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RESEARCH ARTICLE

Impact of climate extremes on agricultural water scarcity and the spatial scale effect

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KEYWORDS

Agricultural water scarcity, compound climate extremes, spatial scale effect, river basin

HIGHLIGHTS

- Extreme precipitation has a greater impact on the agricultural water scarcity index (AWSI) than extreme temperature.
- AWSI assessment at a tertiary basin level better captured the influence of climate extremes than at a secondary basin level.
- AWSI was about 28% higher than the long-term average during dry years and 55% higher under exceptionally dry conditions at a tertiary basin level.
- Compound dry and hot conditions increased AWSI by more than 60% in some regions.

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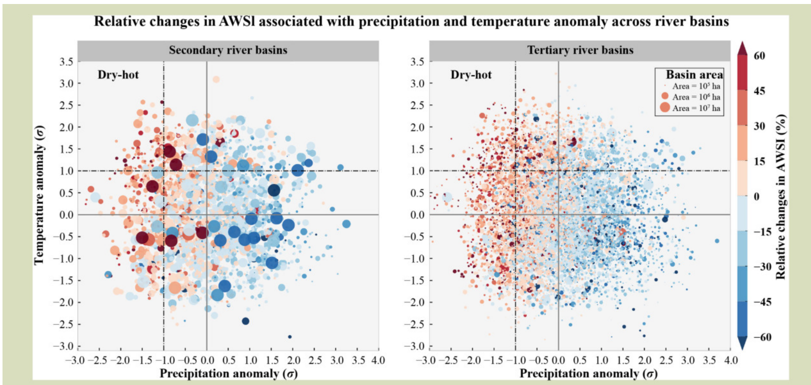
GRAPHICAL ABSTRACT



ABSTRACT

Amid the escalating frequency of climate extremes, it is crucial to determine their impact on agricultural water scarcity to preserve agricultural development. Current research does not often examine how different spatial scales and compound climate extremes influence agricultural water scarcity. Using an agricultural water scarcity index (AWSI), this study examined the effects of precipitation and temperature extremes on AWSI across secondary and tertiary river basins in China from 1971 to 2010. The results indicated a marked increase in AWSI during dry years and elevated temperatures. The analysis underscores that precipitation had a greater impact on AWSI than temperature variation. In secondary basins, AWSI was about 26% higher than the long-term average during dry years, increasing to nearly 49% in exceptionally dry conditions. By comparison, in tertiary basins, the increases were 28% and 55%, respectively. In hot years, AWSI rose by about 6.8% (7.3% for tertiary basins) above the average, surging to about 19.1% (15.5% for tertiary basins) during extremely hot periods. These results show that AWSI assessment at the tertiary basin level better captured the influence of climate extremes on AWSI than assessments at the secondary basin level, which highlights the critical importance of a finer spatial scale for a more precise assessment and forecast of water scarcity within basin scales. Also, this study has highlighted the paramount urgency of implementing strategies to tackle water scarcity issues under compound extreme dry and hot conditions. Overall, this study offers an in-depth evaluation of the influence of both precipitation and temperature variation, and research scale on water scarcity, which will help formulate better water resource management strategies.

1 Introduction

Water scarcity is a condition where the water demands of agricultural and other economic sectors exceed the available water resources[1], and is increasingly of global concern[2]. Since the late 1990s, factors such as climate change, agricultural expansion, industrial development, and population growth have intensified water extraction, thus worsening water scarcity issues in many regions throughout the world[3–6]. Agriculture is the largest global consumer of water resources, and the impact of climate change on agricultural water scarcity is particularly pronounced[7]. This has led to extensive research using global climate and hydrological models to both assess current states and forecast future trends of water scarcity[6,8,9].

Despite its substantial overall water resources, China grapples with the challenge of an uneven distribution of this resource, a situation further exacerbated by rapid population growth and economic development. This imbalance is expected to lead to increasingly acute water resource pressures in various regions[10–15]. Per capita renewable freshwater resources in China are about one-third of the global average, and numerous areas have experienced severe water scarcity in recent years[16,17]. This stress has important consequences, including reduced agricultural yields and diminished water quality[18]. Although previous studies, such as those by Liu et al. [2,8], have primarily focused on global assessments of water scarcity, including an overview of water scarcity in China, they have not examined the spatial characteristics and underlying factors of regional water scarcity to sufficient depth. This deficiency underscores the need to investigate the impact of scale effects on water scarcity and conduct water scarcity studies with more depth at different scales within China.

The prevalent water scarcity index (WSI), primarily based on blue water (comprising accessible freshwater in rivers, lakes, and groundwater), is defined as the blue water use to availability ratio, as indicated in studies by Gosling and Arnell[19], Greve et al.[12], Hanasaki et al.[20,21], and Liu et al.[22] However, this index often excludes the contribution of green water, which is stored as soil moisture and used for plant transpiration, despite terrestrial precipitation encompassing both blue and green water[23,24]. Green water is critical for agriculture as it contributes to about 85% of global crop water consumption[25,26], and yet it is frequently underappreciated in water resource evaluations and scarcity assessments[9]. Recognizing these challenges, several studies, including those by Liu et al.[2,8], have developed an agricultural water scarcity index (AWSI) that integrates both green and blue water resources considering their availability and usage. Despite this advancement, there remains a significant gap in understanding of the impact of compound climate conditions on AWSI. In a world where climate change is driving more extreme temperatures and altering precipitation patterns, comprehending the interplay between compound climate extremes, water supply, and its demand for agricultural productivity and human well-being is becoming increasingly critical. This understanding is essential to support sustainable development and formulate adaptive strategies in the context of the changing climatic conditions in China.

