

Article

High-Resolution Projections and Uncertainty Analysis of Future Drought Across Nine Major Agricultural Regions over China Under Climate Change Scenarios

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Abstract

Drought is a major climatic hazard affecting agricultural production and water resource management. This study investigates the spatiotemporal evolution of summer drought across nine major agricultural regions in China and quantifies associated uncertainties under historical (1981–2010) and future periods (2041–2070 and 2071–2100). Using multi-model simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6) under four SSP scenarios (SSP126, SSP245, SSP370, and SSP585), drought variations were characterized using the Standardized Precipitation Index at a 3-month timescale (SPI-3). Sen's slope estimator combined with the Mann–Kendall test was applied to detect drought trends, and factorial analysis was used to quantify uncertainty contributions. Results show pronounced regional differences in historical drought conditions, with northern arid and semi-arid regions exhibiting stronger precipitation deficits (mean SPI-3 = −0.435), while the Yangtze River Plain and Northeast China Plain show wetter conditions. Historical trends indicate increasing drought conditions in South China, whereas humidification trends dominate several northern and eastern regions. Under future scenarios, most regions show overall wetting trends, but drying tendencies persist in South China. Factorial analysis reveals that regional differences (58.34%) and climate model uncertainty (31.15%) are the dominant contributors to drought variability. Overall, future summer drought in China is characterized by a general wetting tendency with localized intensification of drought conditions.



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Keywords: agricultural drought; CMIP6; SSP scenarios; agricultural regions; factorial analysis

1. Introduction

Drought is a prolonged period of insufficient water availability relative to normal conditions and is generally classified into meteorological, agricultural, hydrological, and socioeconomic drought according to different components of the water system [1–3]. Among

these categories, meteorological drought, mainly caused by persistent precipitation deficits, represents the initial stage of drought development and provides an important basis for understanding drought evolution [4]. Global climate change is profoundly influencing regional water cycle processes and the frequency of extreme climate events [5,6], making drought one of the most widespread natural hazards with extensive spatial impacts, long durations, and severe socioeconomic consequences [7,8]. Rising temperatures under global warming have altered precipitation variability and intensified atmospheric water demand, potentially increasing the frequency, duration, and severity of drought events in many regions [9–11]. Particularly in agricultural systems, drought can reduce crop productivity and threaten food security through water deficits and ecosystem degradation [12,13].

As a nation characterized by a typical global monsoon climate, China exhibits a complex array of climatic types and an uneven spatiotemporal distribution of precipitation; consequently, the responses of its various agricultural regions to climate change display significant spatial heterogeneity [4,14]. Regions such as the Northeast Plain, the Huang–Huai–Hai Plain, the irrigated agricultural zones of the Northwest, and the hilly agricultural areas of the South differ markedly in terms of natural resource endowments, agricultural cropping structures, and water resource conditions—factors that result in pronounced regional variations regarding the dynamics of drought and its associated impacts [15,16]. As future climate change intensifies, the drought severity is likely to escalate, posing a severe challenge to national food security and the sustainable development of agriculture [17,18]. Consequently, researching the characteristics of future drought variations across China’s major agricultural regions is of significant scientific and practical value for formulating regional agricultural adaptation strategies, optimizing water resource management, and enhancing agricultural climate resilience [19,20].

To quantitatively characterize drought variations, various drought indices have been developed based on different hydroclimatic variables. Among them, the Standardized Precipitation Index (SPI) [21,22], recommended by the World Meteorological Organization (WMO), is widely used for meteorological drought assessment. SPI converts precipitation anomalies into standardized values based on probability distributions, allowing comparable assessments of dry and wet conditions across different regions. For detecting long-term drought trends, the Mann–Kendall (MK) test and Sen’s slope estimator have been widely applied in hydroclimatic studies [23,24]. The MK test identifies the statistical significance of monotonic trends, while Sen’s slope quantifies the magnitude and direction of changes, providing a robust framework for evaluating temporal drought variations. In addition, the Coupled Model Intercomparison Project Phase 6 (CMIP6) provides multi-model climate projections under different Shared Socioeconomic Pathways (SSPs), offering essential datasets for investigating future drought changes and associated uncertainties under climate change scenarios [25].

Based on these drought assessment approaches and climate projection datasets, significant progress has been made in research concerning future drought variations [26]. Existing studies have widely employed indices such as the SPI to assess regional drought evolution characteristics [27] and have analyzed drought conditions in the context of future climate change based on multi-model data from CMIP6 [28]. With advances in high-resolution climate models, conducting refined regional-scale drought studies using CMIP6 data has become feasible [29]. Compared to traditional low-resolution climate data, high-precision gridded data can more effectively capture precipitation variations and regional drought characteristics within complex terrain, thereby providing more reliable data support for agro-climatic risk assessment [30]. Furthermore, multi-scenario ensemble projection methods can mitigate uncertainties associated with single models, thereby enhancing the robustness of assessments regarding future drought changes [31]. Consequently, it is essential

to use high-resolution CMIP6 data to conduct systematic research into the medium- to long-term evolution of drought in China's agricultural regions.

However, existing research still faces several challenges. First, although recent studies have increasingly employed high-resolution datasets, the integration of fine-scale spatial information with large-scale assessments remains insufficient for fully capturing the heterogeneous drought responses across China's complex terrain and diverse agricultural regions. Second, quantitative assessments of drought projections often lack a comprehensive evaluation of the uncertainties associated with different climate models, emission scenarios, and future periods, limiting the understanding of the drivers of projected drought changes under diverse climate conditions. Furthermore, regionalized studies focusing specifically on China's nine major agricultural zones remain relatively scarce; consequently, they have not yet fully elucidated the spatial heterogeneity in the evolution of agricultural drought—nor its dominant driving factors—across various future emission pathways.

Therefore, this study aims to systematically investigate the historical evolution characteristics and future change trends of drought across nine major agricultural regions in China using high-resolution climate data and further elucidate the underlying driving mechanisms. Specifically, (1) a $0.25^\circ \times 0.25^\circ$ high-resolution drought dataset was first constructed using outputs from two CMIP6 global climate models (KACE-1-0-G and MIROC6). By combining the historical reference period (1980–2010), the 3-month time-scale SPI (SPI3) index was consistently calculated to develop a multi-model and multi-scenario coherent dataset covering both historical and future periods; (2) based on this dataset, a systematic diagnostic analysis was conducted to characterize the spatiotemporal variability of SPI3 during the historical period (1980–2010) across China's nine major agricultural regions, revealing regional differences and spatial distribution patterns; (3) further, ensemble simulations and comparative analyses were performed for two future periods (2041–2070 and 2071–2100) under four SSPs (SSP126, SSP245, SSP370, and SSP585) in order to examine the scenario dependence and spatial response characteristics of future drought evolution; (4) finally, multilevel factorial analysis (MFA) was conducted to quantitatively assess the relative contributions and interaction effects of climate scenarios, future periods, and climate models on SPI3 changes, thereby identifying the dominant drivers and their spatial heterogeneity. The results will provide scientific support for agricultural adaptation to climate change, optimization of water resource allocation, and regional food security in China.

2. Materials and Methods

This study focuses on the historical evolution and future projection of drought changes in China's agricultural regions. As illustrated in Figure 1, the study establishes an integrated research framework comprising four components: data construction, historical analysis, future projection, and attribution analysis. In the data construction stage, precipitation outputs from the KACE and MIROC6 climate models at a spatial resolution of $0.25^\circ \times 0.25^\circ$ are integrated for subsequent drought analysis. Meanwhile, China's nine major agricultural zoning systems are used to define spatial statistical units, providing a solid data foundation for regional-scale analysis. In the historical analysis stage, drought conditions are quantified using the SPI3, enabling a systematic assessment of drought spatiotemporal variations, including temporal trends, spatial distribution patterns, and regional heterogeneity. In the future projection stage, based on CMIP6 multi-model ensembles, drought changes are simulated and compared under four SSP scenarios (SSP126, SSP245, SSP370, and SSP585) for the mid-term (2041–2070) and long-term (2071–2100) periods, allowing for the identification of scenario-dependent evolution patterns. In the attribution analysis stage, a multilevel factorial analysis method is employed to quantify the main and interaction effects of multiple influencing factors, including climate scenarios, time horizons, climate

models, and agricultural zones, as well as their relative contributions to drought variability. Overall, this study provides a scientific basis for agricultural adaptation to climate change and drought risk management in China.

