and monthly VHI were employed as the baseline indices to identify independent meteorological and agricultural drought events. The 1-month scale was adopted as the baseline accumulation scale to characterize short-term meteorological drought variability and identify drought events at the monthly scale. Meteorological drought events were identified when $\text{SPEI-1} \leq -0.5$, while agricultural drought events were identified when monthly $\text{VHI} \leq 0.40$.

Run theory [46] was applied to the monthly SPEI-1 and VHI time series on a pixel-by-pixel basis to identify individual drought events and quantify their core characteristics. Operationally, for any given pixel, a drought episode was defined as one or more consecutive months during which the drought index remained at or below the predefined threshold.

Based on this definition, all identified drought events during the study period were evaluated to extract three fundamental properties: Duration (D), Severity (S), and Frequency (F). Here, Frequency (F) denotes the total number of drought events for a given pixel; Duration (D) represents the consecutive months over which a drought event persists; and Severity (S) is defined as the cumulative deficit of the drought index throughout the event duration. These event-level characteristics were subsequently aggregated at the pixel scale by calculating the total event frequency, mean event duration, and cumulative severity across all identified events, thereby deriving the pixel-level drought metrics used in the subsequent drought propagation analysis. Because no rapid-intensification criterion was applied, the identified SPEI-1 events are interpreted as short-term meteorological drought events rather than flash droughts.

2.3.2. Quantification of Drought Propagation Metrics

The Pearson correlation coefficient (PCC) method was used to estimate the characteristic propagation timescale between meteorological and agricultural droughts [47,48]. Following previous drought propagation studies, SPEI was calculated at accumulation scales of 1–12 months and contemporaneously correlated with monthly VHI at each pixel. The propagation timescale (PT) was defined as the SPEI accumulation timescale at which the PCC between SPEI and VHI reached its maximum. This PCC-derived PT represents the characteristic response timescale of agricultural drought to antecedent meteorological drought conditions.

To further examine whether a meteorological drought event successfully propagated into an agricultural drought event, an event-matching procedure was conducted using the PCC-derived PT as the event-matching window. For each pixel, meteorological drought events identified from SPEI and agricultural drought events identified from VHI were matched according to their temporal sequence. A meteorological drought event was considered to have propagated into an agricultural drought event when the agricultural drought started after the onset of the meteorological drought and occurred within the corresponding propagation time window. The matching criterion was defined as:

$$propagate = \begin{cases} T, & \text{if } t_{s,AD} \geq t_{s,MD} \text{ and } t_{s,AD} - t_{e,MD} \leq PT \\ F, & \text{otherwise} \end{cases} \quad (1)$$

where T and F indicate successful and failed propagation, respectively. $t_{s,MD}$ and $t_{e,MD}$ denote the start and end times of a meteorological drought event, respectively, while $t_{s,AD}$ denotes the start time of the corresponding agricultural drought event. PT is the PCC-derived propagation timescale used as the event-matching window. This criterion allows the agricultural drought response to occur during or shortly after the meteorological drought event, reflecting the possible temporal overlap between meteorological forcing and vegetation response.

Based on the event-matching results, the propagation rate (PR) was calculated to quantify the probability or efficiency with which meteorological drought events were transmitted to the agricultural drought stage:

$$PR = \frac{n}{m} \quad (2)$$

where m represents the total number of meteorological drought events identified during the study period, and n denotes the number of meteorological drought events that successfully propagated into agricultural drought events according to the matching criterion. Each meteorological drought event was counted only once, even when multiple agricultural drought events satisfied the matching condition. A higher PR indicates a greater likelihood that meteorological drought events propagate into agricultural drought events.

2.4. Identification of Drought Propagation Regimes

2.4.1. Feature Compression via Principal Component Analysis

Drought events were first identified at the pixel/event level, and the resulting event-propagation metrics were subsequently aggregated to the county level using zonal statistics. Accordingly, each county was represented by a vector of eight event-propagation metrics, including D_{met} , F_{met} , S_{met} , D_{agr} , F_{agr} , S_{agr} , PR , and PT . The definitions and interpretations of these metrics are summarized in Table S1.

To address the high dimensionality and multicollinearity inherent in drought event characteristics, such as duration and severity, and propagation metrics, such as propagation time and rate, Principal Component Analysis (PCA) was applied to transform the original correlated variables into a reduced set of orthogonal components. Prior to PCA, the optimal SPEI accumulation scale (PT) was natural-log-transformed, and all eight features were subsequently standardized using the Z-score method to ensure comparability. The principal components were then derived, and the leading components explaining more than 85% of the total variance were retained.

These retained components captured the dominant modes of drought propagation variability while minimizing redundancy and were subsequently used as orthogonal inputs for the spatial clustering analysis.

2.4.2. Regime Classification in Reduced Feature Space

Following the extraction of dominant orthogonal modes via PCA, the K-means clustering algorithm was applied to partition the study area into distinct drought propagation regimes. K-means was selected due to its efficiency and suitability for large-scale hydro-climatic datasets.

Clustering was performed in the reduced principal component space to avoid the influence of multicollinearity present in the original variables. The optimal number of clusters (K) was primarily determined using the elbow method, with the silhouette score used as a supplementary diagnostic. The elbow method indicated that the reduction in within-cluster sum of squares became less pronounced after $K = 3$ (Figure S1). Detailed clustering diagnostics for K values ranging from 2 to 6 are provided in Table S4b.

2.5. Sensitivity Analysis

A sensitivity analysis was conducted to evaluate the robustness of the drought propagation regionalization to the selection of SPEI accumulation scales and drought thresholds. The baseline scenario used $SPEI-1 \leq -0.5$ and $VHI \leq 0.40$. Five alternative scenarios were considered: $SPEI-3 \leq -0.5$, $SPEI-6 \leq -0.5$, a stricter meteorological drought threshold of $SPEI-1 \leq -1.0$, and two stricter agricultural drought thresholds of $VHI \leq 0.35$ and $VHI \leq 0.30$. In each alternative scenario, only one parameter was changed relative to the baseline, while the remaining settings were held constant.

For each scenario, drought event identification and propagation-rate calculation were repeated using the baseline PCC-derived PT as a fixed event-matching window, followed by county-level aggregation, data transformation and standardization, PCA, and K-means clustering. The number of clusters was fixed at three, as determined from the baseline regionalization, to maintain a consistent regime framework and enable direct comparison

among the sensitivity scenarios. The similarity between each sensitivity scenario and the baseline result was evaluated using the adjusted Rand index (ARI), normalized mutual information (NMI), overall county-level agreement, class-specific Jaccard coefficients, and the number of counties assigned to different drought propagation regimes. Because K-means cluster labels are arbitrary, the cluster labels of each sensitivity scenario were aligned with the baseline regimes according to the maximum county-level overlap before calculating the agreement and class-specific metrics. In addition, the sensitivity of the PCA cumulative explained-variance threshold was evaluated for the baseline scenario by comparing thresholds of 80%, 85%, and 90%, while retaining $K = 3$ for clustering.

2.6. Attribution Analysis of Drought Propagation Regimes

2.6.1. Feature Selection and Model Construction

To ensure spatial consistency across multi-source datasets, all gridded environmental and meteorological variables were aggregated to the county level using zonal statistics based on administrative boundaries. The county was thus defined as the fundamental spatial unit for subsequent analysis. Specifically, the anthropogenic indicator, cropland ratio, was derived from land use data by calculating the proportion of cropland area within each county.

Following spatial harmonization, a set of representative variables was compiled to characterize the potential drivers of drought propagation. Recognizing that drought vulnerability is governed by both inherent structural features and gradual environmental shifts, the selected drivers encompass both static environmental baselines (i.e., mean elevation, mean slope, mean GPP, mean soil moisture, and mean temperature) and dynamic evolutionary trends (i.e., GPP trend, soil moisture trend, and temperature trend). The long-term magnitude of these dynamic trends was quantified using the non-parametric Theil-Sen median trend analysis coupled with the Mann–Kendall (MK) significance test. This robust approach was specifically selected due to its high resistance to data outliers and its independence from data distribution assumptions.

To improve the statistical robustness of subsequent machine learning modeling and prevent feature importance distortion, multicollinearity among the selected variables was rigorously evaluated using the variance inflation factor (VIF).

2.6.2. Explainable Machine Learning for Attribution Analysis

To investigate the non-linear relationships between environmental drivers and the identified drought propagation regimes, the eXtreme Gradient Boosting (XGBoost) algorithm was employed. As a boosting-based ensemble of decision trees, XGBoost is capable of capturing complex interactions and hierarchical structures among hydro-climatic variables. Model hyperparameters were optimized using grid search combined with stratified 10-fold cross-validation. Model performance was evaluated using overall accuracy, macro-averaged F1-score, and class-specific precision, recall, and F1-score. To obtain class-specific evaluation results, predictions from the ten validation folds were aggregated as out-of-fold predictions, such that each county was predicted by a model trained without that county. These out-of-fold predictions were further used to construct the confusion matrix. Precision represents the proportion of counties correctly classified among all counties predicted as a given regime, recall represents the proportion of counties correctly identified among all counties actually belonging to that regime, and the F1-score represents the harmonic mean of precision and recall.

Despite its strong predictive capability, XGBoost operates as a “black-box” model. To enhance interpretability, the SHapley Additive exPlanations (SHAP) framework, derived from cooperative game theory, was adopted. Specifically, the Tree SHAP algorithm was

used to efficiently compute exact Shapley values by leveraging the internal tree structure, thereby avoiding the need for exhaustive feature subset enumeration.

It is important to note that SHAP does not establish causal relationships. Instead, it provides a theoretically grounded decomposition of model predictions into feature contributions. In this study, SHAP was used to quantify the relative importance of driving factors and to identify non-linear response patterns and threshold-like behaviors. These results provide an interpretable attribution of model behavior, highlighting how environmental drivers contribute to the model-predicted drought propagation regimes. The propagation regime assigned to each county by the PCA–K-means classification was used as the response variable in the XGBoost model, while the county-level environmental variables were used as predictors.

