

Editorial

Drought Risk Analysis, Forecasting and Assessment under Climate Change

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Abstract: Climate change is undoubtedly one of the world's biggest challenges in the 21st century. Drought risk analysis, forecasting and assessment are facing rapid expansion, not only from theoretical but also practical points of view. Accurate monitoring, forecasting and comprehensive assessments are of the utmost importance for reliable drought-related decision-making. The framework of drought risk analysis provides a unified and coherent approach to solving inference and decision-making problems under uncertainty due to climate change, such as hydro-meteorological modeling, drought frequency estimation, hybrid models of forecasting and water resource management. This Special Issue will provide researchers with a summary of the latest drought research developments in order to identify and understand the profound impacts of climate change on drought risks and water resources. The ten peer-reviewed articles collected in this Special Issue present novel drought monitoring and forecasting approaches, unique methods for drought risk estimation and creative frameworks for environmental change assessment. These articles will serve as valuable references for future drought-related disaster mitigations, climate change interconnections and food productivity impacts.

Keywords: climate change; drought risk; assessment; forecasting

1. Introduction

Drought is a complex natural catastrophe that has plagued civilization throughout history. It usually develops when different hydro-meteorological variables encounter drier than normal conditions. Most parts of the world, even wet and humid regions, suffer from drought, though arid areas are more susceptible because their moisture levels rely on only a few critical rainfall events [1]. Drought can be categorized into several types depending on its impact on the hydrological cycle [2]. Lack of precipitation for an extended period, i.e., several months to years, leads to meteorological drought [3]. Meteorological drought inevitably spreads through the hydrological cycle for a prolonged duration. This may cause crop yield reductions due to reduced soil moisture and is known as agricultural drought [4,5]. Extended meteorological drought may cause a streamflow shortage, called hydrological drought [6].

Drought is monitored using drought indices, which measure deviations from normal local conditions based on historical distributions [7]. Drought indices developed to quantify meteorological, agricultural and hydrological drought include the Rainfall Anomaly Index (RAI) [8], Palmer Drought Severity Index (PDSI) [9], Standardized Precipitation Index (SPI) [10], Reconnaissance Drought Index (RDI) [11], Standardized Precipitation Evapotranspiration Index (SPEI) [12], Crop Moisture Index (CMI) [13], Soil Moisture Drought Index (SMDI) [14] and Standardized Runoff Index (SRI) [15]. Standardized drought indices are widely used due to their versatility and simplicity over various time scales [6], and most only employ a single input indicator for drought monitoring. Single indicator-based

drought indices do not fully reflect drought information and may lead to unreliable results [16]. They are also based on the presumption of stationarity, which is not a valid assumption under changing climate conditions; a more general and robust drought monitoring system is required.

Over the last century, the global climate and the environment have changed remarkably; global warming, which contributes to increased water circulation, has caused severe natural disasters including floods and droughts [17]. In most parts of the world, drought risk has increased significantly since 1970 due to the rise in evapotranspiration without any precipitation enhancement [7]. In East Asia, China is frequently affected by drought due to significant precipitation and temperature variations [18–20]. The Ministry of Water Resources of China [21] reported extreme droughts occurring at an average rate of every two years from 1990 to 2007. The associated crop productivity loss was estimated at almost 39.2 billion kg per year, about 1.47 percent of the gross domestic product. The Australian Agriculture and Resource Economics Bureau reported that the 2006 drought reduced national winter cereal crops by 36 percent and cost AUD \$3.5 billion, leaving numerous farmers in fiscal crisis [22]. Therefore, developing schemes for examining climate change-induced drought impacts on crop productivity is crucial for sustaining global agriculture.

Global temperature increases and rainfall pattern variations are evidence that drought frequency and severity are greatly affected by climate change [23]. Blenkinsop and Fowler [24] assessed climate change impacts on drought characteristics and reported that short-term summer droughts are projected to increase while long-term droughts will become less severe. Sheffield and Wood [25] used soil moisture data to examine shifts in drought incidence by combining multiple General Circulation Models (GCMs) and multi-scenarios. Extensive studies [26–30] focus on univariate and bivariate frequency analyses for drought risk assessment due to climate change. Anthropogenic activities, in addition to climate change, are also a major factor affecting drought phenomena [31]. Urbanization, variation in land use/land cover and industrialization can influence hydrological processes and exert environmental impacts, with substantial implications on water resources and, ultimately, hydrological drought [32]. Many studies have quantified the influence of climate change and human activity on streamflow, but studies on how they affect hydrological drought are very rare [33–35]. All of these investigations utilized conventional drought indices for drought monitoring and are based on stationarity presumptions; this is not valid for varying environmental conditions.