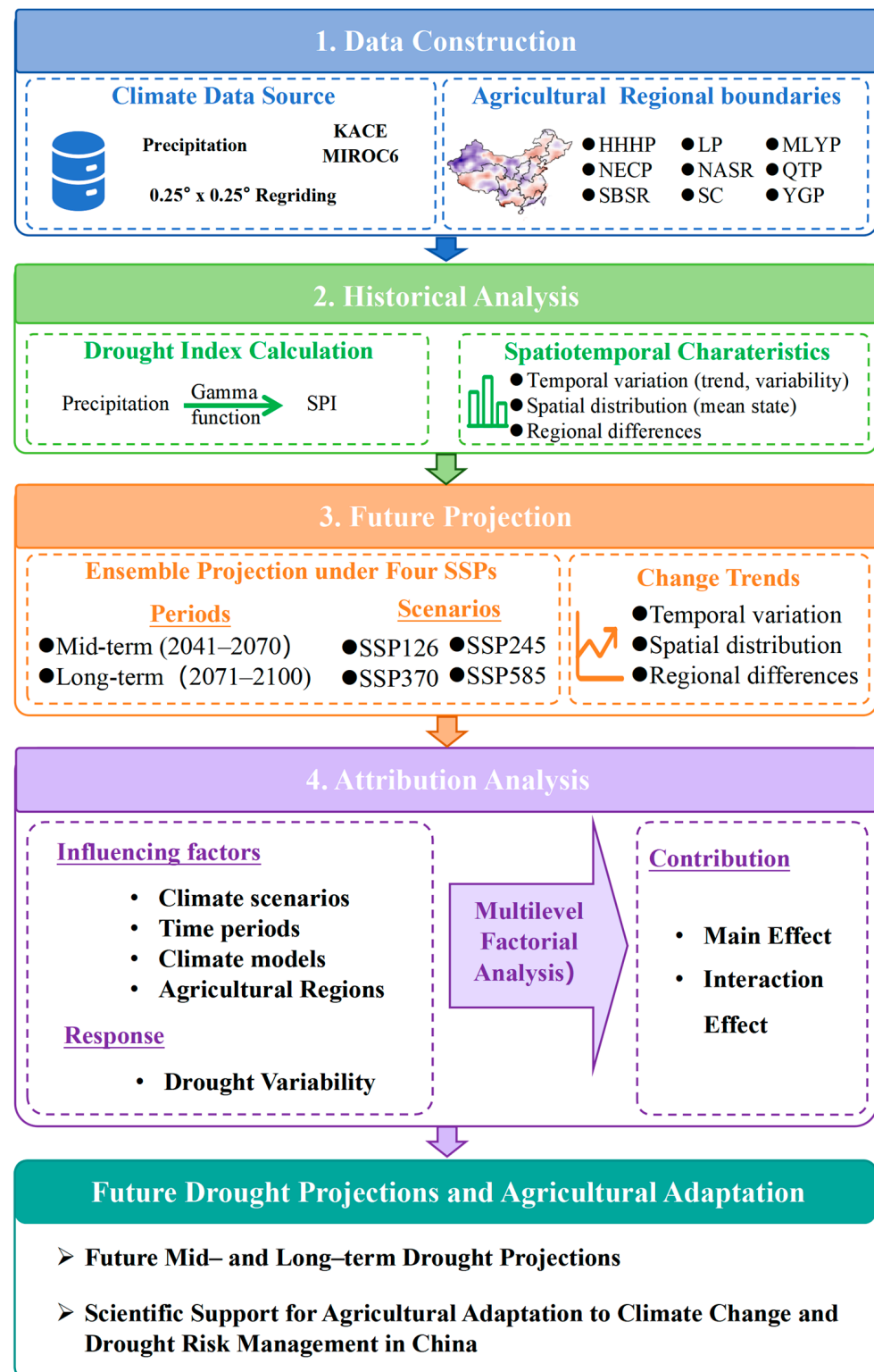


Figure 1. Research framework.

2.1. Data Collection

(1) Climate Data

The daily precipitation data used in this study were obtained from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) dataset, which provides bias-corrected and downscaled CMIP6 climate projections at a spatial resolution of $0.25^\circ \times 0.25^\circ$. Precipitation projections from two climate models, KACE-1-0-G and MIROC6, were adopted to assess future drought variability across China. These two models were selected because they provide complete precipitation projections for all historical and SSP scenarios used in this study at a consistent spatial resolution, making them suitable for regional drought assessment. In addition, they were developed by independent modeling centers and therefore provide complementary representations of climate variability, allowing part of the uncertainty associated with future climate projections to be considered. The study area encompasses the China region, and the temporal scope covers both the historical period and various future SSP scenarios. The historical phase designates the years 1981–2010 as the baseline period, while the future phase comprises two distinct periods: 2041–2070 and 2071–2100. The future climate change scenarios incorporate four representative emission pathways—SSP126, SSP245, SSP370, and SSP585—corresponding to low, low-to-moderate, moderate-to-high, and high-emission development trajectories, respectively. Before analysis, all datasets underwent quality control procedures, including checks for completeness, consistency, and missing values.

(2) Agricultural Regional boundaries

To reveal the spatial heterogeneity of drought changes across China's agricultural regions, this study used the country's nine major agricultural regions as the basic units of analysis. The regional boundary data were obtained from the Resource and Environmental Science Data Platform (<https://www.resdc.cn/>). This agricultural regionalization system comprehensively considers climatic conditions, topography, water resource endowment, agricultural production practices, and cropping systems. It has been widely applied in studies of agricultural resources and agro-climatic assessment in China. The nine agricultural regions include the Northeast Agricultural Region, Northern Dryland Farming Region, Huang–Huai–Hai Agricultural Region, Middle and Lower Yangtze River Agricultural Region, South China Agricultural Region, Southwest Agricultural Region, Gansu–Xinjiang Agricultural Region, Qinghai–Tibet Plateau Agricultural Region, and the Inner Mongolia and Great Wall Agricultural Region (Figure 2).

These agricultural regions exhibit substantial differences in thermal and moisture conditions, cropping systems, and dominant crop types, resulting in distinct sensitivities to climate variability and drought risks. The Northeast Agricultural Region, located in a relatively cold temperate zone, is characterized mainly by a single annual cropping system, with maize and soybean as dominant crops. Crop production in this region is highly dependent on seasonal precipitation and temperature conditions, particularly during the growing season. The Huang–Huai–Hai Agricultural Region, one of the major grain-producing areas in China, commonly practices double cropping or a wheat–maize rotation system, but faces frequent water shortages due to intensive agricultural water consumption and uneven precipitation distribution. The Middle and Lower Yangtze River and South China Agricultural Regions are characterized by abundant heat and precipitation resources, supporting double- or triple-cropping systems and diverse crop production; however, excessive precipitation variability and seasonal drought events can still pose significant risks to agricultural productivity. In contrast, agricultural production in the arid and semi-arid regions of northwestern China and the Qinghai–Tibet Plateau is more sensitive to climate variability due to limited water resources, sparse precipitation, and

harsh environmental conditions. In these regions, agricultural activities rely heavily on irrigation and are particularly vulnerable to prolonged drought conditions and increasing climate extremes. Given the pronounced differences among agricultural regions in climatic resources, cropping systems, and agricultural production patterns, the use of agricultural regionalization provides a more appropriate framework for characterizing agroecosystem responses to climate change and drought events. Therefore, this study employed the nine agricultural regions to analyze and compare the spatiotemporal variations in drought during the historical period and under future climate scenarios, thereby providing scientific support for regional agricultural adaptation and drought risk management under climate change.

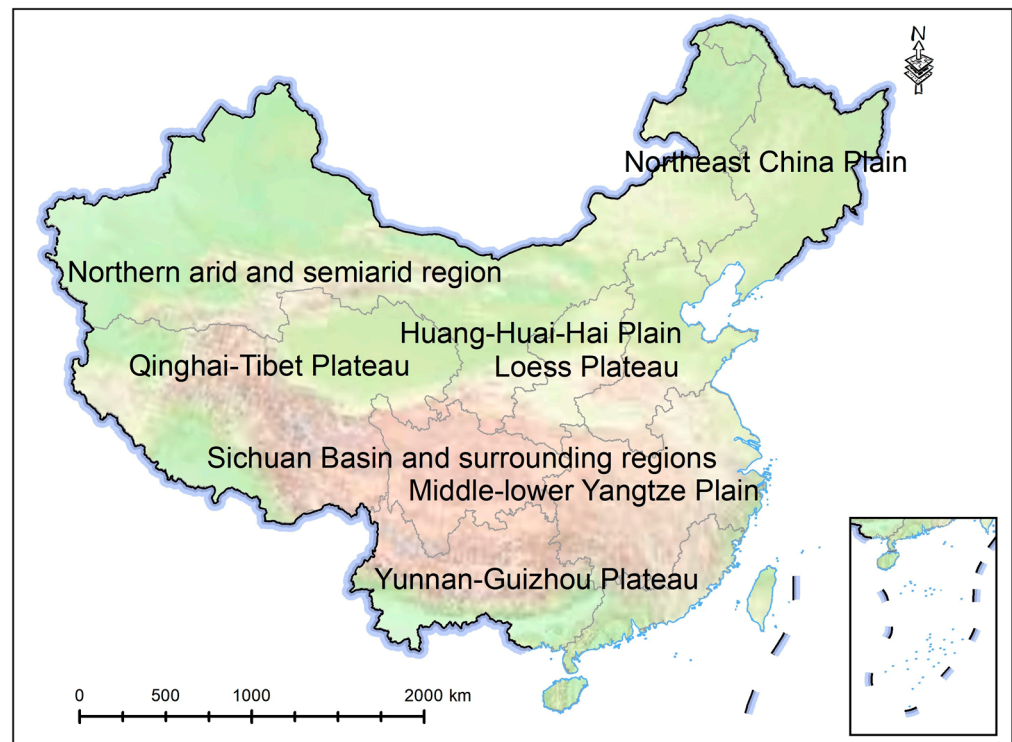


Figure 2. Location map of nine major agricultural regions in China.

2.2. Drought Index Calculation

The SPI was calculated using the precipitation-based approach proposed by McKee et al. [32,33]. Because it relies solely on precipitation data and offers excellent spatiotemporal comparability, the SPI has been widely applied in regional drought monitoring and climate change research [34,35]. Given the significant impact of seasonal-scale droughts on agricultural production and ecosystems, this study selects the SPI3 for analysis. SPI3 effectively captures seasonal moisture anomalies and the characteristics of short-term drought variations. The calculation of the SPI primarily involves the following steps: (1) performing a 3-month moving accumulation of monthly precipitation data; (2) assuming that the accumulated precipitation follows a Gamma distribution; (3) calculating the cumulative probability using a probability distribution function; and (4) standardizing the cumulative probability to a standard normal distribution to derive the SPI value. The suitability of the Gamma distribution was evaluated before probability transformation to ensure an appropriate fit to the precipitation data. The gamma distribution is defined as follows:

$$f(x) = \frac{x^{\alpha-1} e^{-x/\beta}}{\beta^{\alpha} \Gamma(\alpha)}$$

where α and β are the shape and scale parameters, respectively.

