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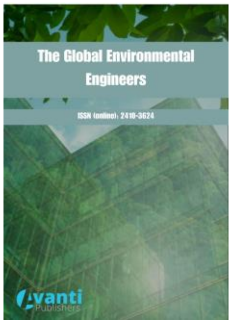

Key Climatic Drivers of Droughts and Floods in Henan, China (1955–2015): Insights from Random Forest and Spatial Analysis

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ABSTRACT

Global climate change continues to occur and induces a series of severe ecological consequences, including an increased risk of droughts and floods. Extensive studies have explored the climatic drivers that may trigger the occurrence of disasters. However, monthly climatic factors have rarely been employed at the county scale for long-term drought and flood assessment. Henan Province, located in central China, is a region prone to natural disasters. This study is dedicated to conducting training and validation analyses of drought and flood intensities in Henan from 1955 to 2015, based on monthly and annual climatic factors using random forest modeling, spatial statistical description, and geographical information system (GIS) techniques. A total of 100 climatic variables were initially considered, and the most important predictors were identified through variable importance ranking in the random forest framework. Model performance was evaluated using out-of-bag (OOB) error and independent validation statistics. The results indicate that early spring temperature serves as a robust signal for predicting annual drought and flood intensities, although slight differences may exist in the temperatures from January to March across the three sub-climatic zones of Henan. This study provides valuable insights into predicting droughts and floods based on early spring temperature, thereby supporting mitigation measures for natural disasters that are expected to increase under global warming.

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1. Introduction

Climate change continues to occur and induces a series of ecological consequences, which is accelerating the global hydrological cycle [1, 2]. Meanwhile, a more rapid but less stable hydrological cycle results in increased occurrences and intensities of floods and droughts in many regions worldwide [3-5]. In recent years, the spatiotemporal patterns of droughts and floods and their driving forces have attracted growing attention [6-12].

Previous studies have demonstrated that climatic factors are closely associated with droughts [13-15] and floods [16, 12]. Numerous studies have shown that global warming tends to induce extreme precipitation events, thereby increasing the risk of floods [17, 18]. Over the past five decades, higher temperatures have led to spring snowmelt floods, and polar warming has caused winter floods in Europe [16]. Rising temperatures affect the intensity and frequency of droughts and can result in water deficits [19, 20]. In Europe, severe precipitation deficits have been observed to follow high-temperature events [13]. Based on historical observations in the United States, droughts and extreme temperatures are closely associated: extreme temperatures can induce droughts and simultaneously exacerbate the impacts of droughts and heatwaves [15]. Additionally, under drought conditions, local temperatures are amplified [15]. Over the past half-century, the reduction in regional precipitation has been found to play a major role in the changing patterns of drought intensity and duration in China [21]. Understanding the causes of droughts and floods in a changing climate is crucial for drought and flood risk prediction and management [2, 22]. However, few studies have addressed the causes of drought and flood disasters at a monthly scale [23]. Most studies have only focused on the interannual or annual variability of climatic variables [24]. It should be clarified that drought and flood disasters constitute a highly complex system involving monthly-level climatic variables [25]. Therefore, a variety of monthly-level climatic factors need to be incorporated for further investigation of this topic to better understand the mechanisms underlying drought and flood disasters [22, 26]. This constitutes the primary motivation for the present study.