In the present study, we used an integrated AWSI[2,7] to study the impact of compound climate extremes, specifically compound extreme precipitation and temperature conditions, on AWSI and the associated scale effect, across secondary and tertiary river basins, in China from 1971 to 2010. By analyzing the trends, the present study aimed to improve understanding of the dynamic interplay between climate extremes and AWSI at various basin scales within China. The insights garnered from this investigation are intended to provide a robust scientific basis for the development of efficient water resource management strategies and adaptive responses to the challenges posed by climate change.

2 Methods and data

2.1 Description of the study area

In this study, we examined agricultural water scarcity in China. With its population exceeding 1.4 billion, food security in China is highly dependent on irrigation given that 75% of its grain output is from irrigated crops covering 40% of its arable land. Also, projections indicate that to accommodate the food demands of its expanding population, China must increase its irrigated land from the current 53 to 73 Mha by 2030[27].

To reveal any scale effects, water scarcity evaluations should be conducted at a spatial scale consistent with physiographical and meteorological catchment characteristics[28], and thus we aggregated the AWSI from the grid level to the secondary and tertiary river basin levels. River basins in China are categorized into three levels: primary, secondary, and tertiary. Given primary river basins are too uneven in their characteristics, we selected the secondary and tertiary level basins, and both have complete hydrological processes. There are 58 and 212 basins at the secondary and tertiary levels, respectively, and the spatial distribution of the annual average precipitation and temperature within secondary and tertiary river basins is shown in Fig. 1. For individual basins, average AWSI for grid cells in that basin was treated as the basin AWSI.

2.2 Estimating the agricultural water scarcity index

The AWSI was obtained by calculating the ratio of unstressed crop water demand to the aggregated water availability for agriculture that incorporates green water, blue water, and environmental flow requirements (EFR), as described by Liu et al.[2]. This index evaluates the adequacy of water resources in fulfilling crop water needs. Crop water demand for 19 crops, including barley, cassava, citrus, cotton, grapes, groundnut, maize, millet, potato, pulses, rapeseed, rice, rye, sorghum, soybean, sugar beet, sugarcane, sunflower, and wheat, was considered in the present study. Essentially, a higher AWSI reflects a more pronounced discrepancy between the crop water demand and overall water availability. AWSI was calculated as:

$$\mathrm{AWSI} = \frac{\mathrm{ET}_c}{\mathrm{WA}_g + \mathrm{WA}_b} \tag{1}$$

where, ET_c is the unstressed water demand of crops (in $m^3 \cdot mth^{-1}$), WA_g is the availability of agricultural green water ($m^3 \cdot mth^{-1}$) encompassing water evaporation from soil moisture or rainwater in both rainfed and irrigated cropland, and WA_b is the availability of agricultural blue water ($m^3 \cdot mth^{-1}$).

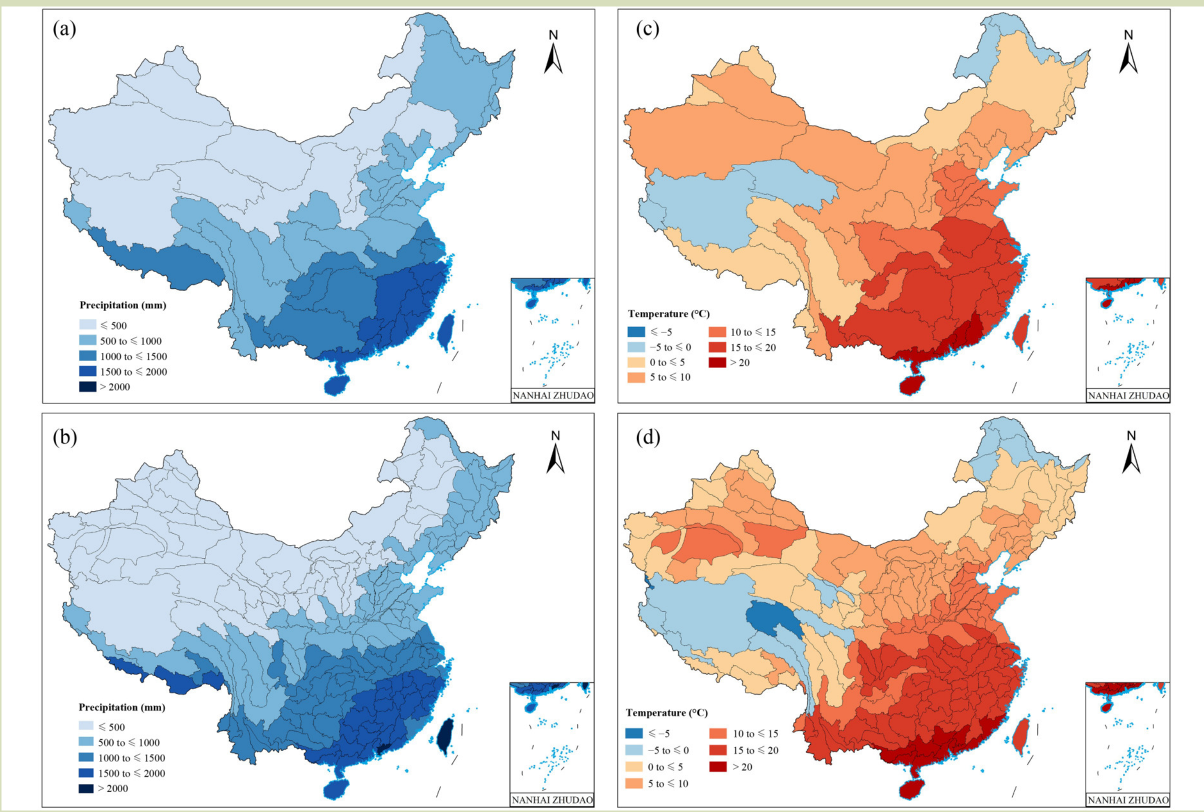


Fig. 1 Distribution of annual average precipitation and temperature for secondary (a, c) and tertiary (b, d) river basins (审图号: GS 京（2024）1698 号).

