

The user wants me to translate a Chinese academic paper title and a note about it being a postprint. The title is: “Drought risk assessment and future scenario prediction in agricultural cropping zones of China” The note is: “后印本” which means “postprint” in academic publishing. The user has provi...

**Authors:** The user has provided a single name: “LIU Xiaohong” . This is a Chinese name that needs to be translated to English. The name is already in Pinyin format, which is the standard romanization system for Chinese names.

In Chinese names: - The family name (surname) comes first - The given name comes second

So “LIU” is the family name (刘) and “Xiaohong” is the given name (小红).

The translation of Chinese names to English typically follows these conventions:  
1. Keep the Pinyin as is  
2. Capitalize the family name and given name  
3. Optionally, the family name can be written in all caps or just capitalized

The user has provided the name as “LIU Xiaohong” which is already in the correct format. The family name is in all caps and the given name has only the first letter capitalized. This is a common and acceptable format for Chinese names in English academic contexts.

Since this is a name, there’s no Chinese text to translate inside tags. The user just provided a name. The instruction says “Translate from Simplified Chinese to English with the highest accuracy and academic tone.” and “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).”

The input is just “LIU Xiaohong” . This is already in English/Pinyin format. I should just return it as is. There’s no need to add any tags since the input doesn’t contain any. The instructions about preserving tags, LaTeX commands, etc., don’t apply here because the input is just a name.

The glossary mentions: 机器学习 => machine learning 深度学习 => deep learning

But these are not relevant to the input “LIU Xiaohong” .

So the output should simply be: LIU Xiaohong

Wait, let me re-read the instructions carefully. The user provided “LIU Xiaohong” as the input. The system prompt says I should translate from Simplified Chinese to English. But “LIU Xiaohong” is already a transliteration of a Chinese name into Latin letters (Pinyin).

Is there any ambiguity? Could “LIU Xiaohong” be considered Chinese text that needs translation? No, it’s already in the target format. The name “刘小红” in Chinese characters would be the actual Chinese text. But the user provided the Pinyin version.

The instructions say “Translate from, LIU Chunhui, The user has provided a single name:” FAN Jiejie” . This appears to be a Chinese name that needs to be translated or romanized.

In Chinese names: - The family name comes first: FAN (范) - The given name comes second: Jiejie (杰杰 or 浩浩 or other possibilities)

However, the user is asking me to translate from Simplified Chinese to English with academic tone, preserving LaTeX commands, citations, and tags. But the input is just a name.

Let me re-read the instructions carefully. The system prompt says: “Translate from Simplified Chinese to English with the highest accuracy and academic tone.”

But the input is just “FAN Jiejie” . This is a proper name. In academic contexts, Chinese names are typically: 1. Kept in their pinyin form (FAN Jiejie) 2. Sometimes written as “Jiejie Fan” (given name first, family name last) in Western contexts 3. The family name might be written in all caps to distinguish it: FAN Jiejie

The instructions mention: - Preserve ALL LaTeX commands and placeholders - Preserve ALL citation commands - **PRESERVE ALL …paragraph wrapper tags EXACTLY** - Maintain academic tone - Use precise technical terminology - Preserve section structure and paragraph organization

But there are no paragraphs, no LaTeX, no citations. It’s just a name.

The output rules say: - Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent). - Keep one output paragraph per input paragraph; do not merge or split paragraphs. - **Maintain exact count and IDs of …tags**

Since there’s no tag in the input, I should not add one. The input is just “FAN Jiejie” .

In academic translation, proper names are typically not translated but transliterated. “FAN Jiejie” is already in pinyin, which is the standard romanization

system.

Possible interpretations: 1. This could be a test to see if I follow the rules about not adding tags when none exist 2. This could be a fragment of a larger document 3. The user might want me to format this name in an academic style

Given the strict rules about preserving tags and not adding anything, The user has provided a name “QIU Chunxia” which appears to be a Chinese name. This is likely a fragment or a test input. Let me analyze what needs to be done:

1. The name “QIU Chunxia” is in Pinyin (Romanized Chinese)
2. The surname is QIU (邱) and given name is Chunxia (春霞)
3. In academic contexts, Chinese names are typically formatted in one of these ways:
  - QIU Chunxia (original order: surname + given name)
  - Chunxia Qiu (Western order: given name + surname)
  - QIU, Chunxia (with comma)

Given the context of academic paper translation and the critical requirements provided, I need to consider:

- The user might be testing if I understand how to handle names
- They might want me to translate/format this name for an academic paper
- The name itself doesn’ t contain any LaTeX, citations, or tags

Since the user hasn’ t provided any actual content with tags or LaTeX, and just gave a name, I should respond appropriately. However, looking at the instructions, they say “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).”

The input is just “QIU Chunxia” . This is already in Pinyin, which is the standard way to represent Chinese names in English academic papers. The translation would be the same, or possibly reordered to Western style.

But wait - the instructions are very specific about preserving tags, LaTeX, etc. Since there are none, I should just provide the name in an appropriate academic format. The most standard format for Chinese names in English academic papers is to keep the original order: QIU Chunxia.

Let me check the glossary - it doesn’ t mention name formatting. The critical requirements say to preserve all structural elements, but there are none here.

I think the most appropriate response is to simply return the name as is, since it’ s already in the standard academic format for English papers (Pinyin with surname first, capitalized). No tags are present, so I don’ t need to add them.

Actually, wait. Let me reconsider. The user might be providing a minimal test case to see if I follow the instructions correctly. The instructions say “Return ONLY the translated text for the given input” . The input is “QIU Chunxia, The user has provided a name” QIU Chunxia” which appears to be a Chinese

name. Based on the context of scientific translation, this is likely an author name that needs to be transliterated into English.

In academic contexts, Chinese names are typically transliterated using the Pinyin system, with the family name first followed by the given name. The standard format is: - Family name: QIU (邱) - Given name: Chunxia (春霞)

The proper academic transliteration would be “QIU Chunxia” (maintaining the capitalization of the family name) or sometimes “Qiu Chunxia” depending on journal style. Since the user provided it in all caps for the family name, I should preserve that format.

However, looking at the instructions more carefully, the user is asking me to translate from Simplified Chinese to English. The input “QIU Chunxia” is already in a transliterated form (Pinyin). There’ s no Chinese characters to translate here.

Wait, let me re-read the instructions. The user provided: “QIU Chunxia”

This is not wrapped in tags. It’ s just a name. The instructions say: - “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).” - “Preserve ALL …paragraph wrapper tags EXACTLY”

But there’ s no tag here. So what should I do?

The name “QIU Chunxia” is already in Pinyin, which is the standard romanization system for Chinese. In academic contexts, this would typically be kept as is, or sometimes formatted as “Chunxia Qiu” in Western order (given name first). However, the original input uses the Chinese order (family name first).

Given that: 1. This appears to be a name 2. It’ s already in Pinyin 3. The instructions emphasize preserving structure and not adding anything

I should probably just return the name as is, since it’ s already in a form suitable for English academic text. The capitalization suggests it’ s formatted for academic use (family name in caps).

But wait - maybe the user is testing if I understand that this is a name and should be kept as is? Or maybe they want me to convert it to Western order?