3. Results

3.1. Spatiotemporal Patterns of Drought Propagation

By applying run theory and event matching on a pixel-by-pixel basis, eight event–propagation metrics were extracted to evaluate spatial patterns across the Loess Plateau. As illustrated in Figure 2b–d, meteorological drought exhibited spatial heterogeneity. The western Loess Plateau generally experienced relatively mild meteorological drought conditions, characterized by low frequency, short duration, and low severity, alongside lower propagation rates and shorter PCC-derived response timescales.

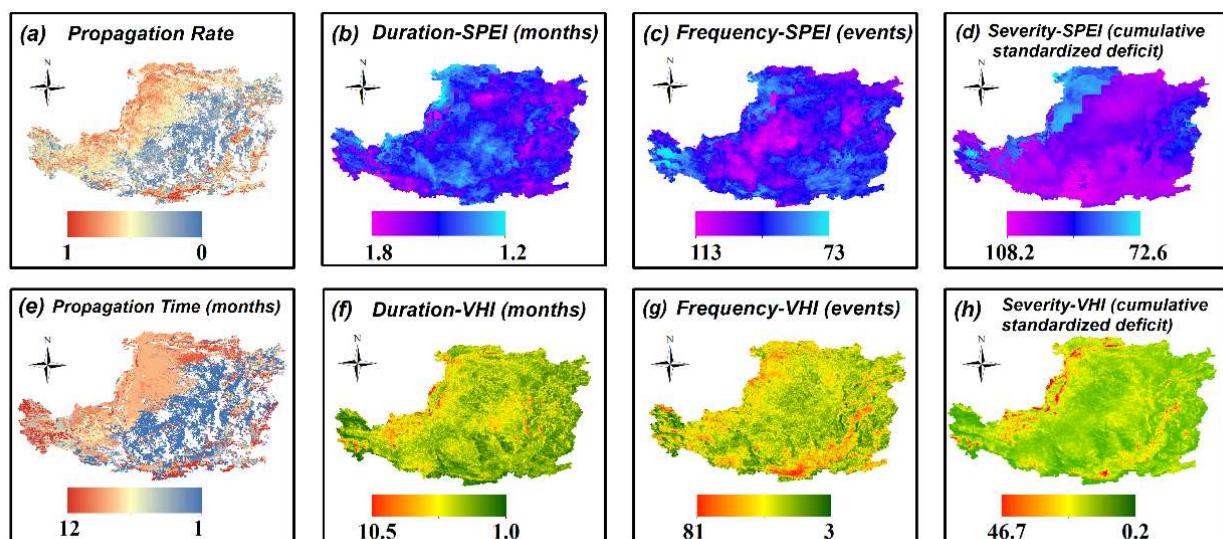


Figure 2. Spatial distribution of drought event characteristics and propagation metrics across the Loess Plateau. (a) Propagation rate derived from event matching; (e) PCC-derived propagation timescale. (b–d) Duration, frequency, and severity of meteorological drought events identified using SPEI. (f–h) Duration, frequency, and severity of agricultural drought events identified using VHI. Severity was calculated as the cumulative deficit below the corresponding drought threshold.

However, a spatial mismatch was observed when tracking the propagation cascade. Relatively mild meteorological drought conditions coincided with severe agricultural drought impacts (Figure 2f–h). Specifically, the western Loess Plateau and certain high-altitude areas in the central-east demonstrated a high susceptibility to agricultural drought, marked by elevated frequency, extended duration, and increased severity. This pattern indicated a vulnerable land surface that may amplify relatively mild climatic deficits.

Conversely, the central region exhibited substantial eco-hydrological resilience. Despite experiencing heterogeneous meteorological drought conditions, agricultural drought indicators in this region remained relatively stable (i.e., low severity and low frequency).

This resistance was further evidenced by longer PCC-derived response timescales or, in several instances, the interruption of the drought propagation continuum.

This spatial decoupling between meteorological forcing and agricultural response indicates that drought propagation is a highly non-linear process modulated by underlying surface conditions. It highlights that relying solely on meteorological anomalies is insufficient to capture the landscape's true eco-hydrological vulnerability. Consequently, to decode these complex land–atmosphere interactions and provide targeted mitigation strategies, it is necessary to partition the Loess Plateau into distinct drought propagation typologies.

3.2. Spatial Regionalization of Drought Propagation Regimes

3.2.1. Principal Component Analysis

The Principal Component Analysis (PCA) effectively condensed the multidimensional feature space of the eight drought propagation metrics into dominant feature dimensions (Figure 3). Specifically, the first principal component (PC1) is dominated by positive loadings from agricultural drought indices (S_{agr} , F_{agr} , D_{agr}) and propagation metrics (PR , PT). In contrast, the second principal component (PC2) is primarily driven by meteorological forcings, exhibiting a strong positive loading for F_{met} and a negative loading for D_{met} . The PCA biplots (Figure 3b,c) demonstrate that these orthogonal dimensions effectively separate the 373 counties into distinct clusters aligned with specific variable vectors, providing a robust statistical foundation for spatial typological classification.

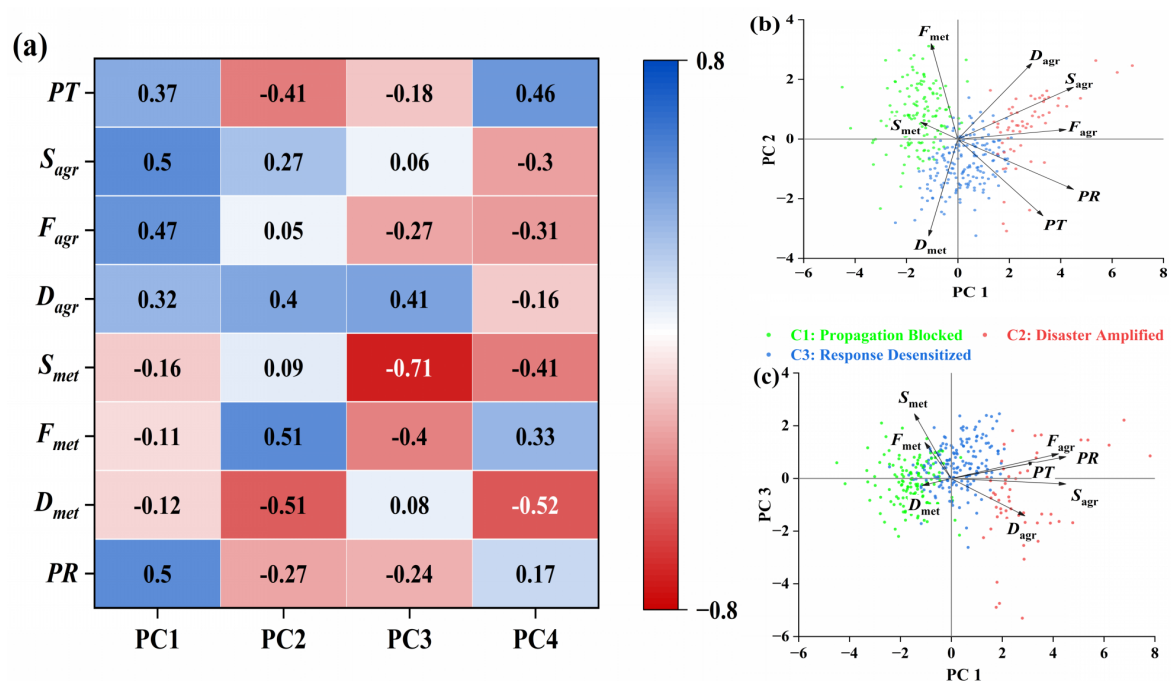


Figure 3. Principal Component Analysis (PCA) of drought propagation metrics. (a) Heatmap of the PCA loading matrix, showing the component loadings of the eight original metrics on the first four principal components (PC1–PC4). Blue and red colors represent positive and negative loadings, respectively. (b,c) Two-dimensional biplots projecting the counties onto the PC1–PC2 and PC1–PC3 planes. Data points are color-coded by their designated clusters (C1: green, C2: red, C3: blue), with arrows indicating the direction and magnitude of the original variables' contributions to the principal components.

3.2.2. Spatial Clustering of Drought Regimes

Building upon the dimensions derived from PCA, the K-means algorithm classified the study area into three distinct drought propagation regimes characterized by contrasting

propagation dynamics (Figure 4). A comparative analysis of these clusters reveals a pronounced spatial decoupling between meteorological forcing and agricultural impacts.