WA_b was calculated as:

$$WA_b = (Q - WW_{os} - EFR) \times IE \quad (2)$$

where, Q is the total quantity of blue water resources ($m^3 \cdot mth^{-1}$), WW_{os} is the water withdrawals for sectors other than irrigation, including industrial, domestic, and livestock uses ($m^3 \cdot mth^{-1}$), and IE is irrigation efficiency (dimensionless).

IE data from the year 2010, obtained from the *Bulletin of Water Resources in China* at the provincial level, was used for AWSI estimation allowing EFR ($m^3 \cdot mth^{-1}$) to be estimated using the variable monthly flow (VMF) method[29]. This is a hydrological technique for large-scale estimation of EFR, using an algorithm that accommodates intra-annual variations. This method markedly refines EFR estimations by enhancing temporal resolution from yearly to monthly intervals, a practice that has been extensively applied and validated[30,31]. Specifically, the VMF method prescribes a tiered allocation of water resources to EFR based on flow conditions: allocating 60% in low flow periods (monthly streamflow less than 40% of the long-term average), 45% during moderate flow periods (monthly streamflow between 40% and 80% of the long-term average) and 30% in high flow periods (monthly streamflow exceeding 80% of the long-term average). This allocation framework optimizes the distribution of water resources across varying hydrological contexts.

Monthly AWSI values were initially estimated and subsequently averaged to yield an annual AWSI for each year. Within each basin, the average AWSI of the grid cells at a spatial resolution of 30 arc-min was considered representative of the AWSI of the basin.

2.3 Defining climate conditions

The standardized anomaly (SA) method was used to quantify deviations in annual temperature and precipitation from their long-term average conditions as described by Li et al.[32] The SA value represents the deviation of a climate condition (temperature or precipitation here) in a given year t (cc_t) from its multiyear average ($\overline{cc}$), normalized by the standard deviation (σ):

$$SA_t = \frac{cc_t - \overline{cc}}{\sigma} \quad (3)$$

where, SA_t is the standardized anomaly for temperature or precipitation in year t. Annual SA values were calculated for each basin from 1971 to 2010.

Subsequently, annual temperature and precipitation conditions were categorized into multiple bins based on SA values considering a 0.5 interval. The categories ranged from extremely low (less than -2.0σ) to extremely high (greater than $+2.5\sigma$), for example, $(-\infty, -2.0\sigma]$, $(-2.0\sigma, -1.5\sigma]$, $(-1.5\sigma, -1.0\sigma]$, $(-1.0\sigma, -0.5\sigma]$, $(-0.5\sigma, 0)$, $(0, +0.5\sigma)$, $[+0.5\sigma, +1.0\sigma)$, $[+1.0\sigma, +1.5\sigma)$, $[+1.5\sigma, +2.0\sigma)$, $[+2.0\sigma, +2.5\sigma)$, and $[+2.5\sigma, +\infty)$. In this study, years with SA lower than -1.0σ were defined as dry (cold) years, whereas those with SA greater than $+1.0\sigma$ were classified as wet (hot) years for precipitation (temperature). Years with SA values between -1.0σ and 0 were considered moderately dry (cold), and those between 0 and $+1.0\sigma$ as moderately wet (hot).

2.4 Assessing the impact of climate variations and extremes on AWSI

The influence of variations in temperature and precipitation on the AWSI within specific basins were quantified using a relative change approach. This approach involved comparing the average AWSI corresponding to each SA category against the long-term average AWSI, calculated for the whole historical period 1971–2010 as:

$$\Delta AWSI_{b,i} = (AWSI_{b,i} - AWSI_{b,m}) / AWSI_{b,m} \times 100\% \quad (4)$$

where, $\Delta AWSI_{b,i}$ is the relative change in AWSI for years within the i_{th} SA category compared to the multiyear average AWSI in basin b (expressed in %), $AWSI_{b,i}$ is the average AWSI for years within the i_{th} SA category and $AWSI_{b,m}$ is the multiyear average AWSI for the basin. This relative change indicates the deviations of AWSI from its long-term trend owing to variations in temperature or precipitation.

After calculating the relative changes in AWSI and the corresponding temperature or precipitation anomalies for each year in each basin, the integrated effects of temperature or precipitation variations on AWSI were determined. This integration involved all basin-year combinations employing an area-weighted aggregation method as described by Li et al.[32]. Relative changes in AWSI for each bin are the weighted average value (by basin area) of basin-year samples within that bin. Also, we further determined the variations in AWSI during years categorized as individual climate conditions, for example, dry, moderately dry, moderately hot and hot, as well as compound dry and hot compared to the multiyear average for each basin.

