Characterization of Regional Drought Over Water and Energy Limited Zones of India Using Potential and Actual Evapotranspiration

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Key Points:
- Restructured SPEI to account for AET and seasonality in drought assessment of India
- Higher drought durations for energy-limited and lower drought intensities for water-limited zones
- AET is more suitable for extreme drought assessment for water-limited zones

Supporting Information:
- Supporting Information S1

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Characterization of Regional Drought Over Water and Energy Limited Zones of India Using Potential and Actual Evapotranspiration

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Abstract Understanding the drought characteristics is critical for water resources management in water stressed countries such as India. Previous studies evaluating drought assessments over India considered precipitation (P) and potential evapotranspiration (PET) as drivers using standardized precipitation-evapotranspiration index (SPEI). The suitability of actual evapotranspiration (AET), which accounts for both water and energy based evaporative demands, in drought characterization is limited. In this study, SPEI is restructured with AET to characterize the regional drought over water and energy limited regions as standardized precipitation actual evapotranspiration index (SPAEI). For this, AET estimated based on Budyko framework and remote sensing-based AET data has been used. The original formulation of SPEI is limited toward capturing the seasonality present in P and PET. The SPEI is restructured to account for the water availability deficit in the drought assessment rather than the actual atmospheric water demand in a given period to capture the strong seasonality of rainfall. The study compared the drought characteristics with both PET and AET for various meteorological homogeneous zones of India, which are characterized as water-limited (Central, North, West, South, and Jammu and Kashmir, J&K) and energy-limited (Northeast and Northeast hills) zones. Overall, the proposed new drought index based on AET can be promising toward drought intensity, extreme drought areal extents, shorter-time scale drought frequencies, and longer-time scale drought durations for water-limited zones. The proposed drought indices based on AET can be robust for the drought assessment under consideration of water energy along with land and vegetation variability and can provide more insights for water-limited regions.

1. Introduction

Drought is one of the poorly understood natural hazards in terms of its occurrence, frequency, severity, and duration which affects millions of people all over the world (Dai, 2011; Sheffield et al., 2012). Major factors affecting the persistence of droughts are water balance changes due to the alterations in water supply (precipitation), energy (potential and actual evapotranspiration), land surface characteristics (vegetation and topography), and climate change (variability) (Budyko, 1974; Liu et al., 2016; Nath et al., 2017; Zhou et al., 2015). Among these factors, the actual evapotranspiration (AET) represents the amount of water evaporated from water and soil along with the water transpired from the plants to the atmosphere. AET is noted to be a promising variable in the drought prediction (Kim & Rhee, 2016) accounting for land surface changes (Liu et al., 2016).

Typically, various drought indices were used to characterize the drought all over India for identifying spatio-temporal behavior of droughts (Kumar et al., 2013; Mallya et al., 2016; Mooley & Parthasarathy, 1984; Parthasarathy et al., 1987; Singh, 2001) Efforts has been devoted to understand the drought assessment considering precipitation (P) as the prominent variable (Aadhar & Mishra, 2017; Mooley & Parthasarathy, 1984; Parthasarathy et al., 1987; Singh, 2001) on different spatial domains using standardized precipitation index (SPI) (McKee et al., 1993). However, SPI can estimate the drought under lack of precipitation but cannot detect the drought conditions under higher than normal atmospheric evaporative demand (Vicente Serrano et al., 2010). Moreover, a drought indicator which can include both precipitation and temperatures will be more suitable, particularly under extreme climates of dry and heat waves (Aadhar & Mishra, 2017; Sharma & Mujumdar, 2017). Hence, a drought indicator which can account for atmospheric demand of moisture in the context of increasing temperatures under climate change will be more appropriate.

The standardized precipitation-evapotranspiration index (SPEI) has been proposed by Vicente Serrano et al. (2010), which considers the potential evapotranspiration (PET) in addition to precipitation and can be implemented at various time scales. Due to the consideration of PET, SPEI combines the sensitivity of the Palmer drought severity index (PDSI) along with the probabilistic and multitemporal nature of SPI. In the recent years, SPEI has been widely used to evaluate drought events worldwide (Aadhar & Mishra, 2017) as well as for Indian subcontinent (Kumar et al., 2013; Mallya et al., 2016; Nath et al., 2017). However, SPEI cannot represent the actual water budget, land and vegetation, or physiological mechanisms. Moreover, SPEI works on (P-PET), which is energy based atmospheric water demand and do not account for the effects of regional land surface changes and actual moisture availability, which is the difference (P-AET) between P and AET. Also, PET is the maximum possible moisture loss limited only by the energy endowment or it is the energy-driven ET (Shelton, 2009). Whereas, AET represents the transfer of moisture from the surface to the atmosphere in response to both the energy demand and available moisture supply and can be a promising variable in the drought estimation (Liu et al., 2016).

Efforts toward the inclusion of AET in drought assessment include DSI (Mu et al., 2012) and U.S. Drought Monitor (USDM) (Svoboda et al., 2002). These indices used AET estimated using remotely sensing data sets and vegetation information from normalized difference vegetation index (NDVI) and tries to account for land surface changes implicitly. Recently, Kim and Rhee (2016) developed standardized evapotranspiration deficit index (SEDI) using the AET estimated from Bouchet hypothesis and the structure of SPEI as a fully ET-based drought index, without consideration of precipitation. Limited studies tried to include AET estimates explicitly in the drought indices using operational meteorological data sets (Liu et al., 2016). Few studies attempted to use AET explicitly in the formulation of SPEI (Dai, 2011; Homdee et al., 2016; Joetzjer et al., 2013; Liu et al., 2016). Homdee et al. (2016) compared SPEI with AET based drought indices, where AET was modeled based on SWAT. However, inclusion of hydrological model driven AET will provide a limitation over the applicability over large spatial scales given with the rigorous catchment characteristic and discharge data requirements. Therefore, an AET based drought index should be able to use operational meteorological data for the ease of drought assessment at various spatial and temporal scales and for the impact assessment under climate variability. Given the debate over the use of PET and AET in formulation of SPEI, while numerous studies have already been carried out to assess drought variability using PET in SPEI all over India (Kumar et al., 2013; Mallya et al., 2016; Nath et al., 2017), the workability of AET in drought assessment has not been tested. Further, the versatility of monsoon rainfall and diverse topography of India demands a comprehensive drought study for water- and energy-limited regions of the country separately. Besides, none of the studies have compared the performance of a drought indices using AET and PET with sufficiently long duration data at homogeneous meteorological zones of India. Therefore, the present study made an effort to compare and characterize the proposed drought indicator for seven homogenous meteorological zones of India.

India being a country associated with strong seasonal rainfall with 78% of total annual rainfall during monsoon period starting from June to September (JJAS) (Mooley & Parthasarathy, 1984), it is important for any drought index to represent such seasonality while characterizing the drought (Wu et al., 2017). To account for the monsoon and nonmonsoon periods of high and low rainfall, respectively, Kironmala and Rajib (2015) have developed a drought index, standardized precipitation anomaly index (SPAI) for monthly precipitation data over entire India and from two meteorological subdivisions, Gangetic West Bengal and Orissa. To account for strong seasonality of Indian monsoon rainfall, the SPAI was structured based on the normalized anomalies of the precipitation rather than normalizing the actual precipitation values. However, the study does not consider the effect of variation of evapotranspiration in the drought characterization. Monish and Rehana (2019) evaluated the SPEI to capture the seasonality over India and found that SPEI is unable to capture the seasonality while the same study also compared the SPEI and SPAI to capture the seasonality and found SPAI is a better formulation to capture the seasonality of monsoon precipitation of India by considering the anomalies corresponding to the long-term average precipitation. Therefore, the present study has restructured the basic formulation of SPEI to account for the seasonality aspects of rainfall and ET to study the drought characteristics over India based on the formulation of SPAI. The restructured drought index of SPEI, with the inclusion of seasonality, was named as standardized precipitation actual evapotranspiration index ($SPAEI_{seasonal}$). Overall, the main objectives of the study are (i) to understand the suitability of PET and AET based drought indices over water- and energy-limited regions and (ii) to capture the seasonality present in precipitation and ET in the drought assessment. Moreover, the study compared AET-based

10.1029/2020EA001264

drought index, SPAEI, with PET-based drought index of SPEI for drought assessment in terms of areal extent, frequency, severity, and duration for meteorological homogeneous zones of India at a fine resolution of 0.25^{o} provided by India Meteorological Department (IMD).

2. Materials and Methods

2.1. Restructuring SPEI With AET

The water budget in a control volume including precipitation (P), runoff (Q), ground water (GW), and storage (S) can be expressed as follows:

$$\Delta S = P + Q_{in} + GW_{in} - GW_{out} - Q_{out} - AET \quad (1)$$

where S is the storage volume, GW_{in} (GW_{out}) is the ground water inflow (outflow) volume, and Q_{in} (Q_{out}) is the surface runoff inflow (outflow) volume. For sufficiently long-time scales, the net change in storage volumes corresponding to ground water can be assumed to be zero. This will direct to a simplified water budget/availability or AET based residual available water (RAW_{AET}) over a region can be expressed as follows:

$$RAW_{AET} = P - AET \quad (2)$$

A drought index that considers the AET will be able to capture the land surface changes such as vegetation which directly influence the water-energy balance (Liu et al., 2017) whereas the actual structure of SPEI depends on the value of climatic water balance or PET based residual available water (RAW_{PET}) and the accumulated time series of RAW_{PET} may take negative values when the PET exceeds rainfall, P.

$$RAW_{PET} = P - PET \quad (3)$$

The original formulation of SPEI used Thornthwaite model, which calculates PET based on the mean temperature. Most of the earlier SPEI based drought studies all over India were also based on Thornthwaite model (Kumar et al., 2013; Mallya et al., 2016). The Thornthwaite model tends to underestimate PET in arid and semiarid regions (Jensen et al., 1990) and overestimates PET in humid and tropical regions (van der Schrier et al., 2011). Hargreaves equation (Hargreaves, 1975; Hargreaves & Allen, 2003) strikes a balance between minimum data requirements and accurate PET estimation (Stagge et al., 2014). The present study employed Hargreaves equation for PET calculation which requires minimum, maximum, and mean temperatures along with the geographical location of the region as follows:

$$PET = 0.0023 * (T_{max} - T_{min})^{1/2} * (T_{mean} + 17.8) * R_a \quad (4)$$

where T_{max}, T_{min}, and T_{mean} represent the maximum, minimum, and mean temperatures, respectively, whereas R_a is the extraterrestrial radiation expressed in equivalent evaporation units and calculated using the latitude of the location and time of the year.

