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Multivariate drought analysis for the temperature homogeneous regions of India: Lessons from the Gomati River basin

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Abstract

Droughts inflict significant loss on agricultural economies. Gomati River basin, the area of the present study, is located within the Ganga River floodplains, which approximately coincide with the north central temperature homogeneous region (NCTHR) of India. Gomati basin is a non-perennial one supporting water intensive agricultural crops. To ascertain the occurrence of droughts (if any) from 1986 to 2015 within Gomati River basin, in terms of inter-dependencies of drought causing variables through study of multivariate drought indices, is the main objective of the present study. Soil Water Assessment Tool (SWAT) was used in combination with the Copula approach to construct multivariate standardized drought indices (MSDIs) for drought onset detection through simulation in the face of data scarcity. Although MSDI based assessment of the basin as a whole did not detect any droughts, in the upper basin, MSDIs indicated the possibilities of impending agricultural droughts marked by their consistent variability around *near-normal* conditions. This methodology can be used to detect drought situations in data scarce non-perennial river basins within the Ganga River floodplains including the NCTHR of India.

KEYWORDS

Copula approach, drought, Gomati River basin, multivariate standardized drought index (MSDI), Soil Water Assessment Tool (SWAT)

1 | INTRODUCTION

The impact and assessment of drought are well documented for the Indian sub-continent (Das et al., 2016; Gautam & Bana, 2014; Mall et al., 2006; Pandey et al., 2021; Spinoni et al., 2019; Zhang et al., 2017). Droughts are studied with the help of various indices, and there are a number of indices already in use to detect, analyse and assess different types of droughts (Dash et al., 2019; Li et al., 2015; Mishra et al., 2014; Oertel et al., 2018).

The 2002, 2006, 2008, 2011 drought incidences that the Northern India had faced are combined outcomes of deficient or delayed summer monsoons along with decreased surface and ground water storages (Goldin, 2016; Pervez &

Henebry, 2015; Zhang et al., 2017). Decrease in the surface and ground water storages is mainly due to the massive withdrawal of water for intensive irrigation of the agricultural fields (Dey et al., 2021; Mall, 2013). About 90% of the total crop production of the country consists of cultivation of rice, wheat and sugarcane, which are water intensive crops (Bhatt et al., 2019; Dhawan, 2017; Mall et al., 2018). With the rising population, the demand for food too has increased, and so has the demand for water in irrigation to grow it (Dhawan, 2017; Goldin, 2016). Recent studies (Ge et al., 2016; Singh et al., 2016) covering Northern India to assess drought frequencies noticed that the type of crop cultivation plays a significant role in deciding drought severity, intensity and duration. The Gomati basin located within the floodplains of the river Ganga falls within the north central temperature homogenous region (NCTHR) of India. Rice, wheat and sugarcane, the dominant crops within the basin like that in the rest of the Ganga plains, are mostly irrigated either by ground water or by both ground water and surface water (including canals/rivers; Sharma et al., 2018).

There are several drought indices to facilitate analysis and assessment of different drought conditions. Sometimes, it is a single drought index that fulfils the need for drought assessment and analysis, but sometimes, application of a group of indices is preferred for a better assessment. Preferences depend up on the type of drought to be studied, ease of application, limitations, advantages and resolution of input data available for the region under study. The standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI), rainfall anomaly index (RAI) and Palmer drought severity index (PDSI) are most often used in meteorological drought studies (WMO, 2016). Aridity index (AI), percent departure from normal (PDN), effective drought index (EDI) and reconnaissance drought index (RDI) as well as SSI and SSMI are commonly used in agricultural drought assessment (Aadhar & Mishra, 2017; Oertel et al., 2018). Generally, the hydrological drought studies are carried out using indices like the standardized stream flow index (SSI), standardized run-off index (SRI), standardized flow index (SFI), soil moisture stress index (SSI) and standardized soil moisture index (SSMI; WMO, 2016). Nevertheless, even SPI, SPEI, SSMI and SSI are also used quite often to understand hydrological responses to drought in river basins. However, indices listed above, which are univariate based mostly on single parameters, fail to address the multivariate nature of drought phenomenon. Weng et al. (2015) pointed out that estimation of SPI is based on the assumption that the entire region under drought assessment could be characterized by same precipitation frequency, which is not always the reality. Also, in the case of hydrological indices like that of hydrological drought severity index (HDSI), run-off is the main parameter based upon which the calculations are made and the low resolution of run-off data renders the index somewhat ineffective. Similarly, RAI, SSI, SRI, SSMI and so forth, individually lack capabilities to evaluate complex multidimensional phenomenon that any drought is due to, because of their single parameter based construct (Chen et al., 2020).

The Gomati River system has been the focus of water quality investigations during the last two decades (Bhatt et al., 2020). The dimension of hydrology has only recently been considered for research, especially in terms of basin's response to variability in climate (Abeysingha et al., 2015; 2017, 2018; Mali et al., 2015, 2017, 2018; Singh et al., 2013). The Gomati basin was identified as a drier one in general, showing greater dryness in its lower parts in particular (Abeysingha et al., 2015).

Normally, drought assessment is carried out using meteorological data like precipitation and temperature and hydrological parameters like run-off and evapotranspiration. In the face of data scarcity, several researchers have made attempts to simulate to get the necessary data sets related to hydrology and agriculture, for example, run-off, evapotranspiration and crop water requirement (Abeysingha et al., 2015; 2017, 2018; Mali et al., 2015, 2017, 2018). In the present study also, the authors have depended upon simulation aid of SWAT model to get the necessary long-term, continuous basin-wide datasets (otherwise unavailable directly) required to finally work out on the onset of drought, its variability and persistence.

The present study proceeds with the understanding that whatever be the type of drought – meteorological, agricultural and hydrological – what matters is the agricultural responses within the basin reflecting dry or drought conditions and situations as the entire basin area is exclusively within the floodplain, which is intensively used for agricultural purpose. So, the present study is basically an attempt to understand agricultural responses under various drought categories. It also tries to explore as to why, of which type and to how much extent the hydrological responses/changes within the basin induce or indicate agricultural drought conditions. The study starts with the estimation of dry conditions in terms of changes in the meteorological, hydrological and agricultural variables of the Gomati River Basin. The study also tries to figure out how various parameters interact with each other to build dry conditions and to see whether such conditions lead to (agricultural) drought events with the help of multivariate drought assessment, which has not been attempted yet.

2 | STUDY SITE

Gomati River is non-perennial '*floodplain*' tributary of the Ganga River with no melt-water contribution from

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glaciers of the Himalayas. The Gomati basin drains an area of about 30,997 km^2 spread in 18 districts of Uttar Pradesh and it joins the Ganga River at village Kaithi in Jaunpur district (Figure 1). The basin lies between the latitudes 25°23′12.62″ N and 28°46′58.75″ N and longitudes 79°57′33.76″ E and 83°11′13.25″ E. The basin is marked by a relief of 170 m with minimum elevation of 57 m and a maximum elevation of 227 m. The river is characterized by interrupted flow regime in the lean period (March–June), with its bed turning into pools. In the upper reaches, for about the first 60 km, the river bed remains semi-dry during the lean period and gets encroached by agricultural activities temporarily (Dutta et al., 2011). Semi-arid to sub-humid tropical climate of the basin is characterized by annual rainfall of 850–1100 mm. The mean temperature ranges between 5°C (minimum) in winter and 45°C (maximum) in summer (Abeysingha et al., 2014; Mishra et al., 2013). The basin falls within north central temperature homogeneous region (Kothawale & Kumar, 2005). Rice, wheat, sugarcane, maize, pearl millet, gram (both red and black), lentil (masoor), pigeon pea, barley, mustard and potato are major crops cultivated in the basin.

3 | DATA AND METHODS

3.1 | Datasets

The present study used different types of datasets like those related to topographical, meteorological, river discharge, and so forth. Sources and necessary details of each of the dataset are described in Table 1. Various methods were adopted to carry out analysis in multiple stages, and the methods have been discussed in detail below.

3.2 | Trend analysis

Daily gridded India Meteorological Department (IMD) datasets of temperature (0.5 × 0.5 degrees) and rainfall (0.25 × 0.25 degrees) from 1983 to 2015 were analysed to identify the trend in the climate variables with the help of *Mann–Kendall (MK) time series trend test*. The Mann–Kendall time series trend test has been extensively used by many researchers (Gocic & Trajkovic, 2014; Hamed & Rao, 1998; Patakamuri & O'Brien, 2019; Pingale et al., 2016; Taxak et al., 2014). Also, Sen's slope estimation was conducted, which is a non-parametric procedure to measure the slope of trend in the time series (Rawshan & Abubaker, 2019; Sen, 1968). The detailed procedure of the mentioned MK test is explained in Section S1.