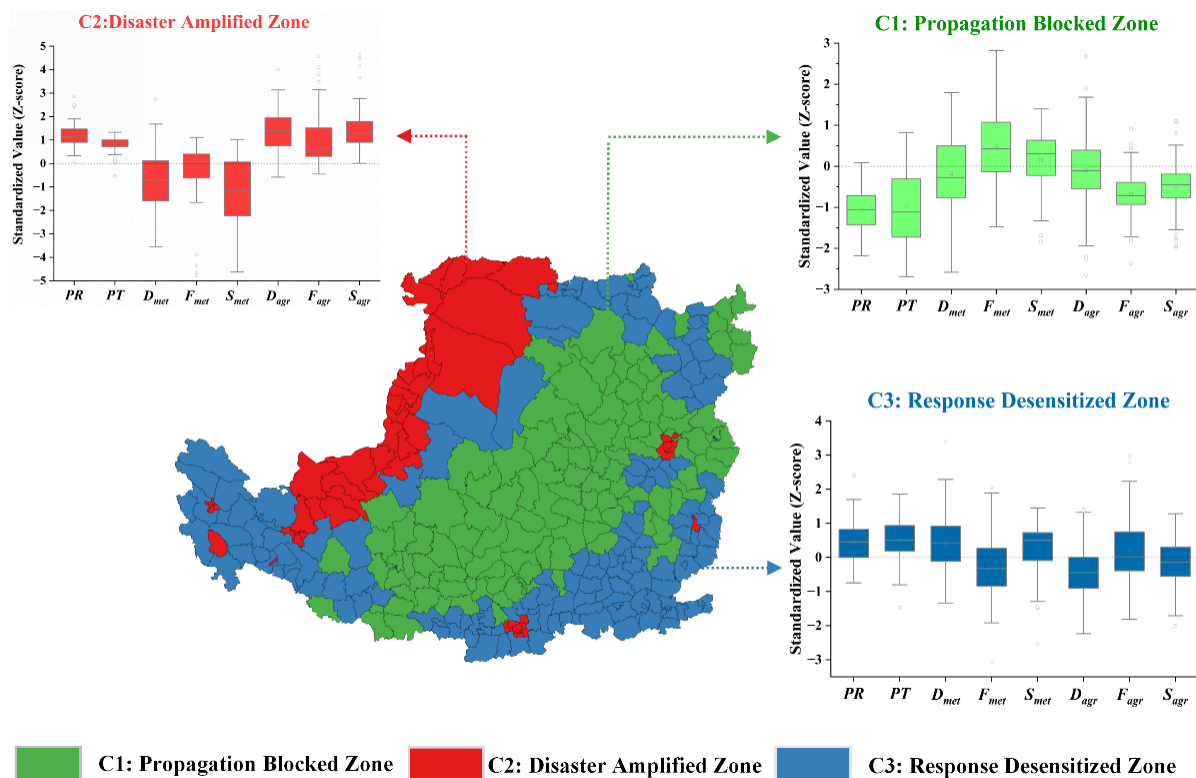


Figure 4. Spatial distribution and characteristic profiling of the three drought propagation typologies. The central map illustrates the spatial classification of the Loess Plateau into three distinct clusters: Propagation Blocked Zone (Cluster 1, green), Disaster Amplified Zone (Cluster 2, red), and Response Desensitized Zone (Cluster 3, blue). The accompanying boxplots display the standardized Z-scores of eight drought propagation metrics (PR , PT , D_{met} , F_{met} , S_{met} , D_{agr} , F_{agr} , S_{agr}) for each respective cluster.

Specifically, the Disaster Amplified Zone (C2, red, northwestern) exhibits the weakest meteorological forcing (lowest S_{met} and F_{met}), yet suffers the most severe agricultural droughts (maximum D_{agr} , F_{agr} , and S_{agr}). This zone also shows the highest propagation rate (PR) and a longer PCC-derived response timescale (PT), indicating a stronger and more persistent linkage between meteorological deficits and agricultural drought responses.

In contrast, the Propagation Blocked Zone (C1, green, central and southern) represents an opposing mechanism. Despite experiencing the highest frequency of meteorological droughts, it records the lowest propagation rate, effectively limiting the translation of meteorological deficits into agricultural impacts, with D_{agr} , F_{agr} , and S_{agr} remaining below the regional average.

The Response Desensitized Zone (C3, blue, peripheral and eastern) exhibits a third distinct pattern. It is subjected to the most severe and prolonged meteorological forcing (highest D_{met} and S_{met}), yet the resulting agricultural drought remains relatively weak (Z-scores near or below zero). This suggests a decoupling mechanism in which strong climatic stress does not translate into proportional agricultural response.

While this comparative classification clearly delineates distinct propagation regimes, it also highlights the need to further identify the environmental drivers underlying these divergent land surface responses.

3.3. Sensitivity of Drought Propagation Regionalization

The drought event characteristics varied systematically across the sensitivity scenarios (Table S2). Increasing the SPEI accumulation scale from 1 to 3 and 6 months reduced the number of meteorological drought events from 4,790,938 in the baseline scenario to 2,667,668 and 1,836,585, respectively, while increasing the mean propagation rate from 0.475 to 0.531 and 0.550. Applying the stricter meteorological drought threshold of $\text{SPEI-1} \leq -1.0$ reduced the number of meteorological drought events to 3,044,746 but resulted in only a limited change in the mean propagation rate (0.469). In contrast, lowering the VHI threshold from 0.40 to 0.35 and 0.30 progressively reduced the number of agricultural drought events from 1,739,214 to 1,291,749 and 886,609, respectively, and decreased the corresponding mean propagation rates to 0.374 and 0.273.

Four principal components were retained in all sensitivity scenarios, explaining 86.19%–91.87% of the total variance (Table S4a). The regionalization exhibited parameter-dependent stability relative to the baseline scenario (Table 2; Table S3; Figure 5). The alternative VHI thresholds produced the highest spatial consistency. The $\text{VHI} \leq 0.35$ and $\text{VHI} \leq 0.30$ scenarios achieved overall county-level agreement rates of 96.51% and 91.15%, respectively, with corresponding adjusted Rand index values of 0.883 and 0.729; only 13 and 33 counties changed their regime assignments. The stricter meteorological drought threshold showed intermediate stability, with an agreement rate of 79.62%, an adjusted Rand index of 0.481, and 76 reassigned counties. Greater changes occurred when the SPEI accumulation scale was increased. The SPEI-3 and SPEI-6 scenarios yielded agreement rates of 69.71% and 69.44%, adjusted Rand index values of 0.313 and 0.344, and 113 and 114 reassigned counties, respectively.

Table 2. Stability of drought propagation regionalization under alternative SPEI accumulation scales and drought thresholds.

Scenario	SPEI Accumulation Scale (Month)	SPEI Threshold	VHI Threshold	ARI	NMI	Overall Agreement (%)	Changed Counties (n)
Baseline	1	−0.5	0.4	1	1	100	0
SPEI-3	3	−0.5	0.4	0.313	0.342	69.71	113
SPEI-6	6	−0.5	0.4	0.344	0.418	69.44	114
Strict SPEI threshold	1	−1.0	0.4	0.481	0.513	79.62	76
VHI threshold of 0.35	1	−0.5	0.35	0.883	0.872	96.51	13
VHI threshold of 0.30	1	−0.5	0.3	0.729	0.695	91.15	33

Note: Cluster labels were aligned with the baseline regimes according to maximum county-level overlap. ARI, adjusted Rand index; NMI, normalized mutual information. Overall agreement represents the percentage of the 373 counties assigned to the same drought propagation regime as in the baseline scenario.

Spatial differences were mainly reflected by county-level adjustments along the boundaries and transitional zones of the baseline regimes. The principal spatial organization of the three drought propagation regimes nevertheless remained evident across the independently refitted scenarios. These results indicate that the regionalization was highly robust to reasonable changes in the agricultural drought threshold but exhibited greater sensitivity to the accumulation scale and threshold used to identify meteorological drought. Varying the PCA cumulative explained-variance threshold from 80% to 90% had little influence on the regionalization. The 80% threshold reproduced the baseline classification exactly, whereas the 90% threshold retained five principal components and achieved an ARI of 0.962 and an overall agreement of 98.93%, with only four counties reassigned (Table S4c).

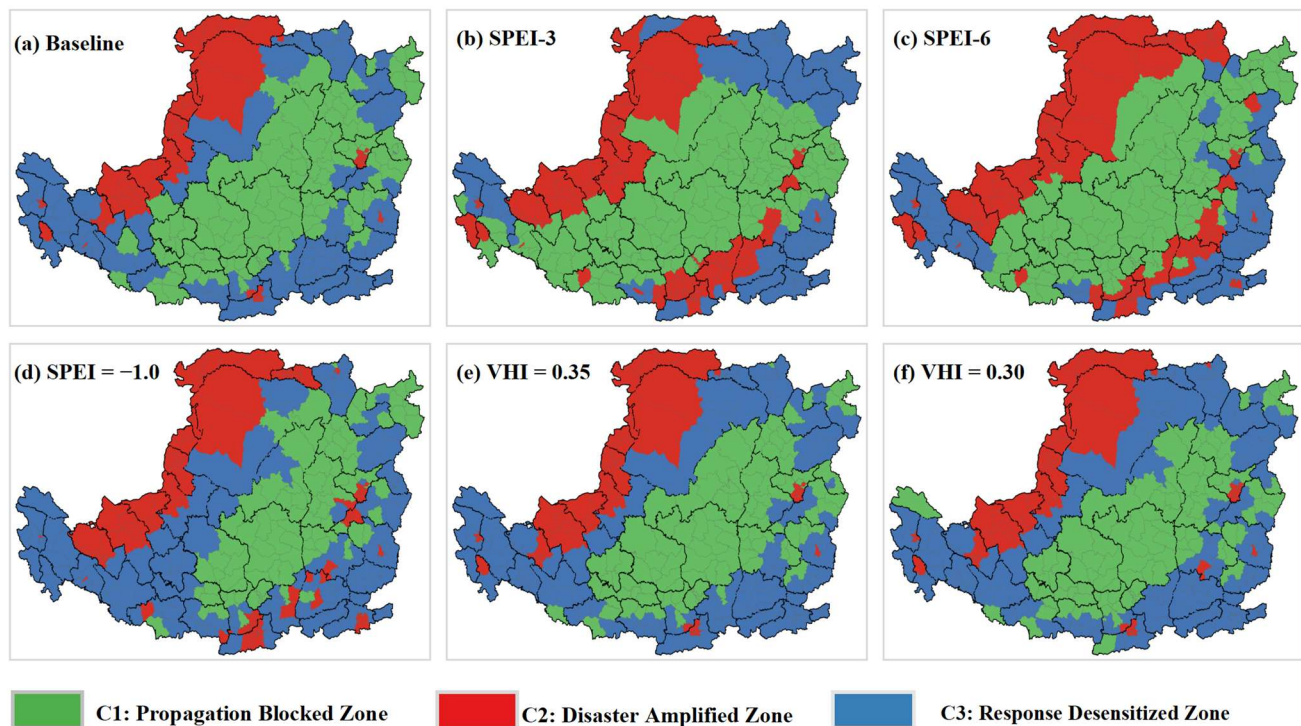


Figure 5. Spatial patterns of drought propagation regimes under the baseline and sensitivity scenarios: (a) baseline scenario, $\text{SPEI-1} \leq -0.5$ and $\text{VHI} \leq 0.40$; (b) $\text{SPEI-3} \leq -0.5$ and $\text{VHI} \leq 0.40$; (c) $\text{SPEI-6} \leq -0.5$ and $\text{VHI} \leq 0.40$; (d) $\text{SPEI-1} \leq -1.0$ and $\text{VHI} \leq 0.40$; (e) $\text{SPEI-1} \leq -0.5$ and $\text{VHI} \leq 0.35$; and (f) $\text{SPEI-1} \leq -0.5$ and $\text{VHI} \leq 0.30$. C1, Propagation Blocked; C2, Disaster Amplified; C3, Response Desensitized.

