Assessment of Drought Risk Changes in China under Different Warming Scenarios (Postprint)

Authors: Lu Dongyan

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Abstract

Drought is one of the most severely damaging extreme climate events, and investigating changes in drought disaster risk against the backdrop of future climate warming facilitates the scientific advancement of disaster prevention and mitigation deployment. Utilizing data from 20 climate models of the Sixth International Coupled Model Intercomparison Project, the Standardized Precipitation Evapotranspiration Index was computed, drought characteristic variables for China were extracted under baseline period and global warming scenarios of 2 °C, 3 °C, and 4 °C, and the drought hazard index was calculated. Based on projected data of hazard-bearing bodies, the drought exposure index and drought vulnerability index were computed, and the drought disaster risk index was comprehensively calculated to analyze the distribution pattern of drought disaster risk in China and conduct spatial attribution analysis of future drought disaster risk changes using the Geographical Detector. The results indicate that: the spatial distributions of drought hazard index, drought exposure index, and drought vulnerability index exhibit relatively high values in the northwest and southeast, high in the east and low in the west, and high in the west and low in the east, respectively; the drought disaster risk index demonstrates an east-high-west-low distribution characteristic, displaying positive spatial autocorrelation dominated by high-value clustering and low-value clustering; as warming levels increase, future drought disaster risk shows a predominant increasing trend, with the most pronounced increase in eastern coastal regions; changes in population, GDP, and proportion of cultivated land are the dominant factors influencing drought disaster risk changes.

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Full Text

Assessment of Drought Risk Changes in China under Different Temperature Rise Scenarios

LU Dongyan[1,2], ZHU Xiufang[1,2,3], TANG Mingxiu[1,2], GUO Chunhua[1,2], LIU Tingting[1,2]

[1]Key Laboratory of Environmental Change and Natural Disasters, Ministry of Education, Beijing Normal University, Beijing 100875, China
[2]Institute of Remote Sensing Science and Engineering, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
[3]State Key Laboratory of Remote Sensing Science, Beijing Normal University, Beijing 100875, China

Abstract

Drought is one of the most damaging extreme climate events. Investigating changes in drought risk against the backdrop of future climate warming is crucial for scientifically advancing disaster prevention and mitigation efforts. Using data from 20 climate models from the sixth phase of the Coupled Model Intercomparison Project (CMIP6), we calculated the Standardized Precipitation Evapotranspiration Index (SPEI) and extracted drought characteristic variables for baseline and global temperature rise scenarios of 2°C, 3°C, and 4°C in China. The Drought Hazard Index (DHI) was computed, and based on projected disaster-bearing body data, we calculated the Drought Exposure Index (DEI) and Drought Vulnerability Index (DVI). These three indices were integrated to compute the Drought Risk Index (DRI), enabling analysis of the spatial distribution pattern of drought risk in China and spatial attribution of future drought risk changes using the Geodetector method. Results show that the spatial distributions of DHI, DEI, and DVI exhibit patterns of relatively high values in the northwest and southeast, high in the east and low in the west, and high in the west and low in the east, respectively. The DRI demonstrates an east-high-west-low distribution characterized by spatial positive correlation dominated by high-value and low-value clustering. As temperature rise levels increase, future drought risk will predominantly increase across China, with the most pronounced increases in eastern coastal regions. Changes in population, GDP, and the proportion of cultivated land emerge as the dominant factors influencing drought risk changes.

Keywords: drought risk; CMIP6; temperature rise scenario; spatial autocorrelation; Geodetector

1. Introduction

Drought represents one of the most severe extreme climate events worldwide. In recent years, under global warming, extreme weather and climate events (including heatwaves, droughts, and heavy precipitation) have become increasingly frequent. According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR6), the global mean temperature in 2010-2019 was approximately 1.09°C higher than pre-industrial levels, with future increases in global temperature projected to intensify hazards. Drought, characterized by high frequency, long duration, and significant damage, adversely affects water resources, agricultural production, and ecological conservation. China, a major agricultural nation frequently affected by drought disasters, experienced average annual crop-affected areas of 3.1$\times10^{\{7\}-7.8\times10}\{7\}$ hm^2 during 2000-2020, with average annual direct economic losses reaching tens of billions of yuan. Research indicates that climate warming has driven an overall drying trend in China over recent decades, a trend projected to continue through the mid-to-late 21st century, threatening sustainable socioeconomic development.