3.3 | SWAT model

SWAT is one of the most used hydrological models applied to investigate a wide range of hydrological problems (e.g., agricultural water use, water quality and climate change impact on water resources) due to its comprehensive simulation capabilities at different watershed scales and in data scarce conditions (Arnold et al., 2012; Gassman et al., 2007; Gayathri et al., 2015; Glavan & Pintar, 2012; Guug et al., 2020; Rehbeh et al.,

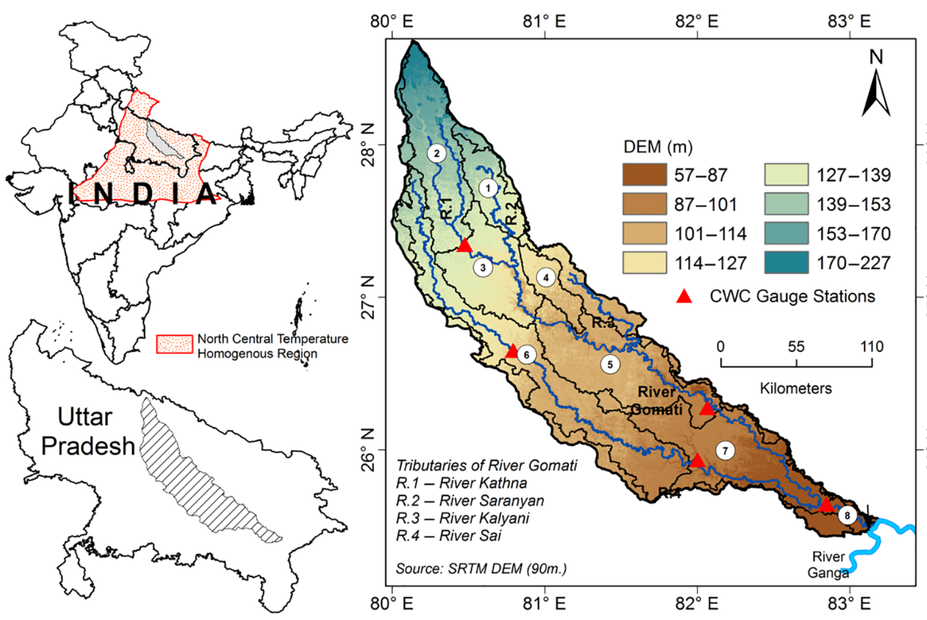

FIGURE 1 Location map of the Gomati basin with sub-basins numbered 1–8

TABLE 1 Datasets used and related details

Data layer	Data description	Primary data sources
Topographic	90 m digital elevation model (DEM) data used to characterize slopes and slope lengths	Shuttle Radar Topography Mission (SRTM): http://gisserver.civil.iitd.ac.in/grbmp/downloaddataset.aspx
Land use	Prepared through supervised classification	USGS LANDSAT 8-L1 Satellite datasets
Soil map/layer data	Resolution of the datasets is 1:5,000,000 scale	Soil dataset of the GeoNetwork, Food and Agriculture Organisation (http://www.fao.org/land-water/databases-and-software/geonetwork/en/
Daily climate	Daily precipitation and maximum and minimum temperature time series from 1983 to 2015	IMD, New Delhi
Discharge data	Monthly discharge data from January 1998 to December 2005 of the Jaunpur gauging site	Central Water Commission (CWC), Government of India

2011). It has also been used in drought assessment around the globe (Dash et al., 2019; Liang et al., 2021; Nyeko, 2015).

SWAT model functions on the principles of hydrological mass balance (Equation 1):

$$\mathrm{SW}_t = \mathrm{SW}_0 + \sum_{i=1}^{t} \left(R_{\mathrm{day}} - Q_{\mathrm{surf}} - E_{\mathrm{a}} - W_{\mathrm{seep}} - Q_{\mathrm{gw}} \right), \tag{1}$$

where SW_t = final soil water content at time period t (mm); SW_0 = initial soil water content (mm); t = time (no. of days); R_{day} = the amount of precipitation on ith day (mm); Q_{surf} = the amount of surface run-off on ith day (mm); E_{a} = amount of evapotranspiration on ith day (mm); W_{seep} = amount of water from the soil profile contributing to ground water recharge on ith day (mm); Q_{gw} = amount of return flow on ith day (mm; Arnold et al., 2012; Karlsson et al., 2016; Meaurio et al., 2015; Suryavanshi et al., 2017). In order to simulate long-term time series of run-off and soil moisture SWAT model was set up for the Gomati basin. A 3-year period was considered for model warm-up. Based on inputs, SWAT model delineated the entire basin into 269 hydrological response units (HRUs) and 8 sub-basins. For calibration, Central Water Jaunpur gauging site of Commission (CWC), Government of India was selected. The model was calibrated on a monthly time scale with the help of monthly discharge data from January 1998 to December 2005. While calibrating a set of 22 parameters (related to elevation, soil, ground water, run-off, and so forth, which were also considered during pre-calibration) were used for further optimization (discussed below in Section 3.3.1 SWAT model verification). To reduce the uncertainties in the simulated run-off, uncertainty analysis was also conducted with the help of the Sequential Uncertainty Fitting (SUFI-2) module provided in the SWAT-Calibration and Uncertainty Programs (SWAT-CUP) software (Abbaspour, 2008). The monthly model validation was done with monthly discharge data from 1991 to 1997 (Jaunpur gauging site).

3.3.1 | Model verification – SWAT model sensitivity, calibration and validation with SWAT-CUP SUFI2

A hybrid (both manual and auto-calibration) scheme of model calibration has been followed in the present study. Selection of 22 parameters was made while undertaking the *manual* calibration. Parameter selection was further refined through *auto-calibration*. The SUFI2 algorithm of the SWAT-CUP software was selected to auto-calibrate the model. As for the objective function, Nash–Sutcliffe efficiency (NSE) was selected and optimized using the observed discharge data to ensure the best possible simulations.

SUFI2 assessed sensitivities of various parameters, minimized uncertainties and maximized the objective function via consistent increment of number of iterations every time setting new ranges for each of the parameters. It can be observed from Table 2 that finally 15 out of the 22 parameters are found to be sensitive. The slope parameter, average slope steepness (HRU_SLP) and the soil conservation service (SCS) curve number (CN2) were found to be the most sensitive parameters in simulating the rainfall–run-off response of the basin. Elevation difference in the basin being very modest, it was important to consider HRU_SLP, which imparted the main channel a characteristic sluggish flow (Figure 2). The CN2 value has been assigned as per the land use type and a 5% reduction from the default CN2 values of the pre-calibrated model has been considered for the

TABLE 2 Model parameterization and sensitivity ranks for the calibrated model

Rank	Parameter name	Fitted value	Min. value	Max. value	*t*-stat	*p* value
1	HRU_SLP.hru	0.00925	0	0.05	−13.726	0.000
2	CN2.mgt	84	35	85	7.534	0.000
3	GW_REVAP.gw	0.0677	0.02	0.08	−2.248	0.027
4	SOL_AWC.sol	0.7175	0.5	1	−1.396	0.166
5	DEEPST.gw	1990	1000	3000	−1.179	0.242
6	ALPHA_BF.gw	0.02825	0	0.05	1.103	0.273
7	REVAPMN.gw	267.5	200.5	400.5	1.083	0.282
8	OV_N.hru	0.0965	0.05	0.15	−0.944	0.348
9	EPCO.hru	0.917	0.8	1	0.923	0.359
10	RCHRG_DP.gw	0.0796	0	0.08	−0.388	0.699
11	ESCO.hru	0.0348	0	0.08	−0.367	0.715
12	GWQMN.gw	4385	3500	4500	0.339	0.736
13	GW_DELAY.gw	31.799	20	60	−0.251	0.802
14	SURLAG.bsn	0.0722	0.05	0.09	−0.240	0.811
15	CANMX.hru	0.49	0	2	−0.055	0.956

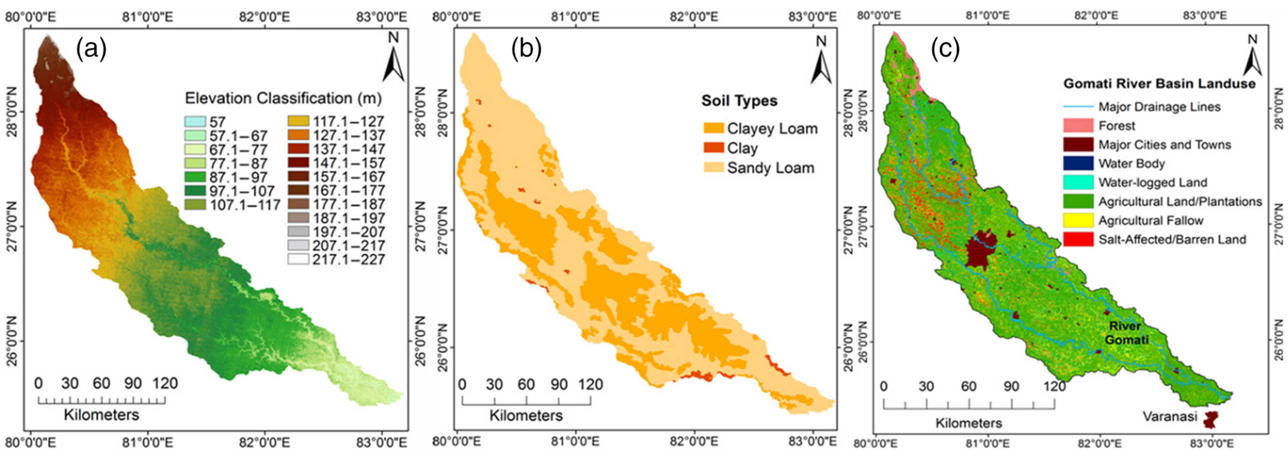

FIGURE 2 Digital elevation model (a), soil layers (b) and land use land cover (c) of Gomati basin