To include AET in SPEI, accurate estimates of AET at monthly scale will be required at finer resolution all over India. There are several AET data products developed based on remote sensing at monthly scale at fine resolution (Zhang et al., 2004). The AET data based on remote sensing can account for the soil properties, spatial vegetation, and land cover fractions (Hengl et al., 2017). The inclusion of remote sensing based AET data in the drought estimation has a potential to account for the changes in land use and vegetation changes to characterize droughts in addition to rainfall. Therefore, the present study used remote sensing-based AET data in the formulation of SPEI as SPAEI to account for the actual water availability and land use changes along with precipitation in the drought estimation over India.

However, given the limitations over spatiotemporal data validation of such global data sets (Mueller et al., 2011) for Indian case studies, use of modeled data sets which works with common operational meteorological data will be more appropriate. In this context, one of the conventional methods to estimate AET in hydrology for many years is to estimate PET first and then applying a limiting factor to account for the water availability and soil (Anabalón & Sharma, 2017; Martens et al., 2017). To this end, several empirical models have been developed for estimating AET which are based on the assumption that AET is limited by the water availability in terms of P under very dry conditions and energy availability in terms of PET under very wet conditions (Budyko, 1974; Zhang et al., 2004). Budyko (1974) has developed a relationship between three hydro-climatic variables: P, PET, and AET. Budyko hypothesis states that the ratio of the AET over precipitation (AET/P) is fundamentally related to the ratio of the PET over precipitation (PET/P) (Budyko, 1974) as follows:

$$\frac{AET}{P} = 1 + \frac{PET}{P} - \left(1 + \left(\frac{PET}{P}\right)^{\omega}\right)^{(1/\omega)} \tag{5}$$

The Fu's parameter "ω" accounts for the effects of climate variability, basin characteristics such as soil, vegetation, and terrain (Donohue et al., 2007). The present study used Budyko equation as implemented by Zhang et al. (2004) for estimating AET at annual scale, given as follows:

$$AET = \left[P\left(1 - exp\left(\frac{-PET}{P}\right)\right)PET\, tanh\left(\frac{P}{PET}\right)\right]^{0.5} \tag{6}$$

The original Budyko equation (Equation 1) is a parametric formulation with parameter "ω" to account for nonclimatic influences of the catchment (Yang et al., 2017) and developed for long-term averages (>1 year) and large catchments (>10,000 km^2) with stationary hydrological conditions as assumptions (Gunkel & Lange, 2017) where long-term soil water storage changes due to ground water recharge and storages due to geological features and human interactions such as water withdrawals are considered to be negligible (Wu et al., 2017). However, the Budyko framework can be applied over short periods of monthly and annual scales (Buytaert & Bièvre, 2012; Liu et al., 2017; Zhang et al., 2008) if the parameter "ω," which represents the joint effect of climate and land surface, is estimated. For a reasonable application of the Budyko equation as developed by Zhang et al. (2004) (Equation 6), the study used a 12-month scale for the estimation of drought indices. Estimation of "ω" based on the observed AET and P values for each individual location/zone is beyond the scope of the present study. It can be noted that to estimate the drought indices lesser then 12-month time scale (annual drought), the Budyko equation as implemented by Zhang et al. (2004) may not be valid, since the storage changes cannot be neglected at drought indices lesser then 12-month time scales. Further, as the study mainly focused on 12-month scale accumulation period, where the seasonality of root zone water storage changes has been neglected, the ability of capturing seasonality cannot be evaluated with modeled AET at annual scale integrated drought indices. However, the present study made efforts to evaluate the capability to capture the seasonality with remote sensing AET based drought index of SPAEI. Furthermore, to implement the Budyko equation in the drought estimation for subannual time scales, one can evaluate the "ω" parameter at subannual time scales with monthly precipitation and observed AET using water balance and remote sensing data (Sinha et al., 2019).

The monthly rainfall and PET (Equation 4) are accumulated to 12-month scale as follows:

$$P_i^k = \sum_{i-k+1}^{i} P_i \text{ where } k = 12 \tag{7}$$

$$PET_i^k = \sum_{i-k+1}^{i} PET_i \text{ where } k = 12 \tag{8}$$

where P_i^k and PET_i^k are the accumulated rainfall and PET in month, i. The accumulated rainfall and PET at 12-month scale will be used in Equation 6 to estimate the accumulated AET values at 12-month scale. After the calculation of accumulated PET and AET, the accumulated RAW_{PET} and RAW_{AET} values were calculated for estimating SPEI and SPAEI respectively, as follows:

$$RAW_{PETi}^{12} = P_i^{12} - PET_i^{12} \tag{9}$$

$$RAW_{AETi}^{12} = P_i^{12} - AET_i^{12} \tag{10}$$

The original formulation of SPEI is based on RAW_{PETi}^{12} which has to be evaluated to account for the strong seasonality existing in rainfall and PET as described in section 2.2.

2.2. Restructuring SPEI to Account for Seasonality

For a monsoon-dominated climatology such as India, where the precipitation is strongly seasonal and periodic (Kironmala & Rajib, 2015), a drought index should be able to capture the variations of precipitation in the drought index values. For arid and dry seasons, the SPI values are lower bounded and fail to indicate the drought occurrence (Wu et al., 2017). The SPAI proposed by Kironmala and Rajib (2015) is based on the rainfall anomalies where long-term mean rainfall for any given time step as the reference as given as follows:

$$y_{i,j} = \left(P_{i,j} - \overline{P}_j\right) \tag{11}$$

where $y_{i,j}$ = rainfall anomaly for the ith year and jth time step of the year; $P_{i,j}$ = rainfall for the ith year and jth time step of the year; and $\overline{P}_j$ = long-term average rainfall for the jth time step of the year. Furthermore, the SPAI follows Weibull's plotting position formula to obtain the empirical cumulative distribution function (CDF) of the rainfall anomaly series. To account for the seasonality aspect of precipitation we combined the basic formulation of SPAI with normalized anomalies of the precipitation $\left(P - \overline{P}\right)$ and SPEI with climatic water balance of (P-PET) to formulate anomalies of climatic water balance of $\left((P - PET) - \overline{(P - PET)}\right)$. That is, the drought index was proposed with water balance deficit ($D_{PET/AET,i,j}$) instead of water balance values to capture the seasonality of Indian monsoon rainfall in drought estimation as follows:

$$D_{PET/AET,\,i,\,j} = \left(RAW_{PET/AET,\,i,\,j} - \overline{RAW}_{PET/AET,\,j}\right) \tag{12}$$

where $D_{PET/AET,i,j}$ is the climate water balance anomaly for ith year and jth time step of the year either with PET or AET; $RAW_{PET/AET,i,j}$ = climatic water balance based on either PET or AET for the ith year and jth time step of the year (Equations 9 and 10); and $\overline{RAW}_{PET/AET,\,j}$ is the long-term mean water balance for the jth time step of the year. After obtaining the climate water balance anomalies, the present study followed the procedure of SPEI by calculating the cumulative distribution function of the water balance using an appropriate probability distribution.

The SPEI formulation necessitates fitting of an appropriate parametric probability distribution for the transformation of accumulated estimates of (P-PET/AET) into standard normal distribution. The choice of an inappropriate probability distribution may lead to bias in the index values leading to inaccurate drought indices (Sienz et al., 2012; Stagge et al., 2014). Moreover, most of the earlier drought studies all over India were based on the original structure of SPEI formulation by Vicente Serrano et al. (2010) following three parameter log-logistic (LL) distribution. However, Stagge et al. (2014) recommended generalized extreme value (GEV) distribution for formulating the SPEI. Few more studies (Homdee et al., 2016) also revealed that GEV distribution fits well for the climatic water balance. Monish and Rehana (2019) compared the performance of various candidate distributions to fit SPEI for various meteorologically homogeneous regions and found that GEV distribution as the best possible distribution for 12-month time scale all over India. Following to this, the present study used GEV distribution to formulate both SPEI and SPAEI. The CDF values, $F(x)$, have been estimated and SPEI/SPAEI values were calculated as follows:

$$SPEI = W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \tag{13}$$

$$\text{where } W = \sqrt{-2ln(p)} \text{ for } P \leq 0.5 \tag{14}$$

where P is the probability of exceeding a determined $D_{PET/AET,i,j}$ value, $P = 1 - F(x)$. If $P > 0.5$, then P is replaced by (1-P) and the sign of the resultant SPEI is reversed. The constants are $C_0 = 2.5515517$, $C_1 = 0.802583$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$. By substituting the C_0, C_1, and C_2 values in Equation 13, we calculate the SPEI/SPAEI values at 12-month scale. The drought severity was identified using the SPEI/SPAEI ranges as described by Vicente Serrano et al. (2010) as follows: A drought event was classified as moderate if SPEI/SPAEI between −1.0 and −1.49, severe if SPEI/SPAEI was between −1.50 and −1.99, and extreme if SPEI/SPAEI was less than −2.0.

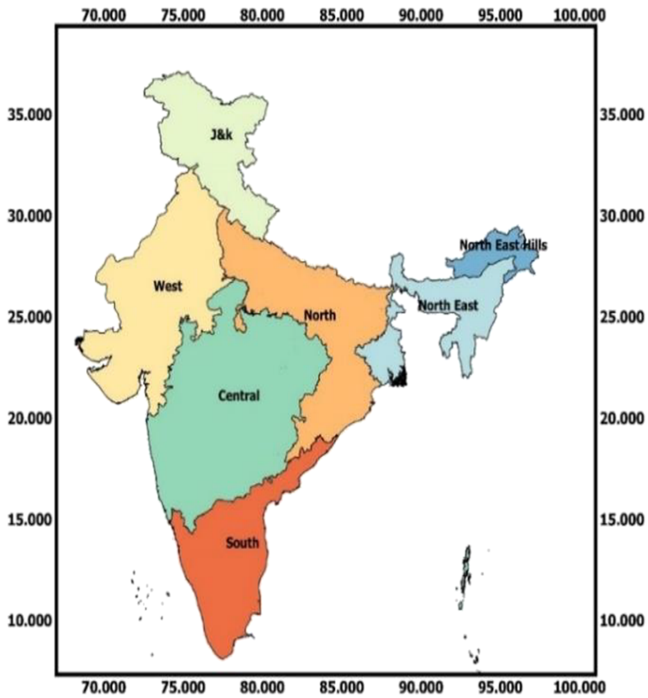

Figure 1. Meteorological homogeneous zones of India.