This Special Issue provides a platform for researchers to fill these gaps with their experience and expertise. Figure 1 shows the climate-influenced relationships between hydrological cycle variables and drought types. This Special Issue covers (1) robust index development for effective drought monitoring; (2) risk analysis framework development and early warning systems; (3) impact investigations on crop productivity; (4) environmental change impact analyses.

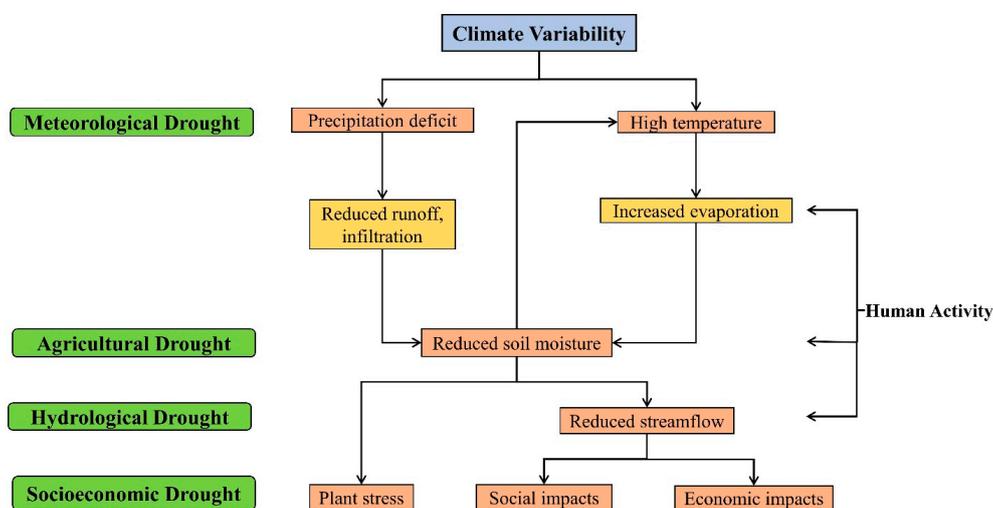


Figure 1. Climate-influenced relationships between hydrological cycle variables and drought types.

2. Special Issue Overview

This Special Issue includes 10 peer-reviewed articles covering a wide range of research topics related to drought monitoring, drought forecasting and drought risk analysis in a changing climate. Specific issues include the development of a modified composite drought index (MCDI) and a non-stationary joint drought management index (JDMI) [36,37], climate change influences on drought patterns and crop yields [38,39], meteorological and hydrological drought risk under future climate change predictions [40,41], extreme drought assessment and its relationship with the Indian Ocean dipole (IOD) mode [42], severe drought prediction using atmospheric teleconnection patterns (ATPs) [43], drought forecasting using stochastic models [44] and hydrological drought risk estimations based on changing climate conditions and human activities [45]. These studies use statistical approaches, field measurements and mathematical methodologies.

Chen et al. [36] developed a new multivariate drought index based on multiple input variables: precipitation, temperature, evaporation and surface water content. They compared the modified composite drought index (MCDI) to the meteorological drought composite index (CI), an existing multivariate drought index, and found a high correlation with drought events in China's Hubei Province. MCDI's drought monitoring accuracy is also compatible with historical drought records. MCDI is a reliable drought monitoring index that represents integrated meteorological and agricultural drought knowledge. In another study, Yu et al. [37] formulated a non-stationary joint drought management index (JDMI) for hydrological drought risk assessments. They formulated a bivariate time-varying copula model using generalized additive models for location, scale and shape (GAMLSS) and determined future low-flow drought using simulated data for South Korea's Soyang River basin. From this, they calculated water supply performance indexes, considering reliability and vulnerability. The outcomes suggest that time-varying models are more suitable for drought modeling under changing environmental conditions. The non-stationary JDMI may serve as a significant model for drought monitoring, planning and mitigation.

Guna et al. [38] examined the influence of climate variation on maize crop productivity during the growing season in Songliao Plain, China. They applied the Mann–Kendall mutation test to determine temperature and precipitation trends and used the standardized precipitation evapotranspiration index (SPEI) to examine drought characteristics. They estimated the relationship between meteorological drivers, drought indices and maize productivity and determined that the correlation between climate yield and temperature is negative, while the correlation between climate yield and precipitation and drought is positive. Using future global warming scenarios (1.5 °C and the 2.0 °C), the results show a decrease in predicted maize productivity from −7.7% to −15.9% using multiple regressions and −12.2% to 21.8% using one-variable regressions. These findings explain potential future security. Similarly, Qutbudin et al. [39] investigated seasonal drought pattern variability using the Mann–Kendall test and SPEI in Afghanistan. Their results indicate increasing Afghan drought severity and frequency. A 0.14 °C/decade temperature increase and rainfall decrease are the primary factors influencing the results, which occur during the rice, corn and wheat growing season in Northwest and Southwest Afghanistan. This methodology can be applied elsewhere and utilized in adaptation and mitigation policy development.