Drought risk refers to the probability of adverse impacts on society, economy, and ecology from drought occurrence, resulting from interactions among hazard, exposure, and vulnerability. The hazard component refers to drought caused by anomalies in the meteorological system, typically analyzed by identifying drought processes using drought indices and extracting characteristic variables (drought duration, intensity, etc.) for quantitative description. The disaster-bearing body comprises human social entities affected and threatened by drought. Under equivalent hazard conditions, greater exposure and vulnerability of disaster-bearing bodies lead to higher risk. Exposure reflects the scale of population and assets exposed to drought, quantifiable using population density and GDP indicators, while vulnerability reflects the sensitivity and coping capacity of disaster-bearing bodies to drought, quantifiable using per capita GDP, land use conditions, and other metrics.

Current drought risk assessments predominantly rely on historical data. However, introducing future scenario data enables forward-looking drought risk estimation. The World Climate Research Programme' s Coupled Model Intercomparison Project Phase 6 (CMIP6) provides state-of-the-art, reliable climate model data widely applied in future climate prediction research. Concurrently, quantitative simulation and projection datasets of socioeconomic elements (population, economy, land use) based on Shared Socioeconomic Pathways (SSPs) have become increasingly available, supporting assessments of disaster-bearing body exposure and vulnerability. While existing studies have projected future drought risk at global and regional scales using climate model and disaster-bearing body projection data, few have focused on different temperature rise scenarios. To address challenges in drought emergency management posed by intensifying global warming, it is necessary to estimate future drought risk under various temperature rise scenarios and analyze its impact on the economy and society.

This study evaluates drought risk in China under 2°C, 3°C, and 4°C temperature rise scenarios using CMIP6 climate model data and disaster-bearing body projection data, aiming to provide a scientific basis for drought resistance and disaster reduction planning under global warming.

1.1 Study Area

China is located in eastern Asia, featuring vast territory, complex terrain, and diverse climate. To compare drought risk characteristics across regions, we divided China into seven natural regions based on previous research: Northeast humid/semi-humid temperate region (NE), North China humid/semi-humid warm temperate region (NC), Central and South China humid subtropical region (CS), South China humid tropical region (SC), Inner Mongolia grassland region (IM), Northwest desert region (NW), and Qinghai-Tibet Plateau region (QT). This regionalization scheme follows principles of geographical location, landform, climate, and vegetation.

1.2 Data

1.2.1 Meteorological Observation Data The CN05.1 dataset, based on observations from over 2,400 meteorological stations in China from 1961 to the present and interpolated using the anomaly approach, provides the most accurate gridded meteorological observation dataset for China with a resolution of 0.25°. This study bilinearly interpolated monthly meteorological elements (precipitation, maximum temperature, minimum temperature, average wind speed, relative humidity, and sunshine duration) from CN05.1 to a 0.5° resolution for evaluating historical climate simulation data.

1.2.2 Climate Model Data CMIP6 climate model data were obtained from https://esgf-node.llnl.gov/projects/cmip6. As one of the most advanced and reliable data sources for climate change prediction research, CMIP6 provides historical climate simulation data for 1850-2014 and future climate projection data for 2015-2100. This study used monthly mean temperature data (1850-2100) to calculate global temperature rise levels and monthly data for precipitation, maximum temperature, minimum temperature, wind speed, relative humidity, surface downward shortwave radiation, and air pressure (1850-2100) to calculate drought indices. The ScenarioMIP designed climate projection scenarios as combinations of different SSPs and radiative forcing levels. We selected the SSP5-8.5 scenario (fossil-fuel-driven development pathway with high radiative forcing), the only scenario capable of reaching 4°C warming levels. Twenty climate models containing required variables were selected (Table 1), with each model' s data bilinearly interpolated to a 0.5° resolution.

1.2.3 Elevation Data The U.S. Geological Survey provides the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) at 7.5 arc-second resolution. This study resampled the mean elevation data to 0.5° resolution using mean aggregation for calculating drought indices.

1.2.4 Population and GDP Data Population and economic projection data for China at 0.5° resolution from 2020–2100, developed by Jiang et al., consider the impact of population policy changes on demographic structure and economy, making them more suitable for China' s context. This study used these datasets to assess disaster-bearing body exposure and vulnerability.

1.2.5 Land Use Data The Land-Use Harmonization (LUH2) dataset serves as the fundamental driving data for CMIP6 experiments, providing global annual land use data at 0.5° resolution. Based on historical data and SSP5-8.5 scenario data, we extracted China' s cultivated land proportion and irrigation proportion for 2020–2100, representing the ratio of cultivated and irrigated area to total grid cell area. Area-weighted averaging unified the resolution to 0.5° for exposure and vulnerability assessment.