3. Study Area and Data

The proposed drought formulations based on PET and AET estimates were implemented on meteorologically homogenous zones of India (Figure 1). India is categorized as seven major meteorological homogeneous zones (Figure 1) based on IMD (Parthasarathy et al., 1987) as North, South, West, Central, Northeast, Northeast hills, and Jammu and Kashmir (J&K). High resolution (0.25°) daily rainfall data from IMD for the period of 1901 to 2014, covering main land region of India with a spatial domain of 6.5°N to 38.5°N and 66.5°E to 100°E, was used in the study (Pai et al., 2014). Similarly, daily maximum, minimum, and mean temperature data sets at $1° \times 1°$ resolution for the period of 1951–2014 from IMD were used in the study (Srivastava et al., 2009). The temperature data sets were brought to a common resolution of 0.25° by bilinear interpolation. The precipitation and temperature data sets were aggregated to monthly scale with valid grid points coming in the boundary of India as a total of 4,964 grids in the drought assessment.

The study adopted Global Land Evaporation Amsterdam Model (GLEAM) satellite-based PET and AET data which provides the land evaporation data considering the evaporation from land, soil, plant surfaces, open water, and transpiration from vegetation along with dynamic land cover information (https://www.gleam.eu/) (Martens et al., 2017; Miralles et al., 2011). Also, GLEAM-based ET estimates have showed high skill scores for most of the land cover types (Yang et al., 2017). Due to the availability of long time series ET data sets of GLEAM for the period of 1980 to 2018 at $0.25° \times 0.25°$ resolution the present study used GLEAM based PET and AET data in the drought characterization which can account for the changes in the land use and vegetation along with rainfall anomalies. GLEAM data sets were widely used in the hydrological assessment studies for world (López López et al., 2017; Yang et al., 2017). The PET data set of GLEAM is calculated using Priestly and Taylor equation by passing near-surface air temperature and surface net radiation as inputs. AET is derived from the PET by using vegetation optical depth by microwave observations and simulated root-zone soil moisture content for the land fractions of bare soil, short canopy, and tall canopy. A multilayer running water balance model based on observed precipitation was used for calculating the root-soil moisture. The performance of these data sets is evaluated in multiple studies (Martens et al., 2017; Miralles et al., 2011). The AET data required for the Indian context is extracted from the original data set at 0.25° spatial resolution and aggregated to a monthly scale for analysis. A common data period of 1980 to 2014 was considered to study the historical drought characterizations including AET and accounting for seasonality over India. A comparison of SPEI and SPAEI has been performed in terms of drought areal extent, severity, frequency, and duration for the period of 1980 to 2014.

4. Results and Discussion

The results of the study have been divided into three sections (sections 4.1–4.3). The first part of the results discusses about the suitability of PET and AET in the drought assessment for Indian climate as provided in section 4.1. The significance of PET and AET in the drought estimation was studied by dividing the entire India into water- and energy-limited zones. Statistical significance test between PET and AET was conducted for each zone to represent the significant differences of PET and AET between water- and energy-limited zones. Correlation coefficients were estimated between PET and AET and SPEI and SPAEI to represent the disparity between the drought indices for water- and energy-limited zones of India.

The new drought index of $SPEI_{Seasonal}$ has been compared with the original formulation of SPEI for monsoon and nonmonsoon months for water- and energy-limited zones to represent the ability to capture seasonality and periodicity of precipitation of both indices as provided in section 4.2. The study compared the drought characteristics such as areal extent, severity, frequency, and duration with PET-based formulation of SPEI with AET based formulation of SPAEI for various time scales for all over India as provided in section 4.3. Such comparison will provide a better understanding toward the variability of droughts in response to climate (SPEI) and with land use and vegetation changes (SPAEI) over India. To elaborate the significance of PET and AET based drought indices characterization, the study adopted one water-limited zone of Western and one energy-limited zone of Northeastern for the comparison of drought severity, intensity, frequency, and durations.

4.1. Significance of PET and AET in the Drought Estimation

Seven meteorological zones of India were characterized as energy or water limited zones by comparing the observed spatial averaged annual total precipitation and PET for the period of 1951 to 2014. If the annual mean precipitation P < PET, then the zone is defined as water-limited zone; whereas if the annual mean P > PET, then the region is defined as energy-limited region (Donohue et al., 2007). Based on such definition, the values of annual (P/PET) values were estimated for Central (1,084/1,800 mm), South (1,248/1,695 mm), West (545/1,768 mm), North (1,180/1,688 mm), and J&K (1,025/1,343 mm) and characterized as water-limited zones whereas the Northeast (2,118/1,473 mm) and Northeast hills (2,715/1,434 mm) were characterized as energy-limited zones. It can be noted that J&K has categorized as water-limited due to high latitude snow dominated region with highly mountainous topography and huge missing data. Padmakumari et al. (2013) characterized entire India as water-limited zone based on the most dependable surface observations from 58 stations covering entire India with pan evaporation data and rainfall. It can be noted that their study has classified the entire India as water-limited zone at continental scale based on the annual mean PET and rainfall. However, given the large diversity present in the precipitation and PET over meteorological zones, such conclusions based on continental scale may not be useful to study the characteristics of water availability and management. The present study compared the regional scale annual mean rainfall and PET to classify the water- and energy-limited zones, which can follow the homogenous nature of precipitation and energy availability. It can be noted that the research findings of the present study are based on gridded precipitation and temperature data sets with modeled PET estimates in the water and energy-limited zonal characterization. Such characterization will help to analyze the suitability and adoptability of PET and AET in drought analysis for India.

To show the significance of use of PET and AET in the drought estimation and its significance for water- and energy-limited zones of India, the study compared the correlations of modeled PET/AET with remote sensing data, SPEI and SPAEI (Budyko) and SPEI and $SPAEI_{RS}$ (Figure 2). There is a strong correlation between modeled PET using Hargreaves equation and remote sensing-based PET data (Figure 2a, left). However, spatial heterogeneity of dependency between modeled AET using Budyko equation and remote sensing based AET data was noted from Figure 2a (right). The correlations were observed higher for Western and Northeast zones and lower correlations for central, North and South zones (Figure 2a, right). Thus, use of either modeled PET or remote sensing PET will not provide much significance in the drought estimation. It is the AET, which will have a pronounced difference and hence a promising variable in drought assessment.

About 99% of the grid points having correlation coefficients greater than 0.5, estimated between AET with Budyko model and AET with remote sensing data, which shows a reasonable agreement for most part of the country. With this, the modeled AET as proposed in the present study can be valuable to predict annual droughts having the limitations toward neglected storages and fixed parametric models at monthly scale.

The SPEI and $SPEI_{Budyko}$ were compared for the period of 1980 to 2014 and found to be strongly correlated with about 99% of grid points having correlation coefficients greater than 0.8 at 12-month accumulation period (Figure 2b, left). If there is a difference between PET and AET based drought indices, such results are not expected. In fact, the modeled AET is uniquely fixed based on PET for energy-limited zones and P for water-limited zones. Alternatively, the study compared the SPEI and $SPAEI_{RS}$ for the period of 1980 to 2014 and found to be significantly correlated with about 91% of grid points having correlation coefficients greater than 0.8 at 12-month accumulation period (Figure 2b, right). Furthermore, the differences between SPEI and $SPAEI_{RS}$ were clearly noted for water-limited zones of western, central, north, and South zones compared to energy-limited regions of India. Moreover, the study made comparison between SPEI and $SPAEI_{RS}$ in terms of correlation coefficients at various time scales for all over India, for Western and Northeastern zones as shown in Figure 2c. Thus, SPEI and $SPAEI_{RS}$ will not make any difference in the drought evaluation for energy limited zones for various time scales, but such differences can be prominent for water-limited regions from Figure 2c. The use of AET based on remote sensing in the drought estimation can also account for the soil moisture and actual water availabilities particularly during winter months which

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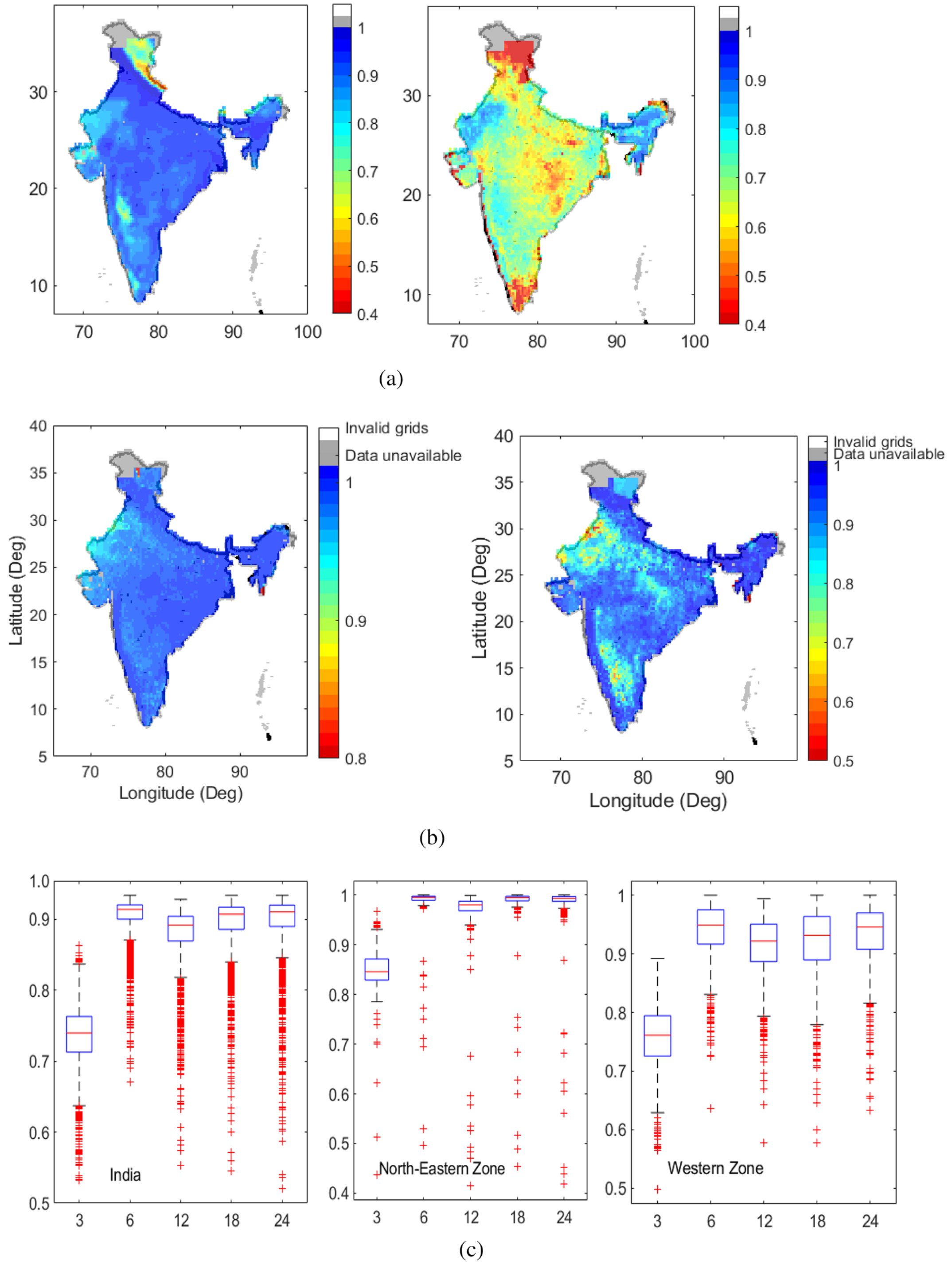

