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Risk analysis of meteorological, agricultural, and hydrological drought events and study of drought propagation features: a case study in the upper Tapti River sub-basin, Central India

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ABSTRACT

As a natural hazard, drought is a complex multivariate phenomenon that requires more comprehensive analysis. In this study, we studied meteorological, agricultural, and hydrological drought events with precipitation, soil moisture, and stream flow data for the study area. The risk analysis for drought duration and severity of three kinds of drought events were analyzed with univariate and three kinds of bivariate return periods based on the copula. Furthermore, the propagation of three kinds of drought was studied. From the investigation, it is observed that agricultural drought events are longer and more severe, besides the risk associated with agricultural drought is high compared to other kinds of drought. Moreover, the average time taken for meteorological drought to propagate into agricultural drought is 4.3 months and for the hydrological drought is 3.8 months for the river basin. The comprehensive study of three kinds of drought is helpful to adopt suitable drought management plans in the region.

Key words: copula, drought, drought propagation, joint return period, kinds of drought

HIGHLIGHTS

- Studied characteristics of meteorological, agricultural, and hydrological drought events in the river basin.
- Found out that agricultural drought events have a long duration and high severity.
- Meteorological drought has less risk compared to the other two kinds of drought.
- The propagation time to agricultural drought from meteorological drought is long compared to the time taken for hydrological drought events.

1. INTRODUCTION

Drought is an economically sensitive and frequently recurring natural hazard due to the deficit of water in various components of the hydrological cycle. Based on the inadequacy of water in different phases of the hydrological cycle, droughts are classified into meteorological drought (MD, inadequacy of rainfall), agricultural drought (AD, inadequacy of soil moisture), and hydrological drought (HD, inadequacy of stream flow) (Goyal *et al.* 2017). In general, MD is first in terms of the order of occurrence of the three kinds of drought. The prolonged rainfall deficiency would subsequently impact other components such as soil moisture and stream flow in the hydrological cycle (Mishra & Singh 2010). Many drought indices (DIs) have been developed to monitor different kinds of drought events. The most popular among them are the standardization principle-based Standardized Precipitation Index (SPI) (McKee *et al.* 1993; Shamshirband *et al.* 2020), Standardized Soil Moisture Index (SSI) (Hao & AghaKouchak 2013), and Standardized Stream flow Drought Index (SDI) (Nalbantis & Tsakiris 2009); which were widely used mainly because of their simplicity and universal adaptability.

In addition to the identification of drought events, the risk analysis of drought characteristics such as duration and severity of drought plays a key role in viable drought planning and management. Given the fact that drought is a multivariate phenomenon, apart from the univariate approach, modelling more than one drought variable is important. In this regard, the traditional multivariate approach poses restrictions such as the marginal distribution of variables needs to be similar (Salvadori & De Michele 2004). Considering this, copula a nonlinear joint probability function was used for joint probability risk analysis of hydro-climatic events (Reddy & Ganguli (2013), AghaKouchak (2015). The copula-based risk analysis of drought was carried out by several authors (Reddy & Ganguli 2013), (Hangshing & Dabral 2018), those works mostly deal with MD. Poonia *et al.* (2021a) covered all three kinds of drought in their study across major river basins in India. Since their work deals with the risk of drought at the large basin level area, this study covers drought at the regional level with three kinds of drought, which will help policymakers with region-specific drought management.

Moreover, the inter-relationship of different kinds of drought occurrence in the terrestrial ecosystem has been approached under the drought propagation concept. Drought propagation refers to the transformation of deficit in one kind of drought to another kind of drought (Eltahir & Yeh 1999). Van Loon *et al.* (2012) expressed several drought propagation features such as pooling (successive MDs collectively merge into a single AD or HD), attenuation (disappearance of small MDs due to availability of water at the initial time of precipitation anomaly), lagging (time lags between the occurrences of various kinds of drought), and lengthening (increasing duration of drought from MD to other kinds of drought). Despite many studies carried out regarding drought analysis, the study of inter-relationship among different kinds of drought under drought propagation is less. Fang *et al.* (2020), Ding *et al.* (2021) and Wang *et al.* (2021) studied drought propagation for MD and HD events. In India, Bhardwaj *et al.* (2020) studied the propagation of MD to HD for large river basins. In this study, an assessment of propagation for three kinds of drought at the sub-basin level was analyzed, which can provide valuable insights to stakeholders and water managers. The area selected in this study is the upper Tapti River basin, which is located in central India. The area is more prone to frequent and severely vulnerable to drought events based on the previous drought vulnerability study (Sahana *et al.* 2021). Concerning three kinds of drought in the Tapti River basin, AD has a high mean duration and frequency compared to the MD and HD events (Poonia *et al.* 2021b).