2.5 Data sources

PCR-GLOBWB[33], a grid-based hydrology and water resources model extensively utilized globally, was employed to examine the AWSI in China. This analysis covered data from

1971 to 2010 at both grid cell (with a spatial resolution of 30 arc-min) and basin levels. PCR-GLOBWB yielded historical monthly potential evapotranspiration, water withdrawals, soil water, and rainwater evaporation. PCR-GLOBWB-derived simulated monthly streamflow, as designated in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) protocol, was utilized to evaluate blue water availability. Agricultural green water availability was calculated using the ISIMIP archive, using variables representing actual green water consumption "arainfusegreen" for rainfed and "airrusegreen" for irrigated cropland as described by Liu et al.[8]

The PCR-GLOBWB model[33] calculates the global daily surface water balance with a spatial resolution of 0.5 arc-deg, effectively capturing water withdrawals to satisfy a broad spectrum of water demands. This model forecasts water withdrawals for irrigation, industry, domestic use and livestock, taking into account variables such as the area under irrigation, crop water requirements, population, per capita gross domestic product, and livestock density. For an in-depth understanding of the model, readers are directed to the report of Wada et al.[33]. The data for the present study were derived from the ISIMIP phase 2a, which is used worldwide.

Under the ISIMIP 2a phase, PCR-GLOBWB simulations were run using three climate datasets, the Global Soil Wetness Project Phase 3[34], WATCH-WFDEI[35,36], and the Princeton[37] dataset, following the ISIMIP 2a protocol. Averaging outputs from these various climate-forcing datasets were used to reduce uncertainties in the analyses. The MIRCA2000[38] dataset was used to identify rainfed and irrigated croplands within the PCR-GLOBWB model for the analysis period.

Historical simulations of the PCR-GLOBWB model accounted for ongoing changes in human activities. To mitigate the socioeconomic effects on the AWSI, historical AWSI was standardized by eliminating the multiyear linear trend; we focused on the impact of climate extremes on AWSI.

3 Results

3.1 Assessment of AWSI across basin scales

There were large regional disparities in AWSI across China from 1971 to 2010 (Fig. 2). Basins with high AWSI values, surpassing the scarcity threshold of one, were primarily situated in the north-western, northern and central eastern areas, especially on the North China Plain. In contrast, regions

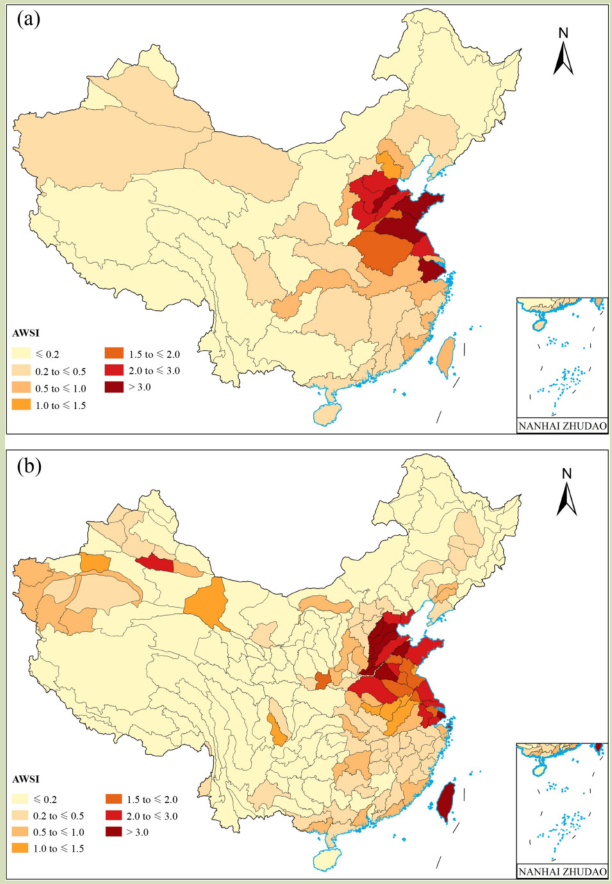


Fig. 2 Average agricultural water scarcity index (AWSI) in China from 1971 to 2010 aggregated to secondary (a) and tertiary (b) river basin levels (审图号: GS 京（2024）1698 号).

in southern China consistently had low AWSI values, underscoring the uneven distribution of AWSI. We also found large differences in AWSI when aggregated to the secondary and tertiary river basin levels. The tertiary level had more severe water scarcity and more regions with AWSI higher than one.

3.2 Variations in AWSI against long-term averages

The relationship between relative AWSI changes and climate anomalies shows that precipitation anomaly strongly influenced AWSI (Fig. 3). When assessed against multiyear AWSI averages, a significant increasing trend emerged as precipitation fell below zero for both secondary and tertiary river basins. Conversely, the influence of temperature anomalies on AWSI was less marked than those of precipitation. When temperature SA exceeded zero, a marginal predominance of secondary and tertiary river basins exhibiting increased AWSI occurred. A large number of basin-year