Let me think about typical academic translation practices: - Chinese names in academic papers are usually kept in Chinese order (family name first) when translated to English - The

**Date:** 2025-12-15T18:04:38+00:00

## Abstract

The user wants me to translate a scientific abstract from Simplified Chinese to English. Let me analyze the requirements:

### 1. Critical Requirements:

- Preserve ALL LaTeX commands and placeholders exactly
  - Preserve ALL citation commands ([?], ??, (??), etc.) exactly
  - **PRESERVE ALL ...paragraph wrapper tags EXACTLY**
  - Maintain academic tone and formal scientific writing style
  - Use precise technical terminology (glossary provided)
  - Preserve section structure and paragraph organization
  - Translate all content completely - no omissions
2. **Output Rules:**
- Return ONLY the translated text (no explanations, quotes, or invented headings)
  - Keep one output paragraph per input paragraph
  - **Maintain exact count and IDs of ...tags**
  - Do NOT add Markdown formatting unless present in source
  - Preserve original line breaks when meaningful; otherwise use standard English sentence spacing
3. **Formatting Guidelines:**
- Keep mathematical expressions in original LaTeX format
  - Preserve equation numbers and references
  - Maintain proper academic paragraph structure
  - Use formal scientific language
  - Never remove or modify ...tags
4. **Glossary:**
- 机器学习 => machine learning
  - 深度学习 => deep learning

Now, let me examine the input text. The user provided a paragraph that appears to be an academic abstract. However, I notice that the input text is already in English, not Chinese. Let me re-read it:

“With ongoing global climate change, drought has become the primary threat constraining food security in China. Traditional assessment frameworks based on administrative boundaries or macro-climatic zoning overlook variation in vulnerability affected by key agronomic practices, such as crop phenology and cropping systems, thereby limiting their accuracy. To address this research gap, this study developed and validated a novel drought risk assessment framework based on agricultural cropping zones (single-, double-, and triple-cropping zones). The framework coupled a Geographical and Temporal Neural Network Weighted Regression (GTNNWR) model for forecasting future crop vegetation dynamics with the Standardized Precipitation Evapotranspiration Index (SPEI) to assess drought risk under historical (2001-2020) and projected future (2021-2100) scenarios. The GTNNWR model achieved R2 values ranging from 0.72 to 0.82 and RMSE values between 0.11 and 0.14 for NDVI prediction, significantly outperforming conventional models. Historical drought risk assessment revealed that drought events were most frequent during summer and concentrated in single-cropping and double-cropping zones. Future projections indicate a substantial intensification of drought risk. Under the Shared Socioeconomic Pathway (SSP)126 scenario, drought risk is projected to increase in the triple-

cropping zones of the middle and lower reaches of the Yangtze River Plain. Under the SSP245 scenario, the frequency of spring and winter droughts is anticipated to rise markedly. Under the SSP585 scenario, drought intensity is projected to intensify in central-eastern single-cropping zones and southwestern double-cropping zones. This assessment framework based on agricultural cropping zones can precisely identify drought risks and facilitate adaptation in agricultural management, such as optimizing irrigation systems and adjusting crop structures.”

This is already English. But the user is asking me to translate from Simplified Chinese to English. This is confusing. Let me check if there might be some Chinese text that I'm missing. The user message starts with “With ongoing global climate change…” which is clearly English.

Wait, maybe the user made a mistake and provided English text instead of Chinese. Or perhaps this is a test to see if I correctly identify that no translation is needed. However, the instructions are very specific about preserving tags, LaTeX, etc., and the glossary mentions 机器学习 and 深度学习, which don't appear in the text.

Let me re-read the user's prompt carefully. The user says: “Translate from Simplified Chinese to English with the highest accuracy and academic tone.” But the provided text is in English.

I have two options: 1. Point out that the text is already in English and no translation is needed 2. Assume there might be a mistake and that I should wrap this English text in tags as specified

Looking at the requirements again, they emphasize preserving …tags. The input doesn't have any such tags. This suggests that maybe the user expects me to add them? But that contradicts

## Full Text

### Preamble

**Journal of Arid Land** (2025) 17(12): 1694–1718  
doi: 10.1007/s40333-025-0113-8; CSTR: 32276.14.JAL.02501138  
Science Press Springer-Verlag

### **Drought Risk Assessment and Prediction in Agricultural Cropping Zones of China Under Future Scenarios**

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**Abstract:** With ongoing global climate change, drought has become the primary threat constraining food security in China. Traditional assessment frameworks based on administrative boundaries or macro-climatic zoning overlook variation in vulnerability affected by key agronomic practices, such as crop phenology and cropping systems, thereby limiting their accuracy. To address this research gap, this study developed and validated a novel drought risk assessment framework based on agricultural cropping zones (single-, double-, and triple-cropping zones). The framework coupled a Geographical and Temporal Neural Network Weighted Regression (GTNNWR) model for forecasting future crop vegetation dynamics with the Standardized Precipitation Evapotranspiration Index (SPEI) to assess drought risk under historical (2001–2020) and projected future (2021–2100) scenarios. The GTNNWR model achieved  $R^2$  values ranging from 0.72 to 0.82 and RMSE values between 0.11 and 0.14 for NDVI prediction, significantly outperforming conventional models. Historical drought risk assessment revealed that drought events were most frequent during summer and concentrated in single-cropping and double-cropping zones. Future projections indicate a substantial intensification of drought risk. Under the Shared Socioeconomic Pathway (SSP)126 scenario, drought risk is projected to increase in the triple-cropping zones of the middle and lower reaches of the Yangtze River Plain. Under the SSP245 scenario, the frequency of spring and winter droughts is anticipated to rise markedly. Under the SSP585 scenario, drought intensity is projected to intensify in central–eastern single-cropping zones and southwestern double-cropping zones. This assessment framework based on agricultural cropping zones can precisely identify drought risks and facilitate adaptation in agricultural management, such as optimizing irrigation systems and adjusting crop structures.

**Keywords:** climate change; agricultural cropping zone; Geographical and Temporal Neural Network Weighted Regression (GTNNWR) model; Standardized Precipitation Evapotranspiration Index (SPEI); run theory; drought risk assessment

**Citation:** LIU Xiaohong, LIU Chunhui, FAN Jiejie, QIU Chunxia. 2025. Drought risk assessment and future scenario prediction in agricultural cropping zones of China. *Journal of Arid Land*, 17(12): 1694–1718. <https://doi.org/10.1007/s40333-025-0113-8>; <https://cstr.cn/32276.14.JAL.02501138>

## 1 Introduction

Amid intensifying global climate change, extreme climate events have become increasingly frequent, and drought now poses a major threat to agricultural production (Vicente-Serrano et al., 2020). Recent research indicates that the frequency and intensity of drought events will continue to increase in the future, posing particularly significant risks for arid and semi-arid areas (Vicente-Serrano

et al., 2022; Yang et al., 2022). In China, a major agricultural nation, drought has become a critical constraint on food security. According to the World Meteorological Organization, drought is responsible for 55.0% of China's economic losses from meteorological disasters and results in an annual reduction of over  $0.5 \times 10^{11}$  kg of food (Jia et al., 2022; Cai et al., 2023). These alarming data highlight the urgent need for comprehensive drought risk assessment and adaptive management.

Crop vegetation, a vital component of terrestrial ecosystems, plays an essential role in energy transfer and material cycling (Yu et al., 2021; Ren et al., 2025) and contributes significantly to soil and water conservation (Ullah et al., 2025). The Normalized Difference Vegetation Index (NDVI) is widely used as a quantitative indicator of crop vegetation status. NDVI is often coupled with robust meteorological drought indices to monitor the impact of drought on crop vegetation. Among these, the Standardized Precipitation Evapotranspiration Index (SPEI) is particularly valuable. Unlike indices based solely on precipitation, SPEI incorporates potential evapotranspiration and thus provides a more comprehensive measure of water balance (Peng et al., 2024). Coupling the analysis of NDVI with drought indices enables accurate assessment of the effects of drought stress on agricultural ecosystems. For example, Ma et al. (2023) employed SPEI to identify drought events and then tracked NDVI anomalies to evaluate vegetation resistance and resilience. He et al. (2024) analyzed correlations of multi-scalar SPEI with NDVI and identified significant time-lag effects of meteorological drought on the vegetation response. Wu et al. (2024) utilized correlation analysis between NDVI and multi-timescale SPEI to analyze variation in the drought sensitivity of different vegetation types and showed that forests and croplands respond to different SPEI timescales. Within agricultural ecosystems, these response metrics (sensitivity, resistance, and resilience) are not uniform, as they are governed by the specific characteristics of the cropping system itself, such as crop phenology, irrigation practices, and rotation schedules.