parameter adjustment procedure. The value of 84 of calibrated CN2 indicated that the basin has characteristics of medium to high potential of run-off generation as permeability factor goes down with increased CN2 (Gao et al., 2018). The reason behind assigning high CN2 value was to increase and calibrate the simulated baseflow and run-off viz-*a*-viz observed baseflow and run-off. The third most sensitive parameter was GW_REVAP, which is a ground water parameter. GW_REVAP is a dimensionless coefficient that controls the rate of water movement between the shallow aquifer and the root zone in unsaturated layers; it is a function of demand of water needed for evapotranspiration (Heuvelmans et al., 2004; Marhaento et al., 2017). This (GW_REVAP) also makes the model sensitive to conditions of baseflow generation (Heuvelmans et al., 2004). Although soil evaporation compensation factor (ESCO) is at the eleventh position among the sensitive parameters, it also needs a special mention. It has been taken care of during manual calibration process itself and then revisited during auto-calibration process too. ESCO is very important as the basin of study suffers very high evaporative losses ranging between 1260 and 2000 mm from its vast irrigated agricultural fields (Figures 1 and 2; Zheng et al., 2018). The reasons that could be held responsible for such high evaporative losses are water intensive cropping pattern, regional irrigation schemes and an observable climatic shift to semi-arid conditions (Bouman et al., 2007; Goroshi et al., 2017; Raju et al., 2013; Shah et al., 2019). Therefore, to account for the total evaporative loss more accurately, ESCO was parameterized within a very narrow range to enable the model to extract water from the deeper soil layers so as to simulate the hydrological balance. Coming to the sensitivity of the selected set of parameters are assigned *t*-stat and *p* value; the closer the *p* value to zero, the more significant was its sensitivity to the run-off simulation (Table 2).

Even after the calibration and sensitivity analysis, the parameters may impart the model some uncertainty. The uncertainty in run-off and discharge simulations of the SWAT could be due to the inherent deficiencies of input data, model-build and knowledge or skill of the model-user (Abbaspour et al., 2018; Arnold et al., 2012). The quantification of the uncertainty is represented by indices known as *p*-factor (0.93) and *r*-factor (0.99), which were found satisfactory. Both these factors/indices together define 95% prediction boundary called '95ppu'. This '95ppu' helps to understand how much (%) of the observed data are bracketed by the 95ppu boundary within the narrowest possible uncertainty band (Khalid et al., 2016; Narsimlu et al., 2015). The *r*-factor was well below the value of 1.5, which is considered as the optimum criterion for stream flow simulation indicating thereby that uncertainty analysis was completed successfully (Dash et al., 2019). Further, the *p*-factor of 0.93 indicated that 93% of the observed data is bracketed by the 95ppu boundary, which points to the fact that the model performed well. Ultimately, the iteration at which *p* and *r*-factors achieved their optimum values and the corresponding ranges of calibration parameters were taken as final.

SWAT-CUP SUFI2 based sensitivity analysis and uncertainty analysis achieved satisfactory model performance, and performance statistics also revealed the same (Table 3). The calibrated SWAT setup for Gomati basin was found to have performed under the prescribed 'very good' category of performance while simulating run-off, keeping the observed run-off as a reference. The measures of performance were estimated with the values of $E_{NS} = 0.89$, $R^2 = 0.92$, RSR = 0.34 and PBIAS = −12.9 during calibration and $E_{NS} = 0.75$, $R^2 = 0.75$, RSR = 0.5 and PBIAS = 2.8 during validation (Figure 3 and Table 3; Moriasi et al., 2012). However, as per the negative PBIAS, the calibrated model performance was 'good' and it was rather over-estimated the run-off. But during validation, the model performance improved further to 'very good' category (Table S1). Positive PBIAS indicated that the model was slightly underestimating the run-off during validation.

SUFI2 conducts sensitivity and uncertainty analysis using the concept of Latin Hypercube Sampling (Iman & Shortencarier, 1984; Khalid et al., 2016; Narsimlu et al., 2015). It samples the parameters through multiple regression method and, therefore, assesses the role of each input parameter influencing the model output. For example, by attempting to enhance the objective function (here NSE), it allots ranks to each of the input parameters as per their estimated sensitivity and in turn reduces the uncertainty of the output (here run-off; Abbaspour, 2015; Khalid et al., 2016; Mehan et al., 2017; Mengistu et al., 2019; Narsimlu et al., 2015).

3.4 | Estimation of standardized precipitation index (SPI), soil moisture stress index (SSI) and standardized run-off index (SRI)

SPI is estimated from the long-term averages of normally distributed precipitation data by identifying the deviations from the long-term average (Shukla & Wood, 2008; Xu et al., 2018). An SPI value of below 0 or further below −1 for a period of time is an indication of drought. SSI is based on percentages of normal precipitation, Palmer *Z*-index and the statistical distribution of SPI. In principle, SSI uses the *z*-score to quantify the standard deviations of the long-term soil moisture time series from the observed long-term mean soil moisture. SSI is more popular than SPI due to its simple and straightforward interpretation with a scope for multi-time scale drought estimation (Xu et al., 2018). SRI relates better to hydrological processes that occur over longer time duration, for it is capable of determining the lag period that it takes for a meteorological signal to be translated to a hydrological one, for example, precipitation pulse translating into river discharge (Shukla &

TABLE 3 General performance ratings for recommended statistics for a monthly time step

Performance rating	RSR	NSE	PBIAS (%)
Very good	0.00 < RSR < 0.50	0.75 < NSE < 1.00	PBIAS < ±10
Good	0.50 < RSR < 0.60	0.65 < NSE < 0.75	±10 < PBIAS < ±15
Satisfactory	0.60 < RSR < 0.70	0.50 < NSE < 0.65	±15 < PBIAS < ±25
Unsatisfactory	RSR > 0.70	NSE < 0.50	PBIAS > ±25

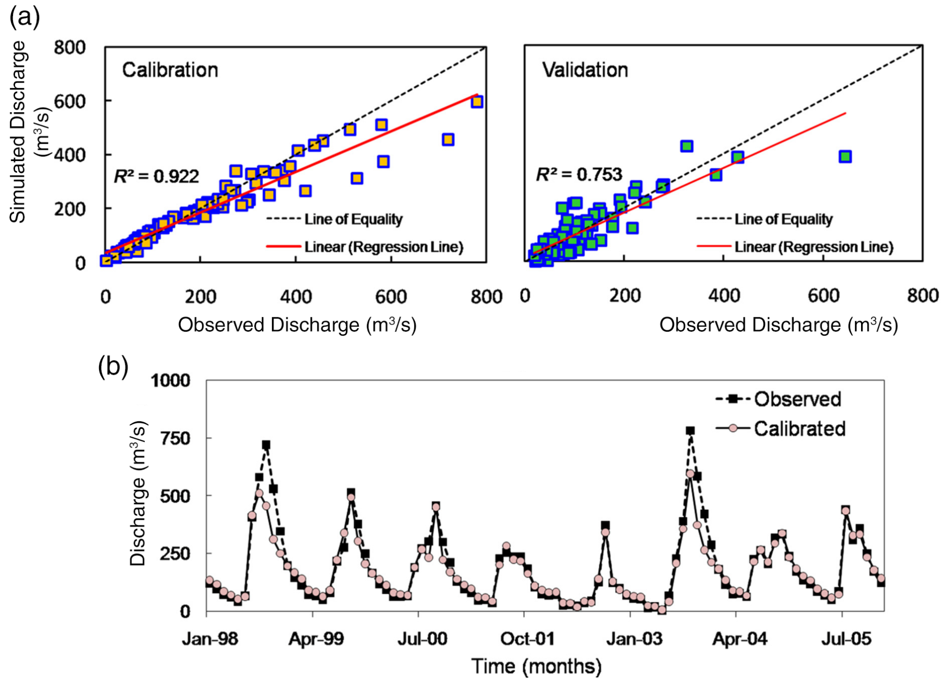

FIGURE 3 SWAT model performance at calibration and validation (a) and the hydrograph of simulated versus observed discharge (b)

Wood, 2008). SRI is also known for ease of its calculation along with the feasibility to multi-time scale drought analysis similar to SPI and SSI (Zhu et al., 2019).

The SWAT model-generated soil moisture content (amount of water in the soil profile) and run-off time series for each of the sub-basins at daily time step from 1986 to 2015 were used for SSI and SRI calculation. As sufficient and satisfactory data on soil moisture and run-off time series are not available because of insufficient gauging in Gomati basin, model-generated soil moisture and run-off time series were used for drought index assessment. The methodology given by Gringorten (1963) and McKee et al. (1993) was used for the calculation of all the three non-parametric drought indices, that is, SPI, SSI and SRI. These indices were estimated at 3-, 6-, 9- and 12-month time scales (Dash et al., 2019; Farahmand & Aghakouchak, 2015). As the results were reasonably good up to 12-month scale, the 15-, 18-, 24-month scales or beyond were not attempted. SPI, SSI and SRI thus developed were further evaluated for interrelationships among them with the help of Pearson's correlation coefficient (PCC).