2. STUDY AREA AND DATA SOURCE

Tapti is a main river in central India that originates from the Satpura mountain ranges and flows West before emptying into the Arabian Sea. The study area is located on the East side of the Tapti basin (Figure 1). The study area falls under the Tropical dry savanna (As) climate type as per Köppen–Geiger climate classification (Rubel & Kottek 2010), with an average annual temperature of 25.1 °C (Sharma *et al.* 2019) and peak temperature 45 °C during peak summer (May) and a minimum

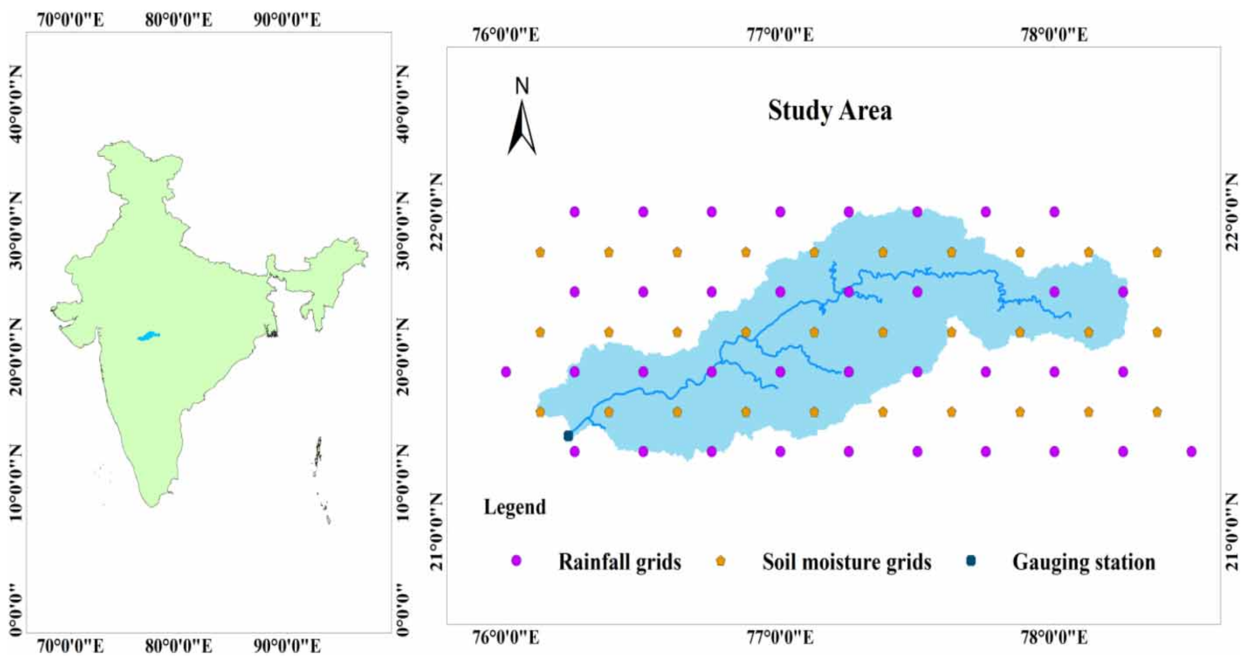

Figure 1 | Study area map.

temperature of around 8 °C in the December month (Shivhare *et al.* 2014). The region's soil type is dominated by clay to loamy clay soil type (Chandra *et al.* 2016; Munoth & Goyal 2019). The Tapti River basin receives maximum annual rainfall up to 2,550 mm, with an average of about 835 mm. 90% of the annual rainfall occurs between mid-June and mid-October during the monsoon season, with 50% of that total occurring between July and August (Sharma *et al.* 2018). The river basin is between 216 and 1,174 m above mean sea level. The important crops cultivated in the Tapti basin are wheat, sugarcane, rice, gram etc. Dryland farming is a common practice followed in the region. The *kharif* crops cultivated in the area are groundnut, soybean, maize and pulses, and the common *Rabi* crops are sorghum and gram.

To monitor MD, AD, and HD events, rainfall, soil moisture and stream flow data were considered in this study. The rainfall data (0.25° × 0.25°) were obtained from Indian Meteorological Department (IMD), Pune, India at a daily time scale. The soil moisture data at root zone depth were collected from the Global Land Data Assimilation System (GLDAS) Noah Land Surface Model L4 in a daily scale 0.25° × 0.25° V2.1 dataset for the identification of AD. Stream flow data of the gauge station was collected from Central Water Commission (CWC), India for the period from 1980 to 2018 to monitor the HD.

3. METHODOLOGY

3.1. Trend analysis of hydro-meteorological data

Modified Mann–Kendall (MMK) trend test was employed in this work to find variations in the temporal trends of hydro-meteorological time series. The MMK test was devised by Hamed & Rao (1998) in response to the issue regarding ignorance of autocorrelation in data with the conventional Mann–Kendall test that was first developed by Mann (1945) and Kendall (1975). Band *et al.* (2022) applied Mann–Kendall test and modelled the time series model of SARIMA (2,0,2) $(1,1,1)_6$ to predict the SPI drought index. In addition to identifying patterns in the time series, the Sen's slope test was employed to quantify trends in terms of numerical value. As part of the process of identifying trends in hydro-meteorological data, the World Meteorological Organization (WMO) advises using this test. Unlike other methods such as linear regression, Sen's slope test is unaffected by the number of outliers and data errors (Aditya *et al.* 2021).