Existing drought assessment frameworks fail to capture these variations in vegetation response driven by agricultural systems, largely because they depend on rigid administrative boundaries (Zhao et al., 2020) or macro-climatic zoning (Yu et al., 2022). For example, administrative boundaries cannot distinguish between differences in the drought sensitivities of single-cropping and double-cropping systems within the same province (Gao et al., 2019). Similarly, while macro-climatic zoning reflects regional climatic patterns, it overlooks the agronomic practices that fundamentally determine drought vulnerability at the field scale (Yu et al., 2022). A classification based on agricultural cropping zones (i.e., single-, double-, and triple-cropping zones) directly accounts for critical human-managed factors, such as crop phenology and rotation schedules, that dictate a region's vulnerability to water deficits (Han et al., 1986). There is thus an urgent need to develop an assessment framework grounded in agricultural cropping classification to enhance the precision of drought risk identification.

Accurately predicting NDVI across diverse agricultural zones presents a significant methodological challenge, as the drivers of crop vegetation growth are characterized by high spatio-temporal non-stationarity. This complexity arises from both geographical heterogeneity (spatial non-stationarity) and the varied phenological cycles inherent to different cropping systems (temporal non-stationarity). Traditional models struggle to capture this duality. For example, Geographically Weighted Regression (GWR) effectively captures spatial heterogeneity (Zhao et al., 2015) but fails to integrate temporal dynamics. Conversely, deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM) can model temporal trends (Scarpa et al., 2018; Zhao et al., 2019) but often struggle to handle complex and localized spatial non-stationarity (Han et al., 2024). While recent hybrid architectures attempt to improve drought propagation modeling or integrate multivariate features (Long et al., 2024), they still face limitations in dynamically and simultaneously weighting both spatial and temporal dependencies. The Geographically and Temporally Neural Network Weighted Regression (GTNNWR) model was developed to overcome these limitations (Wu et al., 2021). GTNNWR innovatively integrates neural networks with geographical regression, using a Spatio-temporal Proximity Neural Network (STPNN) to generate dynamic weights. This structure is specifically designed to address spatio-temporal non-stationarity. Its high performance in scenarios with strong spatio-temporal dependence makes it an ideal approach for modeling complex crop vegetation and climate interactions within diverse agricultural cropping zones of China.

To project these zone-specific drought and vegetation-response risks into the future, we combined the robust predictive model with reliable climate projection data. General Circulation Models (GCMs) provide this foundation. Here, we utilized outputs from the Coupled Model Intercomparison Project 6 (CMIP6) (Chen et al., 2019). CMIP6 models show significant improvements over previous iterations, including higher resolution and more sophisticated physical process representations, resulting in higher accuracy in reproducing historical temperature and precipitation patterns (Bock et al., 2020; Wang et al., 2025b). Furthermore, CMIP6 introduces the Shared Socioeconomic Pathways (SSPs), providing a comprehensive and reliable data source for assessing future drought risks under a range of plausible socioeconomic and climatic conditions.

While previous studies have examined patterns of drought risk assessment, a clear gap exists in research that integrates a fine-grained spatial framework (agricultural cropping zones) with advanced spatio-temporal models (GTNNWR) to assess future drought risk using the latest climate projections (CMIP6). Therefore, the primary objectives of this study are to: (1) propose and validate a drought risk assessment framework based on agricultural cropping zones, overcoming the limitations of traditional administrative or climatic divisions; (2) apply the GTNNWR model to predict future NDVI changes and evaluate its performance in capturing complex spatio-temporal non-stationarity compared with conventional deep learning models; and (3) quantify spatio-temporal heterogeneity in drought frequency, intensity, and duration across three major

cropping zones by characterizing drought risk characteristics and their evolution under different scenarios.

This study not only provides a refined and systematic scientific basis for identifying agricultural drought risks and managing adaptation in China; its assessment framework, which is built upon agricultural cropping-zone stratification, and the successful application of the GTNNWR model also offer a methodological reference for other agricultural zones worldwide, particularly those characterized by complex cropping systems and pronounced spatio-temporal heterogeneity. This research framework possesses strong transferability and scalability potential, and is capable of supporting international efforts in agricultural climate risk early warning, crop adaptation planning, and food security strategy formulation, holding significant regional and global implications.

## 2.1 Study Area

This study focused on the agricultural cropping zones of China. As one of the major agricultural producers globally, China possesses diverse climatic zones and complex cropping systems, making it an ideal region for investigating agricultural drought risks under climate change. China exhibits pronounced regional heterogeneity in precipitation, temperature, soil composition, and water resource distribution, which directly affect the distribution of arable land and the potential for agricultural production (Liao et al., 2021; Ma et al., 2021; Yin et al., 2023). Specific cropping system frameworks have been developed in various regions on the basis of interplay between climatic conditions and resource constraints, providing a scientific foundation for the classification of agricultural cropping zones. We adopted the scheme proposed by Han et al. (1986), in which the agricultural regions of China are divided into three primary agricultural cropping zones (single-, double-, and triple-cropping zones) (Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 2005; Wang et al., 2021b) (Fig. 1 [Figure 1: see original paper]). The boundaries of these cropping systems were determined on the basis of key thermal indicators governing cultivation potential (Table 1). The selection of these specific variables was based on their critical roles in crop physiology and phenology. The Active Accumulated Temperature  $\geq 0.0^{\circ}\text{C}$  (AAT0) served as the primary indicator, representing the total heat resources available during the potential growing season. The Extreme Minimum Temperature (EMT) was a key auxiliary indicator, determining the viability of overwintering crops and thus fundamentally limiting systems to a single harvest in severe cold regions. The period of  $20.0^{\circ}\text{C}$  termination was another crucial auxiliary indicator, defining the safe growing period for thermophilic crops (e.g., late rice), which is a prerequisite for successful triple cropping. This classification reflects spatial differences in climate and resource endowments and provides the spatial framework for drought-risk analysis.

Additionally, the non-agricultural zones depicted in white in Figure 1 encompass pastures, forestry areas, and other non-arable land. It is important to note that

the boundaries of these agricultural cropping zones and non-agricultural zones were assumed to remain static throughout the entire study period, encompassing both the historical (2001-2020) and future projection (2021-2100) phases.

**Fig. 1** Overview of the study area. Note that the map is based on the standard map (GS(2024)0650) of the National Platform for Common GeoSpatial Information Services (<https://cloudcenter.tianditu.gov.cn/>) marked by the Ministry of Natural Resources of the People' s Republic of China, and the boundary of the base map has not been modified.

**Table 1** Indicators for the classification of different agricultural cropping zones in China

Zoning system	AAT0 (°C)	EMT (°C)	Period of 20.0°C termination	Agricultural significance
Single-cropping	<4000-4200	< -20.0	Early August-early September	One growing season per year
Double-cropping	>4000-4200	> -20.0	Early September-late September	Two growing seasons per year
Triple-cropping	>5900-6100	> -20.0	Late September-early November	Three growing seasons per year

*Note: AAT0, Active Accumulated Temperature  $\geq 0.0^{\circ}\text{C}$ ; EMT, Extreme Minimum Temperature.*

## 2.2 Data Acquisition and Processing

The data employed in this study comprise primarily historical data (2001-2020) and future projection data (2021-2100) (Table 2 ). All datasets were resampled to a  $0.5^{\circ}\times 0.5^{\circ}$  resolution via bilinear interpolation to ensure spatial consistency. Historical data encompassed NDVI and meteorological variables. NDVI data were used to characterize crop vegetation dynamics during the historical period; meteorological variables included relative humidity, surface solar radiation, surface wind speed, potential evapotranspiration, precipitation, and temperature, all of which are closely correlated with NDVI (Tuoku et al., 2024). Given that invalid or redundant input data may constitute a primary source of error in neural networks, we used Pearson correlation analysis to exclude two factors exhibiting weak correlations (surface solar radiation and surface wind speed) (Fig. 2 [Figure 2: see original paper]). The remaining four meteorological factors (relative humidity, precipitation, temperature, and potential evapotranspiration) were retained as core input variables for the GTNNWR model.