3.5 | Estimation of Pearson's correlation coefficient (r)

Pearson's correlation coefficient (PCC; generally expressed by '$\boldsymbol{r}$') is used to evaluate the correlations between the univariate drought indices. PCC was estimated between SPI and SSI as well as between SPI and SRI for all the sub-basins as has been done by Dash et al. (2019).

The value of '$\boldsymbol{r}$' ranges from -1 to 1, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, with 0 indicating a state of no relationship. With PCC giving indications into existing correlations among the above-mentioned pairs of univariate drought indices, multivariate standardized drought indices (MSDI) were constructed to include the signals of more than one parameter to conform 'drought' conditions.

3.6 | Drought propagation

Rainfall deficit inducing meteorological drought propagates through the water deficits in subsurface processes of the hydrological cycle and then takes the form of agricultural drought due to deficit of moisture in soil. Further, if the moisture deficit persists and reaches deeper soil layers, the same agricultural drought transforms into hydrological drought, making the streams lose their flow (van Lanen, 2006). That is how there lies a significant link between meteorological and hydrological droughts (van Lanen, 2006; Wang et al., 2016). This propagation of meteorological drought into hydrological drought occurs only when there is continued rainfall deficit. It is also referred to as 'delayed response' of hydrological cycle to rainfall deficit (Figure 4).

As the Gomati basin has been documented to have undergone dry years (Bhatt et al., 2020), it is probable that some of the rainfall deficit might have impacted the hydrological cycle in the basin. Here, correlation analysis (Section 3.5) method used by Wu et al. (2021), was relied

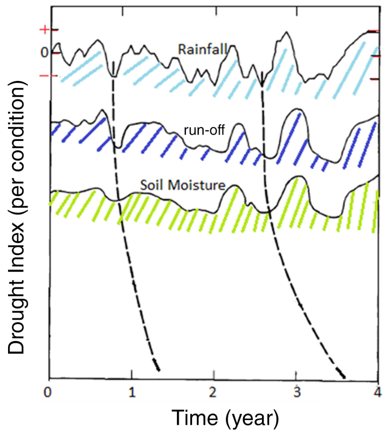

FIGURE 4 A schematic illustration of precipitation deficiencies being translated into delayed responses (with time-lag) of run-off and soil moisture components of any hydrological cycle of any region *Source*: Changnon (1987)

upon to identify propagation of meteorological drought into hydrological drought and then into agricultural drought.

3.7 | Construction of multivariate standardized drought index (MSDI) through Copula approach

The study adopted the *hybrid indicators method* out of the three popular methods of WMO: (i) Single indicator or index method; (ii) multiple indicators or indices method; and (iii) composite as well as hybrid indicators or indices method (Bateni et al., 2018; Huang et al., 2016; Waseem et al., 2015; WMO, 2016). A set of two hybrid indices (hybrid of SPI with SSI and SPI with SRI) have been developed using the *Copula approach* (Dash et al., 2019; Hao & Agha Kouchak, 2013; Luetkemeier et al., 2017; Vo et al., 2020). Copula is a recent method of generating MSDIs by incorporating more information through a combination of two or more univariate indices. By joining two or more univariate distributions into a one-dimensional joint probability distribution *Copula* builds a multivariate distribution building a dependence structure of randomly distributed two/more variables (Favre et al., 2004; Ganguli & Reddy, 2012; Genest & Favre, 2007; Kolev et al., 2006; Salvadori & De Michele, 2004; Sklar, 1973).

To overcome the limitations of univariate drought indices in case of agricultural and hydrological droughts indicated by SPI, SRI and SSI, the *Copula* based approach was adopted to construct bi-variate drought index (p), which not only is capable of addressing the individual univariate indices but also helped in inclusive characterization of drought via consideration of variable individualities (Equations 2 and 3).

$$p_{\text{agr.}} = C[F(\text{SPI}), G(\text{SSI})], \tag{2}$$

$$p_{\text{hyd.}} = C[F(\text{SPI}), G(\text{SRI})], \tag{3}$$

where C is the mapping function, that is, one of the Copula members found statistically fitting to construct the joint probability distribution, out of the marginal probability distributions of SPI are denoted as F (SPI) and of SSI and SRI are denoted by G (SSI) and G (SRI), respectively (Quesada-Molina et al., 2003). The 'Vine Copula' (Version 2.1.8) and 'Copula' (Version 0.999-19.1) packages of 'R′ were applied to both the cases (Equations 2 and 3) and then coupled with the Copula models of the respective multivariate joint probability distributions (Hofert & Mächler, 2011; Kojadinovic & Yan, 2010; Kolev et al., 2006; Schepsmeier, 2015, 2017; Schepsmeier et al., 2018; Yan, 2007).

The selection of Copula members to construct the joint probability distribution is governed by their respective generator functions. The MSDI derived here from such a distribution is given by the following equation:

$$\text{MSDI} = \varphi^{-1}(p),$$

where φ^{-1} is the transformation function (inverse standard normal distribution function) that converts the joint distribution into the same time scale and space as that of the univariate indices and p refers to either of the derived joint functions, that is, $p_{\text{agr.}}$ or $p_{\text{hyd.}}$ estimated by Equations (2) and (3). The MSDI enables its users to take advantage of a platform for assessment of the performances of both univariate as well as multivariate drought indices (Ayantobo et al., 2019; Chen et al., 2013; Das et al., 2020; Dash et al., 2019; Hao & Agha Kouchak, 2013; Sadegh et al., 2017).

3.7.1 | Copula member selection and goodness of fit assessment

The present study evaluated various members of Archimedean Copula family and selected the best members (used in the present study, mentioned later) to apply in the construction of joint probability distributions of rainfall with soil moisture and that of rainfall with run-off for each of the sub-basins. Some of the commonly used Archimedean Copula family members are Clayton, Frank, Gumbel, Ali-Mikhail-Haq and

Joe (Ayantobo et al., 2019; Azam et al., 2018; Fan et al., 2017; Goswami et al., 2018; Reddy & Ganguly, 2011). The criteria of best Copula correspond to a member, which is characterized by the lowest values of Akaike's information criterion (AIC; Akaike, 1974; Maier, 2013; Sadegh et al., 2017; Wang & Liu, 2006). Apart from AIC, Bayesian information criterion can also be opted for the same purpose (Thilakarathne & Sridhar, 2017; Tosunoğlu & Onof, 2019). Selection of Copula member was closely followed as that been followed by Dash et al. (2019). To select Copula member and to test its goodness of fit, AIC method was relied upon. It is an established fact that the uncensored data type is best captured by the 'Archimedean Copula' family members (Quesada-Molina et al., 2003). Therefore, Archimedean Copula family is opted in the present study to construct joint probability distributions of rainfall, discharge and soil moisture datasets, which in fact are uncensored type of time series datasets.

The entire methodology of the present study is aimed at utilization of observed datasets as much as possible to appreciate the basin history for 30 years period. It also makes use of well-calibrated hydrological model to generate hydrological datasets. The time series of hydrological variables were extracted at monthly time steps for all the sub-basins to overcome data unavailability in un-gauged sub-basins. Copula approach enabled the construction of MSDIs to get a better view of drought dynamics for each of the sub-basins. The inter-linkages and inter-dependencies among different approaches adopted in executing the present study are shown in the flow chart (Figure 5).

4 | RESULTS AND DISCUSSION

4.1 | Long-term trend detection

The results show that most of the sub-basins witnessed an appreciable rise in their annual average temperature trends (Table 4). All the sub-basins witnessed decreasing cumulative annual rainfall trends; however, the decrease was not significant in any of the sub-basins. Negative Z, S, Tau of the MK test and Sen's slope values of the cumulative annual rainfall analysis indicated that the sub-basins were affected by decreasing trend of annual rainfall (Table 4). But they were not significant as the *p* values were less than alpha (0.05) in the case of each of the sub-basins. In the case of annual average minimum temperature, the positive Z, S, Tau and Sen's slope values for all the sub-basins suggested that the entire basin had undergone significant (*p* values were less than assigned alpha for each sub-basin) rise in annual average minimum temperature conditions (Table 4). But as far as the maximum temperature trends were concerned, the increase was not found significant (*p* values were higher than assigned alpha for each sub-basin).