Kwon and Sung [41] examined future drought changes using HadGEM2-AO projections in South Korea. They projected future drought based on baseline climatic reference precipitation data and quantitatively assessed changes in future drought's severity and frequency. Their results, which are distinctly different from previous studies due to existing methodology modification, suggest that future drought will be weaker and less frequent due to a rise in precipitation. In future climates, mild drought will occur more frequently, but drought frequency based on baseline climate will decrease. In order to develop better coping strategies for future drought, knowledge about a region's baseline and future climates is essential. To better understand climate variation influences on drought, Kim et al. [40] quantified the future hydrologic risk of extreme drought in South Korea using climate change scenario representative concentration pathway (RCP) 8.5. They adopted the threshold level method to identify

drought events and extract drought characteristics. They used bivariate frequency analysis to determine return periods, taking into account drought duration and drought severity. They calculated that the extreme drought hazard median will be higher in the future than the baseline period's maximum drought. These results will help establish drought risk-based quantitative design standards for water resource systems.

Global rainfall patterns have changed due to climate change, resulting in extreme natural disasters including drought. Yeh and Hsu [44] proposed an early warning system for drought forecasting using stochastic, autoregressive integrated moving average (ARIMA) models based on the standardized precipitation index (SPI) in Southern Taiwan. The ARIMA model yielded determination coefficients (R^2) of more than 80% at each station, with sufficiently low error indicators. This suggests that the ARIMA model is a powerful tool for drought forecasting. Apart from climate change, anthropogenic activities also influence hydrological drought risk. Zhang et al. [45] quantified climate change and anthropogenic activity impacts on the hydrological drought risk for China's Kuye River basin (KRB). They found that the KRB's annual runoff pattern changed significantly after 1979, and drought characteristics (duration and severity) have been considerably worse in more recent times. The quantitative assessment reflects that human activities lead to an increased regional drought risk, and the modeling results can be utilized to plan and control sustainable water supplies.

Two studies improved extreme drought predictability by identifying the relationship between the Indian Ocean dipole (IOD) and atmospheric teleconnection patterns (ATPs). Gao et al. [42] examined extreme droughts in the Indochina peninsula (ICP) and its IOD relationship. They mimicked the drought-sensitive area and various IOD evolution patterns via statistical simulations. The results showed a reduction in extreme drought frequency throughout Vietnam and Southwestern China. In contrast, they saw a drought frequency increase in Cambodia, Central Laos, and along the coastline adjacent to the Myanmar Sea. Gao et al. [43] identified the relationship between extreme droughts and ATPs by selecting a core drought region (CDR) based on historical drought analysis. They chose four principal components (PCs) based on eight teleconnection variances. The extreme spring drought (ESD) predictions showed that the neural network's predictive performance was superior to the Poisson regression. These studies will be helpful in improving extreme drought diagnostic methods.

3. Conclusions

This Special Issue's ten articles advance our understanding of drought's complex phenomena and its interaction with climate change and human activity. The newly proposed drought indices [36,37] will serve as effective tools for drought monitoring under changing environmental conditions. The indices can incorporate multiple inputs for drought calculation, which is more realistic than traditional methods. Two articles [38,39] investigated the effects of climate change-induced drought on various types of crop productivity. These studies showed that temperature increases result in decreases in crop productivity; this is linked to food security. The next two articles [40,41] examined meteorological and hydrological drought risks under future climate change scenarios. The methodologies presented in these two articles are helpful to cope with future natural disasters. Two papers [42,43] improve drought predictability by identifying the relationships between drought and the Indian Ocean dipole (IOD) and atmospheric teleconnection patterns (ATPs). Another article [44] proposed a drought early warning system using a stochastic, autoregressive, integrated moving average (ARIMA) model; this study is very beneficial because advance knowledge is required for effective management.

These articles cover a wide geographic range, across China [36,38,43,45], Taiwan [44], South Korea [37,40,41] and the Indo–China peninsula [42], which covers many contrasting climatic conditions. Hence, their results have global implications: the data, analysis/modeling, methodologies and conclusions lay a solid foundation for enhancing our scientific knowledge of drought's complex mechanisms and relationships to varying environmental conditions.

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