**Table 2** Datasets used in this study

Data type	Variable	Data source	Spatial resolution	Temporal resolution	Period
Historical NDVI	NDVI	United States Geological Survey ( <a href="https://lpdaac.usgs.gov/">https://lpdaac.usgs.gov/</a> )	0.0083333°	Month	2001-2020
Historical climate	Relative humidity, Surface solar radiation, Surface wind speed, Potential evapotranspiration, Precipitation, Temperature	National Tibetan Plateau/Third Pole Environment Data Center ( <a href="http://data.tpdc.ac.cn/">http://data.tpdc.ac.cn/</a> )	0.1°	Month	2001-2020
CMIP6 data	Relative humidity, Precipitation, Temperature, Potential evapotranspiration	CMIP6 (BCC-CSM2-MR) from Copernicus Climate Change Service ( <a href="https://cds.climate.copernicus.eu/">https://cds.climate.copernicus.eu/</a> )	1.125°	Month	2021-2100

*Note: NDVI, Normalized Difference Vegetation Index; CMIP6, Coupled Model Intercomparison Project 6; BCC-CSM2-MR, Beijing Climate Center-Climate System Model 2-Medium Resolution.*

**Fig. 2** Heat map of Pearson correlation coefficients between NDVI and multiple meteorological factors. NDVI, Normalized Difference Vegetation Index; r, correlation coefficient; \*\*, significance at  $P < 0.01$  level.

Future projection data were sourced from the CMIP6 BCC-CSM2-MR model, which includes the four core variables previously identified (relative humidity, precipitation, temperature, and potential evapotranspiration). This model participates in the HighResMIP initiative and has demonstrated high reliability in simulating China's climate. We selected outputs from three SSPs: SSP126 (low emissions), SSP245 (medium emissions), and SSP585 (high emissions). These future meteorological datasets served two primary purposes: (1) as inputs for the pre-trained GTNNWR model to predict future NDVI and (2) for calculating future SPEI values to assess projected drought risks.

## 2.3 Research Methods

In this study, we proposed an integrated drought risk assessment framework to evaluate drought risks and crop vegetation responses across three agricultural zones of China under historical (2001-2020) and future (2021-2100) scenarios (Fig. 3 [Figure 3: see original paper]). The workflow is as follows:

**Step 1:** Train and validate the GTNNWR model using historical meteorological data (relative humidity, precipitation, temperature, and potential evapotranspiration) and NDVI data from 2001 to 2020, then utilize future CMIP6 meteorological data (relative humidity, precipitation, temperature, and potential evapotranspiration) (2021-2100) to predict future NDVI.

**Step 2:** Determine the crop vegetation response time to drought based on 2001-2020 NDVI data and multi-scale SPEI data.

**Step 3:** Employ the optimal SPEI timescale data to identify historical and future drought events using three-threshold run theory.

**Step 4:** Integrate predicted NDVI values with identified drought event characteristics to assess spatio-temporal drought risks in agricultural cropping zones under future scenarios.

**Fig. 3** Workflow of the drought risk assessment in this study. GTNNWR, Geographically and Temporally Neural Network Weighted Regression; TR, time resolution; SR, spatial resolution; CMIP6, Coupled Model Intercomparison Project 6; SPEI, Standardized Precipitation Evapotranspiration Index.

### 2.3.1 GTNNWR Model Training and NDVI Prediction

In this study, we employed historical meteorological data and corresponding historical NDVI data from 2001 to 2020 to train and validate the GTNNWR model. We used data from 2001 to 2015 for training and data from 2016 to 2020 for validation. The GTNNWR model is a regression model whose coefficients vary continuously in both space and time. This model integrates an Ordinary Linear Regression (OLR) model, a Spatio-temporal Weighted Neural Network (STWNN), and several STPNNs (Fig. 4 [Figure 4: see original paper]).

The regression coefficients of the OLR model represent the best unbiased estimates for all sample points (Wu et al., 2021):

$$y_i = \beta_0^{OLR} + \sum_{k=1}^p \beta_k^{OLR} x_{ik} + \varepsilon_i$$

where  $y_i$  and  $x_{ik}$  denote the dependent variable (NDVI) and the  $k$ th independent variable (relative humidity, precipitation, temperature, and potential evapotranspiration), respectively;  $\beta_0^{OLR}$  and  $\beta_k^{OLR}$  represent the constant coefficient and the regression coefficient for the  $k$ th independent variable, respectively;  $\omega_0(u_i, v_i, t_i)$  and  $\omega_k(u_i, v_i, t_i)$  denote the spatio-temporal non-stationary weights for  $\beta_0^{OLR}$  and  $\beta_k^{OLR}$ , respectively;  $u_i, v_i$ , and  $t_i$  are the longitude, latitude, and time point of the estimated point  $x_i$ ;  $p$  denotes the number of independent variables;  $n$  represents the total number of samples; and  $\varepsilon_i$  is the error term.

Since the OLR coefficients reflect a global average relationship within the study area, spatio-temporal non-stationarity can be regarded as fluctuations of this average relationship. Based on this assumption, the spatially and temporally varying coefficients were defined as the product of the OLR estimates and the corresponding spatio-temporal weights. Substituting the OLR estimates into the equation above, the estimated value  $\hat{y}_i$  (predicted NDVI) in matrix form is:

$$\hat{y}_i = \mathbf{X}^\top \mathbf{W}(u_i, v_i, t_i) \beta^{OLR}$$

where  $\top$  is the transpose operator;  $\mathbf{X}$  denotes the independent variable matrix;  $\mathbf{W}(u_i, v_i, t_i)$  is the spatio-temporal weight matrix, defined as follows (Wu et al., 2021):

$$\mathbf{W}(u_i, v_i, t_i) = \text{diag}[\omega_0(u_i, v_i, t_i), \omega_1(u_i, v_i, t_i), \dots, \omega_p(u_i, v_i, t_i)]$$

where  $\omega_p(u_i, v_i, t_i)$  denotes the weight value of the  $p$ th independent variable. The spatio-temporal weight matrix  $\mathbf{W}(u_i, v_i, t_i)$  is determined by the number of input samples  $n$  and the number of independent variables  $p$ .

The core of the GTNNWR model lies in incorporating temporal distance into the Spatial Weighted Neural Network (SWNN), thereby creating a STWNN that accounts for both spatial and temporal distances. Similar to the method by which GTNNWR calculates spatial distances and weights, the STWNN computes a spatio-temporal weight matrix as follows (Wu et al., 2021):

$$\mathbf{W}_{STWNN} = f(\mathbf{d}_{ST})$$

where  $\mathbf{d}_{ST}$  denotes the spatio-temporal distance from estimated points  $i$  to the training samples. To calibrate the STWNN, the spatio-temporal proximity was

generated via the STPNN based on spatial distance  $d_{ij}^S$  and temporal distance  $d_{ij}^T$ , as follows (Wu et al., 2021):

$$\mathbf{d}_{ST} = \text{STPNN}(d_{ij}^S, d_{ij}^T)$$

When the proximity vector has length 1, it may be regarded as the spatio-temporal distance  $d_{ij}^{ST}$ . The fitted values are then:

$$\hat{\mathbf{y}} = \mathbf{S}\mathbf{y}$$

where  $\mathbf{S}$  is the hat matrix of the GTNNWR model.