Cumulative probability transformation is defined as follows:

$$H(x) = q + (1 - q)G(x)$$

where q represents the probability of zero precipitation and $G(x)$ is the cumulative probability of the Gamma distribution.

SPI3 is calculated as follows:

$$SPI3 = \Phi^{-1}(H(x))$$

where Φ^{-1} is the inverse cumulative distribution function of the standard normal distribution.

The resulting SPI values reflect regional wet and dry variations. An $SPI > 0$ indicates a relatively wet state; an $SPI < 0$ indicates a relatively dry state; and an $SPI \leq -1$ is generally considered to signify the occurrence of a moderate or more severe drought event. Based on this foundation, the spatial mean values of SPI3 are further calculated for various periods and scenarios. Because SPI is derived from the statistical distribution of accumulated precipitation, its uncertainty may vary among regions with different precipitation regimes. In particular, areas characterized by low precipitation amounts and high variability may exhibit greater sensitivity in SPI estimation than relatively humid regions. In this study, a consistent statistical procedure was applied to each grid cell using the same reference period (1981–2010) and high-resolution precipitation datasets ($0.25^\circ \times 0.25^\circ$) to improve the spatial comparability and robustness of SPI3 calculations.

Although SPI considers only precipitation anomalies and does not explicitly account for atmospheric evaporative demand, it provides a simple, robust, and widely accepted framework for quantifying precipitation-driven drought and enables consistent comparisons across multiple CMIP6 models and SSP scenarios. Under future climate warming, increased potential evapotranspiration may further intensify agricultural water stress, and therefore, drought severity estimated using evapotranspiration-based indices (e.g., SPEI) could be greater than that indicated by SPI. However, projections of future evapotranspiration are themselves subject to considerable uncertainty because they depend on multiple climatic variables that differ substantially among climate models. Therefore, SPI was considered an appropriate indicator for the objectives of this study, while the potential influence of evapotranspiration should be taken into account in future investigations.

2.3. Trend Analysis

The Mann–Kendall (MK) test [36–38] was applied to determine the statistical significance and direction of SPI-3 trends. Subsequently, Theil–Sen’s slope estimator was used to quantify the magnitude of the detected trends. This combination provides a robust non-parametric approach for evaluating monotonic trends in drought variations [39,40]. Theil–Sen’s slope was used to analyze trend variations in drought indices, thereby quantitatively characterizing the rate of change in drought intensity over time across regions. This method is a non-parametric trend estimation technique that is robust against outliers and does not require the data to conform to a normal distribution; consequently, it is well-suited for analyzing climate and hydrological time series data characterized by high variability and nonlinear features. The fundamental principle underlying Theil–Sen’s slope is to compute the slopes for all possible pairs of data points within a time series and take the median of these slopes as the overall rate of trend change. The calculation formula is as follows:

$$Q = \text{median} \frac{x_j - x_i}{j - i} (1 < i < j < n)$$

In the formula, Q represents the interannual variation trend of drought, x_i and x_j are the drought values for year i and year j , respectively, and n is the length of the time series. This method effectively mitigates the influence of extreme values on trend estimation, demonstrating greater robustness than linear regression. In the context of drought trend analysis, Theil–Sen’s slope can be employed to identify both the direction and rate of change in the SPI3 index across various spatial units or climatic scenarios: a value of $Q > 0$ indicates a tendency toward diminishing drought conditions (a wetting trend), whereas $Q < 0$ signifies an intensification of drought severity. The drought trend was calculated at each grid cell using Sen’s slope estimator. Subsequently, the grid-level trends were spatially averaged within each agricultural region to obtain the regional mean drought change trend.

2.4. Multilevel Factorial Analysis

In this study, MFA [41,42] was applied to quantify the relative effects of different factors (e.g., emission scenarios, climate models, and projection periods) on future drought variations. Using SPI3 as the response variable y —and treating climate scenarios (SSP126, SSP245, SSP370, and SSP585), time periods (2040–2070 and 2070–2100), and climate models (KACE-1-0-G and MIROC6) as influencing factors (x_1, x_2, x_3, x_4)—the analysis quantifies the respective contributions of these individual factors and their interactions to regional drought changes. Each influencing factor x_i has N_i levels, where $i = 1, 2, \dots, n$. According to the analysis of variance (ANOVA) theory, the total sum of the squares (TSS) can be divided into the sum of squares due to individual model parameters and their interactions as follows:

$$TSS = \sum_{i=1}^n SS_i + \sum_{i=1}^n \sum_{j>i}^n SS_{ij} + \dots + SS_{1, 2, \dots, n}$$

where SS_i is the square due to the individual effect of x_i ; SS_{ij} to $SS_{1, 2, \dots, n}$ are the squares due to interactions among k factors. In this model, all interaction terms are summarized into the term SS_{int} .

$$SS_{int} = \sum_{i=1}^n \sum_{j>i}^n SS_{ij} + \dots + SS_{1, 2, \dots, n} = TSS - \sum_{i=1}^n SS_i$$

Then, for each effect, the variance fractions η^2 are derived as follows:

$$\eta_i^2 = \frac{SS_i}{TSS}$$

$$\eta_{int}^2 = \frac{SS_{int}}{TSS}$$

where

$$TSS = \sum_{t_1=1}^{N_1} \sum_{t_2=1}^{N_2} \dots \sum_{t_n=1}^{N_n} (Y^{t_1, t_2, \dots, t_n} - Y^{o, o, \dots, o})^2$$

$$SS_i = \sum_{t_1=1}^{N_1} \sum_{t_2=1}^{N_2} \dots \sum_{t_n=1}^{N_n} (Y^{o, o, \dots, t_i, \dots, o} - Y^{o, o, \dots, o})^2$$

The symbol “o” indicates averaging over the particular index. The value of η^2 indicates the contribution of the independent variable to the total ensemble variance:

$$\sum_{i=1}^k \eta_i^2 + \eta_{int}^2 = 1$$

The MFA primarily addresses the following aspects: (1) the influence of different SSP scenarios on drought variability; (2) the influence of different future time periods on drought variability; (3) the discrepancies in simulation results across different climate models; and (4) the interactive effects between scenarios and time periods. Through this variance analysis, the dominant factors driving future drought changes can be identified, thereby further revealing the spatial heterogeneity that characterizes the intensification of drought risk under high-emission pathways. Furthermore, to enhance the robustness of the results, this study conducts a comparative analysis of the outputs from different models to mitigate the uncertainties associated with relying on a single model. A comprehensive description of the theoretical basis and methodological framework of Factorial Analysis is available in previous studies [43,44], and interested readers are referred to these references for further details.

3. Results and Discussion

3.1. Historical Drought Characteristics in China's Nine Agricultural Regions

Figure 3 illustrates the spatial distribution characteristics, temporal trends, and significance results of the SPI3 in China during the historical period, while Table 1 presents a statistical analysis of drought characteristics across the country's nine major agricultural regions. Overall, significant differences exist among China's various agricultural regions regarding drought severity, fluctuation patterns, and evolutionary trends, indicating that regional climatic backgrounds, topographic conditions, and hydrothermal configurations collectively shape a complex pattern of agricultural drought. Based on historical averages, China's agricultural regions collectively exhibit distinct characteristics of regional dry–wet differentiation. Notably, the arid and semi-arid regions of Northern China have historically been the driest, with an average SPI3 value as low as -0.435 , indicating a long-standing moisture deficit. This phenomenon is closely linked to the region's sparse precipitation, intense evaporation, and fragile ecosystem. The Loess Plateau (-0.261) and Southern China (-0.115) also recorded negative values, suggesting that these regions have historically tended towards aridity. In contrast, the plains of the middle and lower Yangtze River (0.217), the Northeast China Plain (0.144), and the Yunnan–Guizhou Plateau (0.143) all recorded positive average SPI3 values, collectively indicating a relatively humid state. Among these, the plains of the middle and lower Yangtze River exhibited the highest humidity, reflecting the supportive role of abundant monsoon precipitation in sustaining agricultural water resources in the region.

Different agricultural regions not only exhibit variations in their average wetness and dryness conditions, but their climatic variability also displays distinct regional characteristics. In terms of the standard deviation of the SPI3 index, the Northern Arid and Semi-arid Zone (0.796) and the Yunnan–Guizhou Plateau (0.736) exhibit the highest variability, indicating that interannual precipitation fluctuations are severe in these regions and that drought events are highly unstable. This is particularly true for the Yunnan–Guizhou Plateau, where complex topography and the widespread distribution of karst landforms lead to spatially and temporally uneven regional precipitation, making the area more susceptible to periodic severe droughts. In contrast, the Loess Plateau (0.277) and the Northeast Plain (0.364) exhibit lower variability, suggesting that regional fluctuations between wet and dry conditions are relatively stable. This disparity underscores that drought risk in China's agricultural regions depends not solely on average precipitation but is also closely intertwined with the stability of the climate system.