3.4. XGBoost–SHAP Performance and Global Attribution of Driving Factors

3.4.1. Statistical Distribution of Environmental Drivers

Clear yet contrasting patterns of environmental drivers are observed across the three drought propagation regimes (C1–C3) (Figure 6). Topographic conditions show a consistent gradient, with C1 characterized by the steepest slopes and highest elevations, C3 exhibiting intermediate values, and C2 representing the flattest terrain. Climatic and hydrological variables display more heterogeneous behavior. Mean temperature is highest in C3 and lowest in C1, while the warming trend is most pronounced in C2. In contrast, Mean soil moisture showed no significant differences among the three drought propagation regimes (Figure 6e), whereas its temporal trend differed markedly among the regimes (Figure 6h).

Ecological productivity and land use further differentiate the clusters. Both mean GPP and its trend vary significantly ($p < 0.001$), with C1 showing the strongest increase, C3 moderate growth, and C2 the weakest. In addition, the cropland ratio is substantially higher in C3, indicating more intensive agricultural activity.

Overall, C1 is characterized by steep, high-elevation terrain with strong ecological recovery, C2 by flat landscapes with low productivity, pronounced warming, and declining soil moisture, and C3 by warmer, low-elevation regions with intensive agricultural influence and increasing soil moisture.

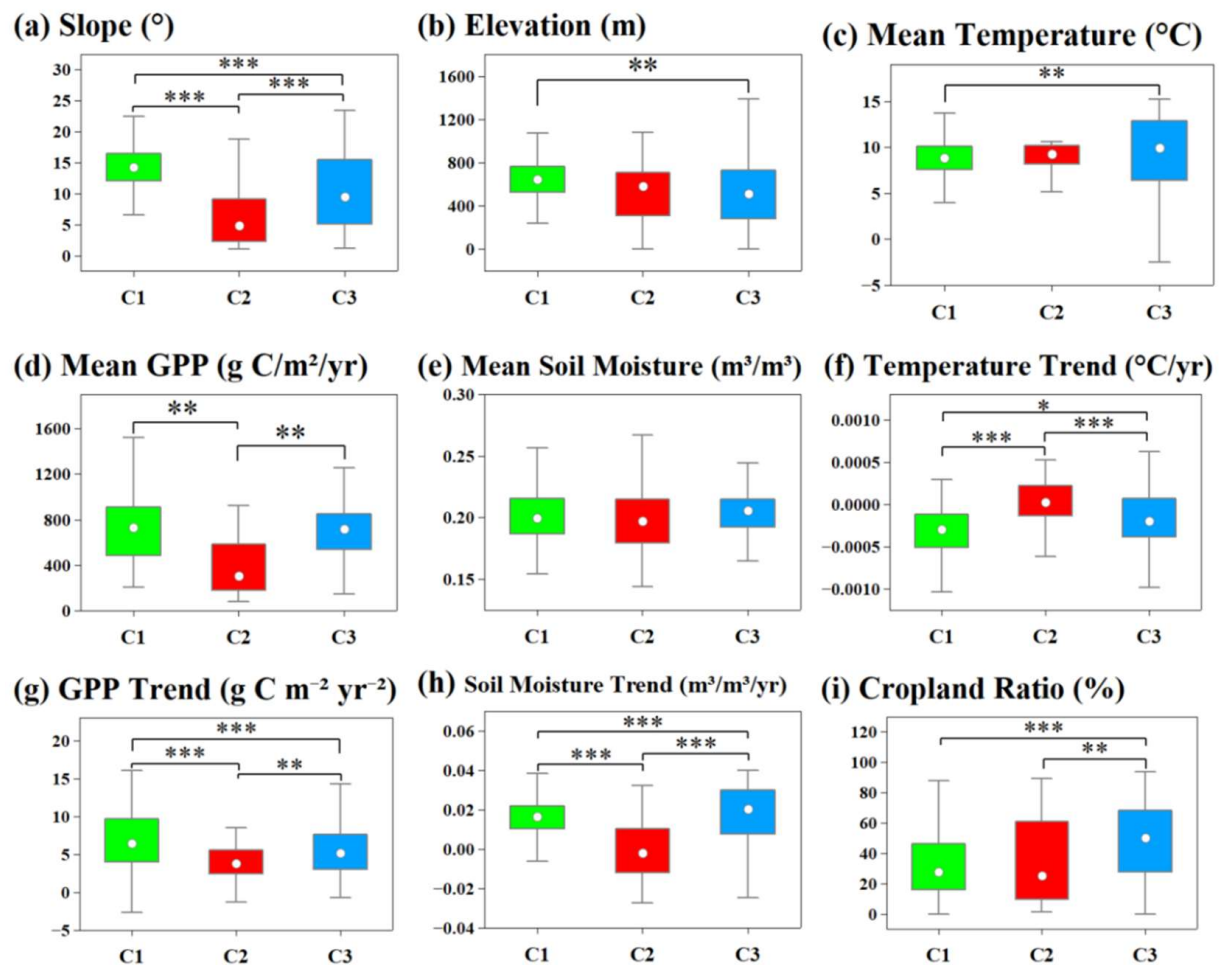


Figure 6. Statistical distributions and comparative analysis of driving factors across the three drought propagation clusters. The boxplots present (a) slope, (b) elevation, (c) mean temperature, (d) mean GPP, (e) mean soil moisture, (f) temperature trend, (g) GPP trend, (h) soil moisture trend, and (i) cropland ratio. Within each box, the white dot represents the median, and the whiskers extend to 1.5 times the interquartile range (IQR). Different colors represent different clusters. Significance levels are determined by the two-sided Mann-Whitney U test, where '*' indicates $p < 0.05$, '**' indicates $p < 0.01$, '***' indicates $p < 0.001$, and 'ns' denotes no significant difference.

3.4.2. Global Attribution and Mechanistic Spectrum

The XGBoost model was trained using county-level samples, with the identified drought propagation regime as the classification target and county-aggregated environmental variables as predictors. Under stratified 10-fold cross-validation, the model achieved an accuracy of 0.799 ± 0.074 and a macro F1-score of 0.792 ± 0.078 , indicating generally consistent discrimination among the three drought propagation regimes. The class-specific F1-scores were 0.809, 0.776, and 0.799 for C1, C2, and C3, respectively (Table S5a). C1 showed a precision of 0.797 and a recall of 0.820, while C3 showed similarly balanced performance, with a precision of 0.794 and a recall of 0.803. C2 achieved the highest precision of 0.818 but the lowest recall of 0.738, indicating that predictions assigned to C2 were generally reliable, although some counties actually belonging to C2 were classified into other regimes. The confusion matrix further showed that 45 of the 61 C2 counties were correctly classified, whereas 13 were misclassified as C3. The other major source of confusion occurred between C1 and C3, with 23 C1 counties classified as C3 and 26 C3 counties classified as C1 (Table S5b). Beyond the statistical differences identified in Section 3.4.1, the SHAP analysis further quantified the non-linear contributions of environmental drivers to the model classification. At the global scale (Figure 7a), eco-hydrological variables showed

the strongest attribution signals, with baseline vegetation productivity (Mean GPP) and soil moisture dynamics (Trend SM) emerging as the two most influential predictors. This suggests that spatial differences in drought propagation regimes are closely associated with local ecological productivity and soil moisture changes, rather than being explained solely by meteorological conditions.

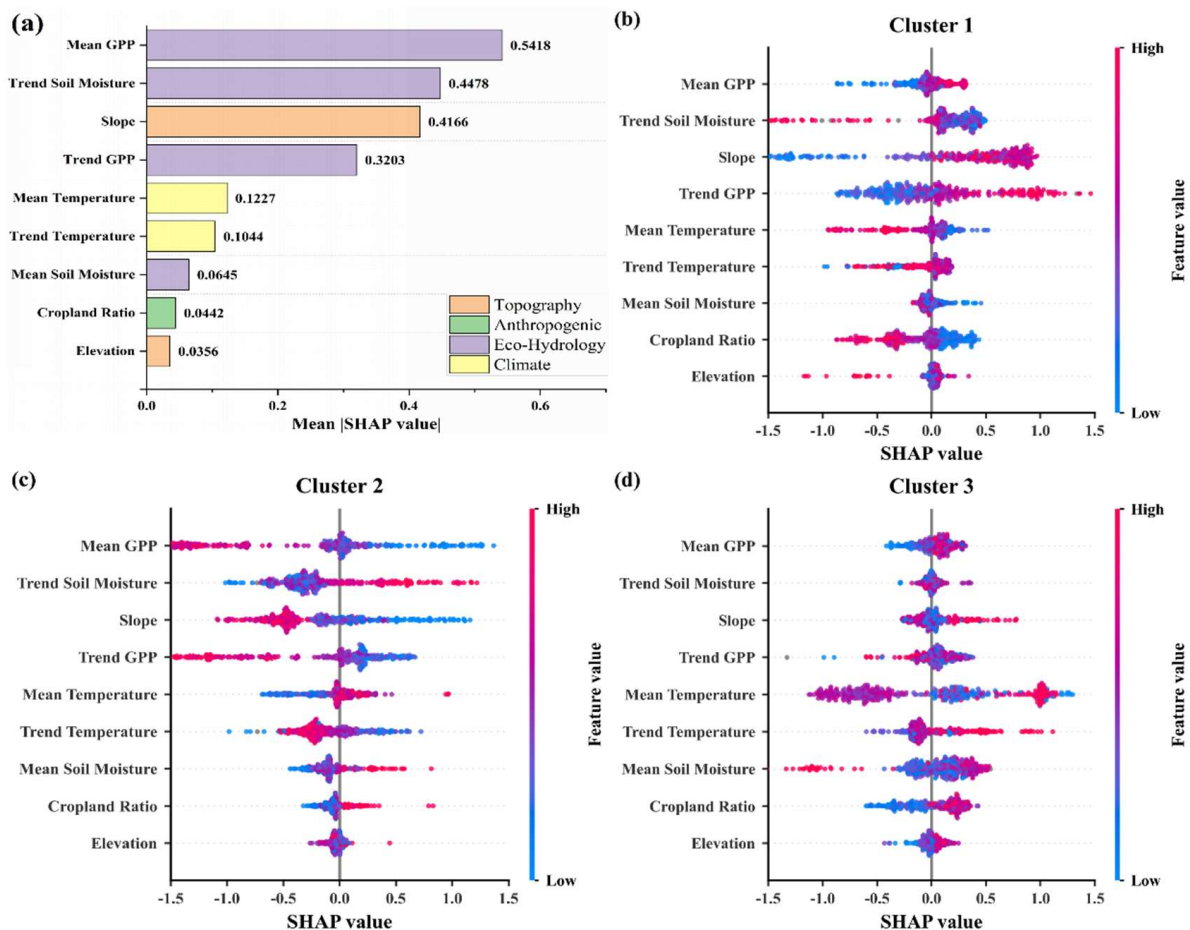


Figure 7. XGBoost-SHAP attribution of environmental drivers for drought propagation regimes. (a) Global feature importance based on the mean absolute SHAP value across all county-level samples. (b–d) Cluster-specific SHAP beeswarm plots for C1–C3, respectively. Each dot represents one county-level sample. The horizontal position indicates the SHAP value, reflecting the contribution of a given environmental variable to the model prediction, and the color gradient represents the corresponding feature value.