Henan Province (hereafter referred to as Henan) is China's largest wheat-producing province, accounting for 10% of the country's total wheat production. With a population of 13 million in 2017, Henan is also one of China's most populous provinces. From these two perspectives, Henan is highly vulnerable to natural hazards such as droughts and floods. Historically, Henan has been a region prone to natural disasters, where droughts and floods have frequently caused substantial losses in human life and the economy. Understanding the key influencing factors of droughts and floods is vital for natural disaster risk management. Such information is utilized in planning crop cultivation and other land use activities, as well as in yield prediction and construction projects. In this study, we identify the key climatic factors influencing drought and flood intensities based on monthly and annual climatic variables at the county scale in Henan Province during the period 1955–2015. We investigate two aspects of the problem: (1) the key climatic factors closely associated with drought and flood intensities at the provincial level and in each sub-climatic zone; and (2) the predictability of these climatic variables for drought and flood intensities. The remainder of this paper is organized as follows: Section 2 describes the study design; Section 3.1 presents potential climatic variables related to droughts and floods; Section 3.2 details the identification of key variables using random forests; Section 4.1 characterizes the spatiotemporal patterns of drought and flood events in Henan; Section 4.2 identifies key climatic influencing factors from 100 climatic variables; Section 4.3 assesses the predictability of drought and flood intensities using the model; Section 5 discusses potential reasons associated with global warming; and Section 6 provides a summary and suggestions for future research. Compared with previous studies that mainly focused on annual or seasonal hydroclimatic indices, this study emphasizes the predictive value of monthly climatic signals, especially temperatures in early spring, for annual drought and flood intensities. The objective is not to establish a complete physical dynamical model, but to identify practically useful climatic predictors and evaluate their predictive potential at the county scale.

2. Study Area

Henan Province, with an area of 167,000 square kilometers and a population of 94.8 million, is the third most populous province in China. It is located in the middle and lower reaches of the Yellow River in central China (110°21'–116°39'E, 31°23'–36°22'N). Most parts of Henan are situated in the warm temperate zone, featuring a humid to semi-humid monsoon climate, characterized by cold and little rainy winters (with scarce snow), dry springs with frequent winds and sandstorms, hot and rainy summers, and clear autumns with abundant sunlight. The annual average temperature ranges from 13℃ to 15℃, with monthly averages varying from –1.57℃ to 3.54℃ in January and 24℃ to 28℃ in July. The annual precipitation is approximately 550–1100 mm, primarily distributed in the southern and western regions. The typical cultivated crops are winter wheat and summer maize. Based on annual climatic parameters, landforms, and major crops, Henan can be divided into three distinct sub-climatic zones [27] (Table **1**).

Table 1: The characteristics of three sub-climatic zones in Henan Province.

Sub-regions	Annual Temperature (℃)	Annual Precipitation (mm)	Annual Sunshine Duration (h)	Main Landforms	Main Crops
Zone1	14.4	569	2109	Mountains	Corn
Zong2	14.8	798	2035	Plains	Wheat
Zong3	15.2	1033	1978	Hills	Rice

3. Data and Methods

3.1. Data Collection

County-level officially recorded drought and flood data in the study area from 1955 to 2015 were obtained from publications by China Meteorological Press, including China Meteorological Disasters Collections - Henan (data from 244 B.C. to 2003 A.D.) and Yearbooks of China Meteorological Disasters (data from 2004 to 2015). The dataset includes the start and end dates of disasters, affected areas, as well as losses related to population, housing, and the economy for each county. These publications were compiled by professional organizations following the principles of respecting historical facts, excluding superstitious information, and recording data in chronological order. In the original records, the intensity of drought and flood disasters was classified into three grades based on human and economic losses: light, moderate, and severe. "Light" was simply recorded as "drought/flood occurred," indicating minor losses; "moderate" was recorded as "major drought/flood causing significant losses"; and "severe" indicates "catastrophic drought/flood resulting in human casualties and severe economic losses." To identify the key influencing factors of drought and flood intensities, the light, moderate, and severe grades were quantified as 1, 2, and 3, respectively. The annual total intensity value of a specific disaster in a county was calculated as the sum of the intensity value multiplied by its frequency. To improve the temporal comparability of the historical records, the original documentary descriptions were reclassified into this unified three-grade system and then aggregated at the county-year scale using the same coding rule throughout the study period. In this study, the derived drought/flood intensity value is regarded as a historical disaster severity index reflecting the integrated severity of documented impacts, rather than a direct physical measure such as precipitation deficit or inundation depth. Therefore, the analysis focuses primarily on relative interannual variability and regional contrasts in drought and flood severity.