Even the monsoon season trend analysis of the long-term temperature and rainfall showed similar pattern as those of annual trends (Table 5). This shows that the seasonal trends of these meteorological parameters were in accordance with their respective annual trends. These findings of the annual and seasonal minimum temperature

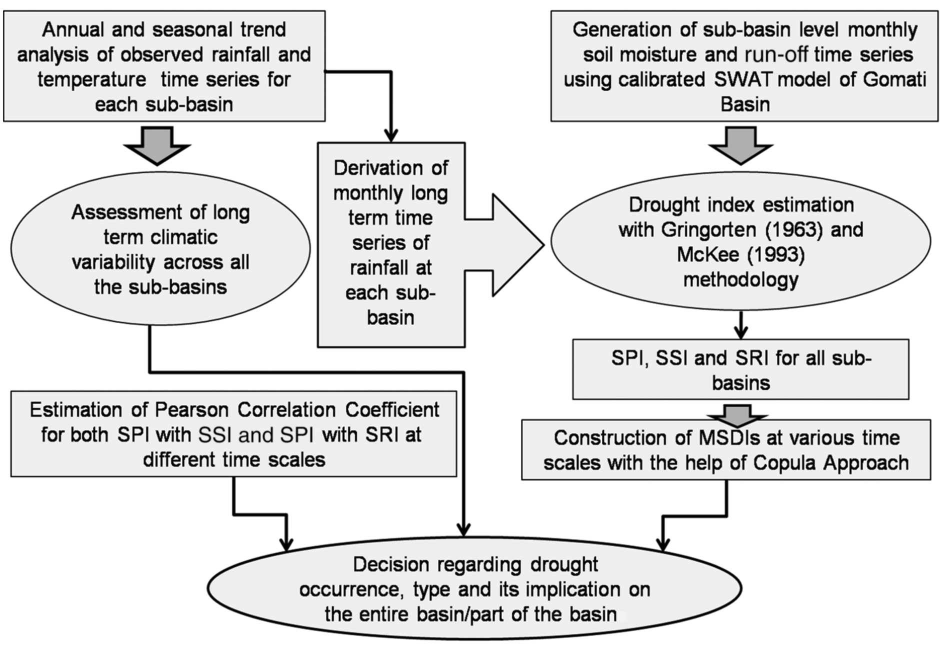

FIGURE 5 Overall view of the entire methodology followed in the study

TABLE 4 The long-term annual trends (1983–2015) of the climatic parameters using Mann–Kendall test at (alpha = 0.05) for the sub-basins of the Gomati River basin

(A) Max. temperature	*Z*-value	Sen's slope	*S*	Var(*S*)	*p* value	Tau
Sub-basin 1	1.144	0.013	85.000	5390.000	0.258	0.135
Sub-basin 2	1.109	0.013	82.400	5390.000	0.275	0.131
Sub-basin 3	1.226	0.015	91.000	5390.000	0.233	0.144
Sub-basin 4	1.230	0.014	91.333	5390.000	0.226	0.145
Sub-basin 5	1.348	0.014	100.000	5390.000	0.179	0.159
Sub-basin 6	1.316	0.014	97.600	5390.000	0.195	0.155
Sub-basin 7	1.294	0.013	96.000	5390.000	0.196	0.152
Sub-basin 8	1.355	0.011	100.000	5389.500	0.287	0.159
(B) Min. temperature	***Z*-Value**	**Sen's slope**	***S***	**Var(S)**	***p* value**	**Tau**
Sub-basin 1	3.242	0.028	239.00	5390.000	0.001	0.379
Sub-basin 2	3.332	0.028	245.600	5390.000	0.002	0.390
Sub-basin 3	3.065	0.026	226.00	5390.000	0.002	0.359
Sub-basin 4	3.065	0.028	226.00	5390.000	0.002	0.359
Sub-basin 5	3.378	0.031	249.00	5390.000	0.001	0.395
Sub-basin 6	3.299	0.029	243.20	5390.000	0.001	0.386
Sub-basin 7	3.537	0.033	260.67	5390.000	0.000	0.414
Sub-basin 8	3.698	0.035	272.50	5390.000	0.000	0.433
(C) Rainfall	***Z*-value**	**Sen's slope**	***S***	**Var(S)**	***p* value**	**Tau**
Sub-basin 1	−0.109	−0.879	−9.000	5390.000	0.903	−0.014
Sub-basin 2	−0.270	−2.120	−20.400	5390.000	0.643	−0.032
Sub-basin 3	−0.354	−2.148	−26.500	5390.000	0.596	−0.042
Sub-basin 4	−0.150	−0.997	−12.000	5390.000	0.881	−0.019
Sub-basin 5	−1.498	−7.026	−111.000	5389.800	0.378	−0.176
Sub-basin 6	−0.951	−4.667	−70.400	5390.000	0.402	−0.112
Sub-basin 7	−0.677	−2.317	−50.000	5390.000	0.312	−0.079
Sub-basin 8	−1.386	−6.153	−102.250	5389.750	0.147	−0.162

trend analysis are in perfect agreement with the all-India and seven homogeneous regions-wide study by Sonali and Kumar (2013). The agreement in the findings of both the studies suggests that the Gomati basin had been experiencing these minimum temperature trends since 1970. Therefore, this history of consistent rising minimum temperature could be taken as an indication of warming (Dash & Hunt, 2007; Kothawale et al., 2016; Kothawale & Kumar, 2002).

4.2 | Drought characterization

The 3-, 6-, 9- and 12-month time scale SPI, SSI, SRI and MSDI were estimated for all the sub-basins. These four indices were estimated using rainfall, run-off and soil moisture data during the period 1983–2015.

4.2.1 | SPI, SSI and SRI

SPI along with SPEI (the evaporation based drought index) enhances accuracy of meteorological drought identification, as was discussed by Mehr et al. (2020). However, close inspections into the meteorological drought propagation in relation to vegetation health, soil moisture, run-off and stream flow conditions allow detection of soil moisture drought as well as hydrological drought (deficits in run-off and stream flow) also (Kwon et al., 2019; Li et al., 2018). Both SSI and SRI are popular in detection of soil moisture and run-off deficit generated droughts; soil moisture deficit is generally connected more with agricultural drought and the run-off deficit with hydrological drought (Carrão et al., 2016; Mishra et al., 2014; Oertel et al., 2018; Shukla & Wood, 2008; Wu et al., 2016, 2017).

TABLE 5 The long-term monsoon season trends (1983–2015) of the climatic parameters using Mann–Kendall test at (alpha = 0.05) for the sub-basins of the Gomati River basin

(A) Max. temperature	*Z*-value	Sen's slope	*S*	Var(*S*)	*p* value	Tau
Sub-basin 1	0.844	0.010	63.000	5390.000	0.402	0.100
Sub-basin 2	0.706	0.008	52.800	5390.000	0.493	0.084
Sub-basin 3	1.117	0.013	83.000	5390.000	0.272	0.132
Sub-basin 4	1.049	0.013	78.000	5390.000	0.295	0.124
Sub-basin 5	1.144	0.016	85.000	5390.000	0.257	0.135
Sub-basin 6	1.457	0.017	108.000	5390.000	0.172	0.171
Sub-basin 7	1.149	0.016	85.333	5390.000	0.253	0.135
Sub-basin 8	1.348	0.018	100.000	5389.500	0.294	0.159
(B) Min. temperature	***Z*-Value**	**Sen's slope**	***S***	**Var(*S*)**	***p* value**	**Tau**
Sub-basin 1	2.125	0.015	157.000	5390.000	0.036	0.249
Sub-basin 2	2.209	0.015	163.200	5390.000	0.033	0.259
Sub-basin 3	1.784	0.012	132.000	5390.000	0.089	0.210
Sub-basin 4	2.030	0.015	150.000	5390.000	0.044	0.238
Sub-basin 5	2.363	0.019	174.500	5390.000	0.029	0.277
Sub-basin 6	2.133	0.017	157.600	5390.000	0.066	0.250
Sub-basin 7	2.556	0.022	188.667	5390.000	0.017	0.299
Sub-basin 8	2.881	0.024	212.500	5390.000	0.014	0.337
(C) Rainfall	***Z*-value**	**Sen's slope**	***S***	**Var(*S*)**	***p* value**	**Tau**
Sub-basin 1	−0.095	−0.531	−7.000	5390.000	0.871	−0.011
Sub-basin 2	−0.226	−1.807	−16.800	5390.000	0.566	−0.027
Sub-basin 3	−0.252	−1.253	−18.500	5390.000	0.553	−0.029
Sub-basin 4	−0.059	−0.474	−4.000	5390.000	0.910	−0.006
Sub-basin 5	−1.165	−4.865	−85.500	5390.000	0.497	−0.136
Sub-basin 6	−0.755	−3.542	−55.600	5390.000	0.440	−0.088
Sub-basin 7	−0.595	−2.157	−44.000	5390.000	0.478	−0.070
Sub-basin 8	−1.488	−6.404	−109.750	5389.750	0.185	−0.174

From the analysis of the precipitation datasets, it was evident that the 12-month SPI was consistently negative for all the sub-basins over the entire study period. This means that the entire basin was affected by near normal to moderate meteorological drought during the post-monsoon period (December). The other two indices SSI and SRI, however, did not capture any drought. Nevertheless, the fifth and the seventh sub-basins did show some sudden extreme fluctuations in the run-off conditions and to some extent even in soil moisture conditions too (third column in Figure 6).