To validate the accuracy of the GTNNWR model in NDVI regression prediction, we compared the prediction results obtained from eXtreme Gradient Boosting (XGBoost), CNN, LSTM, and GTNNWR. The selection of these comparative models has demonstrated effectiveness in NDVI prediction and spatio-temporal modeling. For instance, Li et al. (2021) applied XGBoost to monthly NDVI prediction over China, achieving high explanatory power. Cui et al. (2020) used a CNN-based architecture to forecast NDVI in multiple complex regions. Sun et al. (2023) used a Bidirectional Long Short-Term Memory (BiLSTM) network to simulate large-scale NDVI dynamics from meteorological inputs. We implemented all comparison models within the RStudio environment and executed them using relevant v.4.4.1 R packages. We computed two performance metrics via comparison of the predicted values with the actual values: Coefficient of Determination ( $R^2$ ) and Root Mean Squared Error (RMSE). We employed these two indicators to evaluate the regression and prediction accuracy of the models.

The two performance indicators were calculated using the following formulas (Wu et al., 2021):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where  $\bar{y}$  denotes the mean value of NDVI for all sample points. Following successful model validation, we input CMIP6 meteorological data for three scenarios spanning from 2021 to 2100 into the trained GTNNWR model to forecast future variation in NDVI under different scenarios.

**Fig. 4** Schematic diagram of GTNNWR model solution process. The red dashed box is the Spatio-temporal Proximity Neural Network (STPNN), and the blue dashed box is the Spatio-temporal Weighted Neural Network (STWNN).

OLR, Ordinary Linear Regression;  $P_i$ , any point in space-time requiring estimation;  $d_{ij}^S$ , the spatial distance between the estimated point and all other points in the training dataset;  $d_{ij}^T$ , the temporal distance between the estimated point and all other points in the training dataset;  $h$ , neural network hidden layer nodes;  $q$  and  $m$ , different hidden layer indices in STPNN;  $d_{ij}^{ST}$ , the temporal and spatial distance between the estimated point and all other points in the training dataset;  $\omega_{ip}$ , spatio-temporal non-stationary weights corresponding to the estimated points;  $\beta_p$ , global regression coefficients estimated by the OLR model;  $x_{ip}$ , the independent variable corresponding to the estimated point (relative humidity, precipitation, temperature, and potential evapotranspiration);  $\hat{y}_i$ , the final estimated value of the model.

### 2.3.2 Response Time of Crop Vegetation to Drought

We employed monthly precipitation and monthly potential evapotranspiration data to compute the SPEI for both historical (2001-2020) and future (2021-2100) periods (Liu et al., 2021):

$$D_T = P_T - ET$$

where  $D_T$  denotes the climate water balance (mm);  $P_T$  denotes precipitation (mm); and  $ET$  denotes potential evapotranspiration (mm). Given the potential presence of negative values within the original data series, the  $D_T$  data series were normalized using a three-parameter ( $\alpha$ ,  $\phi$ ,  $\gamma$ ) log-logistic probability distribution, and the corresponding SPEI index was calculated for each value (Wang et al., 2024a):

$$F(D_T) = \left[ 1 + \left( \frac{\alpha}{D_T - \gamma} \right)^\phi \right]^{-1}$$

where  $F(D_T)$  denotes the cumulative probability function;  $\alpha$ ,  $\phi$ , and  $\gamma$  represent the scale parameter, shape parameter, and location parameter, respectively. Finally, the cumulative probability density was normalized (Wang et al., 2024a):

$$L = \begin{cases} F(D_T) & \text{if } F(D_T) \leq 0.5 \\ 1 - F(D_T) & \text{if } F(D_T) > 0.5 \end{cases}$$

When the cumulative probability  $L < 0.5$ , the standardized variable  $\theta$  is computed as (Wang et al., 2024a):

$$\theta = \sqrt{-2 \ln(L)}$$

$$\text{SPEI} = \theta - \frac{c_0 + c_1\theta + c_2\theta^2}{1 + d_1\theta + d_2\theta^2 + d_3\theta^3}$$

In this study, we employed Pearson correlation analysis to determine the response time, equal to a month, corresponding to the maximum correlation coefficient between the SPEI at diverse timescales and the monthly NDVI. Correlation analysis of the monthly NDVI and SPEI series in the  $q$ th month of the year was performed as follows (Ma et al., 2023):

$$r_{q,m} = \text{corr}(\text{NDVI}_q, \text{SPEI}_{q,m}) \quad \text{for } m \in \{1, 3, 6, 9, 12\}$$

where  $r_{q,m}$  denotes the correlation coefficient; and  $m$  denotes different temporal scales. NDVI reflects crop vegetation growth, while SPEI across various temporal scales indicates drought resulting from cumulative water deficits over preceding months. A higher correlation between the two indicates more severe water deficits at that timescale and poorer vegetation growth, suggesting that crop vegetation growth is more sensitive to drought at that particular timescale. A higher  $r$  value indicates greater sensitivity of crop vegetation growth to drought, and vice versa. Ultimately, the SPEI timescale yielding the maximum  $r$  value was regarded as the response time for crop vegetation to drought.

### 2.3.3 Identifying Drought Events Using Run Theory

To identify specific drought events from the continuous SPEI time series, we employed run theory. Run theory is a widely used and robust method for analyzing time series data to extract events based on specific criteria (Ma et al., 2023). Its primary advantage lies in the ability to objectively define the key characteristics of an event based on predefined thresholds, particularly its occurrence, conclusion, duration, and severity. This allows for a more comprehensive analysis than simple time-step assessments. We adopted the three-threshold run theory approach to identify a series of drought events. Using SPEI as the drought index, we extracted the drought event sequence for each grid cell through the following steps (He et al., 2015): (1)  $R_0$  is the threshold for merging adjacent drought events,  $R_1$  is the threshold for drought onset, and  $R_2$  is the threshold for excluding minor drought events. Drought occurrence was defined when the SPEI value falls below  $R_1$ . For example, as illustrated in Figure 5 [Figure 5: see original paper], six candidate drought events (labeled a, b, c, d, e, and f) were identified. (2) If the SPEI value of a preliminary drought event with a one-month duration fell below  $R_2$ , that event was considered a minor drought and was eliminated. In the example presented in Figure 5, drought event a was removed from the list of candidate events, leaving five candidate drought events (b, c, d, e, and f). (3) If two adjacent drought events were separated by only one month and the SPEI value during the intervening month was below  $R_0$ , they were merged. As illustrated in Figure 5, the interval g between drought events

b and c exhibits an SPEI value below  $R_0$ , resulting in the merging of b and c. This process ultimately yielded four distinct drought events: b-c, d, e, and f.

Based on He et al. (2016), we set the thresholds as follows:  $R_0 = 0.10$ ,  $R_1 = -0.50$ , and  $R_2 = -0.65$ .

**Fig. 5** Drought event identification based on the three-threshold run theory method. Black shading area indicates a one-month interval between two consecutive drought events; grid shading area denotes events flagged as potential droughts following preliminary screening.  $R_0$ , the threshold for merging adjacent drought events;  $R_1$ , the threshold for drought onset;  $R_2$ , the threshold for excluding minor drought events; a, b, c, d, e, and f denote the identified candidate drought events; g denotes that two adjacent drought events were separated by only one month, and the SPEI value during the intervening month was below  $R_0$ ; h denotes that two adjacent drought events were separated by only one month, but the SPEI value during the intervening month was above  $R_0$ .

After identifying the drought events, we quantified their key characteristics. For each grid cell, we calculated three primary metrics for both the historical (2001–2020) and future (2021–2100) periods: the count, average duration, and average intensity of drought events.

### 2.3.4 Comprehensive Drought Risk Assessment

To analyze the spatio-temporal evolution of drought risk, we aggregated the count, average duration, and average intensity of drought events under historical and future scenarios by seasons (spring, summer, autumn, and winter). We then mapped their spatial distributions to compare drought risk trends across the different agricultural cropping zones and climate scenarios.