3.2. DIs and drought variables

In this study, the MD, AD, and HD events were identified with mostly considered, the standardization principle-based SPI, SSI, and SDI DIs based on rainfall, soil moisture and stream flow value at 4-month timescale. The historical rainfall data that were fitted with continuous distributions, were then transformed to the standard normal distribution to identify wet and dry conditions. The study also applied the standardization principle to the soil moisture and stream flow data to identify AD and HD, respectively (Hao & AghaKouchak 2013; Kanthavel *et al.* 2022).

To study the characterization of drought, variables including duration and severity of drought events were computed for three kinds of drought from the calculated SPI, SSI, and SDI drought index values. The number of months the DI value is below a given threshold value determines the duration of the drought (Shiau 2006) and the cumulative value of the DI during that time determines the severity of the drought (Mishra & Singh 2010).

3.3. Return period analysis

The estimation of the return period of drought characteristics such as duration and severity for three kinds of drought has a crucial role in the planning and management of water resources. Considering this, univariate and bivariate return periods were computed for drought duration and severity.

The univariate return period of drought variables is estimated using the following expression (Shiau & Shen 2001):

$$T(D) = \frac{\mathrm{EL}}{1 - F_D(d)} \tag{1}$$

$$T(S) = \frac{\mathrm{EL}}{1 - F_S(s)} \tag{2}$$

where $T(D)$ and $T(S)$ indicate the return period of the drought duration and severity, respectively. EL is the expected drought interval time, $F_D(d)$ and $F_S(s)$ indicates cumulative distribution functions of drought duration and severity, respectively. In this study, to carry out univariate analysis, a larger set of marginal distribution functions including normal, log-normal, exponential, Weibull, and Gamma were selected as candidates to fit the duration and severity values. The best-fitted marginal distribution was selected based on the minimum value of the Akaike Information Criterion (AIC) (Akaike 1974).

In order to compute the bivariate return period of duration and severity of drought events, the copula function was applied in this study. Copula is a function used to construct a joint probability function by combining marginal distributions of different random variables.

Sklar's (1959) theorem made the theoretical foundation for copula modelling. According to Sklar's theorem If $FX_1, X_2, \dots, X_m(x_1, x_2, \dots, x_m)$ is a multivariate distribution of m correlated random variables with their marginal distributions $FX1(x_1)$, $FX2(x_2), \dots, FXm(x_m)$, then copula C can be expressed as:

$$FX_1, X_2, \dots, X_m(x_1, x_2, \dots, x_m) = C(FX_1(x_1), FX_2(x_2), \dots, FX_m(x_m)) \tag{3}$$

In the present study with respect to bivariate return periods, two types of return periods: (i) primary return periods ('OR', 'AND' type) and (ii) Kendall return periods were considered to study the risk of drought events. The primary return periods T(OR), T(AND) are expressed as the following (Shiau 2006):

$$\mathrm{T(OR)} = \frac{\mathrm{EL}}{1 - C\{F_D(d), F_S(s)\}} \tag{4}$$

T(OR) represents the joint return period for $D \geq d$ or $S \geq s$, $C\{F_D(d), F_S(s)\}$ and indicates the copula-based joint distribution function of the drought duration and severity, respectively:

$$\mathrm{T(AND)} = \frac{\mathrm{EL}}{1 - F_D(d) - F_S(s) + C\{F_D(d), F_S(s)\}} \tag{5}$$

T(AND) represents the joint return period for $D \geq d$ and $S \geq s$.

The bivariate return periods ('OR', 'AND') are based on conventional univariate return periods and have the risk of underestimation in 'OR' case and waste of money due to overestimation regarding the occurrence of events in the case of 'AND' return period (Salvadori & De Michele 2004). Regarding this, Salvadori & De Michele (2010) proposed a Kendall return period (or secondary return period) based on Kendall's distribution (K_c) by converging multidimensional analysis into univariate analysis in the following way:

$$T(\mathrm{Kendall}) = \frac{EL}{1 - K_c(t)} \tag{6}$$

where K_c stands for the Kendall distribution function and t represent the critical probability level. With copula-based joint probability, the K_c was expressed as follows:

$$K_c(t) = P(C(F(d, s) \leq t)) \tag{7}$$

The K_c value for the Archimedean copula family is:

$$K_c(t) = t - \frac{\varphi(t)}{\varphi'(t)} \tag{8}$$

where φ(t) is generating function and $\varphi'(t)$ is the right derivative of $\varphi(t)$. In this study, the Frank, Clayton, and Gumbel copulas from the Archimedean family were taken into account for joint return period analysis.

3.4. Quantification of drought propagation

The drought transformation from one kind to another is numerically approached with Drought Propagation Intensity Index (DPI) and propagation time in this study.

In order to quantitatively express the propagation process of MD to other kinds of drought, an index of drought propagation intensity was considered by several authors regarding drought propagation (Zhou *et al.* 2019; Wang *et al.* 2021), and its calculation formula is as follows (Zhou *et al.* 2019):

$$\mathrm{DPI} = \frac{\mathrm{AD\ (or)HD}}{\mathrm{MD}}\ (\mathrm{MD} \neq 0) \tag{9}$$

where DPI is the drought propagation intensity index; MD, AD, and HD are the meteorological drought, agricultural drought, and hydrological drought data intensity over a certain period of time.