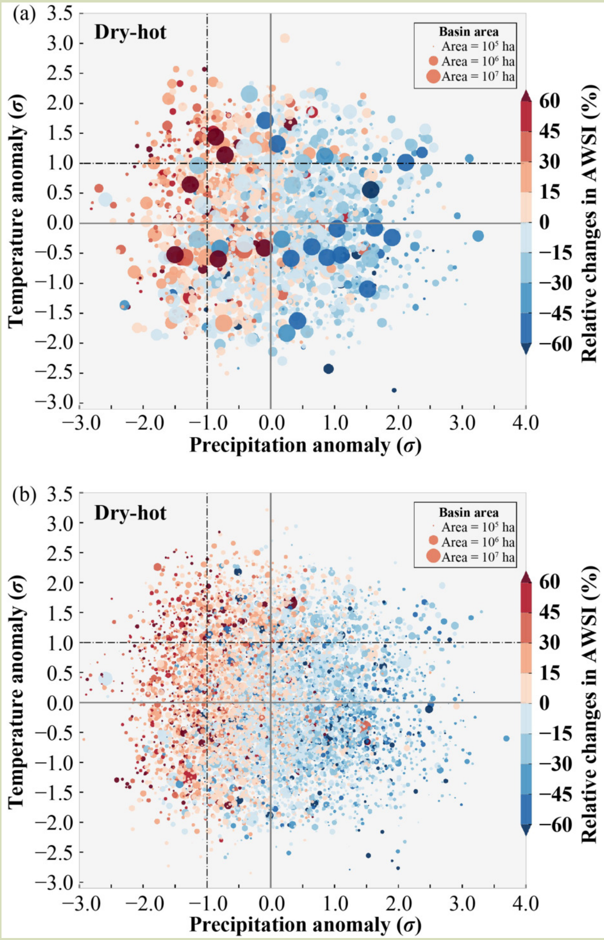


Fig. 3 Relative changes in agricultural water scarcity index (AWSI) resulting from precipitation and temperature anomalies across secondary (a) and tertiary (b) river basins. The datasets comprise 2320 and 8480 basin-year samples for secondary and tertiary river basins, respectively.

samples showing positive changes in AWSI with temperature SA < 0 and precipitation SA < 0 was observed, further confirming the importance of precipitation anomalies in driving changes in AWSI. In contrast, a dominant increasing trend in AWSI was observed for dry-hot conditions (precipitation SA < −1.0 and temperature SA > +1.0), although this condition only accounted for 3.9% and 3.3% of basin-year samples for secondary and tertiary river basins, respectively.

We further aggregated the relative AWSI changes from individual basin-years with different precipitation and temperature anomalies using an area-weighted method (Fig. 4), thereby providing insights into how AWSI responded strongly to fluctuations in temperature and precipitation. At both secondary and tertiary basin levels, a statistically significant increase in AWSI ($p < 0.05$) was observed in dry years.

Basin-year samples with precipitation anomalies falling below -2.0σ recorded an average AWSI increase of about 49% above the long-term mean for secondary basins and an even higher increase of 55% for tertiary basins. This notable rise occurred despite these extreme conditions constituting only about 1% of the overall sample (Fig. 5). Generally, during dry years (SA of precipitation $< -1.0\sigma$), an increase in AWSI was about 26% and 28% for secondary and tertiary basins, respectively, when compared to their respective multiyear averages.

For basin-year samples with temperature anomalies exceeding $+2.5\sigma$, AWSI increased by an average of 19% and 15% above the multiyear average for secondary and tertiary basins, respectively. Overall, in years categorized as hot (temperature SA $> +1.0\sigma$), we found that AWSI was elevated by about 7% for both secondary and tertiary basins relative to the long-term averages.

Notably, the magnitude of AWSI changes tended to be greater in tertiary river basins than in secondary ones. Overall AWSI changes in tertiary river basins also indicate a greater sensitivity to precipitation variations than to temperature. These findings underscore the critical importance of the study scale for a better understanding of water scarcity, particularly in the context of climatic anomalies.

3.3 Impact of individual climate variations on AWSI

Spatial analysis revealed notable increases in the AWSI across all basins during dry years (Fig. 6). These AWSI fluctuations were more pronounced in the northern and eastern basins relative to their southern and western counterparts, indicating a regional disparity in water scarcity under dry conditions. This trend was more distinct in tertiary basins than in secondary basins, indicating a greater sensitivity of tertiary basins to precipitation anomalies. During the periods categorized as hot, AWSI also had an upward trend compared to the multiyear average, consistent with the trends observed during dry years. However, these AWSI changes were less evident than in dry conditions but more evenly distributed across all basins. This uniformity indicates a consistent basin-wide response to elevated temperatures, highlighting the widespread impact of heat anomalies on water scarcity irrespective of basin location or scale. In addition, shifts in relative AWSI changes resulting from the transition from moderately dry to dry conditions were more distinct compared to those caused by temperature anomalies from moderately hot to hot (Fig. 6), highlighting the influence of precipitation on AWSI.