Finally, to specifically quantify the future crop vegetation response to drought, we conducted a pixel-wise Pearson correlation analysis. This analysis correlated the future NDVI time series with the future SPEI time series. We subjected the resulting correlation coefficients to a significance test ( $P < 0.05$ ) to identify regions where the future relationship between crop vegetation and drought is statistically significant.

## 3.1 NDVI Prediction and Error Analysis

We validated the predictive performance of the GTNNWR model using a dataset spanning from 2016 to 2020, comparing it against three conventional models: XGBoost, CNN, and LSTM. We assessed model performance quantitatively using  $R^2$  and RMSE (Fig. 6 [Figure 6: see original paper]). The GTNNWR model consistently demonstrated superior performance across all seasons. It achieved the highest  $R^2$  values, ranging from 0.72 to 0.82, and the lowest RMSE values, ranging from 0.11 to 0.14. In contrast, traditional models exhibited markedly lower accuracy and higher error rates. XGBoost yielded  $R^2$  values of 0.60–0.66 and RMSE values of 0.15–0.18; the performance of CNN was similar,

with  $R^2$  values of 0.53–0.62 and RMSE values of 0.16–0.20.  $R^2$  values and RMSE values for LSTM were 0.59–0.65 and 0.15–0.19, respectively.

**Fig. 6** Performance of GTNNWR (a1–a4), eXtreme Gradient Boosting (XGBoost) (b1–b4), Convolutional Neural Networks (CNN) (c1–c4), and Long Short-Term Memory (LSTM) (d1–d4) models in predicting NDVI for four seasons. The black dashed line represents the ideal 1:1 reference line, while the red solid line denotes the regression fit line between the predicted NDVI and the actual NDVI.

### 3.2 Temporal and Spatial Variation in NDVI Under Historical and Future Scenarios

Based on the GTNNWR model and CMIP6 multi-scenario data, we projected future NDVI values under three scenarios. We analyzed the historical evolution of NDVI across different agricultural cropping zones and examined its response characteristics under projected future climate change.

Figure 7 [Figure 7: see original paper] illustrates the time series trends of annual mean NDVI in different agricultural cropping zones during the historical period (2001–2020) and under three future scenarios (SSP126, SSP245, and SSP585) for 2021–2100; and Figure 8 [Figure 8: see original paper] shows the regional differentiation patterns. The results indicated that, during the historical period, NDVI in different agricultural cropping zones exhibited an overall upward trend, with the triple-cropping zones showing the fastest growth rate of 0.0503/10a. NDVI in certain areas of the northeastern single-cropping zones, the central and western double-cropping zones, and the northern triple-cropping zones exhibited an upward trend. NDVI in certain areas of the northern single-cropping zones, the southwestern Qinghai-Xizang Plateau, and the eastern double-cropping zones exhibited a declining trend (Fig. 8).

Future projections reveal distinct differences in NDVI evolution among the three scenarios (Figs. 7b–d and 8). Under the SSP126 scenario, the overall NDVI trend shows noticeable fluctuations without a clear long-term upward trajectory (Fig. 7b). However, the spatial patterns reveal additional information that is not evident from the time-series curves alone. As shown in Figure 8b1–b4, the central part of the single-cropping zones experiences a clear increase in NDVI during the early and middle 21st century (2021–2060). In the latter half of the century (2061–2080), large portions of the single-cropping and double-cropping zones demonstrate significant NDVI increases, particularly in the central part of the single-cropping zones, the eastern Northeast Plain, and the double-cropping zones in the southwestern Sichuan Basin. Under the SSP245 scenario, NDVI shows a more evident and sustained rise than that under the SSP126 scenario (Fig. 8c1–c4). Most double-cropping zones show an upward trend in NDVI, with particularly significant increases in the central and eastern zones. Under the SSP585 scenario, NDVI growth is accelerated compared with the previous two scenarios, with the most rapid increases primarily concentrating in the central single-cropping zones, the central-western double-cropping zones, and

most areas of the triple-cropping zones.

**Fig. 7** Temporal trend in annual mean NDVI in agricultural cropping zones of China. (a) Historical trends from 2001 to 2020; (b-d) Projected future trends from 2021 to 2100 for the (b) single-, (c) double-, and (d) triple-cropping zones under three shared socioeconomic pathway (SSP) scenarios.

**Fig. 8** Spatial variation in annual mean NDVI in different cropping zones in China from 2001 to 2020 (a) and 2021-2100 under the SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios.

### 3.3 Correlation Between NDVI and SPEI at Different Time Scales

Figure 9a-e [Figure 9: see original paper] shows the correlation between NDVI and SPEI at different time scales. SPEI-1, SPEI-3, SPEI-6, SPEI-9, and SPEI-12 represent SPEI calculated at 1.0-, 3.0-, 6.0-, 9.0-, and 12.0-month scales, respectively. Positive correlations were observed in most areas at all timescales. Regions where NDVI and SPEI were negatively correlated were primarily located in the Xinjiang Uygur Autonomous Region in the northwestern portion of the single-cropping zones and the southwestern Qinghai-Xizang Plateau, where high-altitude climates may adversely affect crop vegetation. As the time scale increased, the areas exhibiting significant NDVI-SPEI correlations expanded markedly. These regions were primarily situated in the central and western single-cropping zones, the western double-cropping zones, and triple-cropping zones.

The response time is determined by comparing the density distributions of correlation coefficients at various time scales (Fig. 9f [Figure 9: see original paper]). The average  $r$  is computed as the mean of the correlation coefficients across the various time scales. The average  $r$  increased for SPEI-1 and peaked for SPEI-12. Therefore, the response time of crop vegetation to drought was determined to be 12.0 months.

**Fig. 9** Spatio-temporal analysis of the correlation between monthly NDVI and SPEI across multiple time scales from 2001 to 2020. (a-e) Spatial distribution of the correlation between SPEI-1 (a), SPEI-3 (b), SPEI-6 (c), SPEI-9 (d), and SPEI-12 (e) and monthly NDVI; (f) Density distribution of correlation coefficient at different time scales. Black dots in Figure 9a-e indicate significant correlations at  $P < 0.05$  level, and  $r$  denotes the correlation coefficient.

### 3.4 Spatial Distribution of Drought Events in Different Seasons Under Historical and Future Scenarios

Based on the SPEI-12 index and the three-threshold run theory identification method, we characterized the patterns of spatio-temporal differentiation and the evolution of seasonal drought events across different agricultural cropping zones during the historical period and under three future scenarios (SSP126,

SSP245, and SSP585) (Figs. 10–13 [Figure 10: see original paper][Figure 11: see original paper][Figure 12: see original paper][Figure 13: see original paper]). Drought risk in different agricultural cropping zones displayed marked heterogeneity across both spatial and temporal dimensions; observed changes also vary markedly under different climate scenarios.

From 2001 to 2020, the frequency of drought events was highest in summer, followed by autumn, spring, and winter (Fig. 10 [Figure 10: see original paper]). Summer drought events were frequent and predominantly concentrated in the Hetao Plain of the central single-cropping zones and the central-western area of the double-cropping zones. In contrast, autumn drought events primarily occurred in the transition zones separating the single-cropping and double-cropping zones, as well as between the double-cropping and triple-cropping zones.

Drought events exhibited the longest average duration in winter, followed by autumn, spring, and summer. In winter, particularly in the single-cropping and double-cropping zones, drought events generally persisted throughout the season. Conversely, summer droughts tended to be short-lived, with most events lasting approximately 1.5 months. The average intensity of drought events was relatively similar across the four seasons; regions experiencing higher drought intensity were primarily located in the western single-cropping zones of the Qinghai-Xizang Plateau and parts of Xinjiang Uygur Autonomous Region. In these areas, drought events not only persisted longer but were also more intense, and drought intensity was markedly higher in high-altitude and arid areas (e.g., the Qinghai-Xizang Plateau and Xinjiang Uygur Autonomous Region) than in eastern agricultural zones, highlighting the heightened climate sensitivity of these ecosystems.