Figure 2. (a) Correlation between modeled and remote sensing PET (left) and AET (right). (b) Correlation between SPEI and SPAEI (Budyko) (left) and SPEI and SPAEI-RS (right) over India for 12-month accumulated period. (c) Correlation coefficients estimated between SPEI and SPAEI-RS over India, North-Eastern, and Western zones estimated for 3-, 6-, 12-, 18-, and 24-month accumulation periods. All values are estimated for a period of 1980 to 2014.

are crucial for Rabi crops such as wheat for India (Davis et al., 2019). Therefore, the study has used remote sensing-based PET and AET data for further comparison of various drought characteristics as SPEI and SPAEI. Now onward, the results SPEI/SPAEI represent PET/AET based drought index with remote sensing-based data.

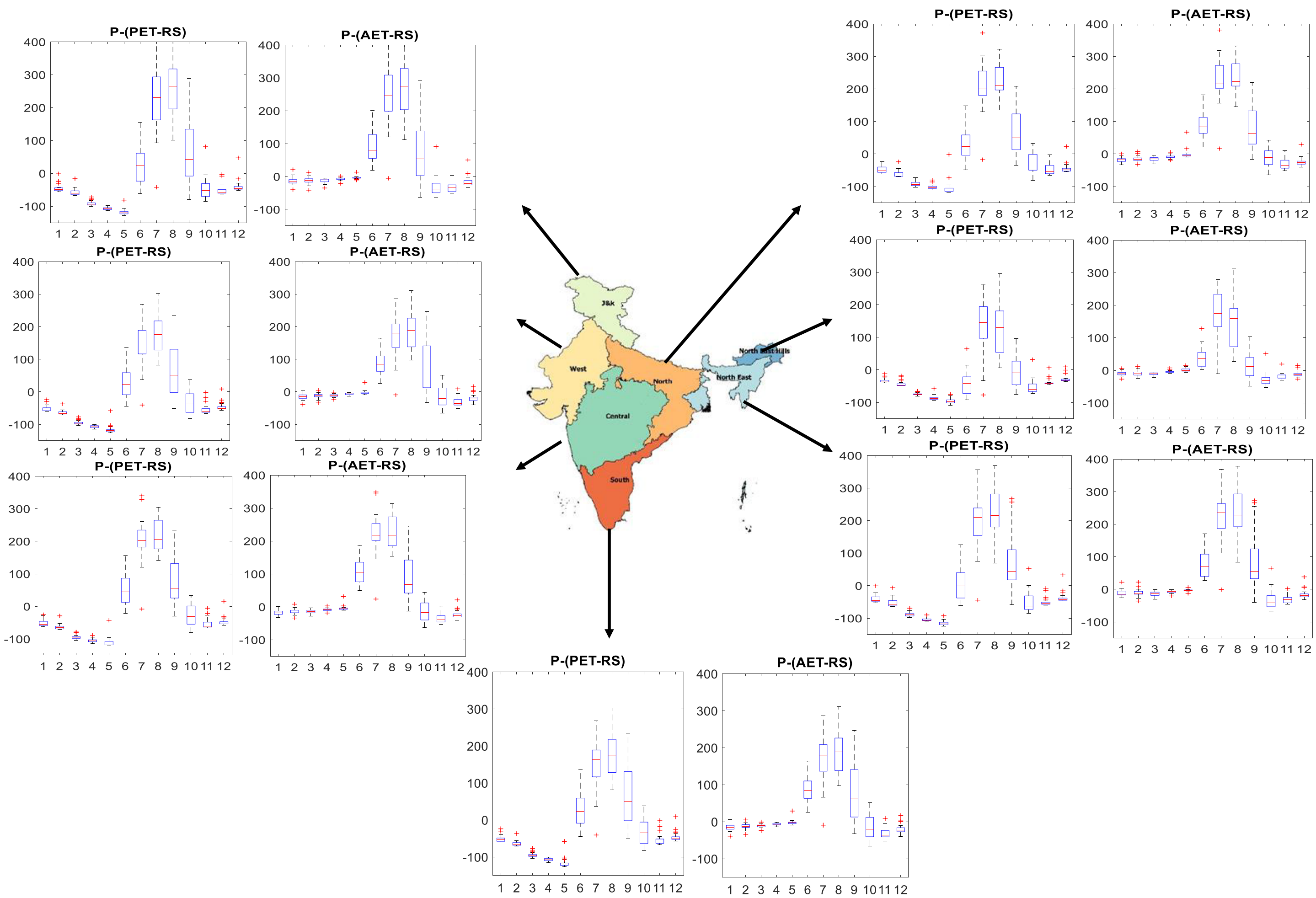

Figure 3. Monthly spatial average of AET based residual available water (RAWAET) (P-AET) and PET-based residual available water (RAWPET) (P-PET) for various meteorological homogeneous zones of India.

Further, to hypothesis that AET reveals more information than the PET-based drought indices, the present study tested whether the difference between two data sets are statistically significant enough for both water- and energy-limited zones. The differences between PET and AET data sets with remote sensing data for a period of 1980 to 2014 were statistically assessed by applying a two-sample *t* test at 5% significance level (Figure S1 in the supporting information). For all water-limited zones, statistically significant differences were noted between both PET and AET compared to energy-limited zones. Such statistically significant differences in PET and AET estimates may continue in the drought indices for arid climates. The spatial monthly water balances based on PET (P-PET, RAW_{PET}) and AET (P-AET, RAW_{AET}) for the period of 1980 to 2014 were compared for both water- and energy-limited zones of India as shown in Figure 3. Positive water balances (P-PET) were noted only for the monsoon months of JJAS, whereas for the remaining months negative water balances were noted for all zones. Whereas, positive water balances (P-AET) for most of the months with higher magnitudes during monsoon and with lower magnitudes during nonmonsoon periods were observed. Differences in monthly variation of water budget based on (P-PET) and (P-AET) were clear between water-limited zones of India. With this, use of PET or AET will not make a difference in the evaluation of water budget for energy-limited zones, but such differences will be more prominent in case of water-limited zones and, therefore, consequent differences in drought assessments with PET and AET. This again stresses on the use of AET in the drought estimation for arid regions instead of PET for the accurate representation of water availability in drought index formulations. Water balance is the resultant of interactions and changes between climate and land surface (Liu et al., 2017), and inclusion of AET can be promising for water-limited regions.

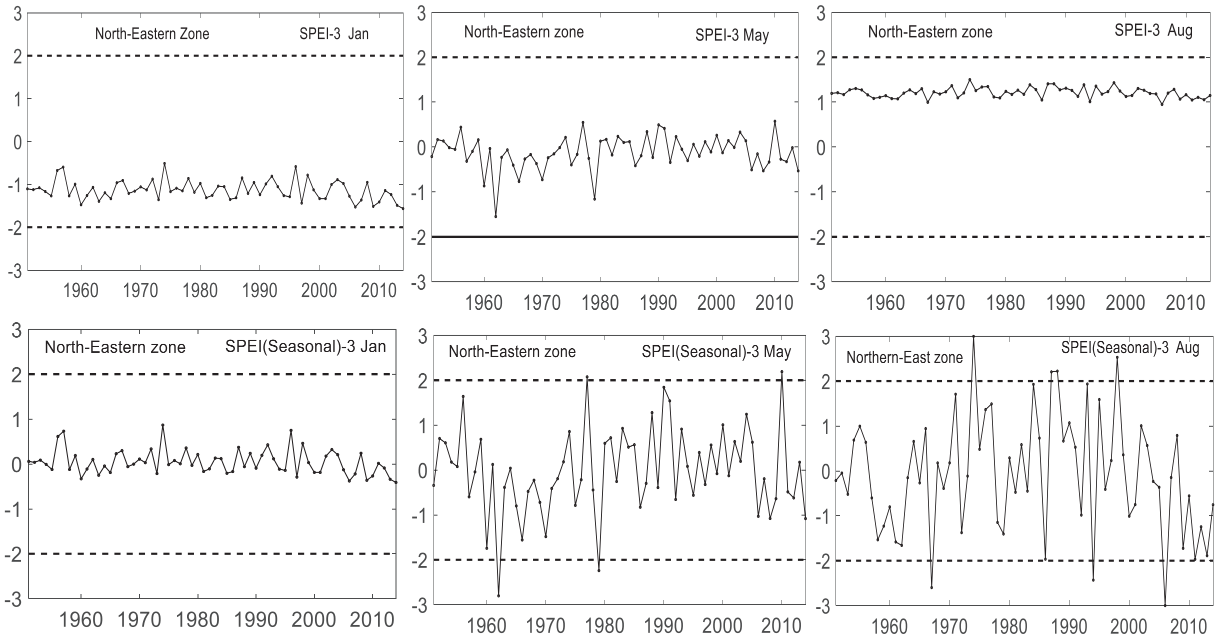

Figure 4. SPEI-3 and SPEI (seasonal)-3 values for water-limited zone of Western zone and energy-limited zone of Northeastern zone for the months of January, May, and August.