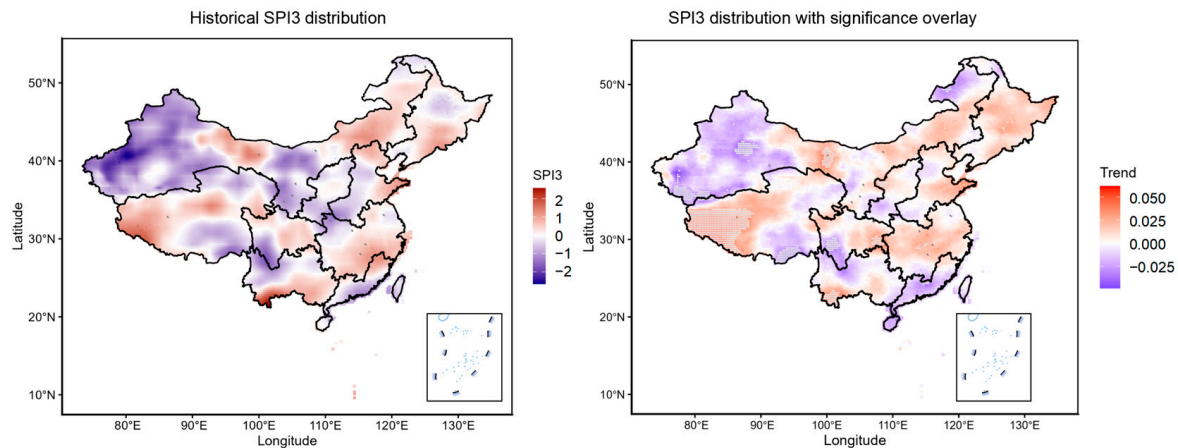


Figure 3. Historical spatial distribution of drought and drought trend characteristics. (a) Historical SPI3 distribution in 2010, with values ranging from -2 to 2 ; negative and positive values represent relatively dry and wet conditions, respectively. (b) The long-term spatial trend of SPI3 over the historical period (1981–2010), estimated using the Mann–Kendall test and Sen’s slope estimator, with trend values ranging from -0.05 to 0.05 ; negative trends indicate increasing drought conditions, while positive trends indicate increasing wetness. Stippling indicates statistically significant trends ($p < 0.05$).

Table 1. Drought conditions in nine major agricultural areas during 1981–2010.

Region	SPI3	Trend Slope	SD_SPI3	Severe Drought Frequency	Extreme Drought Frequency
HHHP	0.013	0.0058	0.578	2.6	0.3
LP	−0.261	-1.00×10^{-4}	0.277	2.4	0.3
MLYP	0.217	0.0087	0.466	1.9	0.1
NECP	0.144	0.0103	0.364	1.8	0.1
NASR	−0.435	−0.0043	0.796	1.7	0.2
QTP	0.079	0.0093	0.648	1.8	0.4
SBSR	−0.076	0.002	0.616	1.6	0.4
SC	−0.115	−0.0121	0.606	3.4	0.3
YGP	0.143	0.0011	0.736	2.9	0.5

Note: Abbreviations are as follows: Huang–Huai–Hai Plain, HHHP; Loess Plateau, LP; Middle–Lower Yangtze Plain, MLYP; Northeast China Plain, NECP; Northern arid and semiarid region, NASR; Qinghai–Tibet Plateau, QTP; Sichuan Basin and surrounding regions, SBSR; Southern China, SC; Yunnan–Guizhou Plateau, YGP.

In terms of the frequency of severe and extreme droughts, significant disparities are also evident across the various agricultural regions. The South China region exhibits the highest frequency of severe droughts, reaching 3.4%—a figure significantly higher than that of any other agricultural zone. Although the South China region generally receives abundant precipitation, it is highly susceptible to the impacts of monsoon anomalies and intensified evaporation driven by high temperatures; consequently, it is prone to prolonged agricultural droughts during years with deficient rainfall. The Yunnan–Guizhou Plateau records relatively high frequencies of both severe droughts (2.9%) and extreme droughts (0.5%), indicating that this region not only experiences frequent droughts but also faces a pronounced risk of extreme droughts. The Huang–Huai–Hai Plain also registers a severe drought frequency of 2.6%, signifying that—as a vital grain-producing hub in China—its agricultural system is subject to considerable water resource stress. In contrast, the Northeast Plain and the Middle–Lower Yangtze Plain record severe drought frequencies of merely 1.8% and 1.9%, respectively; these regions present a relatively lower overall risk, reflecting their more favorable climatic resource endowments.

The trend analysis further reveals regional disparities in the evolutionary trajectory of drought across different agricultural zones (Figure 3b). Broadly speaking, eastern China

and high-latitude regions exhibit a distinct trend toward increased wetness, whereas certain areas in the south and northwest show persistent aridification. Notably, the Northeast Plain demonstrates the most pronounced wetting trend, with a slope of 0.0103, indicating a continuous improvement in regional moisture conditions in recent years. This phenomenon may be linked to enhanced water vapor transport occurring against the backdrop of rising temperatures in high-latitude regions. The Qinghai–Tibet Plateau (0.0093) and the Middle–Lower Yangtze Plain (0.0087) also exhibit significant wetting trends, suggesting improved precipitation conditions in both the plateau region and the core monsoon zone. In contrast, South China exhibits the most pronounced trend toward aridification, with a trend slope of -0.0121 ; this indicates that the region’s agricultural drought risk is continuously intensifying. These results suggest that, despite the high total precipitation in South China, climate change has led to a more uneven spatiotemporal distribution of rainfall, while rising extreme temperatures and increased evapotranspiration have further exacerbated agricultural water deficits. The trend in the arid and semi-arid regions of Northern China is likewise negative (-0.0043), indicating that the already fragile ecological environment in these regions remains at risk of continued deterioration. In comparison, the trend on the Loess Plateau approaches zero, indicating that its long-term drought dynamics have remained relatively stable.

The results of the MK significance test indicate that drought variations across different agricultural regions exhibit distinct spatial clustering. Areas undergoing significant humidification are primarily concentrated in the Northeast Plain, the eastern Qinghai–Tibet Plateau, and parts of the Southwest region; conversely, areas experiencing significant aridification are predominantly distributed along the South China coast and in certain parts of the Northwest. This suggests that the response of China’s agricultural regions to climate change is not uniform and that distinct differences exist in hydrological cycle processes across these regions.

Overall, drought dynamics during the historical period exhibited pronounced regional heterogeneity across China’s nine major agricultural regions. The northern arid and semiarid region remained persistently dry and experienced substantial variability, while Southern China showed the most significant drying trend. In contrast, the Northeast China Plain and the Middle–Lower Yangtze Plain exhibited clear wetting trends. These regional differences in drought intensity, frequency, and evolutionary patterns suggest that future agricultural water-resource management and drought risk mitigation strategies should account for regional climatic conditions and agricultural production characteristics, thereby enabling the development of targeted, region-specific adaptation measures.

3.2. Future Projection of Drought Characteristics

Figure 4 illustrates the spatial distribution characteristics of the mean SPI3 across China during the mid-term (2041–2070) and long-term (2071–2100) future periods under four SSP scenarios: SSP126, SSP245, SSP370 and SSP585. Overall, the spatial patterns of SPI3 show high consistency across all scenarios, whereas the magnitude of dry/wet conditions varies substantially with different emission pathways. During the mid-term period (2041–2070), the nationwide SPI3 spatial distribution features a coexistence of north–south divergence and fluctuating moisture conditions in western China. Lower SPI3 values are found across North China, Northwest China, and parts of the Qinghai–Xizang Plateau, indicating a pronounced intensification of drought; by contrast, the middle and lower reaches of the Yangtze River and South China feature relatively high SPI3 values, indicating a prominent trend toward wetter conditions. Under the SSP126 scenario, drought severity remains generally mild with extensive areas of positive SPI3 values. In comparison, SSP370 and SSP585 scenarios witness expanded coverage of negative SPI3 values, accompanied by a

more robust signal of worsening drought. In the long term (2071–2100), disparities among different scenarios are further amplified. Under SSP126, most parts of China stay near neutral or moderately wet, with limited areas facing exacerbated drought. For SSP245, SSP370 and SSP585, however, negative SPI3 values expand notably across Northwest China, portions of North China, and localized areas in Southwest China, demonstrating a continuous worsening of drought risks and expanded drought coverage under high-emission scenarios. Meanwhile, the southeast coastal regions remain relatively humid yet with amplified moisture variability. Synthesizing the above findings, as radiative forcing rises from SSP126 to SSP585, drought conditions over China tend to deteriorate alongside growing spatial heterogeneity. Northern and inland regions are more sensitive to climate change under high-emission pathways. These results highlight the critical role of future mitigation pathways in mitigating regional drought hazards.

Table 2 shows the regional average variation characteristics of SPI3 in the mid-term (2041–2070) and long-term (2071–2100) for China’s nine major agricultural areas under different SSP scenarios. In general, agricultural areas exhibit clear regional differences and scenario dependence across different emission scenarios, and the difference between regional wetting and aridification is more pronounced under high-emission scenarios. Since higher SPI values indicate more humid conditions, a higher SPI means the drought risk is reduced, and a lower SPI indicates a greater degree of drought.

Table 2. Mid-term and long-term drought conditions in nine major agricultural areas under different SSP scenarios.