Future scenario projections indicate that the evolution of drought risk varies markedly under different scenarios. Under the SSP126 and SSP585 scenarios, the frequency of drought events shows seasonal variation consistent with that observed during the historical period (Fig. 11 [Figure 11: see original paper]). However, under the SSP245 scenario, the frequency of drought events in spring and winter is notably higher than that in autumn. In spring, regions experiencing higher frequencies of drought events are primarily located in the eastern parts of single-cropping zones, the western parts of double-cropping zones, and certain sections of triple-cropping zones. Under the SSP245 scenario, a marked increase in drought event frequency is also observed in winter in the mid-21st century (2041–2060), particularly in the central-eastern region of the triple-cropping zones. These changes suggest that droughts in spring and winter will increasingly affect agricultural production, particularly in regions with high water resource demands.

Similarly, under the SSP126 and SSP585 scenarios, the average duration of drought events also exhibits seasonal characteristics consistent with those observed during the historical period (Fig. 12 [Figure 12: see original paper]). However, under the SSP245 scenario, the duration of winter drought events

significantly reduces, whereas the duration of summer drought events slightly increases. These changes may be closely associated with alterations in climatic conditions under the SSP245 scenario, particularly reduced summer precipitation and intensified high temperatures, which consequently prolong drought events in regions grappling with rising temperatures and diminishing water resources.

Under all three scenarios, the average intensity of drought events will not differ significantly among the four seasons; moreover, under the SSP245 scenario, the spatial distribution of drought intensity across all seasons remains relatively uniform (Fig. 13 [Figure 13: see original paper]). This indicates that, although climate change affects the frequency and duration of drought events to some extent, its impact on drought intensity is relatively weak. In contrast, under the SSP126 and SSP585 scenarios, the average intensity of winter drought events increases significantly in the central-western region of the single-cropping zones and in the double-cropping zones.

**Fig. 10** Spatial distribution of the number (a1-a4), average duration (b1-b4), and average intensity (c1-c4) of drought events in four seasons from 2001 to 2020.

**Fig. 11** Spatial distribution of the number of drought events in different seasons and agricultural cropping zones under the SSP126 (a1-a16), SSP245 (b1-b16), and SSP585 (c1-c16) scenarios from 2021 to 2100.

**Fig. 12** Spatial distribution of the average duration of drought events in different seasons and agricultural cropping zones under the SSP126 (a1-a16), SSP245 (b1-b16), and SSP585 (c1-c16) scenarios from 2021 to 2100.

**Fig. 13** Spatial distribution of the average intensity of drought events in different seasons and agricultural cropping zones under the SSP126 (a1-a16), SSP245 (b1-b16), and SSP585 (c1-c16) scenarios from 2021 to 2100.

### 3.5 Response of NDVI to Drought Under Future Scenarios

Pearson correlation analysis between SPEI-12 and monthly NDVI projections indicate that across all three climate scenarios, NDVI and SPEI-12 in different agricultural cropping zones are strongly correlated throughout all periods (Fig. 14 [Figure 14: see original paper]). Under the SSP126 scenario, NDVI and SPEI are primarily positively correlated across all four periods. Regions with significant positive correlations are predominantly concentrated in the hilly areas of the middle and lower reaches of the Yangtze River Plain in the northern area of the triple-cropping zones, as well as in the hilly regions of South China. This positive correlation suggests that moderate warming may enhance the synergistic effects of water and heat, thereby increasing the sensitivity of crop vegetation to drought. Conversely, regions exhibiting significant negative correlations across all four periods are primarily located in the central-northern part of the single-cropping zones and in the western part of the double-cropping

zones, particularly in the Huang-Huai-Hai Plain.

Under the SSP245 scenario, negative correlations between NDVI and SPEI are observed in a considerable number of regions across all four periods, indicating that during drought events, NDVI does not necessarily decline in some areas, but even increases. Additionally, under the SSP245 scenario, relatively abundant precipitation allows for timely moisture replenishment; consequently, most drought events do not impose long-term stress on crop vegetation. Specifically, areas that consistently exhibit significantly negative correlations across all four periods are predominantly concentrated in the central-southern part of the single-cropping zones and the southern part of the double-cropping zones, whereas regions with significant positive correlations throughout are primarily located in the northeastern hilly areas of the single-cropping zones and the southeastern hilly areas of the triple-cropping zones.

Under the SSP585 scenario, the correlation between NDVI and SPEI is positive in most areas across all four periods. Regions with significant positive correlations are predominantly concentrated in the southwestern area of the double-cropping zones and the northern area of the triple-cropping zones in the middle and lower Yangtze River Plain, indicating that drastic warming and precipitation extremes markedly amplify the effects of drought stress on crop vegetation, particularly in areas with high cropping intensity. However, significant negative correlations are observed in the Qinghai-Xizang Plateau in the southwestern area of the single-cropping zones and the northern area of the double-cropping zones (e.g., northern Huabei Plain).

**Fig. 14** Spatial distribution of the correlation between the annual mean NDVI value of China's agricultural zones and SPEI-12 under the SSP126 (a1-a4), SSP245 (b1-b4), and SSP585 (c1-c4) scenarios from 2021 to 2100. Black dots indicate significant correlations at  $P < 0.05$  level.

#### 4.1 Differences and Causes in Drought Response Mechanisms Across Different Agricultural Cropping Zones

Agricultural zones across China significantly vary in their responses to drought due to the combined effects of regional climate, water and soil resources, as well as agricultural management practices (Wang et al., 2021a). In single-cropping zones, crop growth is highly dependent on rainfall, and precipitation deficits are frequently the primary cause of yield reductions in rain-fed agriculture (Tefera et al., 2024). Wang et al. (2021a) found that precipitation deficits contribute most significantly to agricultural drought in arid rain-fed areas. Consequently, NDVI and SPEI often exhibit high correlations in these regions, with spatio-temporal precipitation variability directly determining crop vegetation growth. In contrast, in the heavily irrigated oasis agricultural zones of Northwest China, the farmland water supply is less affected by immediate precipitation events. Large-scale water diversion for irrigation significantly alleviates soil water stress on crops (Wang et al., 2024b). During meteorological droughts, irrigation sus-

tains crop growth, causing NDVI to increase rather than decrease. This results in a negative correlation between NDVI and SPEI (Javed et al., 2025). The ‘oasis effect’ driven by the artificial water supply is particularly pronounced in arid areas. This finding is consistent with the results of Zou et al. (2020) in arid Central Asia, indicating that irrigation supplemented by glacial and snowmelt runoff can support crop growth during meteorological droughts, thereby masking crop vegetation drought signals.

In double-cropping zones (such as the Huang-Huai-Hai Plain), irrigation and tillage regimes significantly affect the relationship between crop vegetation and drought. Within the winter wheat-summer maize rotation system, spring irrigation is essential for enabling winter wheat to resist drought (Wu et al., 2023). For example, during the severe spring drought of 2022 in the Huang-Huai region, timely water diversion for irrigation supported the growth of winter wheat and prevented significant yield losses. Adequate irrigation inputs partially mitigate the correlation between NDVI and SPEI, reducing the sensitivity of crops to precipitation fluctuations (Mi et al., 2025). However, significant variation exists within the same cropping zone. For example, in the hilly uplands of the southwestern region, where irrigation infrastructure is inadequate, crops rely primarily on natural precipitation to achieve their water requirements. Consequently, the NDVI and SPEI correlation is stronger, and drought has a more direct negative effect on crop growth (Wang et al., 2021a). Chen et al. (2024) also found that the sensitivity of crop vegetation to precipitation anomalies is greater in areas with poorer irrigation conditions, increasing the risk of drought-induced crop yield reductions. Topographical factors also play critical roles. The southwestern mountainous areas experience highly localized climatic variation and low soil water storage capacity, making them more prone to the formation of drought ‘hotspots’ (Javed et al., 2025). The regional differences revealed by this cropping system-based analysis contrast with traditional classifications by administrative or climatic zones. The latter approach often fails to account for variation in crop drought resilience between single- and double-cropping zones within the same province (Wang et al., 2021a), nor does it adequately reflect the buffering effect of irrigation management on drought impacts. This demonstrates that examining drought response mechanisms through the lens of agricultural cropping systems enables more precise characterization of drought effects arising from the interaction between human cultivation practices and climatic factors.