When the DPI is greater than 1, drought propagation is strong. When the DPI is less than 1, is weak. When the intensity index of drought propagation is equal to 1, there is a peer-to-peer propagation from MD to AD and HD (Zhou *et al.* 2019).

The propagation time for one kind of drought to other kinds of drought is mainly estimated through methods such as Pearson correlation-based approach, Wavelet analysis and difference of onset time of matched two kinds of drought events. In the mentioned approaches, based on the studied observation, Wang *et al.* (2021) recommended the onset time difference between matched drought events method as relatively appropriate in drought propagation analysis.

The propagation time is the time difference between onsets of two different kinds of drought events (Wang *et al.* 2021):

$$\text{Propagation Time} = \mathrm{HD_o(AD_o) - MD_o} \tag{10}$$

In this formula, $\mathrm{MD_o}$, $\mathrm{AD_o}$, and $\mathrm{HD_o}$ are the onset time of matched MD, AD, and HD events, respectively (Wang *et al.* 2021).

4. RESULTS AND DISCUSSION

4.1. Trend analysis of hydro-meteorological data

The trend analysis of historical climatological data was carried out using the MMK test and Sen's slope estimator at the 5% significant level (Table 1). The result indicated that no one meteorological variable has shown a significant trend at 5% significance. But, considering the trend of historical data based on the z-value, the precipitation and soil moisture data exhibited a downward trend, while stream flow data witnessed an upward trend. The Sen's slope value for soil moisture data shows a negative trend value.

From the historical observation, the decreasing trend of precipitation, and soil moisture time series indicates a high chance of risk of drought occurrence. The stream flow data witnessed an upward trend but that does not signify in terms of value.

4.2. Drought characteristics – duration (D) and severity (S)

The duration of the drought and its severity were computed based on the run theory for MD, AD, and HD events and shown in Figure 2. From the results, the MDs observed most of the events with a duration of around 1 and 2 months and a few exceptional events of 4 and 5 months, while the duration of HDs varied from 1 to 5 months with few extreme events of 8 and 9 months. In the case of AD, most of the events were above 3 months duration and extreme events reached the extent of 10 months.

The severity of drought proportionally increases along with duration value, with a minimum value of 1.05 (in the case of MD and HD) to a maximum value of 19.9 (AD). Similarly, the mean of drought duration (severity) events for three drought events were 1.6 months (2.43) (MD), 3.8 months (5.70) (AD), and 2.4 months (3.61) (HD). This showed that AD events are lengthy in duration and high severity compared to MD and HD events. The AD's long duration occurrence may be due to

Table 1 | Modified Mann–Kendall and Sen's slope test results of hydro-meteorological data

Parameters	Rainfall	Soil moisture	Stream flow
p-value	0.90	0.52	0.99
z-value	−0.12	−0.64	0.0028
Sen's slope	0	−0.009	0

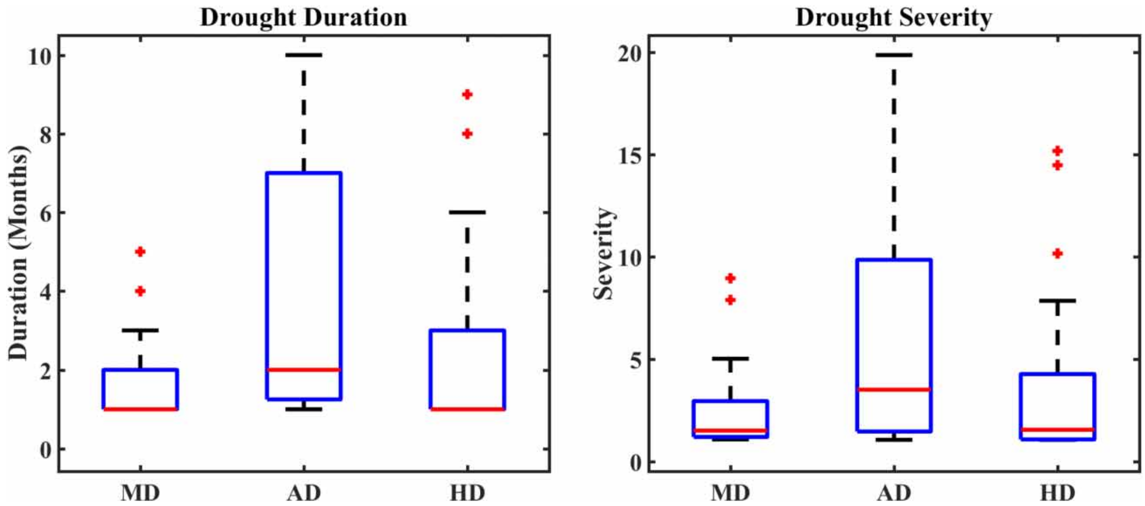

Figure 2 | Drought duration and severity of meteorological drought (MD), agricultural drought (AD), and hydrological drought (HD) events.

land use, agricultural practices, and the nature of soil type. The factors such as compaction on the soil can retard water movement into the soil, and infiltration in the clay soil type may make the occurrence of agriculture drought longer.