At the cluster scale (Figure 7b–d), the dominant attribution signals exhibit pronounced spatial divergence, suggesting distinct environmental backgrounds associated with each regime. In C1 (Propagation Blocked Zone), topographic steepness shows the strongest attribution signal for C1 classification, supported by positive vegetation dynamics. This combination suggests a terrain–ecology buffering effect, where enhanced runoff resistance and vegetation recovery may contribute to the weakened transmission of drought signals to the agricultural system. In contrast, C2 (Disaster Amplified Zone) is mainly associated with ecological baseline conditions. Low vegetation productivity and weak recovery capacity indicate a fragile eco-hydrological system, under which even moderate meteorological deficits may be amplified into severe agricultural drought responses.

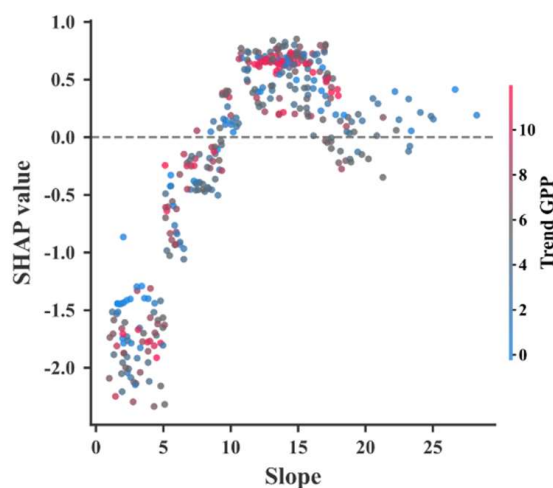
In C3 (Response Desensitized Zone), the dominant drivers shift toward thermal and anthropogenic influences. Elevated temperature acts as a key stressor, while its impact is modulated by soil moisture conditions and agricultural activity. This suggests a po-

tential decoupling effect in which human water management may partly buffer climatic stress, reducing the translation of meteorological drought into agricultural impacts. These results demonstrate that the differentiation of drought propagation regimes is associated with distinct non-linear driver combinations across regions, rather than a uniform control mechanism.

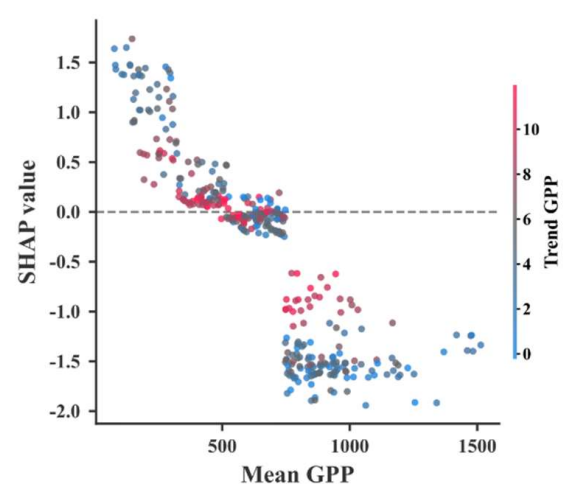
3.4.3. Non-Linear Interactive Mechanisms of Drought Propagation

While global and regime-specific SHAP importance identifies the dominant environmental predictors, it does not directly show how these factors interact non-linearly in shaping model classification. To further examine potential interaction patterns, SHAP dependence plots were constructed using the top-ranking predictors identified from the regime-specific SHAP profiles (Section 3.4.2), thereby reducing subjective feature selection and ensuring that the analyzed interactions were model-driven (Figure 8).

(a) C1: Propagation Blocked



(b) C2: Disaster Amplified



(c) C3: Response Desensitized

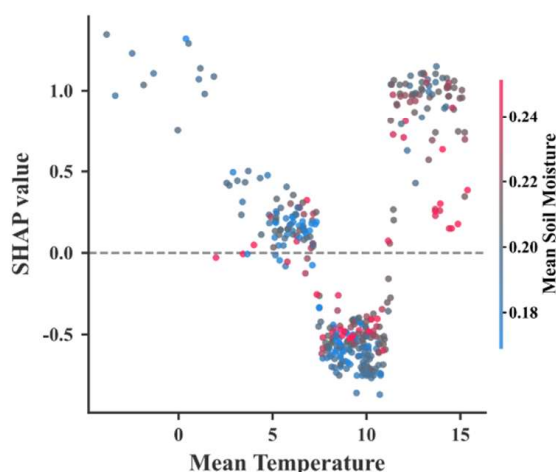


Figure 8. SHAP dependence plots showing non-linear driver interactions and threshold-like effects across the three drought propagation regimes. (a) Slope dependence for the Propagation Blocked Zone, colored by GPP trend. (b) Mean GPP dependence for the Disaster Amplified Zone, colored by GPP trend. (c) Mean temperature dependence for the Response Desensitized Zone, colored by mean soil moisture. The horizontal axis represents the feature value, and the vertical axis represents the SHAP value for the corresponding regime.

For the Propagation Blocked Zone (C1), the SHAP dependence plot indicates a clear interaction between slope and vegetation dynamics (Figure 8a). The contribution of slope to C1 classification increases markedly from low to moderate slope values, suggesting that topographic conditions are closely associated with the differentiation of this regime. Meanwhile, counties with higher GPP trends tend to show stronger positive SHAP values under moderate-to-steep slopes, implying that vegetation recovery may strengthen the terrain-related buffering effect on drought propagation.

For the Disaster Amplified Zone (C2), Mean GPP shows a pronounced non-linear relationship with its SHAP value (Figure 8b). Counties with low baseline productivity generally have positive SHAP values, indicating a higher model tendency to classify them into C2. As Mean GPP increases, the SHAP value declines and becomes mostly negative, suggesting that higher vegetation productivity reduces the likelihood of classification into the Disaster Amplified regime. This pattern supports the interpretation that low ecological productivity and weak vegetation recovery are associated with the amplification of agricultural drought responses under meteorological deficits.

For the Response Desensitized Zone (C3), Mean Temperature exhibits a threshold-like relationship with its SHAP value (Figure 8c). The contribution of temperature becomes strongly positive at higher temperature levels, whereas intermediate temperature ranges show mostly negative SHAP values. The color gradient further indicates that this thermal effect is modulated by soil moisture conditions, with relatively higher soil moisture corresponding to stronger positive temperature-related contributions in some counties. This suggests that the C3 regime is not simply characterized by thermal stress alone, but by the combined influence of warmer conditions and local moisture availability. Therefore, response desensitization may reflect a partial buffering or modulation of agricultural drought response under relatively favorable moisture conditions, rather than a direct effect of temperature alone.

4. Discussion

4.1. Drought Regionalization as a Propagation-Driven Process

Drought regionalization is an essential foundation for regional drought risk identification and differentiated management. Its core objective is to categorize spatially complex drought processes into regional types with similar propagation characteristics. Previous studies on drought regionalization and risk assessment have commonly relied on drought-index statistics or multi-indicator evaluation frameworks. These studies typically utilize meteorological drought indices, such as SPI and SPEI, to identify drought hotspots, or combine multi-source indicators—including RDI, AI, and NDVI anomalies—to delineate high-risk areas for agricultural drought. While these studies provide a crucial basis for characterizing drought occurrence patterns and supporting regional management, their regionalization logic is primarily based on spatial differences in drought intensity, frequency, duration, or overall risk levels. They less explicitly capture the time lag, propagation efficiency, and response variation involved in the transition from meteorological to agricultural drought.

However, drought is not a static condition at a given moment, but rather a dynamic process characterized by continuous propagation, lag, and transformation within the hydrological cycle and ecosystems. Existing event-scale studies indicate that as droughts propagate from precipitation deficits to deficits in evapotranspiration, runoff, and groundwater, they may exhibit prolonged duration, delayed onset, reduced event frequency, and altered spatial extent [49]. The propagation from meteorological to agricultural drought also shows evident time lags, threshold dependence, and spatial heterogeneity, and can be further regulated by factors such as actual evapotranspiration, atmospheric aridity, and

irrigation practices [50,51]. These insights suggest that agricultural drought should not be viewed simply as a direct projection of meteorological drought intensity. Instead, it should be understood as a propagated response of meteorological moisture deficits after modulation by the land surface–vegetation system. The results of the present study further support this perspective: Figure 2 shows that although the frequency, duration, and severity of meteorological droughts in some western parts of the Loess Plateau are not the highest, their agricultural drought responses are more pronounced. Conversely, some central regions exhibit relatively weak agricultural drought responses despite experiencing distinct meteorological drought events. Such spatial mismatches between meteorological drought characteristics and agricultural drought responses indicate that regional differences in agricultural drought cannot be explained solely by meteorological drought intensity. They must also be understood through the propagation efficiency and response patterns of meteorological drought signals within the land surface–vegetation system.