1.3 Methods

1.3.1 Taylor Diagram Method The Taylor diagram is a common method for evaluating climate model performance, displaying three statistics—correlation coefficient (r), standard deviation, and root mean square error—in a single plot to intuitively show differences between simulated and observed values. This study used standardized Taylor diagrams by dividing simulated and observed values by observed standard deviations to eliminate dimensions. In standardized Taylor diagrams, the observation point is located at (r=1, standard deviation ratio=1). Climate models with good performance exhibit r and standard deviation ratios close to 1.

1.3.2 Determination of Different Temperature Rise Scenarios According to IPCC AR6, the observed global warming value for 2011–2020 was 0.85°C relative to 1850–1900. Therefore, we selected 1995–2014 as the baseline period for temperature rise level calculation and drought risk assessment. Based on CMIP6 data, we calculated annual global mean temperatures for 1850–2100. For each model, we computed 20-year moving average temperatures, differenced them from the baseline period mean, and identified years when the temperature anomaly reached 1.15°C, 2.15°C, and 3.15°C. The corresponding 20-year periods centered on these years were defined as the 2°C, 3°C, and 4°C temperature rise scenarios.

1.3.3 Drought Risk Assessment Model **Drought Hazard Analysis.** The Standardized Precipitation Evapotranspiration Index (SPEI) accounts for evapotranspiration sensitivity to temperature changes. We used 12-month SPEI as the meteorological drought monitoring indicator. SPEI ranges for drought classifications are: >-0.5 (no drought), -1.0 to -0.5 (light drought), -1.5 to -1.0 (moderate drought), -2.0 to -1.5 (severe drought), and <-2.0 (extreme drought). SPEI calculation follows the national standard "Grades of Meteorological Drought" using the Penman-Monteith method for potential evapotranspiration. We first calculated SPEI for each model using 1961–2020 data, then applied the fitted parameters to 2020–2100 data.

Using a three-threshold run theory with thresholds of -0.5, -1.0, and -1.5, we identified drought events and extracted three characteristic variables for the baseline and three temperature rise scenarios: drought frequency (average number of drought events per year), drought duration (average duration in months), and drought intensity (average absolute SPEI value during drought events). The Drought Hazard Index (DHI) was constructed by multiplying drought frequency (F), duration (D), and intensity (I), then normalizing:

$$DHI = w_1 \times F_{norm} + w_2 \times (F \times D)_{norm} + w_3 \times (F \times I)_{norm}$$

where w_1, w_2, and w_3 are weight coefficients (all 1/3), and the subscript "norm" indicates normalized values using extremum standardization.

Exposure and Vulnerability Analysis. We quantified exposure using population, GDP, and cultivated land proportion indicators, normalizing and equally weighting them to obtain the Drought Exposure Index (DEI). Vulnerability was quantified using per capita GDP and irrigation proportion (negative indicators), normalizing and equally weighting them to obtain the Drought Vulnerability Index (DVI). For population and GDP, we used 2020–2040 means for the baseline period and 2020–2100 means for future scenarios. For land use indicators, we used 2020–2040 means for the baseline and 2020–2100 means for future scenarios.

Drought Risk Index Calculation. The three comprehensive indices were multiplied to calculate the Drought Risk Index (DRI) for each scenario:

$$DRI = DHI \times DEI \times DVI$$

1.3.4 Spatial Pattern and Change Analysis of DRI Spatial Autocorrelation Analysis. Using GeoDa software, we performed spatial autocorrelation analysis. Global Moran's I detected spatial autocorrelation across the entire study area, with values ranging from -1 to 1 (positive, negative, or random spatial correlation). Local Indicators of Spatial Association (LISA) analyzed spatial clustering characteristics. Using quantile classification, we divided DRI values into five grades (G1-G5) for spatial distribution mapping.

Geodetector. Geodetector analyzes spatial heterogeneity and its driving factors through factor detection, interaction detection, risk zone detection, and ecological detection. We analyzed factors influencing spatial heterogeneity of drought risk changes using factor and interaction detection to obtain q-values measuring explanatory power. The dependent variable was DRI change (difference between each temperature rise scenario and baseline), while independent variables included changes in drought frequency, duration, intensity, population, GDP, cultivated land proportion, per capita GDP, and irrigation proportion. The "GD" package in R was used for optimal discretization and Geodetector analysis.

2.1 Climate Model Performance Evaluation

We evaluated CMIP6 model accuracy in simulating precipitation and PET using CN05.1 data, with performance in standardized Taylor diagrams showing proximity to observations as optimal. Correlation coefficients between simulated and observed precipitation ranged from 0.52 to 0.71, while PET correlations ranged from 0.88 to 0.93. Standard deviation ratios ranged from 0.93 to 1.39 for precipitation and 0.78 to 1.32 for PET. Overall, models demonstrated good performance in simulating precipitation and PET, suitable for analyzing drought hazard in China.