4.2. Significance of Seasonality in Drought Estimation—Comparison of SPEI and Restructured SPEI to Capture Seasonality of Indian Monsoon

The SPEI-3 and restructured SPEI to capture the seasonality ($SPEI_{Seasonal}$-3) were compared for one water-limited zone of Western and one energy-limited zone of Northeastern zone of India for nonmonsoon months of January and May and for monsoon month of August from 1951 to 2014 as shown in Figure 4. The SPEI works on fitting a probability distribution on the atmospheric water demand (P-PET) in a given period whereas restructured $SPEI_{Seasonal}$ works on fitting a probability distribution of atmospheric water demand deficit observed in a particular accumulation period when compared to long term average rather than the actual atmospheric water demand in a given period $\left((P-PET)-\overline{P-PET}\right)$. Here, to compare how the restructured SPEI was able to capture the seasonality, the study considered 3-month time accumulation period for monsoon month of August and nonmonsoon months of January and May (Figure 4) for strong drought year of 2002, which was also considered as drought year all over India (Mallya et al., 2016; Nath et al., 2017). The SPEI-3 index values for January, May, and August for the water-limited region of western zone were estimated as 0.13, −1.79, and 0.04, respectively, for year 2002 whereas $SPEI_{Seasonal}$-3 values for January, May, and August were estimated as −0.24, −0.18, and −3.0, respectively, for year 2002. Although the year 2002 was one of the severe drought years affected most part of the country, the SPEI-3 value in August indicating wet conditions for western zone. For another drought year, 2009, drought intensities for the months of January, May, and August were noted for SPEI ($SPEI_{Seasonal}$) for 3-month accumulated period for Western zone as 0.22 (−0.05), −1.86 (−0.27), and 0.81 (−1.17), respectively. Similarly, failure of SPEI to capture seasonality was studied for another water-limited zone of India, the Central zone, with values of SPEI for the months of January, May, and August as −0.33, −1.86, and 1.10, respectively, in earlier research findings by Monish and Rehana (2019). Hence, the restructured SPEI is able to capture the drought intensities for water-limited zones during drought years compared to the original formulation of SPEI.

Coming for energy-limited region of Northeast zone, the SPEI-3 values for the months of January, May, and August were estimated as −1.00, 0.14, and 1.30, respectively, for year 2002 whereas $SPEI_{Seasonal}$-3 values for the months of January, May, and August were noted as 0.18, 0.63, and 1.00, respectively, for the year 2002 (Figure 4). While for another drought year, 2009, drought intensities for the months of January, May, and August were noted for SPEI ($SPEI_{Seasonal}$) for 3-month accumulated period for Northeastern zone as −1.51 (−0.36), −0.33 (−0.64), and 1.067 (−1.72), respectively. Accounting for the water availability deficits $((P - PET) - \overline{P - PET})$ is more critical during monsoon months (August) compared to winter or summer months (January and May). With this, the original formulation of SPEI has failed to capture the seasonality aspects of precipitation and PET for both water and energy-limited regions of India. The restructured form of $SPEI_{Seasonal}$ of the present study has potential to account for the seasonality and periodicity of precipitation and PET in the drought intensity estimations. Thus, the $SPEI_{Seasonal}$ is found to be more suitable and promising as a meteorological drought index for monsoon dominated regions having strong seasonality in the precipitation patterns (Kironmala & Rajib, 2015). With this, the present study used the formulation of $SPEI_{Seasonal}$ with remote sensing based PET/AET to formulate SPEI/SPAEI in the drought characterization using the water availability deficits $((P - PET/AET) - \overline{P - PET/AET})$.

4.3. Comparison of Spatial and Temporal Drought Characteristics of SPEI and SPAEI Based on Remote Sensing PET and AET Data

To assess suitability of PET and AET in drought assessment, the drought characteristics such as severity, frequency, duration, and areal extent of droughts for each meteorologically homogeneous zone and all over India were studied. As SPEI is based on PET, it can capture the drought variability under climate. While SPAEI is based on AET, it can account for the impact of both land and vegetation changes along with climate on drought variability (Liu et al., 2017). Both SPEI and SPAEI were able to capture major droughts all over India and for each zone occurred in 1982, 1985, 1986, 1987, 2002, 2004, 2009, and 2014 (Mallya et al., 2016) (Figures 5 and S2). To study the drought areal extents with SPEI and SPAEI, yearly drought percentage of area experiencing drought was compared for all over India for moderate, severe, and extreme conditions as shown in Figure S2 and Table 1. The areal extent of drought was estimated as percentage of area experiencing drought in each category (moderate, severe, and extreme) to the total grid points in a region. The spatial extent of droughts was noted as increasing all over India over the period of 1980 to 2014 for both with SPEI and SPAEI (Figure S2). Specifically, the linear trend lines of SPEI values have shown significant increasing trends at 0.05 significance level for moderate (2.2%/decade), severe (1.3%/decade), and extreme (0.5%/decade) drought areal extents for the period of 1980 to 2014 all over India. Such increasing trends of drought area with SPEI over India have been noted in the studies by Das et al. (2016) and Mallya et al. (2016). In another study by Kumar et al. (2013), an increasing trend of moderate drought percent area with SPEI has been noted for the period of 1951 to 2010.

Similarly, SPAEI also has shown significant positive trends of moderate (3.7%/decade), severe (2.2%/decade), and extreme (0.97%/decade) drought areal extents for the period of 1980 to 2014 for all over India. The moderate, severe, and extreme drought percentage areal extents have been increased in recent years for India, which is consistent with the earlier research findings based on SPEI (Kumar et al., 2013; Mallya et al., 2016).

Further, compared to PET based drought index (SPEI), AET based drought index (SPAEI) has shown highly intensified increase in drought areal extents in recent years of 1980 to 2014. The SPAEI is enforced with AET data which considers the land use, vegetation, and other surface water fluxes into account. The increasing trends of drought areal extent of SPAEI indicates changes in climate and land surface have pronounced impact on water availability of India (Paul et al., 2016).

To study the areal extent of drought in each category with SPEI and SPAEI, percentage of area experiencing droughts was compared for all over India and for both water- and energy-limited zones estimated for a period of 1980 to 2014 as given in Table 1. The annual drought areal extents for both SPEI and SPAEI for each water- and energy-limited zone of India are given in Table 1. The SPEI has identified higher drought areal percentages compared to SPAEI for all drought categories all over India. The difference of percentage of drought areal extents between SPEI and SPAEI was estimated for moderate as 26%, severe as 44%, and extreme as 64%. From this, the extreme drought categorization will have much more deviation due to the use of PET and AET compared to moderate and severe drought categories (Figure 5). Therefore, the study compared the extreme drought areal extents resulting from SPEI and SPAEI for each zone and all over India at annual time scale (Figure 5). At zonal scale also, the difference between moderate and severe drought affected areas of SPEI and SPAEI was observed to be relatively less compared to extreme drought, for all water-limited zones. For example, the percentage difference between SPEI and SPAEI areal extents for Central zone was estimated as 36% for moderate, 46% for severe, and 74% for extreme drought. Similarly, for West zone, the percentage difference between SPEI and SPAEI was estimated as 50% for

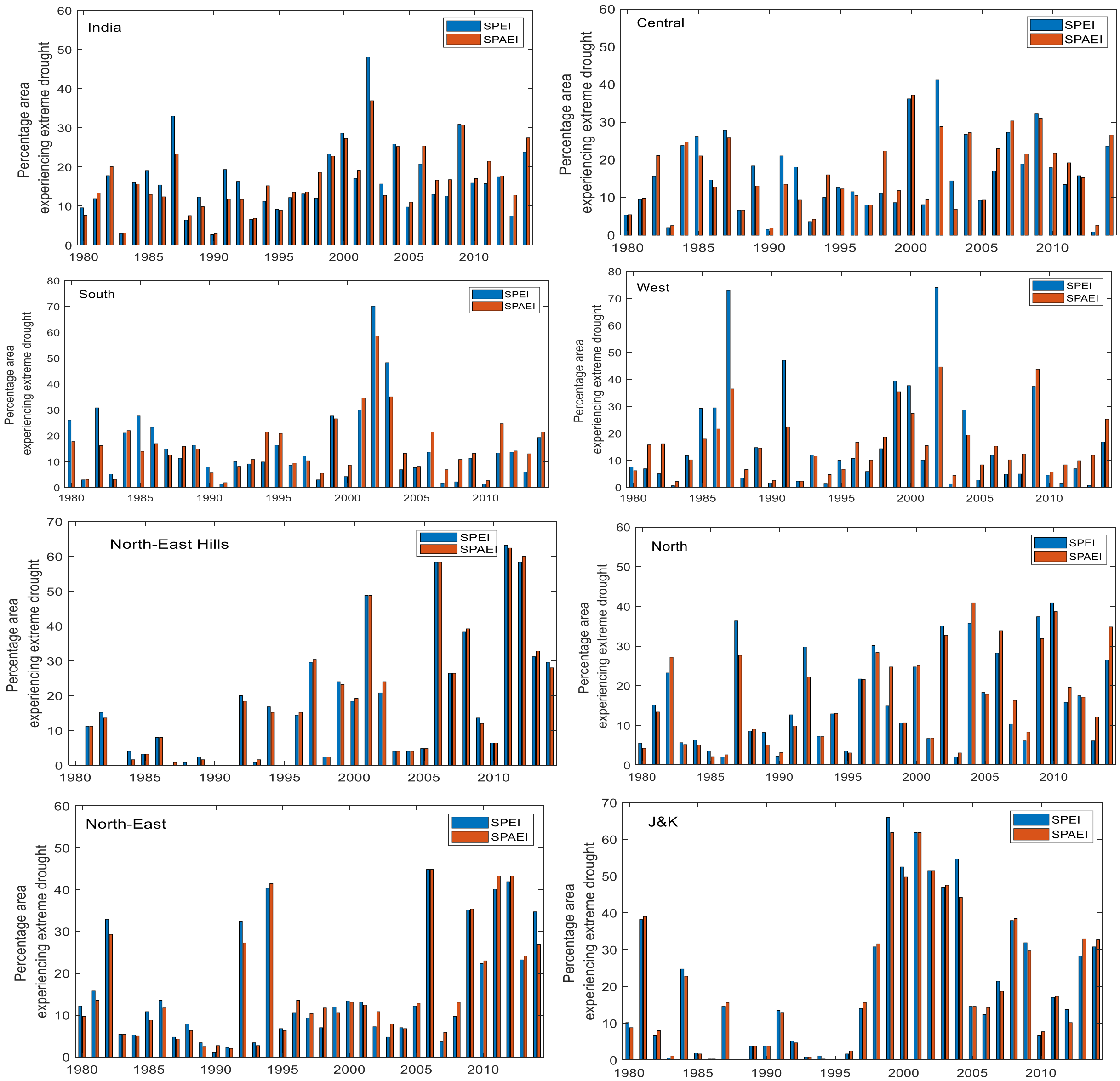

Figure 5. Percentage of extreme drought (SPEI/SPAEI < −2) areal extent estimated by SPEI and SPAEI for each meteorological zone and for all over India for period of 1980 to 2014.