4.3. Return period analysis

The risk of occurrence of drought events was approached with univariate and bivariate return periods for drought variables. The log-normal distribution was identified as the best fitted distribution for the duration and severity of all three kinds of drought. Drought duration (D) and severity(S) for three kinds of the drought was computed at six theoretical return periods (2, 5, 10, 20, 50 and 100 years) (Table 2). The AD has a high duration and severity value compared to the other two kinds of droughts (MD and HD) for chosen return period, which indicates more risk regarding soil moisture deficiency. As the return period increases, the difference between AD and other kinds of drought event's duration and severity also widen. In the case of MD, the drought duration is 57–227% less, for the HD it is 17–43% less compared to AD duration from 5- to 100-year return period, respectively. This shows that MD has less risk compared to the other two kinds of drought and the risk of AD increases as the return period extend.

The bivariate risk study was carried out for the following three different criteria: (i) 'AND', (ii) 'OR', and (iii) 'Kendall' for each kind of drought (Figure 3). Gumbel copula was selected as the best one based on the minimum AIC value. Overall, the AD poses a high risk in the bivariate cases also, which can be identified from the contour lines of the joint occurrence of drought duration and severity at a particular return period is high for the AD. For example, the return period of severity value (4.57) and duration (2.88 months) in MD is 15.94, AD is 5.88 and HD is 6.18 years. This shortening of return periods indicates high risk. Considering, the three different return periods, T(Kendall) return period value is in between the T(AND) and T(OR) return period criteria which can be identified from the three-contour diagram for a particular kind of drought.

Table 2 | Univariate return periods of duration (D) (months) and severity (S) of MD, AD, and HD

	MD		AD		HD	
Return period (year)	**D**	**S**	**D**	**S**	**D**	**S**
2	1.62	2.34	1.00	1.07	1.64	2.46
5	2.33	3.62	3.66	5.15	3.13	4.68
10	2.88	4.57	5.91	8.92	4.48	6.66
20	3.40	5.64	8.33	13.81	6.02	9.52
50	4.10	7.08	11.75	20.75	8.34	13.42
100	4.59	8.20	15.00	29.46	10.5	19.83