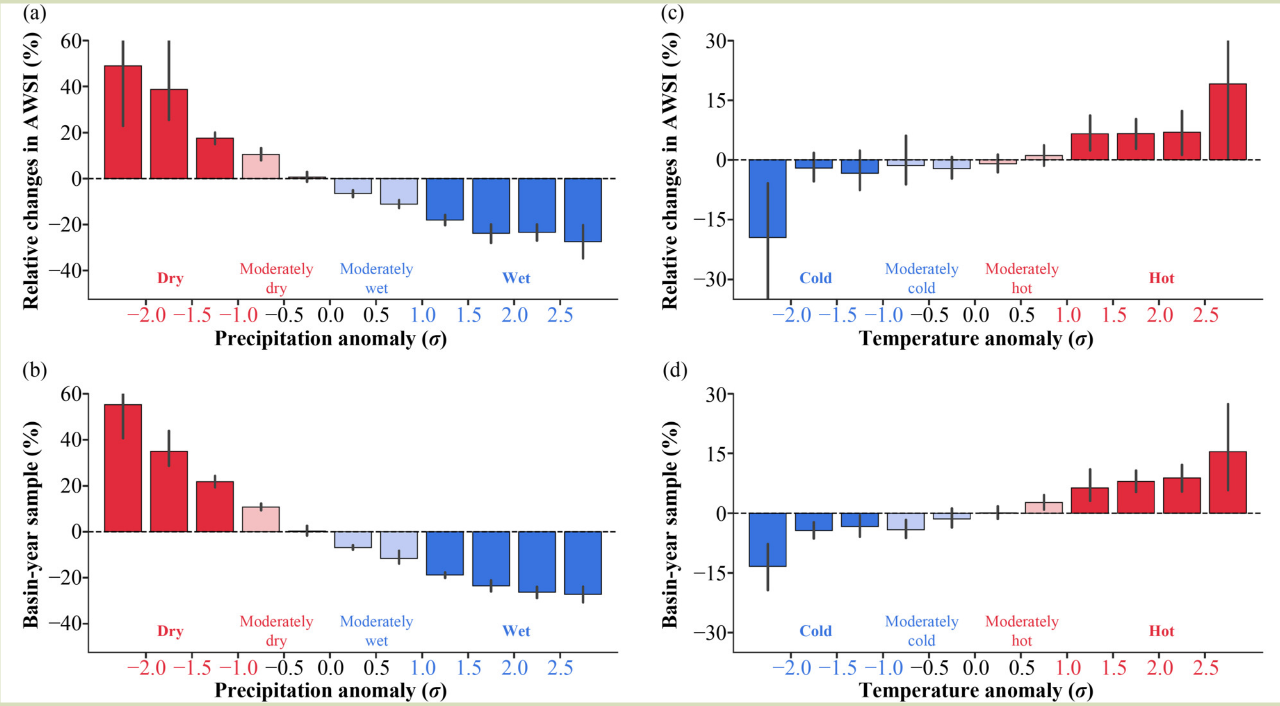


Fig. 4 Variations in the agricultural water scarcity index (AWSI) in response to precipitation and temperature anomalies. Each subplot illustrates the overall relative change (%) in AWSI, adjusted for basin areas, using data from basin-year samples. Error bars in the graphs represent a 95% confidence intervals, calculated from 1000 bootstrap estimates. Years with precipitation anomalies lower than –1.0 standard deviation (σ) are classified as dry years whereas those with anomalies higher than 1.0σ are considered wet years for secondary (a) and tertiary (b) river basins. Similarly, temperature anomalies below –1.0σ categorize years as cold and those above 1.0σ as hot for secondary (c) and tertiary (d) river basins.

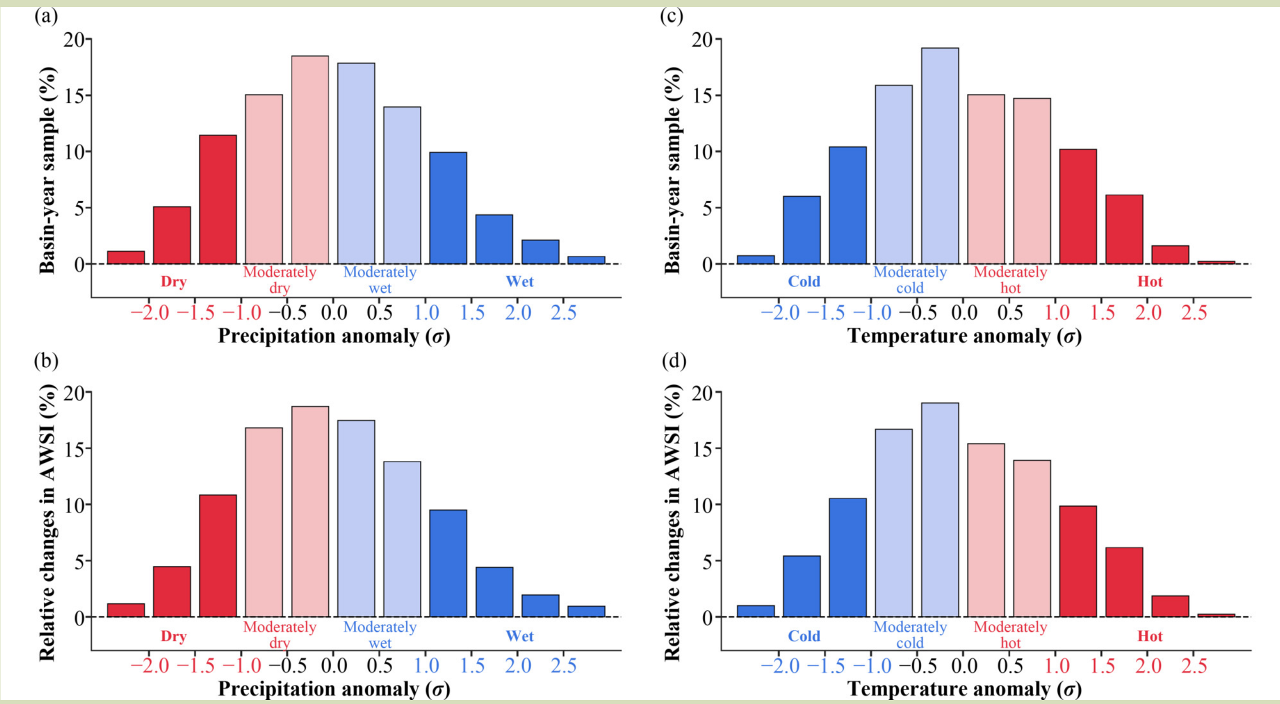


Fig. 5 Basin-year sample ratios (%) with different precipitation and temperature anomalies for secondary (a, c) and tertiary (b, d) river basins.