Region	SSP126		SSP245		SSP370		SSP585	
	2041–2070	2071–2100	2041–2070	2071–2100	2041–2070	2071–2100	2041–2070	2071–2100
HHHP	0.74	0.76	0.75	0.64	0.7175	0.847	0.912	0.693
LP	1.36	1.33	0.48	0.49	1.3876	1.261	0.677	0.589
MLYP	0.31	0.29	0.24	0.33	0.1828	0.219	0.353	0.432
NECP	0.57	0.66	0.19	0.49	0.5288	0.936	0.482	0.502
NASR	0.46	0.40	0.15	0.28	0.6001	0.652	0.247	0.342
QTP	0.19	0.21	0.36	0.36	0.1777	0.540	0.467	0.900
SBSR	0.56	0.73	0.28	0.31	0.4455	0.472	0.180	0.371
SC	−0.37	−0.55	0.03	0.18	−0.6576	−0.505	0.138	0.382
YGP	0.56	0.68	0.31	0.40	0.2480	0.122	0.309	0.583

From a regional perspective, the Loess Plateau showed higher SPI values under most scenarios, especially in the SSP370 scenario. The mid-term and long-term SPI values reached 1.3876 and 1.261, respectively, indicating that future precipitation conditions may be significantly improved and that the regional wetting trend is prominent. The Huang–Huai–Hai Plain also maintained a high SPI level overall across various scenarios, particularly in the middle of SSP585, reaching 0.912, indicating that the region’s wetting characteristics are more pronounced under the background of future climate warming. In contrast, although the SPI of the Qinghai–Tibet Plateau and the arid and semi-arid regions in the north have increased, the overall value remains relatively low, indicating that improvements in regional water conditions are limited and drought sensitivity remains high. It is worth noting that the SPI in South China is negative under the SSP126 and SSP370 scenarios. For example, the long-term value of SSP126 is −0.55, and the medium-term value of SSP370 is −0.66, indicating a potentially significant future drought trend in the region. This indicates that even under low-emission scenarios, some humid areas may still face the risk of drought intensification due to changes in the spatial and temporal distribution of precipitation. The Yunnan–Guizhou Plateau as a whole shows a trend toward more moderate to more humid conditions, with values reaching 0.583 over the long term under

SSP585, indicating that a high-emission scenario in the future may enhance regional water vapor transport and precipitation intensity.

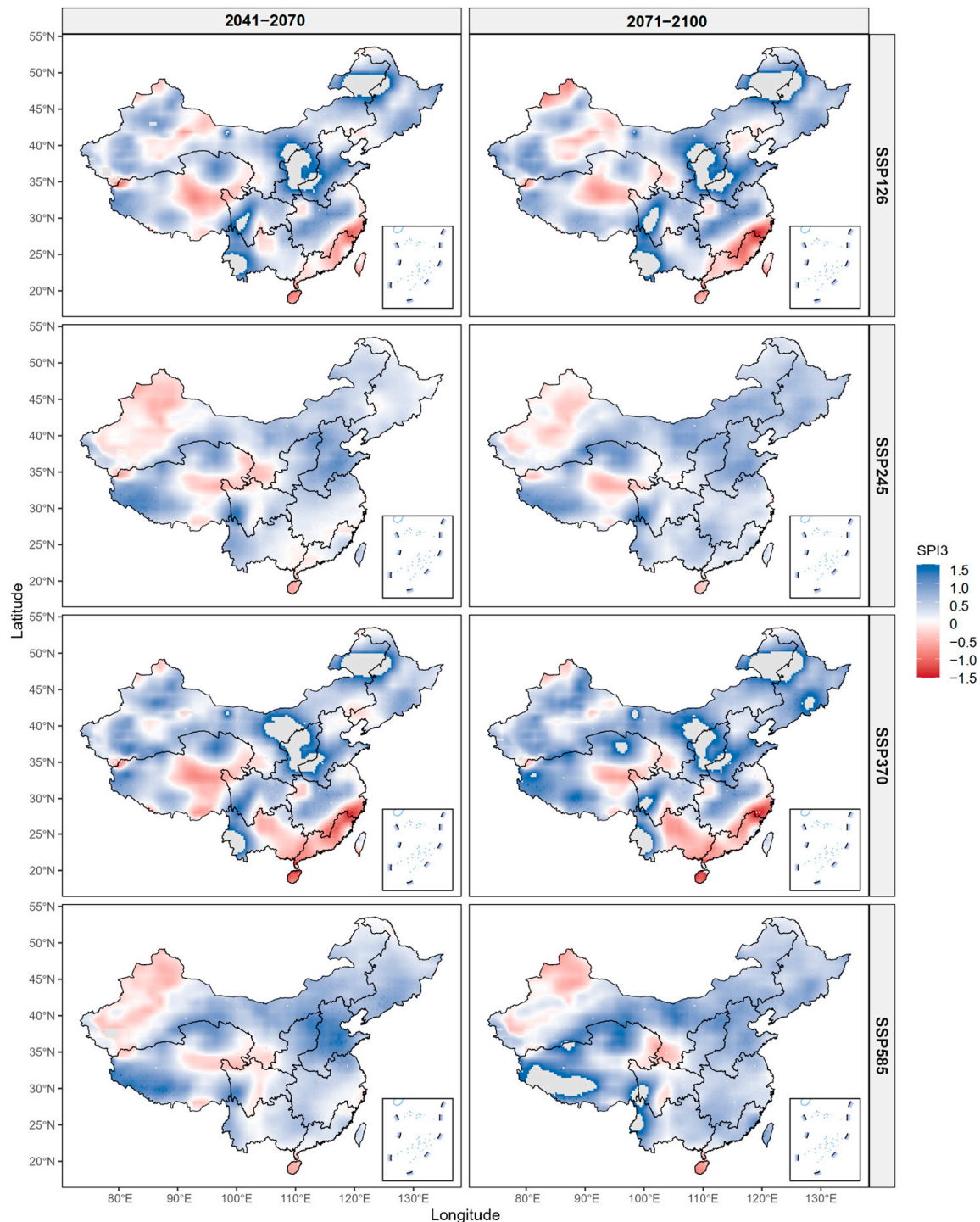


Figure 4. Spatial distribution of the mean SPI3 during the mid-term (2041–2070) and long-term (2071–2100) periods in China under different SSP scenarios. The color scale represents the multi-year mean SPI3 values for each period, ranging from -1.5 to 1.5 . Negative SPI3 values indicate drier-than-normal conditions, whereas positive values indicate wetter-than-normal conditions.

From the perspective of scenario changes, SPI in most agricultural areas under the high-emission scenario (SSP585) is higher than under the low-emission scenario, indicating that future warming may enhance atmospheric water-holding capacity and increase precip-

itation in some areas, thereby reducing meteorological drought in some areas. However, responses across regions are inconsistent. For example, the SPI of the Sichuan Basin in the middle of SSP585 is only 0.18, which is significantly lower than 0.56 in the middle of SSP126, indicating that the regional topography and monsoon system may complicate its response to future climate change. In general, future SPI changes in China's agricultural areas exhibit clear spatial heterogeneity. The wetting trend is mainly concentrated in the Huang–Huai–Hai Plain, the Loess Plateau, and the Northeast Plain, while regions such as South China may face the risk of continuous drought.

Figure 5 illustrates the spatial patterns of drought change trends in China under four SSP scenarios during the mid-term period (2041–2070) and the long-term period (2071–2100). Overall, drought changes exhibit pronounced spatial heterogeneity and regional disparities across all scenarios and time horizons, indicating that future drought evolution is jointly controlled by the greenhouse gas forcing pathway and regional climatic background. From a temporal perspective, the mid-term period (2041–2070) shows relatively weak overall changes across all scenarios, although spatial heterogeneity is already evident. Under SSP126, most regions of China exhibit weak alternating positive and negative trends. Slight drying tendencies appear in parts of Northwest and North China, while southern China generally shows weak wetting signals. Under SSP245 and SSP370, spatial differentiation becomes more pronounced, with the central and eastern agricultural regions showing increasingly evident negative trends, suggesting a heightened drought risk. Under SSP585, spatial variability further intensifies in the mid-term period, with strong-forcing conditions amplifying extreme climate signals and significantly expanding drying areas in northern arid zones and the Huang–Huai–Hai Plain. In the long-term period (2071–2100), differences among scenarios become substantially larger, indicating a clear pathway-dependent response. Under the low-emission SSP126 scenario, drought trends across most regions are alleviated, and some areas even exhibit weak wetting signals, suggesting a relatively stable regional hydrological cycle under low radiative forcing. Under SSP245 and SSP370, drying trends become more pronounced in northern China, particularly in the North China Plain, southern Northeast China, and the inland Northwest. In contrast, southern China shows a mosaic pattern of wetting and drying, reflecting intensified regional contrasts driven by water–heat redistribution. Under SSP585, long-term changes are most severe, with widespread and persistent drying trends across central and eastern China. Key agricultural regions such as the Huang–Huai–Hai Plain and parts of the middle and lower Yangtze River Basin experience significantly elevated drought risk. At the same time, Northeast China shows localized wetting signals but with weak spatial coherence.

In terms of spatial patterns, future drought changes show distinct regional differences across China, characterized by stronger variations in northern and inland regions compared with southern and coastal areas. The arid and semi-arid regions of Northwest China generally exhibit increasing drought trends under different scenarios, indicating a higher likelihood of future drought intensification. In contrast, humid regions in southern China display more heterogeneous drought responses, with both increasing and decreasing trends observed, which may be associated with the combined effects of precipitation changes and atmospheric evaporative demand. Key agricultural regions, including the North China Plain, Northeast China Plain, and the middle and lower reaches of the Yangtze River Basin, show increased drought risks particularly under medium- and high-emission scenarios. Overall, future drought evolution in China is strongly influenced by emission pathways and exhibits substantial spatial heterogeneity. Lower-emission scenarios tend to reduce the magnitude of drought changes, whereas higher-emission scenarios generally intensify drought variations and increase regional disparities. These findings provide important

insights for developing region-specific drought adaptation strategies and improving water resource management under future climate change.