Although documentary disaster archives inevitably contain some uncertainty associated with historical reporting, these data remain one of the few continuous county-level sources available for long-term disaster assessment in Henan. The records were continuously compiled by local government departments and subsequently edited by professional institutions, which provides an important basis for interannual and spatial comparison after unified classification.

The climate data used to identify influencing factors were obtained from the official meteorological observation network; monthly and annual data can assist in early prediction of disasters. Additionally, land surface air temperature and precipitation data from 109 meteorological stations in Henan were collected, including monthly and annual mean, minimum, and maximum temperatures (℃) and precipitation (mm) for the previous year and the current year during the study period. Before analysis, the meteorological observations were subjected to basic quality control, including completeness screening, consistency checking, and correction of obvious abnormal records. For a limited number of missing observations, interpolation based on adjacent temporal records or neighboring stations was used to maintain the continuity of the climatic series. The station-based climatic variables were then spatially interpolated and transformed to the county scale so as to be consistent with the spatial unit of the drought and flood disaster records. Through scale transformation, it maintains consistency with the spatial scale of drought and flood natural disasters. GIS-based spatial interpolation and mapping were performed using ArcGIS 10.2 software.

3.2. Identification of the Key Climatic Variables

A training and validation approach was adopted to identify the key climatic variables influencing drought and flood intensities. The collected dataset was divided into two parts: training data (70% of the total data) and validation data (30% of the total data). The purpose of the training process was to explore the response of drought and flood intensities to climatic parameters, while the validation process provided a dataset that could be directly compared with observed records to evaluate model accuracy, identify optimal models, and predict drought and flood intensities using the validation data. This training and validation approach has been widely applied in studies on various aspects of climate and natural hazards [28-31].

Because the response relationships between drought/flood intensity and climatic predictors may be nonlinear and involve complex interactions, a random forest approach was adopted in this study. Random forest has been widely used in environmental and climatic studies because it is relatively robust to high-dimensional predictors, nonlinear responses, and multicollinearity among explanatory variables [32-34].

Based on previous studies on the effects of climatic variables on droughts and floods [35], monthly and annual mean, minimum, and maximum temperatures (℃) and precipitation (mm) were selected as potential influencing climatic variables (100 variables in total). These variables were coded as follows: 1MeanT to 12MeanT represent the monthly mean temperatures from January to December; 1MinT to 12MinT and 1MaxT to 12MaxT represent the monthly minimum and maximum temperatures from January to December, respectively; 1Pre to 12Pre represent the monthly precipitation from January to December; AnnT and AnnPre represent the annual mean temperature and annual precipitation, respectively. Variables marked with "L" (e.g., 1MeanLT, 1MinLT, 1MaxLT, 1LPre, AnnLT, AnnLPre) represent the monthly mean, minimum, and maximum temperatures, as well as monthly and annual temperatures and precipitation from the previous year. Drought and flood intensities were treated as response variables. Random forest analysis, proposed by Breiman [32], was used to identify the key predictors of drought and flood intensities among the various climatic variables. In the present analysis, the random forest model was implemented in the RF package in R software. The model was constructed using 500 trees (ntree = 500), and the number of variables randomly selected at each split (mtry) was determined according to the regression setting of the algorithm and further checked using the out-of-bag (OOB) error. Bootstrap samples were repeatedly drawn from the training dataset to construct an ensemble of regression trees, and the final prediction was obtained by averaging the predictions from all trees. Variable importance was then used to rank the climatic predictors and identify the dominant variables associated with drought and flood intensities. This procedure is particularly suitable for the present study because it can reduce, although not completely eliminate, the risk of overfitting caused by a large number of potentially correlated climatic variables. Therefore, the random forest model was used here mainly as a data-driven tool to detect the most informative climatic signals and to evaluate their predictive potential.