The 3-month time scale of SRI indicated the hydrological drought conditions. Almost all the sub-basins experienced sudden drops in the SRI time series, which suggested that the occurrences are frequent but are not severe drought events. The 6-month SRI closely followed 6-month SSI but was only identified in the third, fourth, sixth and eighth sub-basins where there were fluctuations in SRI despite the SSI being relatively stable (Figure 6; first column).

The estimated SSI time series for the 6-month time scale suggested that even in monsoon season some of the sub-basins: second, fifth and seventh compared with others were affected by agricultural drought conditions because of deficit in soil moisture content (Figure 6; second column).

4.2.2 | Estimation of PCC (*r*) between various time scales of SPI, SSI and SRI

Cross-correlations between SPI accumulation periods of 1–12 months with SSI and SRI accumulation periods of 1–12 months were estimated to identify the time scales

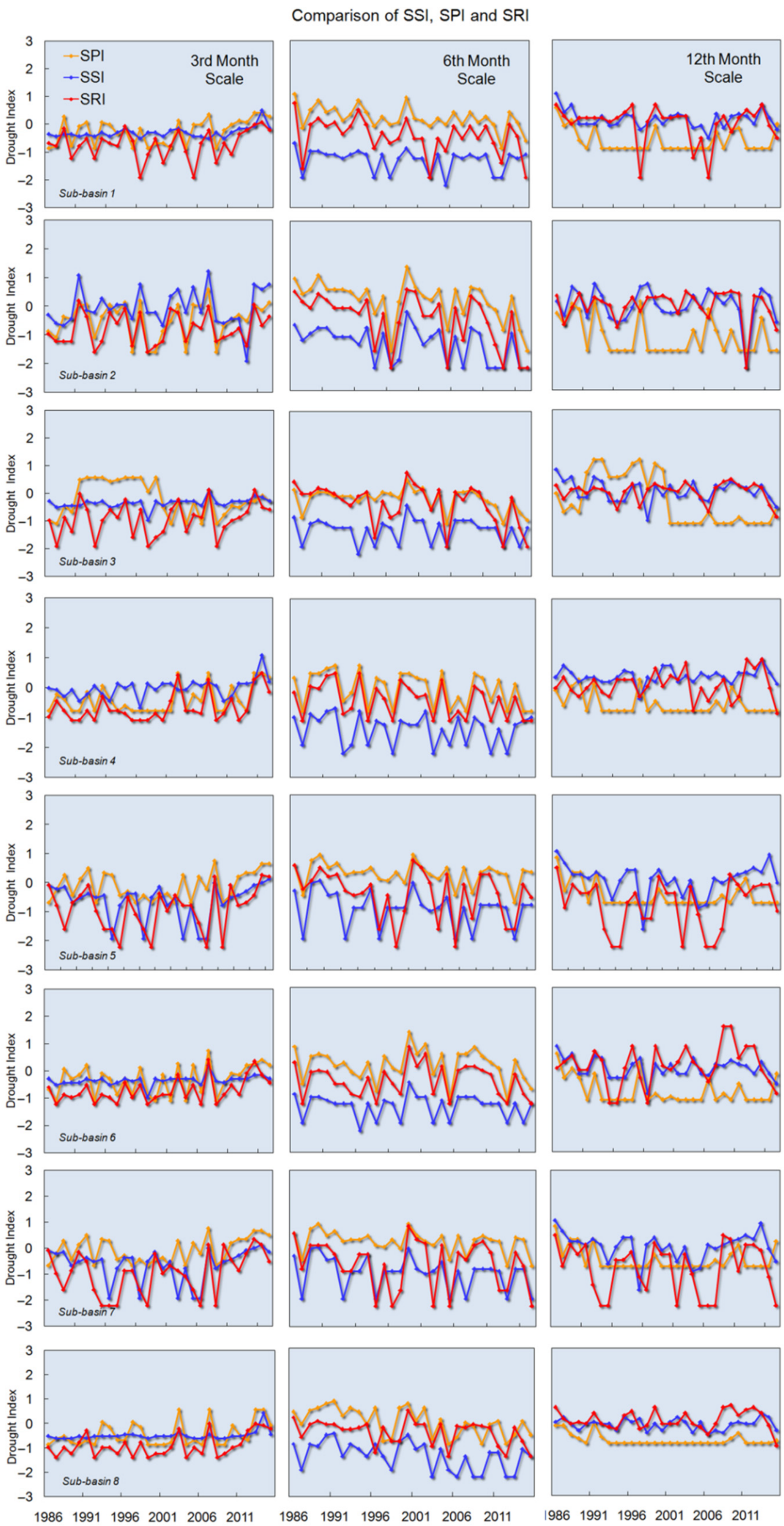

FIGURE 6 Comparison of the time series of SPI, SSI and SRI for the study period over the eight sub-basins of the Gomati basin (arranged from first to eighth, from top to bottom)

over which the rainfall deficits carried through the hydrological cycle induce agricultural and hydrological droughts. Correlation coefficients have been in regular use in assessment of drought propagation (Barker et al., 2016; Kwon et al., 2019; Oertel et al., 2018; Wanders et al., 2017).

The estimated PCCs at 6-month SPI with 6-month SSI and with 6-month SRI were the most prominent correlations observed in the study for the entire basin. Correlation coefficients of the 6-month (June) time scale showed significant positive correlation (PCC ≥ 0.8; Table 6). This indicates that the rainfall in the month of June over the entire study period naturally improved the soil moisture, and as a result of which run-off in the sub-basins increased with even low rainfall pulse received in July. Nevertheless, a considerably high PCC value can also be interpreted to be indicative of strong relationship; if ever the rainfall received in June is scanty, then immediately even the run-off of June may too fall. PCC near to 0.75 at 9-month time scale for the sub-basins 2 and 6 also indicates that they received sufficient rainfall during September, which improved soil moisture and run-off (Figure 6 and Table 6). Apart from June and September, even the rainfall of March (3-month time scale) contributed to maintain sufficient soil moisture and run-off in the fourth and sixth sub-basins (Table 6). Sub-basins 2, 4

TABLE 6 PCC (***r***) between different time scales of SPI, SSI and SRI ('sub-' for sub-basin)

		SSI3	SSI6	SSI9	SSI12	SRI3	SRI6	SRI9	SRI12
Sub-1	SPI3	0.313	−0.214	−0.183	−0.214	0.514	−0.197	−0.262	−0.197
	SPI6	−0.231	*0.675*	0.089	0.179	−0.128	**0.881**	0.177	0.07
	SPI9	−0.055	−0.149	*0.662*	0.198	−0.041	−0.174	*0.701*	*0.573*
	SPI12	−0.252	0.282	−0.057	*0.597*	0.084	0.227	0.171	*0.593*
Sub-2	SPI3	0.543	**−0.456**	−0.295	−0.057	0.8	**−0.477**	0.026	−0.157
	SPI6	−0.304	**0.868**	0.434	0.087	−0.349	**0.954**	0.316	0.224
	SPI9	−0.039	0.155	*0.576*	0.247	−0.057	0.31	***0.75***	*0.621*
	SPI12	−0.195	0.396	0.288	0.12	−0.18	0.386	0.103	0.288
Sub-3	SPI3	0.046	0.319	0.037	*0.523*	−0.118	0.397	−0.158	−0.089
	SPI6	0.046	0.319	0.037	*0.523*	−0.118	0.397	−0.158	−0.089
	SPI9	−0.292	0.024	*0.587*	0.049	−0.248	0.085	0.49	0.305
	SPI12	−0.366	−0.025	0.05	0.003	−0.169	0.134	0.067	−0.09
Sub-4	SPI3	**0.904**	−0.179	−0.042	0.294	0.345	−0.434	0.044	0.079
	SPI6	−0.329	***0.745***	−0.142	−0.154	−0.503	**0.978**	−0.112	0.021
	SPI9	−0.07	−0.52	0.411	0.386	0.158	−0.28	*0.719*	*0.562*
	SPI12	−0.215	0.268	−0.336	−0.418	−0.222	0.302	−0.305	−0.269
Sub-5	SPI3	0.379	−0.211	−0.064	0.116	0.379	−0.371	−0.125	−0.131
	SPI6	0.145	**0.876**	−0.064	0.116	−0.054	*0.728*	0.094	0.323
	SPI9	0.025	−0.066	*0.684*	*0.578*	−0.093	0.158	*0.69*	0.202
	SPI12	0.32	0.269	0.204	0.335	0.215	0.214	0.224	0.321
Sub-6	SPI3	*0.519*	−0.257	−0.225	−0.234	**0.812**	−0.369	−0.255	−0.201
	SPI6	0.055	**0.843**	0.248	0.279	−0.286	**0.957**	0.247	0.113
	SPI9	−0.305	0.025	*0.682*	0.143	−0.298	0.041	***0.746***	*0.704*
	SPI12	−0.158	0.269	−0.18	0.441	−0.162	0.132	−0.218	−0.078
Sub-7	SPI3	0.145	−0.211	−0.064	0.116	0.379	−0.266	−0.105	−0.172
	SPI6	−0.033	**0.876**	0.161	0.2	−0.054	*0.669*	0.125	0.31
	SPI9	0.025	−0.066	*0.684*	*0.578*	−0.093	0.003	*0.604*	0.182
	SPI12	0.32	0.269	0.204	0.335	0.215	0.209	0.033	0.162
Sub-8	SPI3	*0.589*	−0.22	0.006	0.231	0.69	−0.241	**−0.463**	−0.208
	SPI6	−0.086	**0.882**	0.204	0.204	−0.165	0.463	0.268	0.05
	SPI9	−0.123	0.122	0.373	0.22	−0.109	0.247	0.3	0.053
	SPI12	−0.223	0.199	−0.179	0.201	−0.046	0.235	0.367	0.233

Note: Bold values shown Highly strong positive correlations beyond 0.75 (or closer to 0.75) and those which are negative and related to case studies of sub-basin 2 and 8 have been high lighted.

and 8 were affected by negative correlation (less than −0.4) in 3-, 6- and 9-month time scales as far as the rainfall and run-off were concerned (Table 6). This suggests that rainfall of March was not always able to sufficiently contribute to the soil moisture and run-off. The observation of the estimated positive r be it between SPI and SSI or between SPI and SRI indicates that there is no lag in response time of the hydrological variables to those of the meteorological ones. But in the cases of second, fourth and eighth sub-basins deficient rainfall conditions in March did result in reduced soil moisture and run-off in the month of June, indicating a lag period of 3 months in the responses of both the physical processes.