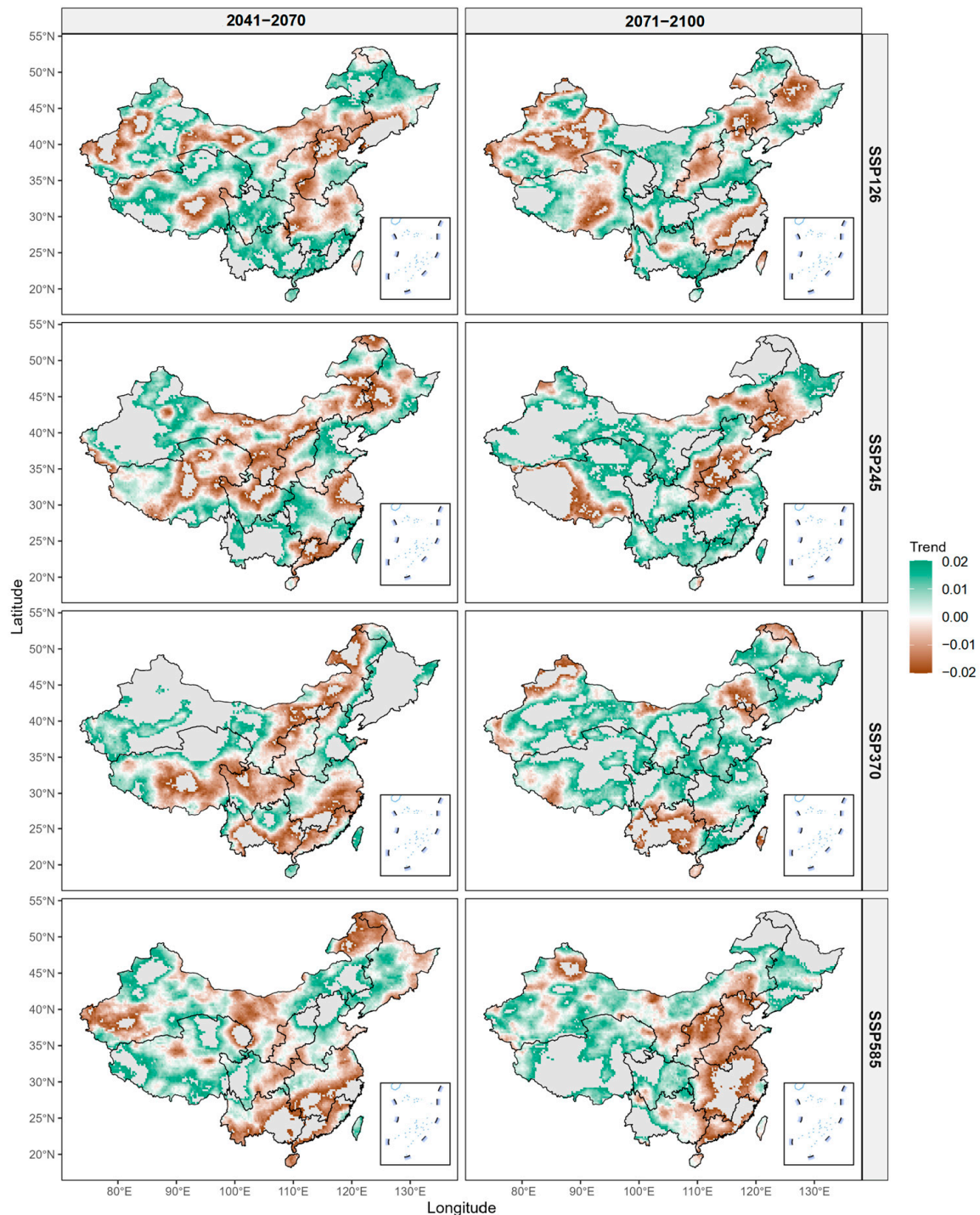


Figure 5. Spatial distribution of future SPI-3 trends during the mid-term (2041–2070) and long-term (2071–2100) periods in China under different SSP scenarios. The color scale represents the trends of future SPI3, with values ranging from -0.02 to 0.02 ; negative trends indicate increasing drought conditions, while positive trends indicate increasing wetness.

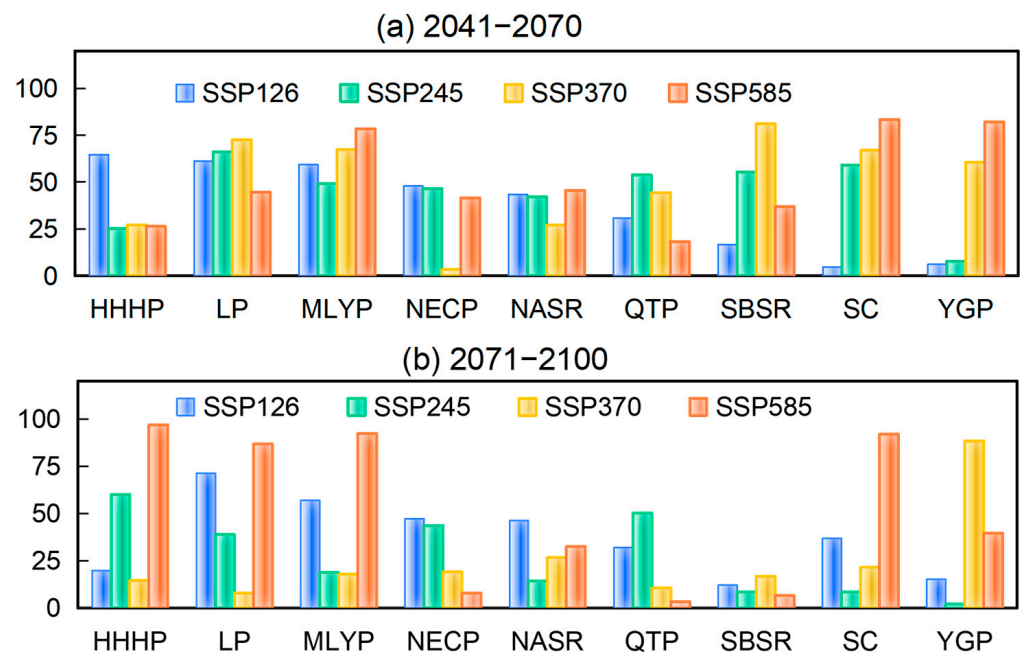
Table 3 presents regional statistics for SPI3 trends across agricultural regions, with the trend value representing the average of grid-level trends within each region. A positive SPI trend indicates a gradual wetting tendency, whereas a negative trend suggests increasing drought severity. Overall, future SPI trends exhibit pronounced spatial heterogeneity across

China's agricultural regions, and the magnitude of trend fluctuations generally increases under higher-emission scenarios. During the historical period, most agricultural regions exhibited slight wetting trends. For example, the Northeast China Plain recorded the highest historical trend (0.011/year) among all regions, indicating a notable improvement in regional moisture conditions over recent decades. In contrast, Southern China showed a historical trend of -0.012 /year, suggesting a long-term drying tendency. Under future climate scenarios, these regional differences become more pronounced. The Huang-Huai-Hai Plain exhibited positive trends during the mid-century period under both SSP245 and SSP370, reaching 0.010/year under SSP585. This suggests a potential enhancement of wetting conditions in the future. However, the trend shifted to -0.010 during the late-century period under SSP585, indicating that drought conditions may re-emerge under extreme warming. The Loess Plateau exhibited more complex trend patterns. Negative trends dominated during the mid-century period under SSP126 and SSP245, whereas the trend increased to 0.014/year during the late-century period under SSP370, suggesting that moderate-to-high emission scenarios may promote increased precipitation in the later period. The Northeast China Plain maintained positive trends under most future scenarios, with the highest value (0.033/year) occurring during the late-century period under SSP370. This was the largest trend among all regions, indicating that the Northeast is likely to experience the most pronounced wetting in the future. In contrast, the Middle-Lower Yangtze Plain showed persistent negative trends under SSP585, reaching -0.016 /year by the late-century period, implying a substantial increase in drought risk under high-emission conditions. In addition, Southern China exhibited negative trends under several scenarios, particularly under SSP585, with values of -0.013 /year and -0.016 /year during the mid- and late-century periods, respectively. These results suggest that extreme warming may substantially intensify drought risk in this region. The Sichuan Basin and surrounding areas generally displayed weak positive trends, indicating relatively stable hydroclimatic conditions. Overall, future SPI trends suggest that drought evolution across China's agricultural regions will not follow a uniform pattern of intensification or alleviation. Instead, substantial regional disparities are expected, with the Northeast China Plain and Huang-Huai-Hai Plain tending toward wetter conditions. At the same time, Southern China and parts of the Middle-Lower Yangtze Plain may continue to experience increasing drought risk.

Figure 6 shows the proportion of grid points with negative SPI trends across agricultural regions, indicating the share of areas where drought is worsening within each region. This indicator reflects the extent of drought risk expansion within the area. The results indicate significant differences in the proportion of areas experiencing worsening drought across agricultural regions and that under future high-emission scenarios, drought risks will be markedly heightened in certain areas. Historically, the proportion of area under worsening drought in southern China is the highest, at 88.9%, indicating that most grid points in the region have experienced a long-term downward SPI trend and highlighting significant drought risk. The proportions for the Yunnan-Guizhou Plateau and the northern arid and semi-arid regions were 55.8% and 54.6%, respectively, indicating significant climate vulnerability in these areas. In contrast, the northeastern plain had a historical proportion of only 12.4%, indicating an overall trend towards wetness in the region.

Table 3. Drought change trends ($\times 10^{-2}$ /year) in nine major agricultural regions under different SSP scenarios during the mid-term and long-term periods.