To characterize this dynamic propagation process more accurately, this study develops an event–propagation indicator framework comprising meteorological drought event attributes, agricultural drought event attributes, and propagation attributes. Unlike regionalization approaches that mainly rely on individual drought indices or aggregated drought-state characteristics, this indicator system concurrently captures meteorological drought occurrence characteristics, agricultural drought event characteristics, and the propagation efficiency from meteorological to agricultural drought. The PCA results further indicate that this indicator system captures meaningful regional differentiation (Figure 3): propagation rate, propagation time, and agricultural drought event characteristics jointly constitute the primary differentiation dimensions, indicating that the regionalization results reflect coupled variations in agricultural response and propagation efficiency. Consequently, this study identifies regional disparities from the dual perspectives of event response and propagation efficiency, rather than merely depicting spatial patterns of drought intensity.

4.2. Mechanistic Interpretation and Management Implications of Drought Propagation Regimes

The three drought propagation regimes do not represent a simple gradient of drought intensity, but rather contrasting pathways through which meteorological drought signals are modified before being expressed as agricultural drought. Previous studies have demonstrated that meteorological-to-agricultural drought propagation is not deterministic, but is jointly modulated by soil moisture, vegetation conditions, temperature, and human activities [52–54]. The environmental distributions and SHAP results obtained in this study further indicate that the three regimes are associated with distinct combinations of topographic, ecological, hydrological, and anthropogenic conditions.

The C1 Propagation Blocked Zone is characterized by frequent meteorological drought but a low propagation rate and relatively weak agricultural drought responses. Its steeper slopes, higher elevations, and stronger GPP growth suggest that topographic water redistribution and vegetation dynamics may jointly attenuate the transmission of meteorological drought signals. Topography can influence vegetation responses to drought by regulating runoff, local water retention, microclimatic conditions, and vegetation moisture availability [55]. However, vegetation restoration should not be interpreted as an exclusively beneficial buffering mechanism. Increased vegetation water consumption may shorten the propagation timescale from meteorological to agricultural drought and lower the agricultural drought trigger threshold [56]. The propagation blockage observed in C1 therefore more likely reflects the integrated influence of topography, soil moisture conditions, and vegetation dynamics rather than vegetation restoration alone. From a management perspective, existing soil and water conservation measures should be maintained, while vegetation

density and water consumption should be monitored to prevent restoration intensity from exceeding local water-carrying capacity.

The C2 Disaster Amplified Zone is associated with relatively weak meteorological forcing but severe agricultural drought, together with a high propagation rate and a long PCC-derived response timescale. Its low mean GPP, weak GPP growth, pronounced warming, and declining soil moisture indicate limited ecological productivity and hydrological buffering capacity. Vegetation productivity can exhibit lagged and threshold responses to meteorological drought, while water stress and atmospheric aridity increase the risk of GPP loss [57]. Soil moisture deficits and high vapor pressure deficit further intensify vegetation moisture stress and contribute to threshold-like declines in productivity [58]. Consequently, the combined effects of low productivity, warming, and moisture depletion may allow relatively modest meteorological deficits to develop into severe agricultural drought responses [59]. From an agronomic perspective, soil physical conditions, water-retention capacity, and crop root morphological traits can further influence crop responses under water stress, suggesting that soil- and crop-management practices may partly modify agricultural drought sensitivity [60,61]. It should be emphasized that GPP was not used to define agricultural drought events; VHI was used for event identification, whereas GPP represented an independent ecological background variable reflecting baseline productivity and long-term recovery. The importance of GPP should therefore be interpreted as evidence of ecosystem productivity modulation rather than as a redundant description of VHI-derived drought. Management in C2 should prioritize earlier agricultural drought warning, soil-moisture conservation, drought-tolerant cropping systems, agronomic practices that improve soil water retention, and supplemental irrigation where water availability permits.

The C3 Response Desensitized Zone experiences severe and persistent meteorological drought but comparatively weak agricultural drought responses, indicating a partial decoupling between meteorological forcing and agricultural impacts. Its higher temperature, greater cropland proportion, and increasing soil moisture suggest that irrigation or other forms of human water management may partly buffer agricultural systems. Irrigation can substantially alter meteorological-to-agricultural drought propagation and delay the emergence of agricultural drought impacts [62,63]. More broadly, delayed irrigation, precision irrigation, regulated deficit-irrigation scheduling, and optimized irrigation decision-making can improve crop water productivity and regulate crop responses under water-limited or changing climatic conditions [64–68]. Nevertheless, C3 should not be interpreted as an inherently low-risk region. The attenuation of agricultural drought responses may depend on irrigation, groundwater extraction, or other external water inputs, and its apparent resilience may therefore conceal increasing pressure on regional water resources. Management should focus on water-saving irrigation, improved irrigation scheduling, groundwater-use monitoring, and the joint evaluation of agricultural drought resistance and long-term hydrological sustainability.

Overall, the three regimes correspond to different drought-management priorities. C1 requires the maintenance of natural and ecological buffering capacity without excessive vegetation water consumption; C2 requires proactive drought warning and improvements in soil and crop water resilience; and C3 requires more efficient and sustainable management of irrigation and groundwater resources. These differentiated strategies demonstrate how propagation-based regionalization can support spatially targeted agricultural drought management rather than applying uniform interventions across the Loess Plateau.

The sensitivity analysis further showed that the stability of the regionalization depended on the parameter being modified. Alternative VHI thresholds and PCA cumulative explained-variance thresholds produced highly consistent regionalization patterns,

whereas changes in the SPEI accumulation scale and meteorological drought threshold resulted in greater county-level reassignment. Longer SPEI accumulation scales smooth short-term climatic variability, merge adjacent meteorological drought episodes, and modify event duration and event-matching relationships, thereby affecting propagation rates and subsequent regionalization. The identified regimes should therefore be interpreted as robust but not completely invariant spatial patterns, with their principal organization remaining stable while some counties in transitional zones depend on the meteorological drought definition.

4.3. Uncertainties and Future Perspectives

While the proposed framework delineates the eco-hydrological continuum of drought propagation, the quantification of this complex eco-hydrological system contains inherent uncertainties: (1) Spatial characterization is inherently constrained by administrative boundaries. Aggregating continuous gridded datasets (e.g., soil moisture and GPP) to the county level not only obscures local spatial heterogeneity but also introduces the Modifiable Areal Unit Problem (MAUP) [69]. (2) The quantification of anthropogenic buffering predominantly relies on the cropland ratio. The absence of fine-scale socio-economic indicators (e.g., GDP) and actual groundwater extraction rates restricts our ability to uncover the precise economic underpinnings and sustainability thresholds of this human-induced resilience [70]. Integrating spatially explicit socio-economic datasets is essential to quantify the hidden hydrological costs of agricultural intensification. Future studies could further integrate irrigation infrastructure, water-use intensity, and adaptive irrigation decision-making information to distinguish true ecological resilience from management-induced response desensitization. (3) Although the XGBoost–SHAP framework excels at deciphering non-linear interactions, it remains a retrospective, associative approach. Future studies should extend this associative framework toward causal and predictive modeling. By incorporating causal machine learning (e.g., Causal SHAP) and coupling these attribution frameworks with Global Climate Models (GCMs) under various Shared Socioeconomic Pathways (SSPs), future research can shift from post-event attribution to forecasting the dynamic evolution of drought propagation under projected climate extremes. The thresholds, dominant propagation timescales, and environmental controls identified for the Loess Plateau may not be directly transferable to humid, extremely arid, or strongly irrigated regions. Applications in other hydroclimatic settings should therefore recalibrate the drought thresholds, accumulation scales, and clustering structure using locally representative observations. Future studies should also evaluate SPEI-12 to examine how annual-scale water-balance memory influences drought propagation metrics and regionalization.

5. Conclusions

This study investigates drought propagation across the Loess Plateau in China from a process-based perspective and yields the following key conclusions:

- (1) A pronounced spatial decoupling exists between meteorological drought and agricultural response. Regions experiencing relatively weak meteorological deficits can still exhibit severe agricultural drought, while strong climatic forcing does not necessarily lead to proportional impacts. This highlights the limitation of traditional hazard-based assessments in representing actual drought risk.
- (2) Drought propagation exhibits clear spatial heterogeneity and can be classified into three distinct regimes: Propagation Blocked, Disaster Amplified, and Response Desensitized. These regimes reflect fundamentally different land surface responses to the same climatic forcing, indicating that drought propagation is not a uniform process across space. Sensitivity experiments confirmed that the principal spatial organization

of these regimes was highly stable under alternative agricultural drought thresholds, although greater county-level adjustments occurred when the SPEI accumulation scale or meteorological drought threshold was changed.

- (3) Eco-hydrological conditions showed the strongest attribution signals for differentiating drought propagation regimes. At the regional scale, vegetation productivity and soil moisture dynamics showed stronger attribution signals than meteorological factors. At the local scale, the associated environmental patterns differed substantially, including terrain–vegetation modulation, low-productivity eco-hydrological conditions, and potential human water regulation.
- (4) The identified propagation patterns can be interpreted as different manifestations of land surface buffering capacity. Natural conditions and anthropogenic activities jointly influence whether meteorological drought signals are amplified, suppressed, or partially decoupled during transmission to the agricultural system.

Overall, this study demonstrates that drought should be understood as a dynamic propagation process rather than a static climatic state. The proposed framework provides a basis for identifying region-specific drought risks and supports the development of targeted management strategies under changing environmental conditions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agriculture16151660/s1>, Table S1. Event–propagation metrics used in PCA and K-means clustering. Figure S1. Elbow method for cluster-number selection. The reduction in the within-cluster sum of squares became less pronounced after $k = 3$, supporting the selection of three drought propagation regimes. Table S2. Drought-event characteristics and propagation rates under the baseline and sensitivity scenarios. Table S3. Detailed stability metrics of drought propagation regionalization under the baseline and sensitivity scenarios. Table S4a. PCA performance across the baseline and sensitivity scenarios. Table S4b. Cluster-number diagnostics across the baseline and sensitivity scenarios. Table S4c. Sensitivity of drought propagation regionalization to the PCA cumulative explained-variance threshold. Table S5a. Class-specific performance of the XGBoost model for identifying drought propagation regimes. Table S5b. Confusion matrix of the XGBoost model based on out-of-fold predictions from stratified 10-fold cross-validation.