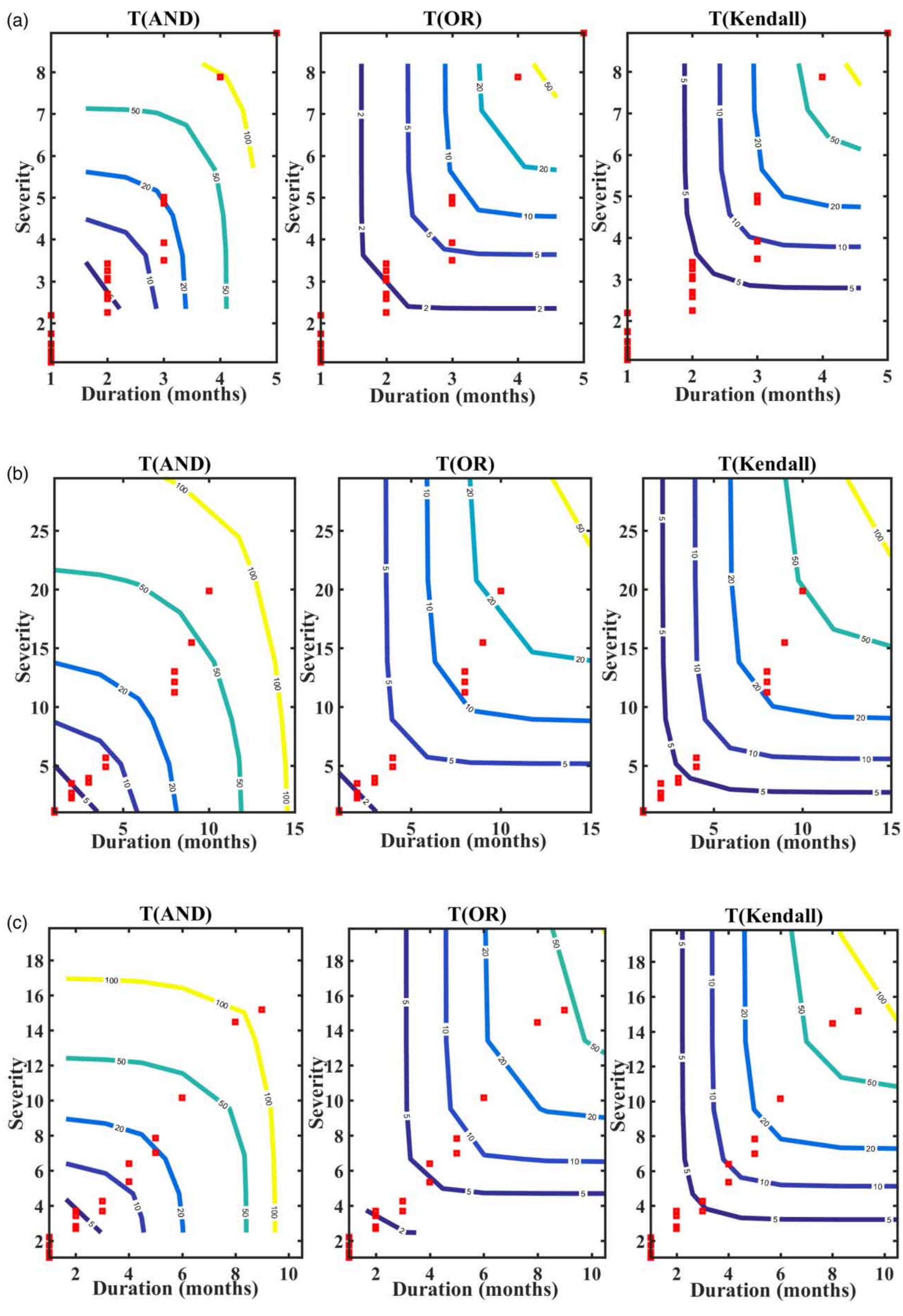

Figure 3 | Three kinds of bivariate return periods for (a) meteorological drought (MD), (b) agricultural drought (AD), and (c) hydrological drought (HD) events.

Three return periods for MD duration (2.88 months) and severity (4.57) are 7.25(T(OR)), 15.94 (T(AND)), and 12.44 year T(Kendall). This shows the variation in drought risk based on the return period analysis.

A similar finding was reported in Ganguli & Reddy (2014) and Maeng *et al.* (2017) study, while considering three kinds of the return period.

The variation between the three kinds of return periods can be linked to the method of identification for each kind of return period. The adaptability of the return period depends upon drought risk management of the study area since it is complex to select a consistently performing return period (Serinaldi 2015; Maeng *et al.* 2017).

4.4. Propagation of drought events

The study about drought propagation would be helpful for the study area to adopt an effective drought prevention strategy and water resource management plan by being aware of how the transformation of one kind of drought to another kind takes place in the study area. In this aspect, the propagation time, DPI and different drought propagation features were studied.

The propagation time for transformation from one kind of drought into another kind of droughts is computed based on the onset time of respective drought events. In this study, we identified propagation time under the following three scenarios: meteorological drought to agricultural drought (MD–AD), meteorological drought to hydrological drought (MD–HD), and hydrological drought to agricultural drought (HD–AD) (Figure 4). From Figure 4, the propagation time of MD–AD scenario is relatively high compared to the other case. Average propagation time for MD–AD was computed as 4.3 months, for MD–HD was 3.8 months, and for HD–AD was 2.7 months. The propagation time for MD into HD is shorter in time than for the AD, thus conveys that the availability of a shorter time to mitigate HD when the rainfall deficiency-oriented MD start. The response of AD–MD can be affected by agricultural practice such as irrigation (Bhardwaj *et al.* 2020). Unlike other kinds of drought occurrence, AD is mostly influenced by external factors such as irrigation, and soil texture. The irrigation factor can restrict soil moisture deficiency to go further level; similarly, the high clay content in the soil of the study area can be attributed to high water holding capacity and retard the water evaporation from the soil. Soil texture impact with respect to drought occurrence was discussed in the previous study also (Almendra-Martin *et al.* 2021). In that study, they discussed the percentage of clay content in soil texture impact regarding the trend of drought occurrence. Based on the similar time difference between the onset of two drought event methods, Wang *et al.* (2021) identified a propagation time of 1–47 days for MD–HD events in their study.

4.4.1. Drought propagation intensity index

The nature of propagation of drought from one kind to another is quantified based on the DPI as shown in the Figure 5.

Based on the DPI, the transition of drought from MD–AD and HD–AD is high compared to the MD–HD event. The average intensity of drought transition for MD–AD and HD–AD was 2.22 and 2.03, respectively, but for the MD–HD was 1.80. The high DPI value for transformation into AD implies its long and highly intensive drought pattern. The nature of drought

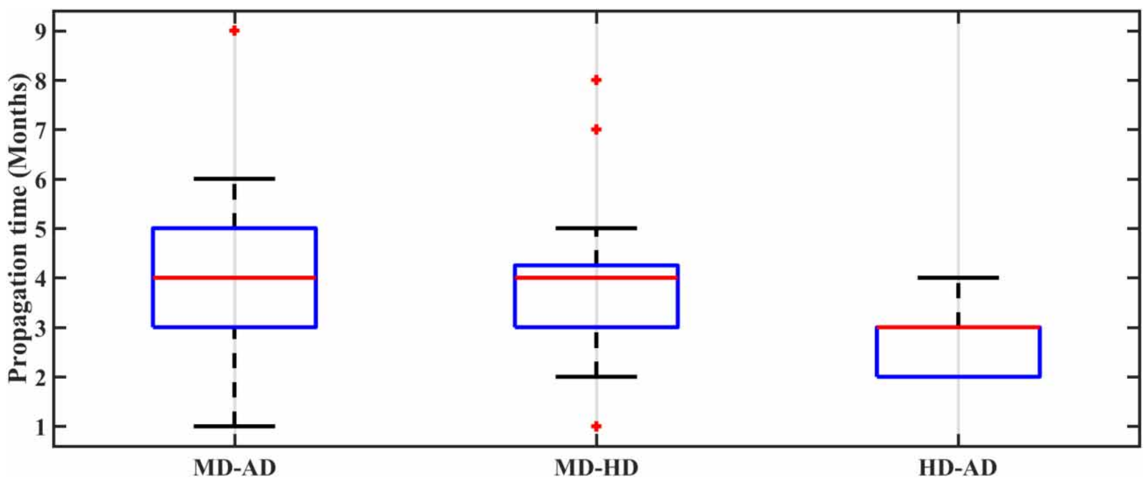

Figure 4 | Drought propagation time between two kinds of drought.