moderate, 94% for severe, and 134% for extreme drought areal extents whereas such difference between the area under extreme droughts captured by SPEI and SPAEI is relatively small for energy-limited zones of Northeast, Northeast Hills, and J&K (Figure 5 and Table 1). Therefore, it can be concluded that notable differences in extreme drought affected area were noticed between PET and AET based drought indices for all water-limited zones (Central, North, South, and West), while such differences were less for energy-limited zones (Northeast, Northeast Hills, and J&K). Therefore, the research findings of the study

Table 1
Percentage of Drought Area for Various Homogeneous Zones and All Over India for SPEI and SPAEI (Values in the Bracket) at 12-Month Accumulation Period

Drought category	India	Central	North	South	West	Northeast	Northeast Hills	J&K
Moderate	48.93 (37.57)	41.32 (28.84)	35.05 (32.71)	70.13 (58.65)	74.05 (44.59)	7.21 (10.81)	20.80 (24.00)	51.37 (51.37)
Severe	26.16 (16.77)	17.88 (11.19)	14.65 (14.19)	47.80 (40.88)	48.82 (17.51)	1.35 (2.48)	12.80 (13.60)	12.64 (12.09)
Extreme	10.16 (5.25)	5.48 (2.51)	2.81 (3.17)	25.47 (20.60)	20.91 (4.12)	0.23 (0.68)	4.00 (4.00)	1.65 (1.37)

reveal that the use of AET in the drought characterization perhaps provides more information toward the assessment of extreme droughts over water-limited zones of India. As the PET based atmospheric demand (P-PET) is the maximum limit and AET based atmospheric demand (P-AET) is the minimum limit, the deviations from the normal are more prevailing in the case of extreme drought categories compared to moderate and severe.

The major drought years between the period of consideration of 1980 to 2014 were identified as 1985, 2002, and 2009 (Mishra, 2020), and the drought intensities classification were compared between SPEI and SPAEI for all over India (Figure S3). Furthermore, to compare how water- and energy-limited zones respond in terms of drought intensity with use of PET and AET in drought assessment, the present study compared western (water limited) and Northeastern (energy limited) zones for various time scales (3, 6, 12, 18, and 24 months) for the major drought years of 1985, 2002, and 2009 (Figures 6a and 6b). It can be noted that SPEI categorize the drought years as severe and extreme droughts compared to SPAEI particularly for water limited zones (Figure S3). The West zone has categorized drought areal extent with SPEI (SPAEI) in terms of moderate as 74.05% (44.59%), severe as 49% (17.51%), and extreme as 20.9% (4.12%) while the Northeast zone has categorized drought areal extent with SPEI (SPAEI) in terms of moderate as 7.21% (10.81%), severe as 1.35% (2.48%), and extreme as 0.23% (0.68%) (Table 1). The percentage of area which was categorized under extreme droughts was found to be less with SPAEI indicating lower extreme drought areal extents compared to SPEI. Therefore, PET-based drought indices characterize droughts as extreme compared to AET based drought indices particularly for water-limited zones. Furthermore, the difference in drought intensities can be clearly noted for Western zone compared to North as shown in Figure 7. The comparison was for the spatial average of SPEI and SPAEI for 3-, 6-, and 12-month time accumulation period for the period of 1980 to 2014 for both Western and Northeastern zones of India has been shown in Figure 7. For example, the spatial averaged drought intensity values for the major drought years of 1985, 2002, and 2009 for SPEI-12 (SPAEI-12) was noted as −0.4 (0.15), −1.22 (−0.79), and −0.62 (−0.72), respectively, for Western zone. However, such differences between PET and AET based drought indices were nominal in the case of energy-limited zone of Northeast. For example, the spatial averaged drought intensity values for the major drought years of 1985, 2002, and 2009 for SPEI-12 (SPAEI-12) was noted as 0.13 (0.25), −0.10 (−0.17), and −0.82 (−0.80), respectively.

The variation of drought frequency categories for SPEI and SPAEI for the period of 1980 to 2014 were compared for India (Figure S4) and Western and Northeastern Zones (Figure 8). The difference between the number of drought events with SPEI and SPAEI was observed to be relatively small for all over India. The spatial-averaged drought frequencies of India for various categories with SPEI (SPAEI) were obtained in terms of moderate as 20.73 (20.6), severe as 10.79 (10.37), and extreme as 5.15 (5.31) at 12-month accumulation period. Such relatively small differences of drought frequencies between PET and AET based drought indices were noticed for shorter accumulation time periods also. For example, with SPEI-3 (SPAEI-3) the all over India spatial averaged drought frequencies were obtained in terms of moderate as 10.19 (10.14), severe as 5.86 (5.84), and extreme as 8.15 (8.29) estimated from the period of 1980 to 2014. Similarly, the SPEI-12 (SPAEI-12) drought frequency categories for Western zone were obtained for moderate as 37.67 (38.03), severe as 19.4 (18.04), and extreme as 9.0 (8.89) for the period of 1980 to 2014 (Figure 8). Such small differences of drought frequencies have observed for shorter time accumulation periods also for Western zone, SPEI-3 (SPAEI-3) for moderate as 15.73 (16.4), severe as 10.47 (10.5), and extreme as 14.51 (15.22).

Coming to energy-limited zone (Northeast), the PET- and AET-based drought frequencies were obtained almost similar. For example, the SPEI-12 (SPAEI-12) drought frequency categories were obtained as moderate as 34.98 (34.5), severe as 18.05 (18.01), and extreme as 10.7 (10.7) for the period of 1980 to 2014 (Figure 8). However, smaller differences between the drought frequency categories were observed for shorter time periods of SPEI-3 (SPAEI-3) as moderate as 22.48 (22.11), severe as 11.46 (11.01), and extreme as 13.96 (14.23) for the period of 1980 to 2014 for Northeast zone. The study observed that inclusion of AET in the drought characterization instead of PET has not affected the drought frequencies for energy-limited zones, however, with small differences for water-limited zones particularly at shorter accumulation time periods. Such results are evident for shorter accumulation periods due to the substantial differences between the residual water availabilities (RAW_{PET} and RAW_{AET}) based on PET and AET (Figure 3) compared to annual scales.

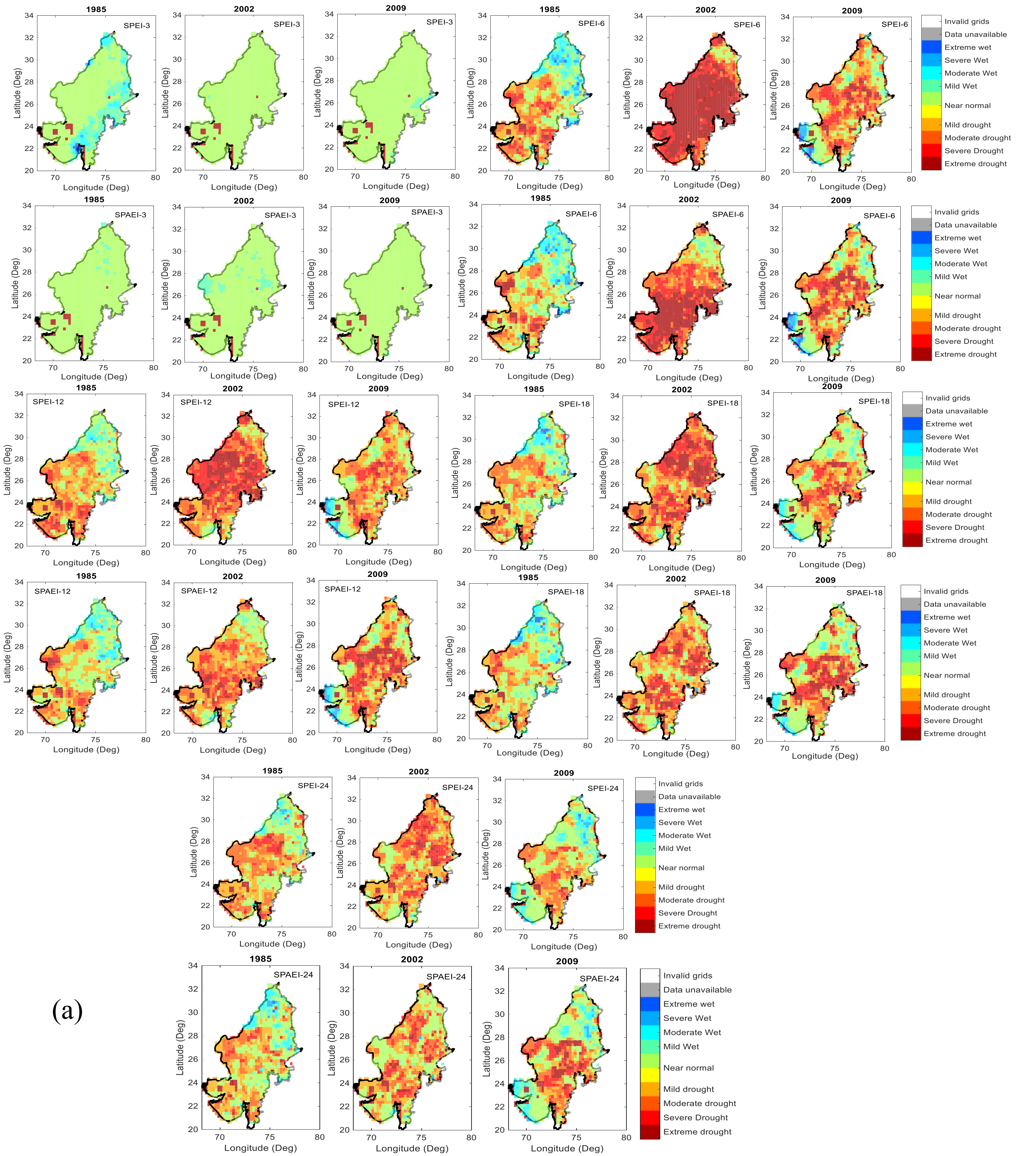

Figure 6. (a) Drought intensity for 1985, 2002, and 2009 drought years as estimated by SPEI and SPAEI for (a) Western zone (b) North-Eastern zone for various time scales of 3, 6, 12, 18, and 24 months.