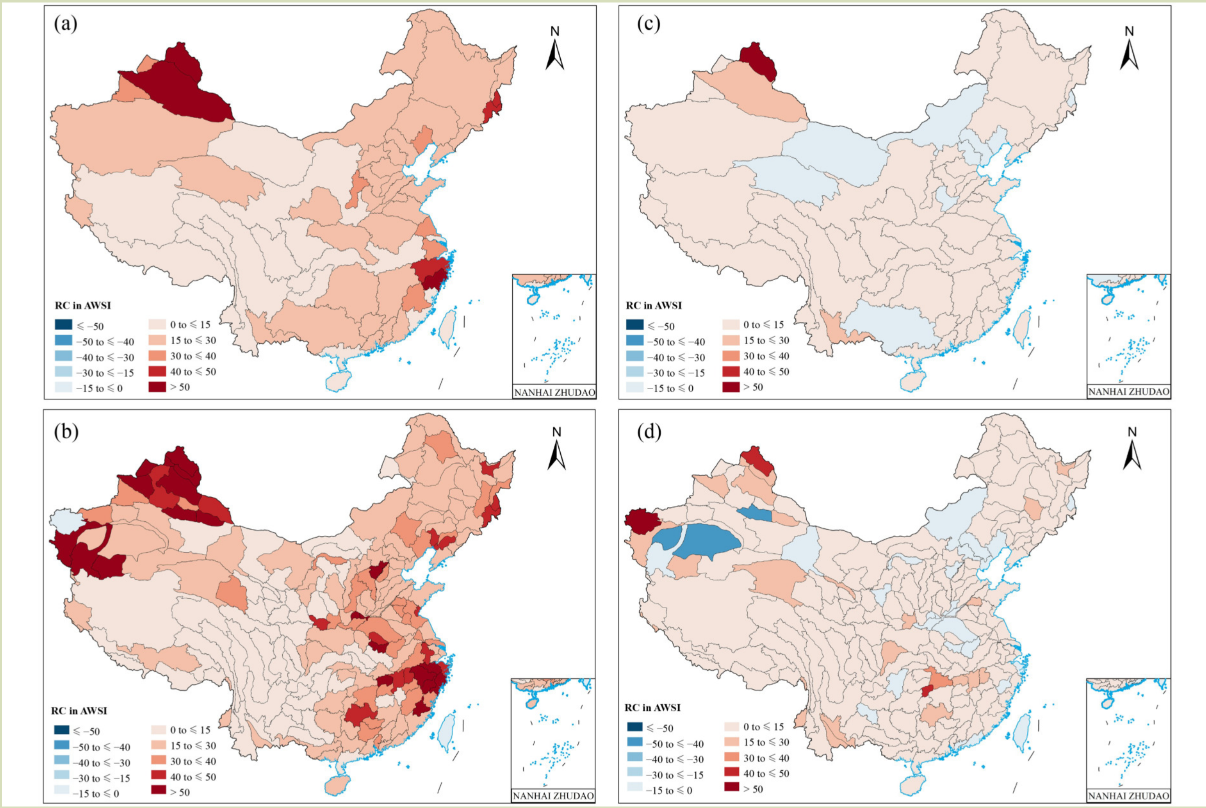


Fig. 6 Relative changes (RC) in agricultural water scarcity index (AWSI) from multiyear averages under dry and hot conditions for secondary and tertiary basins (审图号: GS 京（2024）1698 号). Dry conditions for secondary (a) and tertiary (b) basins, and hot conditions for secondary (c) and tertiary (d) basins.

3.4 Impact of compound climate extremes on AWSI

During the years with compound dry and hot conditions, a marked increase in AWSI was observed across most secondary and tertiary basins, surpassing that observed from either high temperatures or drought in isolation (Fig. 7). For example, the increase in AWSI was below 30% in many secondary river basins in both dry and hot conditions, but higher than 30% in most cases. In addition, in many river basins, especially at the tertiary level, compound dry and hot conditions were not detected. This indicates that compound dry and hot conditions were rare but had a large impact.

4 Discussion

4.1 Spatial scale effects on AWSI

The assessment of water scarcity is substantively influenced by the scale of the analysis, as demonstrated by Liu et al.[2] and Gao et al.[11], highlighting the diversity in water scarcity when viewed across varying scales. Our analysis shows that evaluations at tertiary river basins yielded a more detailed and accurate understanding of water scarcity dynamics, in contrast to those of secondary river basins. Tertiary basins can better capture inherent nuances and complexities in hydrological processes because of their more granular scale, as shown by Greve et al.[12] and Postel et al.[4] The scale effect is particularly crucial for countries like China, where the distribution of water resources is particularly uneven, as described by Qin et al.[5] and Vörösmarty et al.[14]

Our study underscores the importance of considering scale effects when analyzing the impact of climatic anomalies on water scarcity. However, model resolution represents one of the challenges in current large-scale hydrological model research. The data for the present study were sourced from ISIMIP at a spatial resolution of 30 arc-min from the PCR-GLOBWB model, which has been widely used. A high-resolution simulation of hydrological processes, for example, at 5 arc-min, would better reveal the scale effect. We constructed a high-resolution PCR-GLOBWB model to obtain a 5 arc-min simulation and recommend that future studies should