Model performance was evaluated primarily using the out-of-bag (OOB) error and the root mean squared error (RMSE). In the revised manuscript, Fisher’s P statistic and Akaike information criterion (AIC) were removed because they are not appropriate goodness-of-fit criteria for nonparametric random forest models. The validation data were used to compare predicted and observed drought/flood intensity values and to assess the predictive skill of the selected climatic variables. The correlations between drought/flood intensities and climatic variables may vary across different sub-climatic zones; therefore, random forest analysis was conducted separately for each sub-climatic zone using RF package in R software. This zonal analysis was intended to capture possible differences in climatic controls among sub-climatic regions with distinct topographic and climatic backgrounds.

4. Results

4.1. Spatial-temporal Pattern of Drought and Flood Intensities

In Henan, droughts and floods were closely associated across the sub-climatic zones during 1955–2015 (Fig. **1**). For both drought and flood intensities, the western region of Henan, belonging to Zone 1, reached the highest levels. The middle region (Zone 2) followed, whereas the northern and southern regions of Henan Province exhibited relatively lower drought and flood intensities. Overall, the spatial distribution indicates that the more mountainous and transitional areas in western and central Henan experienced higher cumulative drought and flood severity during the study period, whereas the northern and southern counties showed comparatively lower cumulative intensity values. This spatial contrast suggests that the long-term drought and flood severity index varied considerably across the province and provides the basis for subsequent zonal analysis.

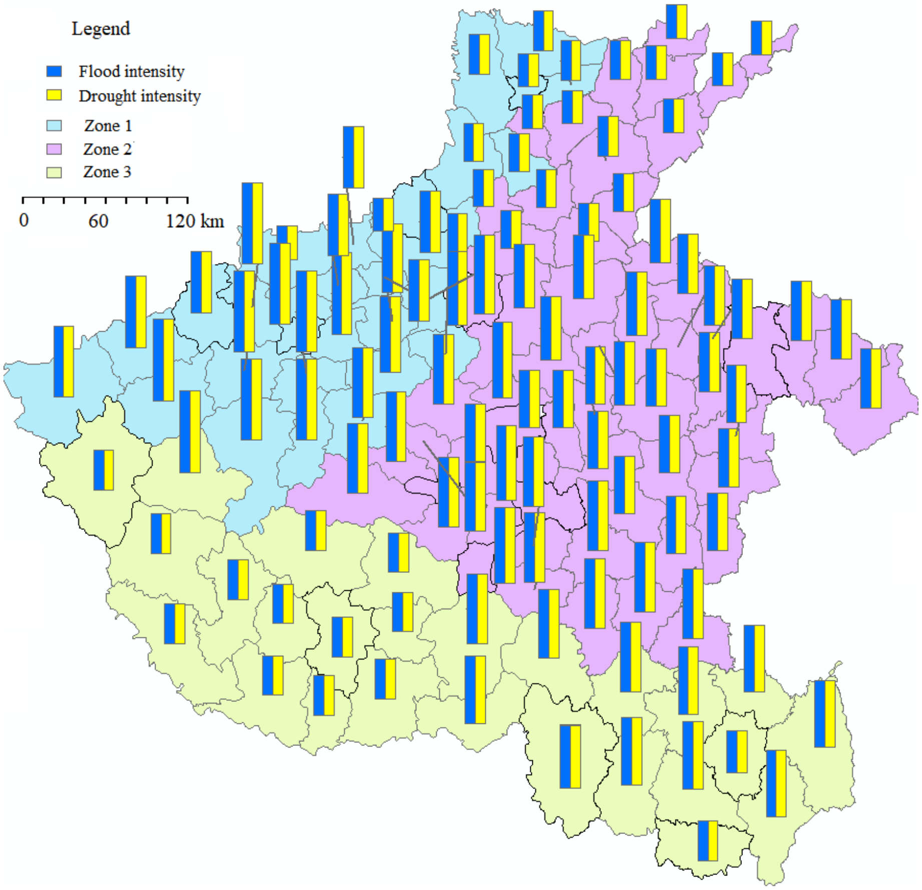

Figure 1: Spatial distribution of drought and flood intensities in each county during 1955–2015 in Henan Province, China. The color of each county indicates the sub-climatic zone. The columns in each county indicate the cumulative drought and flood intensities during 1955–2015.