2.2 Temperature Rise Scenario Determination

Analysis of 20-year periods when 20 climate models reached specific warming levels revealed that all models achieved 2°C and 3°C warming, while 14 models reached 4°C warming (Table 2).

2.3 Results of Three Comprehensive Indices

DHI, DEI, and DVI Grade Distributions. Using quantile classification, DHI grades showed relatively high values in northwest and southeast China, corresponding to long drought duration and intensity in the northwest and high drought frequency in the southeast. DEI grades exhibited an east-high-west-low pattern, increasing over time, while DVI grades showed a west-high-east-low pattern, decreasing over time—consistent with China' s socioeconomic development gradient. Overall, DHI increased with temperature rise levels, indicating a future warming-drying trend.

2.4 DRI Spatial Pattern Analysis

DRI grades displayed an east-high-west-low distribution, increasing with temperature rise levels. Global spatial autocorrelation analysis yielded significant Moran' s I values ($P<0.001$) across all scenarios, indicating positive spatial correlation. LISA cluster maps classified grid cells into five types: not significant, high-high, low-low, low-high, and high-low clusters. High-value clusters were mainly distributed in eastern monsoon regions, while low-value clusters were concentrated in western regions. Moran scatter plots showed most points falling in quadrants I (high-high) and III (low-low), confirming spatial clustering dominated by high and low values.

Box plots revealed that DRI maximum, median, and mean values increased sequentially from baseline to 2°C, 3°C, and 4°C scenarios, with increasing ranges and means exceeding medians. Regionally, the highest DRI maximum values appeared in region SC across all scenarios, while the highest medians and means occurred in regions SC and CS. Overall, DRI increased with temperature rise levels across all seven natural regions.

2.5 Drought Risk Change Analysis

DRI changes relative to baseline were predominantly positive, with more pronounced increases in eastern coastal areas. As temperature rise levels increased, DRI increments grew larger.

Factor detection showed that changes in population, GDP, and cultivated land proportion were the dominant factors affecting drought risk changes, with all q-values passing significance tests at the 0.001 level. In the 2°C scenario, cultivated land proportion change had the highest explanatory power (q=0.31), while in 3°C and 4°C scenarios, population change showed the greatest influence (q=0.32 and q=0.36, respectively). Interaction detection revealed two-factor enhancement and nonlinear enhancement effects. The most influential factor pairs across all scenarios were cultivated land proportion change population change and cultivated land proportion change GDP change, with interaction q-values exceeding 0.40—demonstrating that exposure changes strongly explain drought risk changes. Interaction effects provided better explanations than single factors.

3. Discussion

Current research on future drought risk projection in China remains limited, with most existing studies being regional. Our results, incorporating future projection data, show spatial distributions similar to historical data-based studies, confirming reliability. Compared with previous research, this study assesses drought risk from different temperature rise perspectives and analyzes driving factors of future risk changes, offering valuable insights for climate change risk prevention. However, uncertainties remain due to future climate complexity, human activity dynamics, and climate model limitations. The SSP5-8.5 scenario results carry substantial uncertainty, and whether China' s future climate will continue warming-drying requires further investigation. Additionally, index selection, data processing methods, and weight settings introduce uncertainties. While this study conducted global driving force detection across all grid cells, dominant factors may vary regionally due to differing natural and socioeconomic conditions—warranting future local-scale driving force analysis.

4. Conclusion

Using CMIP6 climate model data and disaster-bearing body projection data, this study evaluated hazard, exposure, and vulnerability to calculate DRI under 2°C, 3°C, and 4°C temperature rise scenarios and analyzed changes relative to baseline. Main conclusions are:

1) DHI, DEI, and DVI show distinct spatial patterns: DHI is relatively high in northwest and southeast China; DEI is high in the east and low in the west; DVI is high in the west and low in the east. With increasing temperature rise, drought hazard increases significantly, exposure generally rises, and vulnerability decreases.

2) DRI exhibits clear spatial clustering, with high-value clusters in eastern monsoon regions and low-value clusters in western regions, maintaining an east-high-west-low pattern across baseline and future scenarios.

3) Compared with baseline, DRI increases across all temperature rise scenarios, most notably in eastern coastal areas. Risk increments grow with temperature rise levels. Global driving force detection reveals that population change, GDP change, and cultivated land proportion change are primary drivers, with factor interactions providing stronger explanatory power than single factors.

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Note: Figure translations are in progress. See original paper for figures.