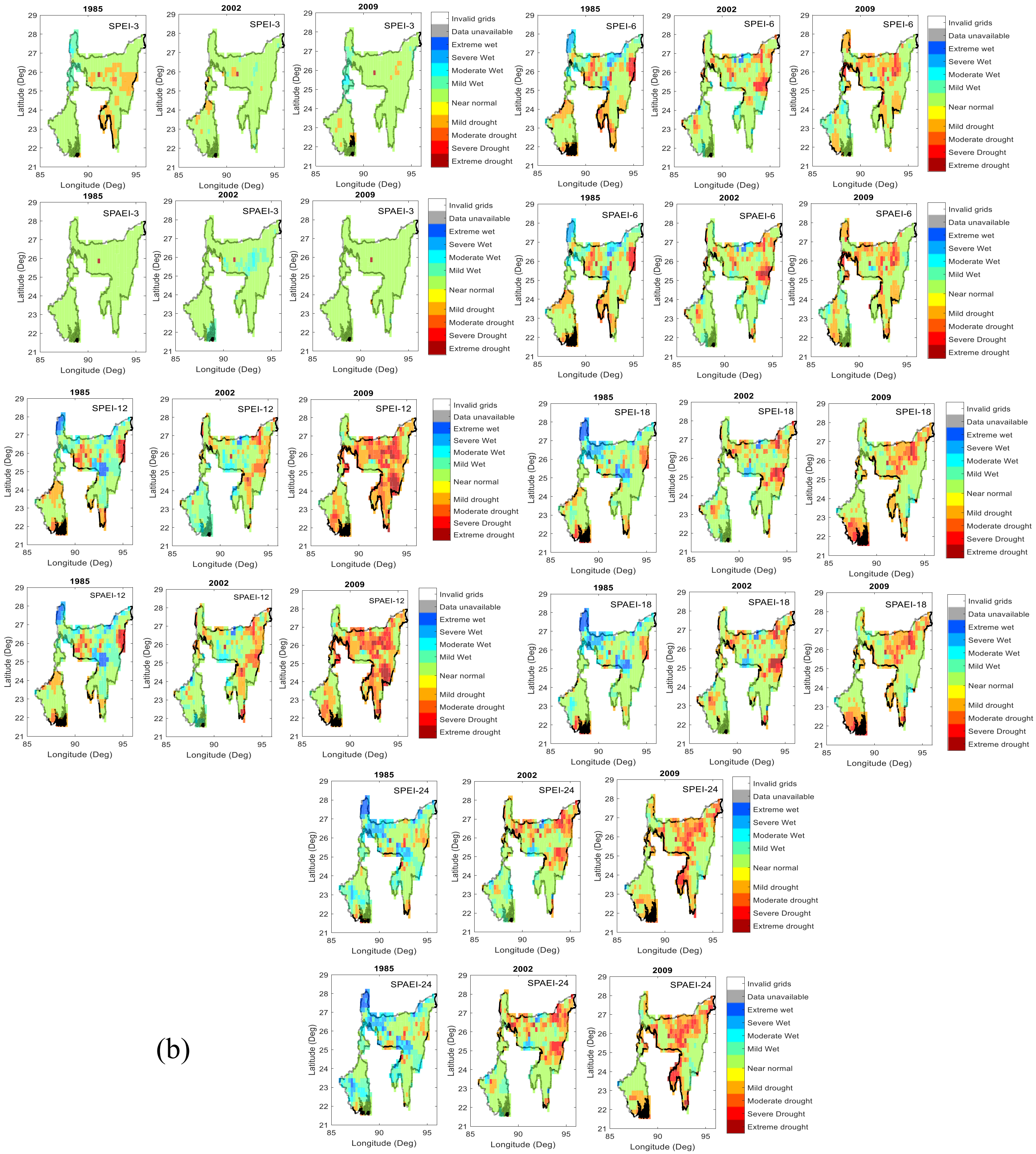

Figure 6. *(continued)*

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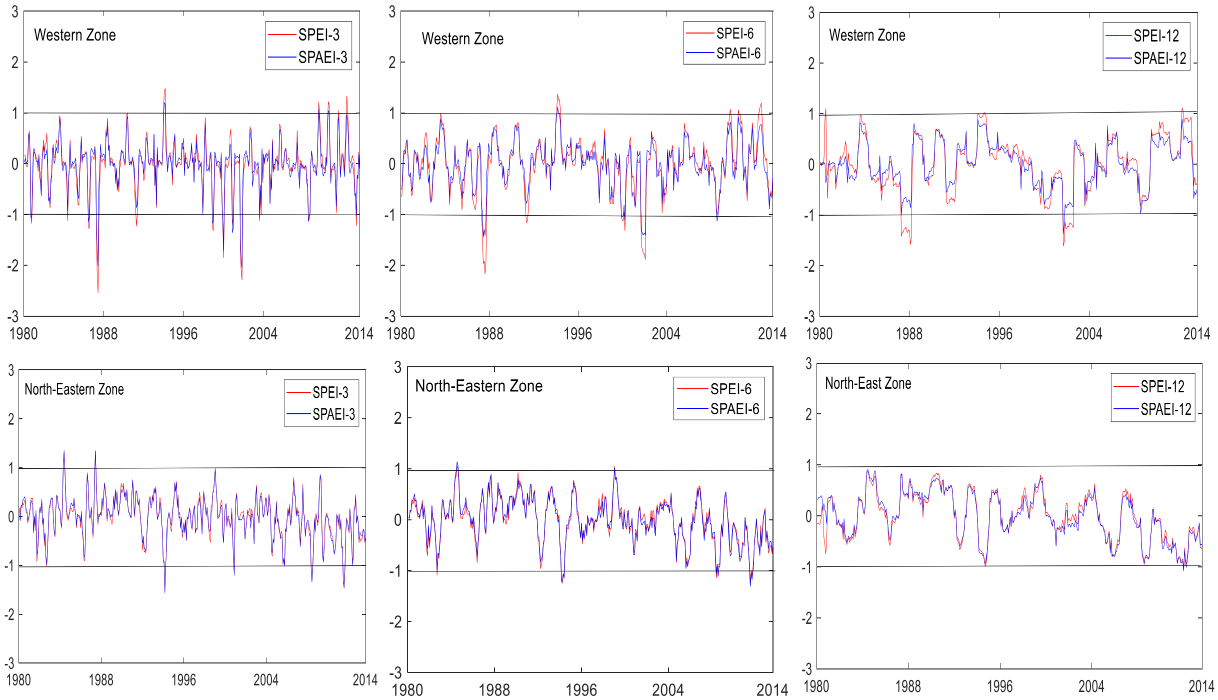

Figure 7. Spatial averaged SPEI and SPAEI values for Western and Northeastern zones for 3-, 6-, and 12-month accumulation time periods from 1980 to 2014.

To investigate whether the drought frequencies based on PET and AET have significantly increased the annual droughts of SPEI and SPAEI were considered for the period from 1980 to 2014. Nonparametric Mann-Kendall trend test (Kendall, 1955; Mann, 1945) was applied to detect trends in drought frequencies for various categories. Both PET and AET based drought frequencies (SPEI-12/SPAEI-12 < -1) have shown significant increasing trends all over India using Mann-Kendall trend test at 5% significance level (Figure S4), which is consistent with the earlier research findings based on SPEI (Kumar et al., 2013; Mallya et al., 2016). For example, increase of drought frequencies based on SPEI during recent time period of 1977 to 2010 all over India, particularly over Central and South peninsula, was noted by Kumar et al. (2013). About 36% (39%), 29% (32%), and 15% (20%) of area has shown with increasing trends of moderate, severe, and extreme drought frequencies with SPEI-12 (SPAEI-12), respectively. Hence, pronounced increasing trends were observed in drought frequencies all over India in recent years under changes of climate, land and vegetation (P-AET) compared to climate (P-PET) (Figure S4).

Drought durations with SPEI and SPAEI for 12-month accumulation time period for Western and Northeastern zones were estimated from 1980 to 2014 for various categories as shown in Figure 9. Shorter drought duration months were noted with SPAEI compared to SPEI for all over India (Figure S5) and for Western zone (Figure 9). The spatial-averaged drought duration months for all over India with SPEI-12 (SPAEI-12) for moderate, severe, and extreme drought categories were estimated as 6.2 (5.9), 4.2 (3.9), and 2.2 (2.1), respectively, estimated from the period of 1980 to 2014. Such findings were similar for Western zone also, with the average drought duration months for moderate, severe, and extreme with SPEI-12 (SPAEI-12) as 6.6 (5.7), 4.7 (3.2), and 2.3 (1.2), respectively, from the period of 1980 to 2014 whereas, for Northeastern zone, the drought duration months estimated with SPEI-12 (SPAEI-12) as 5.7 (5.9), 4.2 (4.4), and 2.5 (2.5) for moderate, severe, and extreme categories, respectively. Hence, the study concludes that there will not be any difference in drought duration estimations between PET (SPEI) and AET (SPAEI) based drought indices for energy-limited regions of India. However, this will have a substantial difference for water-limited regions of India, with longer drought durations with PET based drought index compared to AET based drought index. Such results are evident due to increase of short-term positive water availabilities with PET (P-PET) (more drought months) compared to AET (P-AET) (less drought months) (Figure 3).