The time series of drought and flood intensity during 1955–2015 showed strong interannual fluctuations (Fig. **2**). The intensities of drought and flood had several peaks, and high-intensity events became more frequent after 1980. In general, drought intensity was higher than flood intensity during most of the study period. It is also notable that drought and flood were temporally associated, and they often occurred in the same period or in successive years. A possible lagged relationship was observed in several episodes, with drought tending to occur after years with relatively high flood intensity. For example, the drought peak in 1986 followed the flood-dominated period of 1983–1985, and the drought event in 1966 followed the flood peak in 1964. However, these temporal associations should be interpreted cautiously, as they do not by themselves demonstrate a causal lag mechanism.

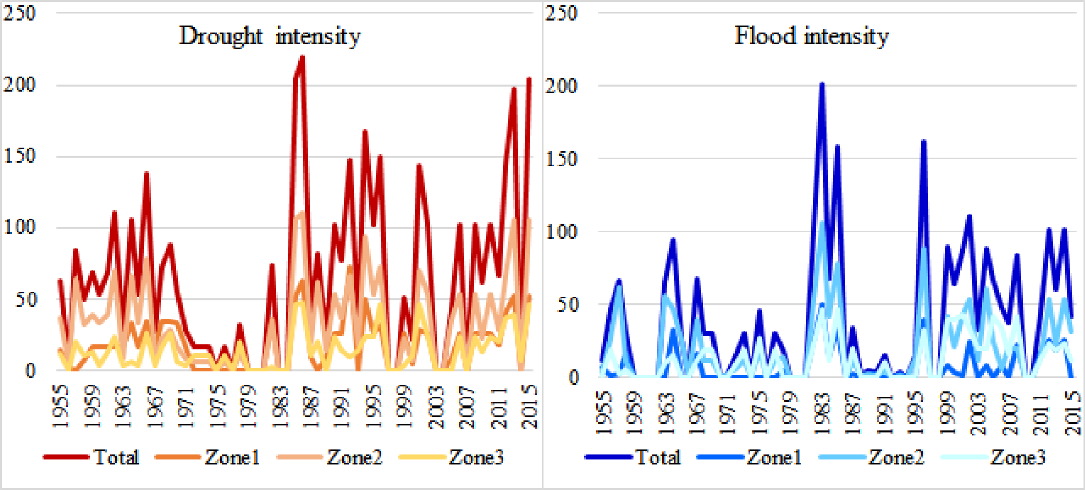

Figure 2: The annual drought (left) and flood (right) intensities in Henan and each sub-climatic zone during 1955–2015.

4.2. Key Climatic Variables

The random forest models consistently identified the mean and maximum temperatures in February as the main predictors of drought intensity in Henan, followed by the maximum temperature in March, the mean temperature in January, the maximum temperature in January, and the mean temperature in March (Fig. **3**). These results indicate that temperature conditions in late winter and early spring were the most informative climatic signals for drought intensity at the provincial scale. For the three sub-climatic zones, the maximum temperature in January and the mean temperature in February were identified as the strongest predictors in Zone 1; the maximum temperatures in February and March were the dominant predictors in Zone 2; and the mean temperature in June together with the maximum temperature in January showed the highest predictor importance in Zone 3. This zonal difference suggests that the climatic controls on drought intensity were not spatially uniform across Henan.

Similarly, the maximum temperatures in January, February, and March, together with the mean temperature in February, were identified as the main predictors of flood intensity in Henan. By further identifying the most credible predictors of flood intensity in each sub-climatic zone, we found that, among the 100 climatic variables, the mean temperatures in January and February had the highest predictor importance in Zones 1 and 2, whereas the maximum temperatures in February and March were the dominant predictors in Zone 3. Taken together, these results indicate that early spring temperature-related variables were consistently among the most important predictors for both drought and flood intensity, although the relative importance of specific months differed among the sub-climatic zones.