## 4.2 Projected Trends in Drought Risk Under Different Future Scenarios and Implications for Agricultural Production and Food Security

Under different future emission scenarios, the risk of agricultural drought in China increases, but notable differences are observed among scenarios. This will have profound implications for regional crop production and food security (Liu et al., 2024; Linh and Shabbir, 2025). Under the low-emission sce-

nario (SSP126), precipitation increases slightly overall but remains unevenly distributed. Consequently, drought frequency and intensity in some regions increase marginally but remain relatively moderate overall (Linh and Shabbir, 2025). For example, projections suggest that under a 1.5°C warming scenario, the area of Chinese farmland exposed to drought will still expand, albeit to a lesser extent than under high-emission scenarios (Jia et al., 2022). Under the SSP245 scenario, heightened temperature and precipitation variability significantly increase seasonal drought risks (Su et al., 2021). Spring drought frequency increases markedly across all cropping zones relative to current conditions, potentially reducing germination rates for spring-sown crops; winter droughts become abnormally frequent, threatening the overwintering survival rate of winter wheat. Under the SSP585 scenario, extreme heat and precipitation variability increase dramatically, making future droughts more frequent and severe (Li et al., 2023). Summer droughts under high-temperature conditions are particularly severe. Previous research indicates a substantial increase in the risk of severe drought during maize tasseling in the North China Plain in the SSP585 scenario (Jia et al., 2022).

Overall, the severity of drought-induced yield losses in major grain crops is directly proportional to how closely the future scenario aligns with high-emission pathways. Comparative studies on drought sensitivity across the world's three major grain-producing regions reveal that China's maize and soybean yields are highly sensitive to variation in drought. Under high-emission scenarios, China faces some of the highest risks of yield losses globally (Liu et al., 2024). These scenario projections indicate that without adaptation measures, future climate change may severely threaten the food security of China through more frequent agricultural droughts (Linh and Shabbir, 2025).

The impact of climate change varies among cropping systems. In single-cropping zones, where only one harvest occurs annually, a single drought season can affect the entire year's yield. In double-cropping zones, inter-seasonal compensation may slightly offset losses, whereas triple-cropping zones, with their intensive crop cycles, face heightened risks of consecutive crop failures during extreme drought or combined drought-heatwave events. These regional differences highlight the need for differentiated strategies in national food security planning. Grounded in multi-scenario drought risk analysis and in line with global assessments (Wang et al., 2025a), this study provides refined regional-specific insights for China. Our findings demonstrate that future climate change will exacerbate the regional imbalance and complexity of agricultural droughts, creating food security challenges that are both global and highly regional (Vicente-Serrano et al., 2022).

### 4.3 Limitations

Owing to the absence of human agricultural management factors, such as irrigation, within the training input data, the GTNNWR model is currently unable to explicitly account for the effects of these factors. In regions characterized by

intensive irrigation practices (such as the Huang-Huai-Hai Plain), we observed relatively low correlations between NDVI and SPEI. Such weakened associations suggest that by omitting irrigation data, the model fails to capture the buffering effect of human intervention, potentially underestimating the true impact of drought conditions (Minoli et al., 2022). Future work should integrate remotely-sensed irrigation datasets or agricultural water-use statistics to improve the model's sensitivity to agricultural management practices on drought risk.

Moreover, our scenario projections rely on a single climate model (BCC-CSM2-MR), which introduces uncertainty. Different climate models can produce divergent outcomes due to variations in resolution and parameterization (Vetter et al., 2017). The reliance on a single GCM implies that the projected drought trends might not capture the full range of possible futures. Multi-model ensemble approaches should be adopted in future analyses to enhance robustness, as this would allow assessment of inter-model variability and improve the credibility of long-term drought projections.

Furthermore, the complexity of the GTNNWR model and high computational demands pose challenges for broader applicability. As a hybrid of deep learning and geographically weighted regression, the model contains many parameters and requires substantial training time. This complexity increases the risk of overfitting, especially when applied at finer spatial resolutions or over large geographic scales. Future research should prioritize improving the model's efficiency and generalizability. Model performance can be maintained at larger scales by employing regularization techniques, simplifying model architecture, or conducting rigorous cross-validation.

Finally, our study did not integrate socioeconomic variables, which are essential for comprehensive drought risk assessment. Factors such as population distribution, cropping patterns, and water resource management policies significantly influence drought vulnerability and adaptive capacity (Serkendiz and Tatli, 2023), but have not yet been incorporated into the current assessment framework. Incorporating such socioeconomic data alongside biophysical variables would provide a more holistic understanding of drought risk. Future research should therefore extend the framework by coupling the biophysical model with socioeconomic indicators (e.g., demographic trends, land-use practices, and policy measures) to better capture the role of human-environment interactions in drought dynamics.

An additional limitation of this study stems from the use of a static agricultural cropping zoning scheme. Our classification, based on the climatic conditions documented by Han et al. (1986), was held constant throughout the historical and future projection periods. However, it is well-established that the geographical boundaries of cropping systems are not fixed; they are likely to shift in response to ongoing climate change, particularly through the poleward and upward migration of thermal resources (Zhang et al., 2025). This static assumption means that our future drought risk projections for each zone

do not account for the potential that some current double-cropping areas may evolve towards triple-cropping systems, or that single-cropping zones may gain the potential for double-cropping. Consequently, while our assessment accurately reflects drought risk within the current spatial configuration of cropping systems, it may not fully capture the evolving drought vulnerability at the dynamic frontiers of these agro-climatic zones. Future research should prioritize the development of dynamic cropping zone projections under climate change scenarios to provide a more temporally coherent and realistic assessment of future agricultural drought risks.

## 5 Conclusions

This study proposed a drought risk assessment framework for agricultural cropping zones, employing the GTNNWR model for future NDVI projections and integrating it with SPEI to evaluate past and future drought risks across China's agricultural zones. The GTNNWR model effectively captured the non-stationary relationship between crop vegetation and climate across different cropping zones, outperforming traditional methods. From 2001 to 2020, agricultural cropping zones exhibited distinct spatio-temporal differentiation in drought risk; summer was a high-incidence period for drought events, and such events were particularly concentrated in single-cropping and double-cropping zones. Future projections indicate that under the SSP126 scenario, drought risk shows an intensifying trend in the triple-cropping zones of the middle and lower reaches of the Yangtze River Plain. Under the SSP245 scenario, the occurrence frequency of droughts in spring and winter rises substantially. Under the SSP585 scenario, drought intensity is significantly aggravated in the central-eastern parts of single-cropping zones and the southwestern parts of double-cropping zones. These findings highlight the importance of zone-specific drought management strategies. Our research also demonstrates the effectiveness of the GTNNWR model in capturing the complex spatio-temporal dependencies of crop vegetation dynamics and provides a methodological framework for improving drought risk assessments. These results will help guide adaptive strategies in agricultural management, such as optimized irrigation systems and crop restructuring, to mitigate the effects of climate change on food security. Future research should incorporate socioeconomic factors and higher-resolution data to further refine the drought risk assessment models and enhance their applicability to regional agricultural planning.

## Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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