Region	Historical	SSP126		SSP245		SSP370		SSP585	
		2041–2070	2071–2100	2041–2070	2071–2100	2041–2070	2071–2100	2041–2070	2071–2100
HHHP	0.7	−0.5	0.9	0.9	−0.6	0.7	0.9	1.0	−1.0
LP	0.2	−0.3	−0.3	−0.5	0.9	−0.4	1.4	0.6	−1.0
MLYP	0.8	0.0	−0.3	−0.2	1.4	−0.6	1.0	−1.1	−1.6
NECP	1.1	−0.3	0.0	0.0	0.7	3.3	0.9	0.2	1.9
NASR	−0.2	0.4	0.2	0.6	0.18	1.6	0.8	0.2	0.5
QTP	1.0	0.7	0.8	−0.1	−0.5	0.6	1.6	0.8	2.1
SBSR	0.3	1.1	1.6	−0.2	1.7	−0.6	1.4	0.8	1.6
SC	−1.2	1.6	0.1	−0.4	1.0	−0.5	1.1	−1.3	−1.6
YGP	0.0	1.8	1.2	2.2	1.6	−0.5	−1.6	−1.1	0.9

**Figure 6.** Proportion of area with increasing drought severity in nine major agricultural regions under different SSP scenarios: (a) mid-term (2041–2070); (b) long-term (2071–2100).

In future scenarios, different agricultural regions exhibit markedly different evolutionary characteristics. In the Huang–Huai–Hai Plain, the proportion of area under worsening drought reaches 64.7% in the mid-term of SSP126. Still, it drops to 14.7% in the long term for SSP370, suggesting that the area's wetness may expand under medium- to high-emission scenarios. However, in the long-term SSP585 scenario, this proportion surges to 96.9%, indicating a dramatic increase in drought risk in the area under extreme high-emission conditions. The Loess Plateau maintains a high proportion of drought area across most scenarios, reaching 72.5% in the mid-term under SSP370, suggesting this region may remain one of the most drought-sensitive regions in the country. In the central and lower reaches of the Yangtze River Plain, proportions of drought area reach 78.3% and 92.2% in the mid and late periods of SSP585, respectively, indicating a significant intensification of drought trends under extreme warming conditions. Southern China also shows significant fluctuations, with a ratio of only 4.7% at mid-term under SSP126, indicating a potentially significant short-term wetting trend. However, in the long term, SSP585 rises to 91.9%, reflecting the

high instability of drought risk under high-emission scenarios. The northeastern plain and the Tibetan Plateau maintain relatively low proportions, particularly the northeastern plain, which has only 8.0% in the long term under SSP585, further indicating a predominant trend towards wetness in this region in the future.

Overall, the proportion of areas experiencing worsening drought in China's agricultural regions exhibits significant spatial heterogeneity, with regional differences further exacerbated under high-emission scenarios. Southern China, the Loess Plateau, and the central and lower reaches of the Yangtze River may become key areas where drought risk is rapidly increasing in the future. At the same time, the northeastern plain may continue to show a notably predominant trend towards wetness. It should be noted that the drought variations presented in this study are based on SPI3, which primarily reflects precipitation-driven moisture anomalies. Under future warming conditions, enhanced atmospheric evaporative demand may further intensify agricultural water stress, suggesting that the actual drought impacts could be stronger than those indicated solely by precipitation-based drought metrics.

3.3. Differences in Dominant Controlling Factors of Uncertainty for Drought Evolution

Analysis of the sources of uncertainty reveals that the controlling factors influencing changes in the mean SPI3 and the SPI3 trend are markedly different, indicating that future drought conditions and drought evolution processes are driven by distinct mechanisms. As shown in Table 4, for the mean SPI3 (Contribution_SPI3), regional differences (Region) are the primary influencing factor, accounting for 58.34% of the variation, significantly higher than other factors. This indicates that inherent differences in climatic background, topographic conditions, and water–heat distribution among agricultural subregions are the primary determinants of the spatial differentiation of future drought conditions. The contribution rate of the model factor reached 31.15%, indicating significant systematic differences among CMIP6 climate models and that model uncertainty is a major source of variation in SPI3 predictions. In contrast, the contribution rates of emission scenarios and future periods were only 2.19% and 1.03%, respectively, indicating that, on average at the regional scale, the impact of different SSP and future time periods on the mean SPI3 is relatively limited. Furthermore, the contribution of the Model $\times$ SSP interaction was 6.98%, indicating that different climate models exhibit some variation in their response to changes in emission scenarios; however, the overall contribution remains significantly lower than the main effects of region and model. The contribution rates of the remaining interaction terms were all below 1%, suggesting that complex higher-order interactions have a weak influence on the mean SPI3. Overall, changes in the mean SPI3 are primarily driven by spatial heterogeneity and model uncertainty, which together account for approximately 89% of the variation. At the same time, the contributions of emission scenarios and future periods are relatively small. This suggests that the spatial pattern of drought conditions in future agricultural regions is highly stable, with inherent differences between regions far outweighing the effects of scenario changes.

Compared with the SPI3 mean, the contribution structure of SPI3 trends (Contribution_trend) differs markedly. The third-order interaction (Model $\times$ SSP $\times$ period) has the highest contribution rate, reaching 28.12%, followed by regional factors (Region, 27.04%) and the Model $\times$ SSP interaction (21.60%). This result indicates that future drought trends are not dominated by a single factor but are influenced by the combined effects of the model, emission scenario, and time period. Regional factors continue to play a significant role, contributing 27.04%, suggesting substantial spatial heterogeneity in the future evolution of drought across agricultural regions. However, compared to the analysis of SPI3 mean values, the regional contribution has decreased significantly, indicating that trend changes

are more influenced by dynamic climate change processes rather than being determined solely by regional background conditions. Notably, the main contribution of the model effect was only 0.09%, which is virtually negligible, whereas the contribution of the Model $\times$ SSP interaction reached 21.60%. This indicates that although different climate models do not exhibit significant systematic bias in overall trends, their responses to different emission scenarios vary markedly; that is, inter-model differences primarily manifest in sensitivity to future greenhouse gas emission pathways rather than in the trends themselves. At the same time, the contribution rates for the future period and the Model $\times$ period interaction were 6.28% and 8.50%, respectively, indicating that drought evolution differs between the mid-century and late-century stages and that simulation results for this temporal evolution vary across models. The main effect of SSP contributed 6.09%, which is higher than the results of the SPI3 mean analysis, indicating that emission scenarios have a more pronounced impact on drought trends than on drought conditions. Overall, changes in SPI3 trends are primarily governed by higher-order interactions and regional differences. The cumulative contribution of the top three factors (Model $\times$ SSP $\times$ period, Region, and Model $\times$ SSP) reaches approximately 77%, indicating that future drought evolution exhibits significant nonlinearity and complexity and that the coupling effects among different models, emission scenarios, and time periods are key determinants of trend changes.

Table 4. Comparative analysis of factors influencing mean drought conditions and trend changes in future scenarios.

Effect	Contribution_SPI3	Contribution_Trend
Region	58.34	27.035
Model	31.15	0.087
SSP	2.19	6.090
period	1.03	6.278
Model:SSP	6.98	21.596
Model:period	0.01	8.498
SSP:period	0.25	2.299
Model:SSP:period	0.05	28.117

Figure 7 illustrates the relative contributions of different driving factors to mean drought conditions and drought change trends across nine agricultural regions in China, highlighting pronounced spatial heterogeneity. As shown in Figure 7a, the dominant factors controlling mean drought conditions vary substantially among regions. The “Model” factor plays a leading role in most areas, particularly in the Middle–Lower Yangtze Plain (89.0%), the Sichuan Basin and surrounding regions (70.7%), and the Huang–Huai–Hai Plain (71.5%), indicating that inter-model uncertainty is the primary source of variability in historical mean drought conditions. In contrast, regions such as the Qinghai–Tibet Plateau and the northern arid and semiarid region exhibit a more balanced contribution among multiple factors, with relatively higher contributions from SSP-related terms and interaction effects (Model $\times$ SSP), suggesting stronger modulation by future scenario assumptions. For drought change trends (Figure 7b), the dominant controlling mechanisms shift from model-driven uncertainty toward scenario- and interaction-dominated effects. In particular, the SSP $\times$ period interaction and SSP-related factors contribute substantially in most regions, such as the Yunnan–Guizhou Plateau (SSP $\times$ period: 53.7%), the Northern arid and semiarid region (SSP: 48.0%), and the Northeast China Plain (SSP: 34.9%), indicating an increasing influence of future emission pathways on drought trend evolution. Meanwhile, some regions, such as the Sichuan Basin (period: 56.2%), still show a strong dominance of temporal variability, implying that internal climate variability remains important in shaping regional drought trends.