The predominance of temperature variables over precipitation variables in the variable-importance ranking does not imply that precipitation is unimportant for drought and flood occurrence. Rather, within the present modeling framework and historical disaster index, temperature variables provided stronger predictive information for interannual variations in drought and flood intensity.

4.3. Validating

Based on the above identified climatic variables in Fig. (**3**), we used the recorded data in the regions to verify the predicted values calculated by the random forest models. The validation results showed that the selected climatic variables provided reasonable predictive performance for drought and flood intensity in Henan and in the three sub-climatic zones. Consistent with the revised methodology, model performance was evaluated mainly using R^2 and RMSE, together with the out-of-bag error from the random forest model, rather than significance testing. The R^2 values for all zones were higher than 0.8, whereas all RMSE values were lower than 0.5, indicating

Figure 3: Random forest mean predictor importance (% increase in MSE) of the 100 climatic variables with respect to drought (above) and flood intensities (below) across all counties (left) and within each sub-climatic zone (right). Higher values indicate greater predictor importance in the random forest model.

that the predicted values were generally consistent with the recorded values (Fig. **4**). Therefore, the selected climatic variables, especially temperature-related variables in early spring, showed good predictive potential for the historical drought and flood intensity index used in this study.

Nevertheless, these validation results should be interpreted with caution. Because the response variable is a historical composite severity index derived from documentary disaster records, the high agreement between predicted and observed values should be understood as evidence of relative predictive skill rather than exact reconstruction of physical drought or flood magnitude. Overall, the validation analysis supports the usefulness of the identified climatic variables for regional drought and flood prediction, while also indicating that predictive performance differed slightly among the sub-climatic zones.

5. Discussion

Our study indicates that higher temperatures in January, February, and March are important climatic signals associated with the occurrence of droughts and floods in the same year. Several previous studies have also shown that increased temperatures can lead to severe droughts [19, 20, 15]. Consistent with these studies, our results suggest that temperatures in late winter and early spring may provide useful early-warning information for drought and flood prediction and prevention in Henan [36]. Droughts in Henan are relatively severe in spring and summer, moderate in autumn, and mild in winter [37]. Hence, the indicative effect of high spring temperatures is more pronounced. Since Henan is one of the core grain production areas in China, spring and summer droughts severely affect crop production [38]. In Henan, evaporation in spring is far greater than precipitation. Rising spring temperatures accelerate soil water evaporation, which further damages wheat seedlings and increases drought losses. This interpretation is also consistent with previous findings that warming can intensify drought impacts through enhanced atmospheric evaporative demand and land–atmosphere feedbacks, even when precipitation changes alone cannot fully explain disaster severity [19, 39, 40].