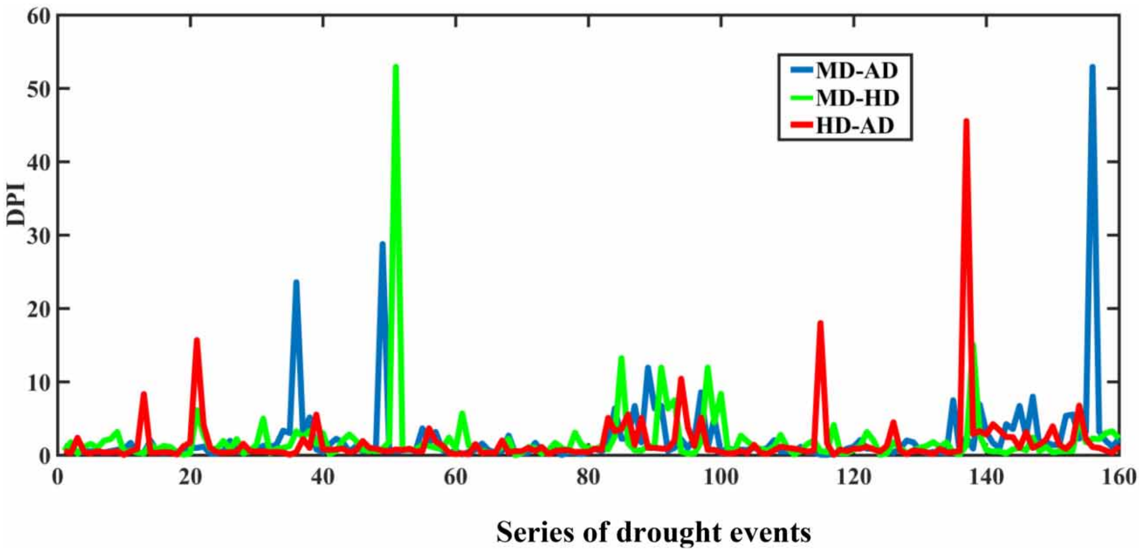

Figure 5 | DPI for drought transformation.

propagation (either strong or weak) was computed based on the DPI value criteria, as per those criteria in the MD–AD drought propagation 42% of drought events were strong where DPI is more than one, in the case of MD–HD and HD–AD drought propagation it was 49 and 33%, respectively.

Overall the MD transform into other two kinds of drought was observed strong in most cases. This shows the intensification of soil moisture and stream flow deficit by rainfall deficit.

In the study area, water guzzling crops such as rice, sugarcane and wheat are prominent as per the crop pattern. The crops may experience frequent moisture stress as a result of the highly intensive AD. This conveys a better cultivation technique concerning severe AD transformation from the rainfall deficit as per high DPI value.

4.4.2. Drought propagation features in the river basin

The drought propagation features such as pooling, attenuation, lagging, and lengthening have been highlighted for MD–AD (Figure 6) and MD–HD (Figure 7) for the river basin.

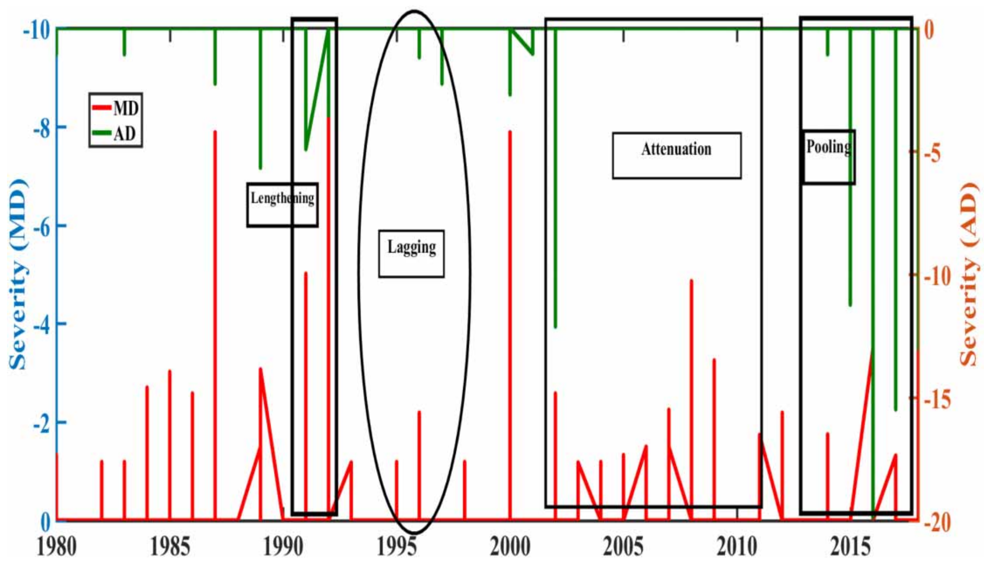

Figure 6 | MD to AD propagation features.