However, it would be inappropriate to decide on drought occurrences just based on the outcomes of correlation. For final drought assessment, it would be more appropriate to further look into cumulative results of indices. For, even if the r values were found considerably significant, there still remains scope of r values getting over-powered by any of the parameters, which quite likely would carry away the decision makers in their decisions regarding drought monitoring and assessment. Further, there is possibility of participation of other meteorological or hydrological or anthropogenic parameters, which might affect the correlations. With such possibilities of disturbances, to capture the drought signals and to infer the type of drought, MSDI could be very useful. As discussed earlier (Section 3.5), the desirability of MSDI comes from its very nature of inclusiveness of multiple parameters.

4.2.3 | Drought propagation

In this study, SPI, SSI and SRI were used to represent the meteorological, agricultural and hydrological conditions, respectively. Therefore, the relationships between SPI and SSI as well as between SPI and SRI have been considered as indications of meteorological to agricultural and to hydrological drought propagation.

Propagation time was estimated with the help of PCC. These correlations were estimated at different time scales. Studies conducted by Oertel et al. (2018) and Ma et al. (2019) have also commonly relied on the strength of correlation between various variables to study drought propagation in semi-arid river basins similar to the present study area. The longest propagation time is estimated for the sub-basin 8 where the rainfall deficit (meteorological drought) in the month of March has led to run-off deficits (hydrological drought) in the month of September (PCC = −0.46). Propagation time estimated for the sub-basin 2 with a 3 months lag time in response to the rainfall deficits in March manifested into soil moisture and run-off deficits in the month of June (PCC = −0.45 and −0.47, respectively). This points towards the susceptibility of the upstream region (sub-basin 2) to various drought conditions. Sub-basin 4 too has also shown propagation time 3 months for rainfall (in March) deficit to propagate to hydrological deficit (in June; PCC = −0.43). While the shortest propagation time could be assumed for sub-basin 2, that is, a zero lag time during the month of June, the rainfall deficits in the month are very much prone to manifest into soil moisture and run-off deficits without much delay (as already mentioned in Section 4.2.2).

4.3 | Selection of Archimedean Copula member

Selection of Copula member involves paired assessment of related pairs univariate drought indices. Joe, Gaussian/Normal and Gumbel Copula are *Archimedean Copula family* members, which were found statistically best fitted in the construction of joint multivariate distribution at the 3-, 6-, 9- and 12-month time scales for most of the sub-basins. The results of test goodness of fit were used to identify the best fitting Copula members (Table 7; Azhdari et al., 2021; Bazrafshan et al., 2021). The density and cumulative density function of the non-parametric bi-variate MSDI along with its corresponding contour structures are illustrated in Figures 7 and 8.

4.3.1 | Performance assessment of MSDI

Figure 9 illustrates the performance of three of the MSDIs considered for detailed evaluation of the second and eighth sub-basins. The reason behind choosing the second sub-basin is that the second sub-basin had maximum as well as consecutive occurrences of dry conditions followed by wet periods, while the eighth sub-basin was selected as it reported considerable reduction in run-off due to diminished rainfall (Table 6). Also, as the eighth sub-basin is the downstream most, it appropriately fits into the scheme to assess hydrological mass balance. The decrease in run-off at the end of monsoons raised concern and prompted the need for further evaluation of this (eighth) sub-basin. In the second and eighth sub-basins, analysis pertaining to the impact of rainfall on other hydrological variables reflected conditions prompting an examination of the interactions further (Table 6 and Figure 6).

MSDI1 and MSDI2 were developed from the joint probability distribution of 3-month SPI with 6-month SSI and 3-month SPI with 6-month SRI, respectively, for the

TABLE 7 Goodness of fit assessment of Copula members

Sub-basin	Constructed MSDI	Copula function	Parameter	*p* value	Lag period
Sub-basin 2	MSDI1	Joe	1.77	0.52	3 months
	MSDI2	Gumbel	1.47	0.87	3 months
Sub-basin 2	MSDI1	Gaussian	0.95	0.8	0 months
	MSDI2	Gaussian	0.96	0.6	0 months
Sub-basin 8	MSDI3	Joe	1.48	0.73	6 months

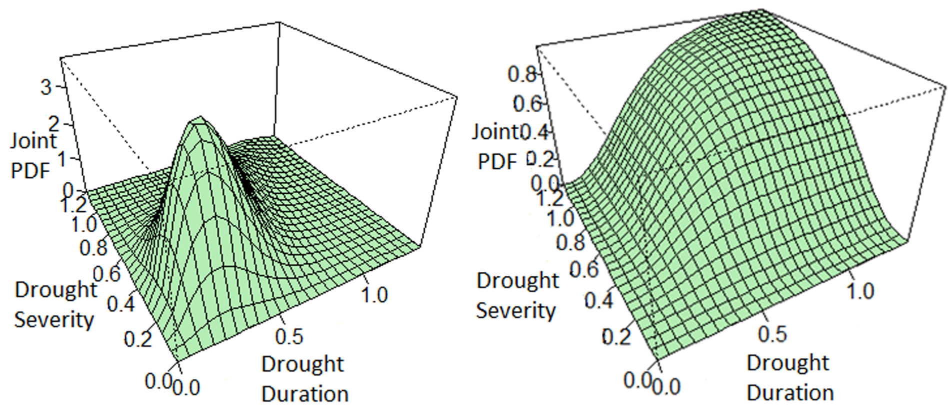

FIGURE 7 Joint probability density function (PDF) generated using Joe Copula

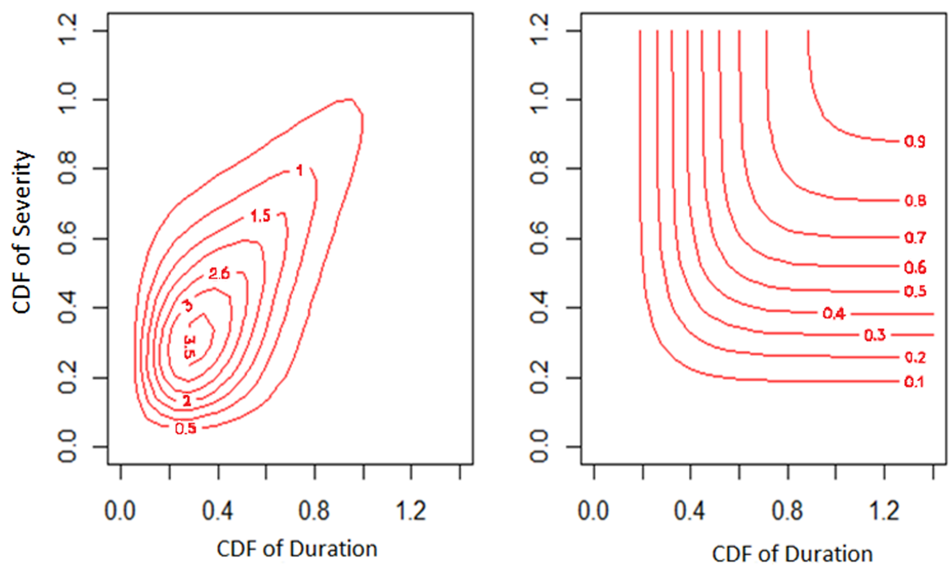

FIGURE 8 Cumulative density function (CDF) contours of the Joe Copula corresponding to the joint probability density function (PDF)

second sub-basin (Figure 9a). MSDI1 and MSDI2 shown in Figure 9b were developed from the joint probability distributions of 6-month SPI with 6-month SSI and 6-month SPI with 6-month SRI, respectively. MSDI3 is the joint probability distribution of 3-month SPI and 9-month SRI for the eighth sub-basin (Fi.9c). Normally, researchers club third/sixth month with third/sixth month time scale drought indices in joint probability distribution to construct MSDIs, but we have clubbed third month with sixth/ninth month time scale drought indices (the joining of probabilities of two different time scales of drought index was possible through the application of Copula function) only to ensure certain type of drought is not declared too early and which may not persist long enough. Figure 9a,b shows that even though SPI, SSI and SRI individually indicated (index value less than −2) occurrences of frequent droughts (1996, 1998, 2005, 2012 and 2014) but yet, neither the MSDI1 nor the MSDI2 confirmed any such drought incidences. In Figure 9b, both the MSDIs are seen to be in conformity with each other