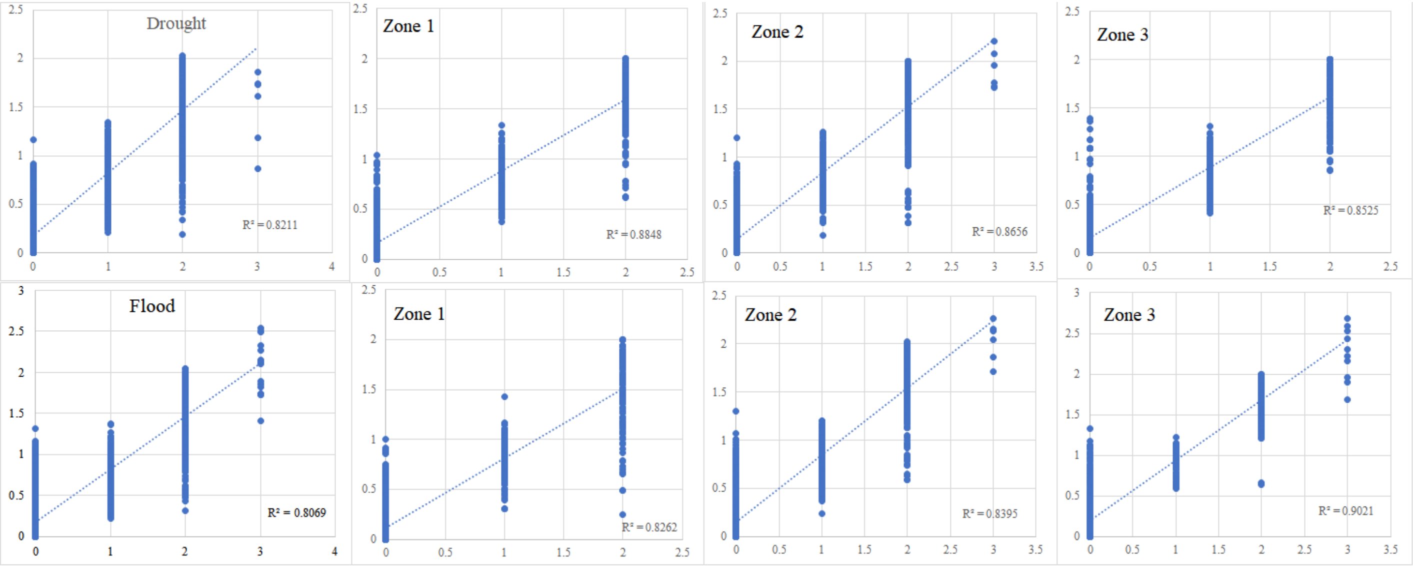

Figure 4: The linear relationships between the recorded values (x-axis) and predicted values (y-axis) for drought intensity (above) and flood intensity (below) in the entire Henan Province (left) and the three sub-climatic zones (right).

In Henan, floods are mainly caused by heavy storms and occur frequently in summer. In our study, the occurrence of summer floods was also associated with high spring temperatures. This relationship should be interpreted cautiously. Rather than implying that early spring warming directly causes summer floods, the results suggest that spring temperature may function as an integrated climatic signal reflecting antecedent land-surface conditions and the seasonal evolution of regional atmospheric circulation. According to the characteristics of the hydrological cycle in Henan, and due to the strong stability of the Eurasian atmospheric circulation, seasonal changes in the intensity and location of the Western Pacific Subtropical High and the Siberian High can easily bring warm and moist airflows to central and southern Henan [41]. Under such circulation backgrounds, anomalous spring temperature may be associated with subsequent changes in moisture transport and convective conditions over the Yellow River and Huaihe River basins. In addition, cold air activity from higher latitudes may interact with warm and moist air transported northward, thereby enhancing the likelihood of heavy rainfall events in Henan [42]. This interpretation is more consistent with the regional monsoon setting than a simple one-factor explanation. Globally, rising temperatures are expected to enhance the atmospheric water-holding capacity [12]. An atmosphere with increased water-holding capacity may alter the frequency of extreme meteorological events and trigger catastrophic floods [43]. A warmer climate has also been found to increase the intensity and frequency of extreme precipitation events, which can lead to floods [44]. Recent studies have further shown that warming can intensify compound and connected hydroclimatic extremes by modifying atmospheric moisture availability, circulation persistence, and antecedent surface conditions [40, 45, 46]. However, the mechanism by which early spring temperatures can indicate the possible occurrence of summer floods in our study requires further detailed investigation.

Relevant research has shown that the trend of climate warming in Henan Province has been significant over the past 50 years [37, 47]. Rising temperatures can amplify drought intensity, as drought losses are driven not only by significantly higher temperatures that directly harm crops but also by high evapotranspiration caused by high temperatures [39]. In Jordan, there has been a significant increase in the concurrent occurrence of droughts and heatwaves [39]. More broadly, recent studies have emphasized that climate warming increases the probability of interacting and sequential extremes, which may aggravate agricultural and hydrological risks beyond the effect of a single climatic factor [45, 46, 22]. Our case study likewise suggests that rising temperatures, especially early spring warming, are closely associated with both severe droughts and floods in Henan. However, the present results should be understood as evidence of predictive association rather than deterministic physical causation. From the perspective of meteorological disaster prevention, more attention should be paid to monthly temperature increases rather than annual climate changes [22]. In particular, monitoring monthly thermal anomalies in January–March may provide practical information for seasonal disaster preparedness in this important agricultural region.