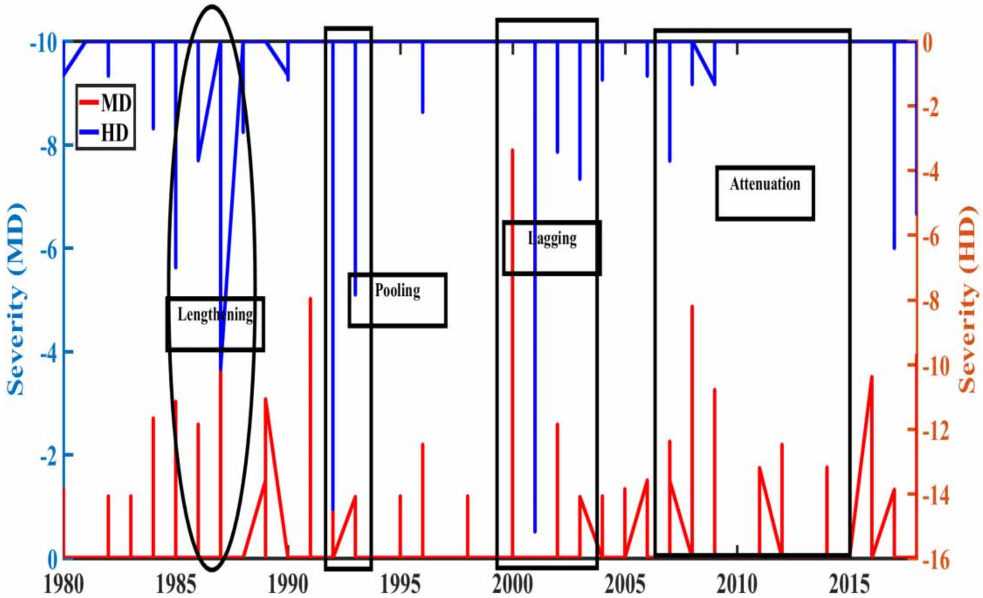

Figure 7 | MD to HD propagation features.

A remarkable occurrence of drought pooling was noticed after 2015, where a string of subsequent meteorological dry spells turned into an AD with the worst effects between 1980 and 2018. In contrast, a MD in 2008 with a severity magnitude of nearly 5 (Figure 6) was attenuated, as a result of the high moisture content in the root zone. The years 1991 and 1992 served as an example of how ADs can last longer than previous MDs. Regarding the time lag effect, it was discovered that between 1995 and 1998, there was a discernible lag between AD and MD (more precisely, the period between the onsets of two different types of drought).

Similarly, drought propagation features were observed in the case of MD–HD but in different periods (Figure 7). The time span of 2006–2015 witnessed attenuation of MD due to high water levels in the river. The rainfall deficit and low water level in the river led to the pooling of both MD and HD events in the year 1992. After 1985, the high severity of HD compared to MD led to the lengthening phenomena. The time lag between two drought events was observed in 2002 and 2003.

This type of understanding of drought propagation features in the past time will provide a strong idea for monitoring and forecasting AD and HD occurrence from the rainfall deficiency point of view.

5. CONCLUSION

In the present study, MD, AD, and HD events were identified with their respective DIs for the study area. The drought duration and severity were computed and analyzed to study the characterization of droughts. The drought risk was estimated in univariate and bivariate return periods based on the duration and severity of the three kinds of drought. The drought propagation features were examined for the three kinds of drought.

The main conclusions that could be drawn from this study are as follows:

- For the three hydro-meteorological data considered in the study, during the entire study period (1980–2018) the precipitation and soil moisture observed a strongly decreasing trend, and stream flow witnessed an increasing trend but not at a remarkable level.
- Out of the three kinds of drought, AD events are observed in long duration and high severity.
- Regarding the risk of occurrence of drought events, AD was identified as high risk and MD events were observed as less risk in univariate and bivariate return period analyses.
- The transformation of MD into AD is highly intensive and took more time.

It can be concluded that the nature of drought occurrence varies with the kind of drought. For an effective drought management strategy, the drought analysis should be comprehensive in terms of coverage of all kinds of droughts. Despite this study analyzed three kinds of drought at one time scale, the findings of this study will be helpful for the selected area to build up suitable strategies for comprehensive drought management. Furthermore, an in-depth understanding of the drought propagation on at daily or monthly basis considering drastic climate change in a shorter period would be helpful to enhance the drought monitoring strategy.

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AUTHOR CONTRIBUTIONS

The conceptualization, planning, and development of methodology as well as the initial framing of this research manuscript were made by P.K., C.K.S. and R.K.S. are the Guide (Promoter) and Co-Guide (Co-Promoter), respectively, who have supervised the work right from conceptualization till the preparation, correction, and the final format of this manuscript.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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