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polishing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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References

1. Dai, A. Increasing drought under global warming in observations and models. *Nat. Clim. Change* **2013**, *3*, 52–58. [\[CrossRef\]](#)
2. Disasa, K.N.; Yan, H.; Zhang, J.; Wang, G.; Zhang, C.; Zhang, D.; Wang, B.; Hao, B. Comprehensive review of drought characteristics and intensification under climate change: Implications for agriculture and water resources. *J. Hydrol.* **2026**, *664*, 134571. [\[CrossRef\]](#)
3. Disasa, K.N.; Yan, H.; Bao, R.; Zhang, J.; Zhang, C.; Wang, B.; Wang, G. Modelling the impacts of future climate variable changes on rainfed maize production, evapotranspiration, and adaptation measures in Northeast China. *J. Hydrol.* **2025**, *662*, 134051. [\[CrossRef\]](#)
4. Leng, G.; Hall, J. Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. *Sci. Total Environ.* **2019**, *654*, 811–821. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Chauhdary, J.N.; Li, H.; Ragab, R.; Rakibuzzaman, M.; Khan, A.I.; Zhao, J.; Akbar, N. Climate Change Impacts on Future Wheat (*Triticum aestivum*) Yield, Growth Periods and Irrigation Requirements: A SALTMED Model Simulations Analysis. *Agronomy* **2024**, *14*, 1484. [\[CrossRef\]](#)
6. Chauhdary, J.N.; Li, H.; Pan, X.; Zaman, M.; Anjum, S.A.; Yang, F.; Akbar, N.; Azamat, U. Modeling effects of climate change on crop phenology and yield of wheat–maize cropping system and exploring sustainable solutions. *J. Sci. Food Agric.* **2025**, *105*, 3679–3700. [\[CrossRef\]](#) [\[PubMed\]](#)
7. He, W.; Liu, Y.; Sun, H.; Taghizadeh-Hesary, F. How does climate change affect rice yield in China? *Agriculture* **2020**, *10*, 441. [\[CrossRef\]](#)
8. Liu, Y.; Chen, Q.; Ge, Q.; Dai, J.; Qin, Y.; Dai, L.; Zou, X.; Chen, J. Modelling the impacts of climate change and crop management on phenological trends of spring and winter wheat in China. *Agric. For. Meteorol.* **2018**, *248*, 518–526. [\[CrossRef\]](#)
9. Zheng, Z.; Hoogenboom, G.; Cai, H.; Wang, Z. Winter wheat production on the Guanzhong Plain of Northwest China under projected future climate with SimCLIM. *Agric. Water Manag.* **2020**, *239*, 106233. [\[CrossRef\]](#)
10. Iqbal, B.; Alabbosh, K.F.; Jalal, A.; Suboktagin, S.; Elboughdiri, N. Sustainable food systems transformation in the face of climate change: Strategies, challenges, and policy implications. *Food Sci. Biotechnol.* **2025**, *34*, 871–883. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Rasool, G.; Guo, X.; Wang, Z.; Ullah, I.; Chen, S. Effect of two types of irrigation on growth, yield and water productivity of maize under different irrigation treatments in an arid environment. *Irrig. Drain.* **2020**, *69*, 732–742. [\[CrossRef\]](#)
12. Weng, Z.; Niu, J.; Guan, H.; Kang, S. Three-dimensional linkage between meteorological drought and vegetation drought across China. *Sci. Total Environ.* **2023**, *859*, 160300. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Almonacid, L.; Pessacg, N.; Diaz, B.; Peri, P.L. Climate regionalization of Santa Cruz province, Argentina. *Atmósfera* **2023**, *37*, 245–258. [\[CrossRef\]](#)
14. Carbone, G.J.; Gao, P.; Lu, J. Regionalization of hydroclimate variables in the contiguous United States. *Theor. Appl. Climatol.* **2024**, *155*, 4767–4779. [\[CrossRef\]](#)
15. Huang, C.; Hu, S.; Ali Baig, M.H.; Huang, Y. Framework for monitoring the spatiotemporal distribution and clustering of drought characteristics in Hunan Province. *Appl. Sci.* **2021**, *11*, 11524. [\[CrossRef\]](#)
16. Fang, W.; Huang, S.; Huang, Q.; Huang, G.; Wang, H.; Leng, G.; Wang, L.; Guo, Y. Probabilistic assessment of remote sensing-based terrestrial vegetation vulnerability to drought stress of the Loess Plateau in China. *Remote Sens. Environ.* **2019**, *232*, 111290. [\[CrossRef\]](#)
17. Li, X.; Philp, J.; Cremades, R.; Roberts, A.; He, L.; Li, L.; Yu, Q. Agricultural vulnerability over the Chinese Loess Plateau in response to climate change: Exposure, sensitivity, and adaptive capacity. *Ambio* **2016**, *45*, 350–360. [\[CrossRef\]](#) [\[PubMed\]](#)
18. Barker, L.J.; Hannaford, J.; Chiveron, A.; Svensson, C. From meteorological to hydrological drought using standardised indicators. *Hydrol. Earth Syst. Sci.* **2016**, *20*, 2483–2505. [\[CrossRef\]](#)
19. Li, L.; Liu, J.; Peng, Q.; Wang, X.; Xu, J.; Cai, H. Propagation process-based agricultural drought typology and its copula-based risk. *Irrig. Drain.* **2024**, *73*, 1496–1519. [\[CrossRef\]](#)
20. Wang, C.; Yang, P.; Xia, J.; Huang, H.; Chen, L.; Sun, K.; Lu, X. Drought onsets and their driving factors for multiple drought types in the Yangtze River Basin. *Clim. Dyn.* **2026**, *64*, 5. [\[CrossRef\]](#)
21. Zscheischler, J.; Naveau, P.; Martius, O.; Engelke, S.; Raible, C.C. Evaluating the dependence structure of compound precipitation and wind speed extremes. *Earth Syst. Dynam.* **2021**, *12*, 1–16. [\[CrossRef\]](#)
22. Gond, S.; Gupta, N.; Patel, J.; Dikshit, P.K.S. Spatiotemporal evaluation of drought characteristics based on standard drought indices at various timescales over Uttar Pradesh, India. *Environ. Monit. Assess.* **2023**, *195*, 439. [\[CrossRef\]](#) [\[PubMed\]](#)

23. Rahman, G.; Jamalzi, A.R.; Voora, V.A.; Borzooi, S.; Kang, S.; Kwon, H.-H. Characterization of drought in the Arabian Peninsula: A multi-index approach. *J. Hydrol. Reg. Stud.* **2026**, *64*, 103250. [[CrossRef](#)]
24. Qin, Y.; Jiang, Q.; Zhao, Y.; Wang, Z.; Tao, M.; Li, B. Dynamic responses of gross primary productivity to compound hot extremes and drought across different geographical regions of China. *Front. Plant Sci.* **2026**, *16*, 1715432. [[CrossRef](#)] [[PubMed](#)]
25. Zhou, Z.; Xue, P.; Zhou, X.; Wang, T.; Ding, Y.; Zhao, Y.; Chen, P.; Wang, X. Assessing the soil moisture–vegetation mutual feedback relationship in different climatic regions of mainland China. *CATENA* **2025**, *249*, 108684. [[CrossRef](#)]
26. Han, Z.; Huang, Q.; Huang, S.; Leng, G.; Bai, Q.; Liang, H.; Wang, L.; Zhao, J.; Fang, W. Spatial-temporal dynamics of agricultural drought in the Loess Plateau under a changing environment: Characteristics and potential influencing factors. *Agric. Water Manag.* **2021**, *244*, 106540. [[CrossRef](#)]
27. Su, J.; Fan, L.; Yuan, Z.; Xue, S. Dynamics of vegetation response patterns to drought and its driving factors across China's Loess Plateau. *J. Environ. Manag.* **2025**, *393*, 126946. [[CrossRef](#)] [[PubMed](#)]
28. Hu, R.; Yuan, S.; Jin, J.; Zhu, L.; Liu, Y. Long-term changes in the drought propagation characteristics in the Yangtze River Basin. *J. Hydrol. Reg. Stud.* **2026**, *63*, 103014. [[CrossRef](#)]
29. Liu, X.; Wang, S.; Zhou, Y.; Wang, F.; Li, W.; Liu, W. Regionalization and spatiotemporal variation of drought in China based on Standardized Precipitation Evapotranspiration Index (1961–2013). *Adv. Meteorol.* **2015**, *2015*, 950262. [[CrossRef](#)]
30. Suriano, Z.J.; Leathers, D.J.; Benjamin, A.E. Regionalization of Northeast US moisture conditions: Analysis of synoptic-scale atmospheric drivers. *Clim. Res.* **2020**, *79*, 193–206. [[CrossRef](#)]
31. Santos, J.F.; Pulido-Calvo, I.; Portela, M.M. Spatial and temporal variability of droughts in Portugal. *Water Resour. Res.* **2010**, *46*, W03503. [[CrossRef](#)]
32. Mulyanti, H.; Istadi, I.; Gernowo, R. Comprehensive regionalization of dry season rainfall for enhanced drought risk management in monsoonal region of Indonesia. *Stoch. Environ. Res. Risk Assess.* **2026**, *40*, 35. [[CrossRef](#)]
33. Wu, F.; Liang, Y.; Liu, L.; Yin, Z.; Huang, J. Identifying eco-functional zones on the Chinese Loess Plateau using ecosystem service bundles. *Reg. Sustain.* **2023**, *4*, 425–440. [[CrossRef](#)]
34. Luo, X.; Ji, X.; Zou, Y.; Wang, S.; Liu, X.; Wu, X.; Li, J.; Li, Y. Disentangling the impacts of climate, catchment, and morphological characteristics on hydrological drought propagation and recovery. *CATENA* **2026**, *264*, 109799. [[CrossRef](#)]
35. Fan, Y.; Zhang, J.; Biswas, A.; Cheng, S.; Ren, X.; Zhan, C. Driving mechanisms and nonlinear responses of ecological drought in Northern China's Agro-Pastoral Ecotone. *J. Hydrol. Reg. Stud.* **2026**, *64*, 103174. [[CrossRef](#)]
36. Long, J.; Xu, C.; Wang, H.; Li, Z.; Xu, F. Reconstruction of drought propagation pathways: A global analysis of multitype propagation chains and nonlinear mechanisms. *Glob. Planet. Change* **2026**, *256*, 105144. [[CrossRef](#)]
37. Abatzoglou, J.T.; Dobrowski, S.Z.; Parks, S.A.; Hegewisch, K.C. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Sci. Data* **2018**, *5*, 170191. [[CrossRef](#)] [[PubMed](#)]
38. Muñoz-Sabater, J.; Dutra, E.; Agustí-Panareda, A.; Albergel, C.; Arduini, G.; Balsamo, G.; Boussetta, S.; Choulga, M.; Harrigan, S.; Hersbach, H.; et al. ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth Syst. Sci. Data* **2021**, *13*, 4349–4383. [[CrossRef](#)]
39. Kogan, F.; Guo, W. Early detection and monitoring droughts from NOAA environmental satellites. In *Use of Satellite and In-Situ Data to Improve Sustainability*; Kogan, F., Powell, A., Fedorov, O., Eds.; Springer: Dordrecht, The Netherlands, 2011; pp. 11–18. [[CrossRef](#)]
40. Dorigo, W.; Wagner, W.; Albergel, C.; Albrecht, F.; Balsamo, G.; Brocca, L.; Chung, D.; Ertl, M.; Forkel, M.; Gruber, A.; et al. ESA CCI Soil Moisture for improved Earth system understanding: State-of-the-art and future directions. *Remote Sens. Environ.* **2017**, *203*, 185–215. [[CrossRef](#)]
41. Sun, H.; Xu, Q. Evaluating machine learning and geostatistical methods for spatial gap-filling of monthly ESA CCI soil moisture in China. *Remote Sens.* **2021**, *13*, 2848. [[CrossRef](#)]
42. Liang, S.; Zhao, X.; Liu, S.; Yuan, W.; Cheng, X.; Xiao, Z.; Zhang, X.; Liu, Q.; Cheng, J.; Tang, H.; et al. A long-term Global Land Surface Satellite (GLASS) data-set for environmental studies. *Int. J. Digit. Earth* **2013**, *6*, 5–33. [[CrossRef](#)]
43. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [[CrossRef](#)]
44. Crippen, R.; Buckley, S.; Agram, P.; Belz, E.; Gurrola, E.; Hensley, S.; Kobrick, M.; Laval, M.; Martin, J.; Neumann, M.; et al. NASADEM global elevation model: Methods and progress. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2016**, *41*, 125–128. [[CrossRef](#)]
45. Vicente-Serrano, S.M.; Beguería, S.; López-Moreno, J.I. A multiscalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index. *J. Clim.* **2010**, *23*, 1696–1718. [[CrossRef](#)]