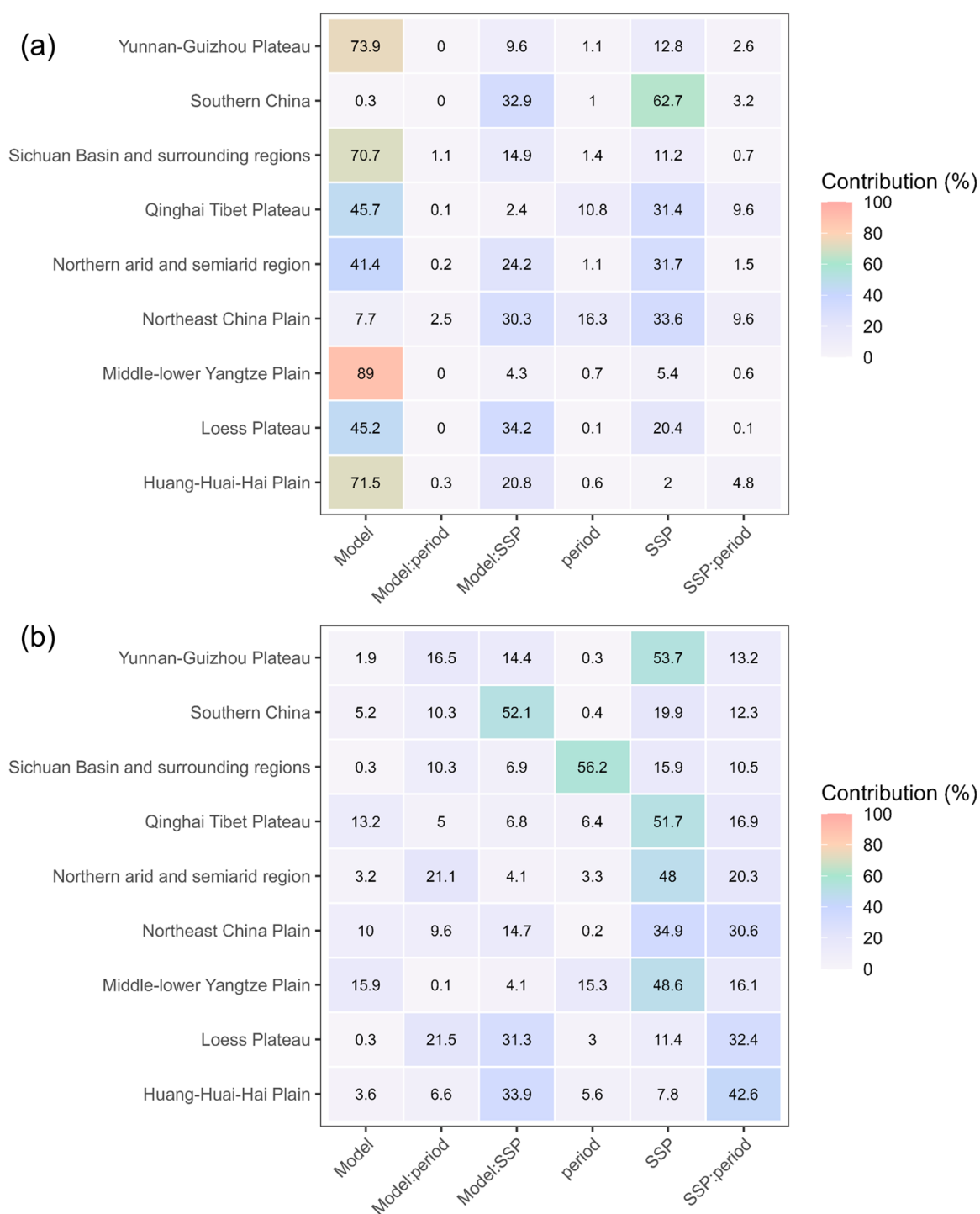


Figure 7. Regional comparison of factors influencing mean drought conditions and trend changes across nine agricultural zones in China. (a) Drought conditions; (b) Drought change trends.

Overall, the results suggest that the mean drought conditions in China are primarily controlled by model uncertainty. In contrast, drought trend changes are increasingly governed by scenario pathways and their interactions with time scale, reflecting a more complex and regionally heterogeneous mechanism of future drought risk.

4. Discussion

The projected drought changes identified in this study are generally consistent with previous studies, which have reported increasing spatial heterogeneity of drought responses

under future climate change. Our results show that drought evolution in China varies substantially across regions, with stronger drying trends mainly occurring in northern and inland areas, while southern regions exhibit more complex patterns. These differences may be related to the regional variability of precipitation changes under different climate scenarios. The results further demonstrate that future drought changes are strongly influenced by emission pathways. Lower-emission scenarios (e.g., SSP126) generally show weaker drought variations, whereas higher-emission scenarios (e.g., SSP370 and SSP585) exhibit more pronounced changes. This indicates that climate mitigation can help reduce the magnitude of future drought changes. The increased drought risk projected in major agricultural regions, including the North China Plain and Northeast China Plain, highlights the importance of developing region-specific drought adaptation and water management strategies.

Several limitations should be acknowledged. First, this study used two CMIP6 climate models to investigate future drought variations. Although these models provide consistent spatial-resolution precipitation projections and represent independent climate modeling systems, a larger multi-model ensemble could further quantify climate model uncertainty. Future studies should incorporate more CMIP6 models to improve the robustness of projections. Second, drought assessment in this study was based on the SPI-3 index, which primarily reflects precipitation-related drought conditions. Although SPI is widely used for meteorological drought monitoring, it does not directly consider temperature-driven atmospheric evaporative demand, soil moisture processes, or vegetation responses. Future research could combine SPI with indices such as the SPEI [45,46] and soil moisture-based drought indicators to provide a more comprehensive assessment [47]. Future research should focus on improving drought projections through multi-model ensembles, incorporating land–atmosphere interactions, and developing integrated drought risk assessment frameworks. Combining climate projections with agricultural, hydrological, and socioeconomic datasets could help identify vulnerable regions and support more effective climate adaptation planning.

5. Conclusions

This study, based on CMIP6 multi-model ensemble data, systematically investigated the spatiotemporal evolution characteristics and driving mechanisms of agricultural drought across China's nine major agricultural regions during the historical period (1981–2010) and under future SSP scenarios (2041–2100). The analysis employed the SPI3 index, Sen's slope trend estimation, Mann–Kendall significance testing, and variance decomposition. The main conclusions are as follows:

(1) During the historical period, agricultural drought in China exhibited pronounced spatial heterogeneity. The northern arid and semi-arid region remained the most drought-prone area over time, while the Loess Plateau and South China also showed a certain tendency toward drying. In contrast, the Middle and Lower Yangtze River Plain, the Northeast Plain, and the Yunnan–Guizhou Plateau generally remained relatively wet. Clear differences in climate variability were observed among regions, with the northern arid and semi-arid region and the Yunnan–Guizhou Plateau showing the largest SPI3 fluctuations, indicating higher drought risk. Trend analysis further revealed significant wetting tendencies in the Northeast Plain, Qinghai–Tibet Plateau, and the Middle and Lower Yangtze River Plain. In contrast, South China exhibited a persistent drying trend, highlighting it as a key drought-sensitive region in the future.

(2) Under future SSP scenarios, the spatial pattern of agricultural drought in China is projected to broadly retain the historical spatial differentiation, while inter-regional disparities are expected to intensify. In most agricultural regions, mean SPI3 values show

an overall increasing trend, indicating a general shift toward wetter conditions. Among them, the Loess Plateau, the Huang–Huai–Hai Plain, and the Northeast Plain exhibit the most pronounced wetting signals. However, South China continues to exhibit negative SPI characteristics under the SSP126 and SSP370 scenarios, suggesting a persistent drought risk. With increasing emission levels, regional response differences become more pronounced: some regions experience enhanced wetting, whereas others show aggravated drying under high-emission scenarios.

(3) Future drought trends exhibit big regional differences and scenario dependence. The Northeast Plain, Qinghai–Tibet Plateau, and northern arid and semi-arid regions generally show a persistent wetting trend across most scenarios, with the Northeast Plain exhibiting the strongest wetting signal under the long-term SSP370 scenario. In contrast, South China and the Middle and Lower Yangtze River Plain tend to experience significant drying under high-emission scenarios, particularly during the late period of SSP585, where drought risk increases markedly. Spatial analysis of drought deterioration areas further indicates that South China, the Loess Plateau, and the Middle and Lower Yangtze River region are likely to become the most prominent drought-expansion hotspots. In contrast, the Northeast Plain consistently maintains a strong wetting tendency.

(4) Factor decomposition analysis indicates that different mechanisms drive future drought states and drought evolution trends. Changes in mean SPI3 are primarily controlled by regional factors (58.34%) and climate model differences (31.15%), jointly explaining nearly 89% of the variance. This suggests that regional climatic background conditions and model-related uncertainties largely determine the spatial pattern of future agricultural drought. In contrast, SPI3 trend changes are mainly governed by the three-way interaction among Model $\times$ SSP $\times$ Period (28.12%), regional effects (27.04%), and the Model $\times$ SSP interaction (21.60%). This highlights the strong nonlinearity and complexity of future drought evolution, where interactions among climate models, emission pathways, and temporal stages play a dominant role.

Overall, agricultural drought in China is projected to exhibit a pattern of “general wetting with locally intensified drought risk” in the future. The Northeast Plain, the Huang–Huai–Hai Plain, and parts of plateau regions are likely to benefit from increased precipitation and become wetter, whereas South China and the Middle and Lower Yangtze River region may continue to face substantial drought risks under high-emission scenarios. Future agricultural water resource management and drought adaptation strategies should fully account for regional heterogeneity and scenario uncertainty and implement differentiated disaster prevention and water regulation measures in key drought-sensitive regions to enhance the resilience of agricultural systems to climate change.

Although SPI provides a standardized framework for comparing drought characteristics across different climate regions, uncertainties associated with precipitation distribution fitting and data variability may differ spatially, particularly between arid and humid regions. Future studies could further quantify SPI uncertainty using ensemble precipitation products, resampling methods, or multiple drought indicators to better characterize uncertainty propagation in large-scale drought assessments. In addition, future work could compare SPI with SPEI and soil moisture indicators to quantify the extent to which increasing atmospheric evaporative demand modifies projected drought severity across China’s major agricultural regions.

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