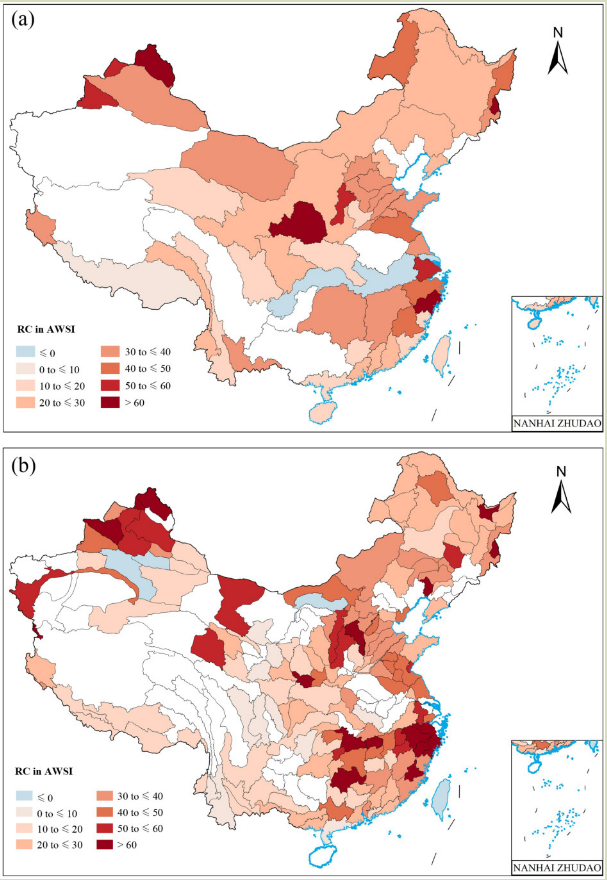


Fig. 7 Relative changes (RC) in agricultural water scarcity index (AWSI) from multiyear averages under compound dry and hot conditions for secondary (a) and tertiary (b) river basins (审图号: GS 京（2024）1698 号). White color indicates no compound dry and hot conditions.

incorporate high-resolution data to further advance understanding of scale effects.

4.2 Impact of integrated climate variations on AWSI

An integrated analysis of temperature and precipitation anomalies offers a holistic view of their combined influence on water scarcity. Our findings show that precipitation anomalies exerted a greater impact on the AWSI than temperature variations, particularly during extreme drought conditions[32,39]. In addition, our results are consistent with the substantial rise in AWSI during such periods described by Hanasaki et al.[21] Also, our study underscores the intensified effects on water scarcity when hot and dry conditions occurred concurrently, leading to notable increases in AWSI across a majority of basins. Therefore, a thorough understanding of the combined effects of simultaneous temperature and precipitation anomalies, especially for hot and dry conditions, is crucial for the development of resilient agricultural practices and water management policies, particularly in basins susceptible to these climate extremes.

Generally, there was a positive correlation between sectoral water usage (combined crop and other sector water demand) and AWSI, that is, AWSI increased when sectoral water usage rose and vice versa. In contrast, runoff/soil moisture and AWSI presented a negative correlation, that is, AWSI decreased when runoff/soil moisture increased and vice versa. For example, Mekonnen and Hoekstra[40] found that increasing water availability estimates worldwide and for each month by 20% reduces the number of people facing severe water scarcity during at least 1 month of the year by 2%. Therefore, it is necessary to unravel the complex interplay between precipitation and temperature and the related variables influencing AWSI with in-depth studies. Understanding this intricate relationship is crucial for developing comprehensive approaches to address the challenges posed by combined climatic extremes. In contrast, other variables, for example, solar radiation, wind, and humidity, of extreme climate conditions could also greatly influence AWSI. Analyzing their effects is beyond the scope of the present study but deserves future investigation.

4.3 Limitations of the research

The present study primarily focused on China, its severe water scarcity issue, and its uneven distribution of water scarcity. Broadening the scope of analysis to encompass a global perspective[41] would not only provide a more comprehensive understanding of agricultural water scarcity patterns in the context of evolving climate extremes globally but also facilitate the formulation of more effective and adaptable strategies for water resource management.

Additionally, the AWSI might not fully encompass all aspects of water scarcity, particularly in terms of domestic and industry water demands[5,42]. In addition, AWSI covers several important processes of human activities, crop growth, and hydrological cycles. They all have uncertainties in multiple resources as a consequence, for example, estimation of crop water consumption [43] and computation of water resources[12]. All of the above indicate an area for further exploration and refinement of the index, and the uncertainty inherent in the climate datasets remains significant and should not be ignored. In addition, the synergistic/antagonistic effects and nonlinear responses of changes in AWSI under compound conditions represent a topic worthy of in-depth investigation. However, related analyses are beyond the scope of the present study.

Our study did not consider groundwater a component of blue water resources, which may have resulted in an overestimation in the analysis of AWSI. However, most current assessments lack groundwater-related indicators for evaluating water scarcity. In future studies, groundwater should be incorporated into our assessment indicator. Finally, our study revealed the impact of climate extremes over a historical period. Subsequent studies should focus on the effects of compound precipitation and temperature extremes on agricultural water scarcity.

5 Conclusions

The present study underscores the necessity for strategies to address water scarcity in the context of compound extreme dry and hot conditions. It also provides a comprehensive analysis of how variations in precipitation and temperature, along with the scale of the analysis, impact water scarcity. These insights are important for developing more effective strategies for water resource management and adaptation for specific regions.

We found that in secondary basins, the AWSI increased by about 26% over the long-term average during dry years, reaching about 49% in extremely dry conditions. Tertiary basins showed similar trends, with AWSI increasing by 28% and 55%, respectively. Regarding hot years, AWSI rose by about 6.8% (7.3% in tertiary basins) from the long-term average, peaking at about 19.1% (15.5% in tertiary basins) during extremely hot years.

Additionally, the present study demonstrates that water scarcity assessments are more uniformly and precisely conducted in tertiary than in secondary river basins. Future studies should therefore focus on the impact of different research scales on agricultural water scarcity. Efforts should also be directed toward developing more inclusive and detailed metrics for measuring water scarcity, enhancing the accuracy and comprehensiveness of associated assessments. In addition, future methodology involves executing simulations of the AWSI with high-resolution data and in response to diverse future climate scenarios.

In summary, our study provides a comprehensive analysis of the effects of variations in precipitation and temperature, as well as the impact of scale on water scarcity assessment. Therefore, we advocate for a strategic prioritization in the management of water resources and the development of climate adaptation strategies.

Acknowledgements

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Compliance with ethics guidelines

Jiongjiong Liu, Yilin Zhao, and Wenfeng Liu declare that they have no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

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