Several limitations should also be acknowledged. First, the drought and flood intensity index used in this study was derived from historical disaster records and reflects integrated disaster severity rather than a direct physical hydrometeorological variable. Second, although random forest is suitable for identifying dominant predictors from multiple climatic variables, the detected associations may still be influenced by collinearity and by the temporal structure of the data. Third, the physical mechanisms discussed above remain inferential and should be further examined using reanalysis datasets, circulation diagnostics, and stricter temporal and spatial validation frameworks. Despite these limitations, the present study provides useful evidence that early spring temperature contains important predictive information for drought and flood risk assessment in Henan under a warming climate.

6. Conclusion

For effective drought and flood risk management, understanding the key influencing factors and thereby making predictions is crucial [48]. Because these factors are closely associated with crop production, industrial development, settlement construction, and human safety in both the present and the future, it is necessary to consider the impacts of climate change. Currently, global climate change, primarily warming, will increase the probability of more natural hazards. In the context of the present study, our results suggest that warming—especially higher temperatures in early spring—may enhance the intensity of droughts and floods in Henan by altering the climatic background conditions associated with these hazards [49]. Rather than implying deterministic causation, our climate-based analysis indicates that early spring temperature provides useful predictive information for annual drought and flood intensity. The occurrence of concurrent droughts and floods is likely to increase with climate warming, exacerbating their impacts. Recent studies have further emphasized that warming may intensify compound and connected extremes, thereby increasing socioeconomic vulnerability and disaster risk [40, 45, 46]. Based on this study, we anticipate that these increased drought and flood events will be accompanied by severe socioeconomic losses. Local and global food production may be disrupted, and public settlements, health, and quality of life may also be impaired. Our study provides valuable insights into predicting droughts and floods based on early spring temperatures. Policymakers can incorporate early spring warming into the prediction of potential natural disasters in the same year and consequently formulate a series of land use measures to prevent and mitigate these threats. In particular, monitoring temperature anomalies from January to March may help improve seasonal preparedness for agricultural production and disaster prevention in this important grain-producing region.

In the study area, there are no accurate long-term records of drought and flood intensities at the watershed scale; therefore, the roles of slope, landform, and other land surface processes in drought and flood occurrence cannot be investigated in detail. Moreover, the drought and flood intensity used in this study is a historical composite severity index derived from documentary records, rather than a direct physical hydrometeorological variable. The presented results are based on a physically consistent climate scenario, and droughts and floods predicted using random forests may differ from those in real climatic and environmental conditions with complex terrains and landforms [50]. Future research should therefore focus on incorporating landforms, land use, and watershed-scale analyses. Human processes affecting droughts and floods, most notably land use changes caused by human activities, were not considered in the current study. Incorporating land use changes and processes into climate-based natural disaster prediction studies would therefore provide valuable insights. In addition, future studies should strengthen the physical interpretation of the identified climatic signals by integrating reanalysis datasets, atmospheric circulation diagnostics, and stricter temporal and spatial validation frameworks. Despite these limitations, the climate variable-based modeling approach applied in this study provides a framework for analyzing the meteorological drivers of natural hazard events. Overall, this study shows that monthly climatic variables, especially temperatures in early spring, can provide useful predictive signals for drought and flood risk assessment in Henan under a warming climate.

Conflict of Interests

The authors have no relevant financial or non-financial interests to disclose.

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Data Availability

Data used for this work was accessed from public sources. Drought and flood event records were obtained from the published books, climate variables were obtained from China Meteorological Data Service Centre, available at http://data.cma.cn/data/detail/dataCode/A.0012.0001.S011.html

Author Contributions

Conceptualization: YP, EL. Study design and methodology: YP. Material preparation, data collection, and analysis: NP, YP, EL. Writing - original draft and review: all authors. All authors read and approved the final manuscript.

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