46. Yevjevich, V.M. *An Objective Approach to Definitions and Investigations of Continental Hydrologic Droughts*; Hydrology Paper No. 23; Colorado State University: Fort Collins, CO, USA, 1967.
47. Yang, X.; Wu, F.; Yuan, S.; Ren, L.; Sheffield, J.; Fang, X.; Jiang, S.; Liu, Y. Quantifying the impact of human activities on hydrological drought and drought propagation in China using the PCR-GLOBWB v2.0 model. *Water Resour. Res.* **2024**, *60*, e2023WR035443. [[CrossRef](#)]
48. Yuan, H.; Liang, X.; Chen, J.; Shi, H.; Tian, Y.; Zheng, C. Climate change-driven propagation of meteorological–hydrological–groundwater drought: Insights from the Pearl River Basin, China. *J. Hydrol.* **2026**, *669*, 135121. [[CrossRef](#)]
49. Dong, S.; Li, L.; Zhou, Z.; Fu, Q.; Li, M.; Xue, P. Groundwater drought propagation and the drought resistance capacity in different climatic regions of China. *Agric. Water Manag.* **2025**, *312*, 109425. [[CrossRef](#)]
50. Li, W.; Reichstein, M.; O, S.; May, C.; Destouni, G.; Migliavacca, M.; Kraft, B.; Weber, U.; Orth, R. Contrasting drought propagation into the terrestrial water cycle between dry and wet regions. *Earths Future* **2023**, *11*, e2022EF003441. [[CrossRef](#)]
51. Wang, Z.; Huang, S.; Huang, Q.; Duan, W.; Leng, G.; Guo, Y.; Zheng, X.; Nie, M.; Han, Z.; Dong, H.; et al. Seasonal propagation characteristics from meteorological to hydrological drought and their dynamics in the headstreams of the Tarim River Basin. *J. Hydrometeorol.* **2022**, *23*, 1487–1506. [[CrossRef](#)]
52. Huang, S.; Huang, Q.; Chang, J.; Leng, G.; Xing, L. The response of agricultural drought to meteorological drought and the influencing factors: A case study in the Wei River Basin, China. *Agric. Water Manag.* **2015**, *159*, 45–54. [[CrossRef](#)]
53. Ma, Y.; Ren, J.; Kang, S.; Niu, J.; Tong, L. Spatial-temporal dynamics of meteorological and agricultural drought in Northwest China: Propagation, drivers and prediction. *J. Hydrol.* **2025**, *650*, 132492. [[CrossRef](#)]
54. Xu, Z.; Jiang, B.; Guo, X.; Wu, Z.; Fan, S. Initial soil moisture conditions dominate variation in event-scale propagation time from meteorological to agricultural drought. *Agric. Water Manag.* **2026**, *325*, 110128. [[CrossRef](#)]
55. Garrido-Leiva, J.; Durán-Gárate, L.; Pérez-Martínez, W. Topographic modulation of vegetation vigor and moisture condition in Mediterranean ravine ecosystems of Central Chile. *Forests* **2026**, *17*, 201. [[CrossRef](#)]
56. Zheng, W.; Shi, S.; Askari, K.; Roig, F.A.; Liu, X.; Liu, W.; Wang, F. Vegetation restoration mitigates meteorological drought on the Loess Plateau. *J. Hydrol.* **2026**, *668*, 135012. [[CrossRef](#)]
57. Guo, W.; Huang, S.; Huang, Q.; Leng, G.; Mu, Z.; Han, Z.; Wei, X.; She, D.; Wang, H.; Wang, Z.; et al. Drought trigger thresholds for different levels of vegetation loss in China and their dynamics. *Agric. For. Meteorol.* **2023**, *331*, 109349. [[CrossRef](#)]
58. Wang, X.; Cai, H.; Zheng, Z.; Yu, L.; Wang, Z.; Li, L. Modelling root water uptake under deficit irrigation and rewetting in Northwest China. *Agron. J.* **2020**, *112*, 158–174. [[CrossRef](#)]
59. Raheem, A.; Bankole, O.O.; Danso, F.; Musa, M.O.; Adegbite, T.A.; Simpson, V.B. Physical management strategies for enhancing soil resilience to climate change: Insights from Africa. *Eur. J. Soil Sci.* **2025**, *76*, e70030. [[CrossRef](#)]
60. Ali, A.B.; Yan, H.; Li, H.; Wu, Y.Y.; Elshaikh, N.A.; Hussein, G.; Pandab, S.; Hassan, S. Enhancement of depleted loam soil as well as cucumber productivity utilizing biochar under water stress. *Commun. Soil Sci. Plant Anal.* **2019**, *50*, 49–64. [[CrossRef](#)]
61. Zhang, W.; Wu, Q.; Sun, C.; Zhang, W.; Ge, D.; Cao, J.; Yin, Y.; Li, H.; Cao, H. Biomass-based root morphological parameter models of rice (*Oryza sativa* L.) under different drought intensities and drought durations in juvenile differentiation stage. *Agron. J.* **2025**, *117*, e70205. [[CrossRef](#)]
62. Xue, R.; Zhang, C.; Yan, H.; Li, J.; Ren, J.; Akhlaq, M.; Hammad, M.U.; Disasa, K.N. Physiological response of tomato and cucumber plants to micro-spray in high-temperature environment: A scientific and effective means of alleviating crop heat stress. *Agronomy* **2023**, *13*, 2798. [[CrossRef](#)]
63. Liang, W.; Zhang, W.; Jin, Z.; Yan, J.; Lü, Y.; Li, S.; Yu, Q. Rapid urbanization and agricultural intensification increase regional evaporative water consumption of the Loess Plateau. *J. Geophys. Res. Atmos.* **2020**, *125*, e2020JD033380. [[CrossRef](#)]
64. Chen, Y.; Yu, Z.; Han, Z.; Sun, W.; He, L. A decision-making system for cotton irrigation based on reinforcement learning strategy. *Agronomy* **2024**, *14*, 11. [[CrossRef](#)]
65. Lakhari, I.A.; Yan, H.; Zhang, C.; Wang, G.; He, B.; Hao, B.; Han, Y.; Wang, B.; Bao, R.; Syed, T.N.; et al. A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints. *Agriculture* **2024**, *14*, 1141. [[CrossRef](#)]
66. Wang, L.; Lin, M.; Han, Z.; Han, L.; He, L.; Sun, W. Simulating the effects of drought stress timing and the amount irrigation on cotton yield using the CSM-CROPGRO-Cotton model. *Agronomy* **2024**, *14*, 14. [[CrossRef](#)]
67. Xing, D.K.; Wu, Y.Y.; Fu, W.G.; Li, Q.L.; Hu, L.S.; Wu, Y.S. Regulated deficit irrigation scheduling of *Orychophragmus violaceus* based on photosynthetic physiological response traits. *Trans. ASABE* **2016**, *59*, 1853–1860. [[CrossRef](#)]
68. Xue, R.; Li, H.; Shi, B. Review of advancements and challenges in delayed irrigation: Enhancing crop water productivity and sustainable crop production. *Agric. Water Manag.* **2025**, *318*, 109739. [[CrossRef](#)]

69. Nazir, M.J.; Li, G.; Nazir, M.M.; Zulfiqar, F.; Siddique, K.H.M.; Iqbal, B.; Du, D. Harnessing soil carbon sequestration to address climate change challenges in agriculture. *Soil Tillage Res.* **2024**, *237*, 105959. [[CrossRef](#)]
70. Chen, X.; Jiang, Y.; Wang, T.; Zhou, K.; Liu, J.; Ben, H.; Wang, W. Enhancing farmer resilience through agricultural insurance: Evidence from Jiangsu, China. *Agriculture* **2025**, *15*, 1473. [[CrossRef](#)]

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