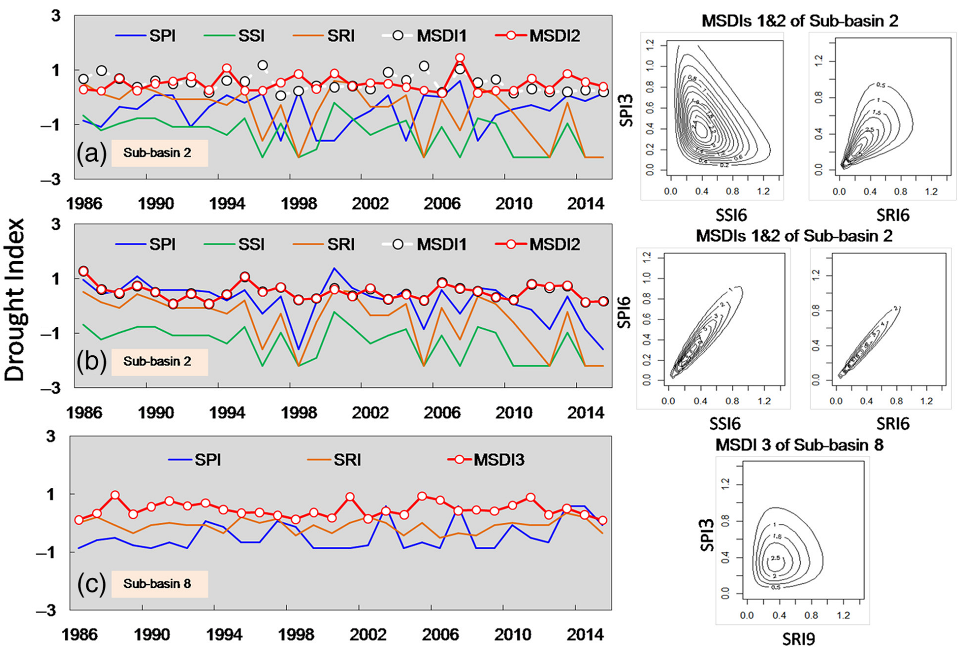

FIGURE 9 Estimated MSDIs and their corresponding contour plots of the joint distribution generated using case-specific Archimedean Copula members

as far as responses of second sub-basin are concerned with a small variation between them. Their conformity indicates that the sixth month (June) was constantly below a drought index value of 1 except in 1986 and 1995. That means, as per MSDIs, the second sub-basin essentially experienced drought events with less severity and also of short duration contrary to what has been indicated by SPI, SSI and SRI (more severe and of longer duration droughts). Both MSDIs indicated towards probabilities of a condition of the second sub-basin being *dry* rather than being drought affected in June. The second sub-basin has a considerable spatial coverage: three (Pilibhit, Shahjahanpur and Kheri) entire districts and parts of two (Sitapur and Hardoi) more districts with their decadal population growth rates being above 17% fall within the sub-basin (Census of India, 2011; Tiwari, 2015). Such a population growth rate is an indication of the sub-basin being under obvious pressure to meet the demands for water of both the agriculture and domestic sectors. The staple crops of rice and wheat in the sub-basin are irrigated using the surface and ground water resources, and as a consequence of which the same suffered depletion aggravating the dry condition. The fourth and the eighth sub-basins have also come under similar pressure as the second sub-basin.

Nevertheless, MSDI3 performed well and was in tandem with both the 3-month SPI and 9-month SRI (Figure 9c). Overall, MSDI1, MSDI2 as well as MSDI3 varied over a confined range of index variation (from ~0.1 to ~1) for the entire period (1986–2015) under study. This narrow range of variation of the multivariate indices indicated a condition to be more appropriately called as '*drying*' rather than '*dry*' and to be placed under the drought category known as *near normal* (Bayissa et al., 2018). If frequent and significant deficient rainfall event(s) occur in near future, then the MSDIs may show a broad range of variation and a negative MSDI would then be bound to confirm the drought event(s) for certain.

Now, a very frequent variation of MSDI within a value range between −1 and +1 (Figure 9) strongly confirms that there are no occurrences of severe meteorological or hydrological drought(s). However, the corresponding variations of SSI with MSDI indicate that the second sub-basin was constantly under reduced soil moisture conditions (Figures 5 and 9a,b). Nonetheless, agricultural drought was not captured by any of the MSDIs; it may be because the reduced soil moisture condition was rendered ineffective by regular long period irrigation supplements and probably even the crop yields were not affected in the second sub-basin due to this same reason. The regular irrigations came at the cost of either ground water or surface water (canals) sources. Recalling the findings of Ge et al. (2016) mentioned earlier (in the introduction), depletion of groundwater (to irrigate the fields under reduced soil moisture conditions) indicates onset of drought. The Gomati basin area being largely under agricultural activity, indications of an imminent agricultural drought could be presumed through the results of the present study. Also in future, in the case of a deficient monsoon or any loss of flow in the streams/canals in lean periods, conditions may get worse especially in the upstream regions (second sub-basin) of the basin.

There has been an observable climatic shift all over India in which the dry sub-humid regions are reported to have shifted to semi-arid climate conditions (Raju et al., 2013). Very likely, as has often been reported, the increase in semi-arid region indicates increased aridity, which is an obvious pointer of probable onset of droughts (Jayasree & Venkatesh, 2015; Oertel et al., 2018; Schwabe & Connor, ; Surendran et al., 2019; Zhang & Jia, 2013). The NCTHR of which the basin of study is a part) experiences mainly semi-arid and dry sub-humid climates. Bisht et al. (2018) undertook a country-wide evaluation of changes in drought characteristics of monsoon homogeneous regions to confirm changes if any in climate. Their study led them to conclude that the drought severity, duration and occurrences will increase in future (Bisht et al., 2018). Another study on the drought projections under climate change scenario confirmed that it is the Northern India that would face increased droughts in near future than southern India (Gupta & Jain, 2019).

5 | CONCLUSIONS

Based on univariate drought indices, both the agricultural and hydrological drought events were identified to have affected the basin time to time within the period from 1986 to 2015. On the other hand, the multivariate analysis of probability of drought for the basin confirms that when various parameters are involved in collaborative drought index development, the developed index may not agree with the respective individual responses of the constituent variables. As such, the MSDIs estimated for the study period for the Gomati basin also did not indicate any drought events. In that way, the MSDIs were in disagreement with the SPI, SSI and SRI, which indicated frequent occurrences of drought.

As far as detection of onset of drought using univariate indices is concerned, the basin was found very sensitive to deficits in the soil moisture. The present study on Gomati basin reveals that soil moisture deficits got translated into dry agricultural conditions (reduced soil moisture), which further turned into dry hydrological conditions (reduced run-off; Figure 5). Indeed, deficit conditions of sub-basins 2, 4 and 8 (Table 6) are exceptions: for, in these cases, the PCCs were less than −0.4. and there was 3 months lag in hydrological responses. The deficit in rainfall in March by and large affected the basin-wide soil moisture and consequent run-off in June, as has been mentioned earlier.

On the whole, the given MSDI based analysis suggested that the upper Gomati basin had undergone a consistent drying in the month of June but has not shown any '*drought event*' in particular. The month of June is crucial for *kharif* crops, namely rain-fed cultivation of rice, sesame, millet, maize, black gram and pigeon pea. Soil moisture availability during the sowing period plays a crucial role, especially for such crops during this period (June). Going by the trend of results, it can be said that the agricultural area under rain-fed *kharif* crops, especially in the upper basin, requires irrigation during field preparation itself. That means, relying solely on rains may adversely impact these crops in this region. The results finally indicate possibility of impending *agricultural drought* in the upper part of the Gomati basin. Agricultural management strategies have to be planned and implemented to avert such imminent drought(s).

Therefore, considering this entire study as a representative of the NCTHR, it is clear to a certain extent that MSDIs could be used not only for comprehensive drought assessments of smaller- and medium-sized basins within alluvial plains but can also help screen larger homogeneous regions which are expected to witness drought(s) in future.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Diva Bhatt: Conceptualization (supporting); data curation (lead); formal analysis (lead); investigation (equal); methodology (supporting); software (lead); validation (equal); visualization (lead); writing – original draft (equal); writing – review and editing (equal).

Rajesh Kumar Mall: Conceptualization (lead); data curation (equal); formal analysis (supporting); funding acquisition (lead); investigation (equal); methodology (equal); project administration (lead); resources (lead); supervision (lead); visualization (supporting); writing – review and editing (equal). **K N P Raju:** Methodology (supporting); writing – review and editing (supporting). **Shakti Suryavanshi:** Software (supporting); validation (supporting); visualization (supporting).

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