To investigate possible trends in drought durations based on PET- and AET-based drought indices, the annual SPEI and SPAEI were considered for the period of 1980 to 2014. Both PET and AET based drought

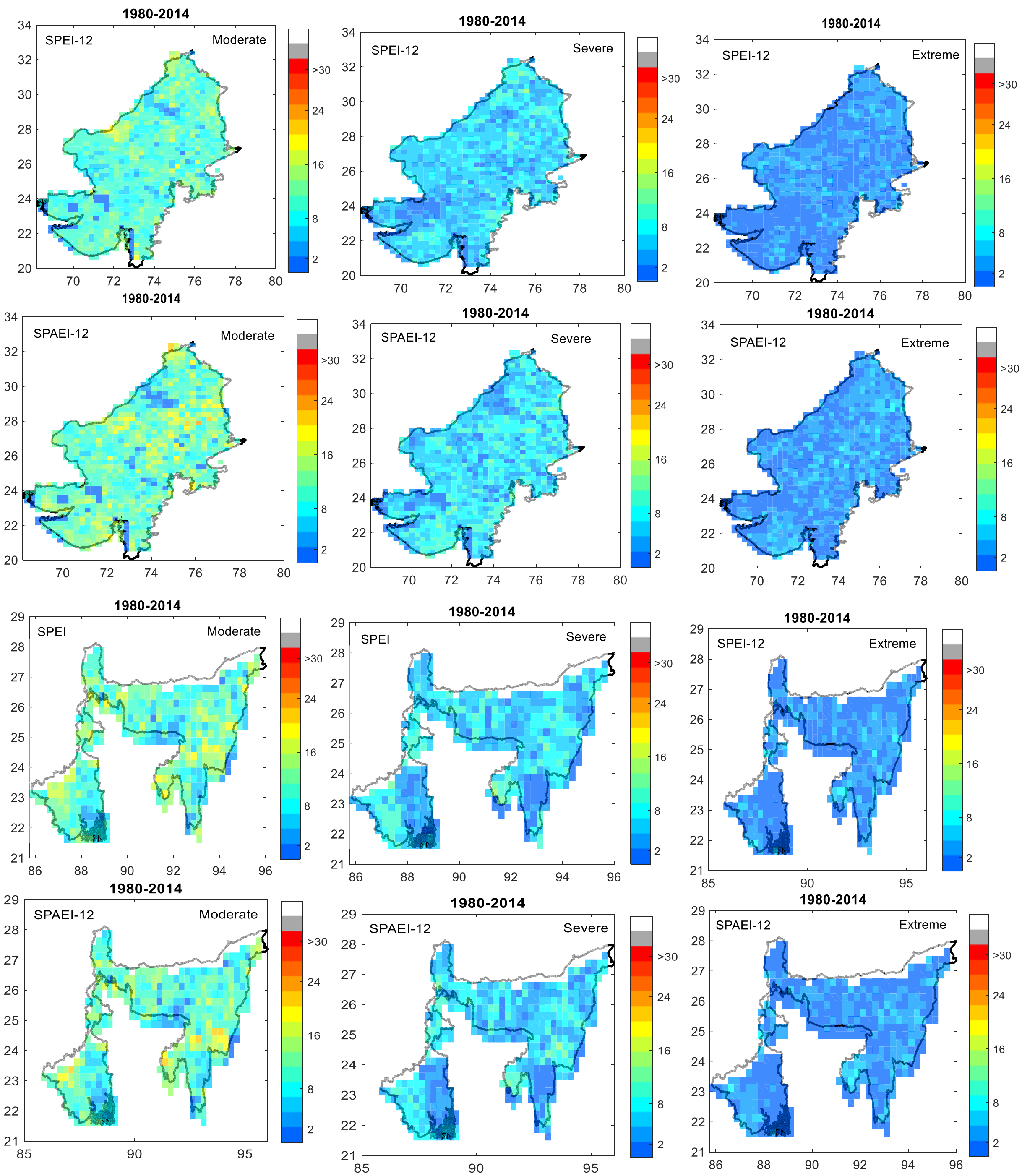

Figure 8. Spatial variation of average frequency of droughts estimated for the period from 1980 to 2014 with SPEI-12 and SPAEI-12 for moderate, severe, and extreme for Western and Northeastern zones.

duration months (SPEI-12/SPAEI-12 < −1) have shown significant increasing trends all over India using Mann-Kendall trend test at 5% significance level (Figure S5) (Mallya et al., 2016). Such increasing trends of drought durations based on SPEI have also been noted in the earlier studies by Das et al. (2016), Kumar et al. (2013), and Mallya et al. (2016). For example, Das et al. (2016) have identified an increasing trends in the drought duration for all homogenous regions of India in the last 109 years with data of 1901 to 2008. About 25% (21%), 33% (28%), and 46% (41%) of area has shown with increasing trends of moderate, severe, and extreme drought duration months with SPEI-12 (SPAEI-12), respectively. Thus, SPEI has

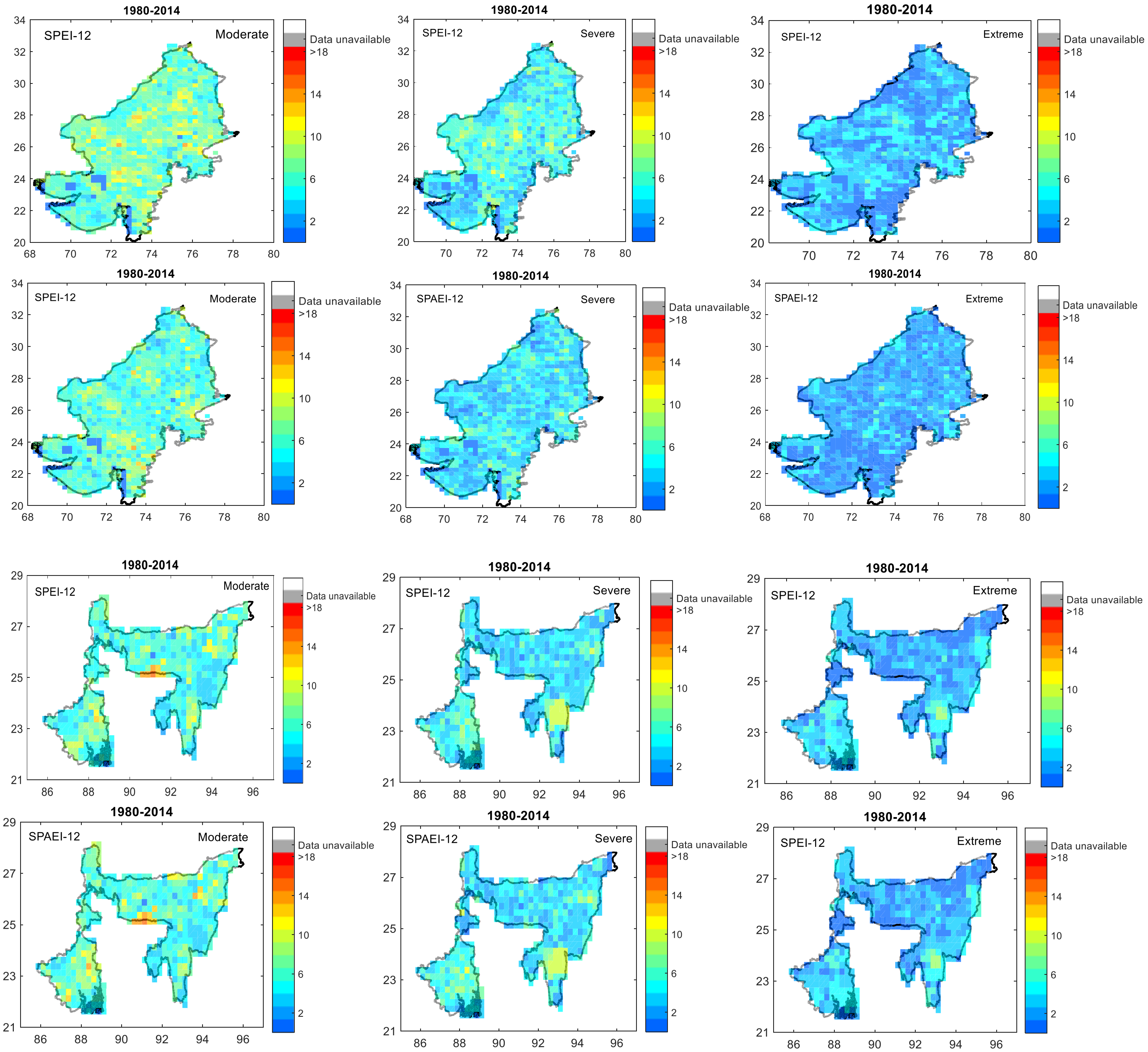

Figure 9. Spatial variation of average duration of droughts estimated for the period from 1980 to 2014 with SPEI-12 and SPAEI-12 for moderate, severe, and extreme for Western and Northeastern zones.

observed to have higher area under increasing trends of drought durations of various categories compared to SPAEI. It can be noted that energy-based ET (PET) will have water availabilities (P-PET) for shorter time periods and, therefore, higher number of drought durations persist whereas both water- and energy-based ET (AET) will have long time periods of water availabilities (P-AET) and, therefore, a smaller number of drought durations persist (Figure 3). Overall, pronounced increasing trends were observed in drought duration months for India in recent years with PET compared to AET.

5. Discussion

The study restructured the SPEI to account for both water- and energy-based evaporative demand (P-PET/AET) in drought characterization over water- and energy-limited zones of India. For this, state-of-the-art global remote sensing data with high resolution and available for sufficiently long period was used. Furthermore, Budyko framework, which is a classical model for estimation of AET relating P and PET, has been used. It can be noted that the Budyko formulation is suitable for long-term-average scale, and therefore, the study mainly focused on 12-month scale drought characterization to avoid the use of short-term soil moisture storages which forms one of the basic limitations of the study. It can also be noted that the adopted Budyko approach for the estimation of AET is based on aridity index (PET/P) and constant basin characteristics parameter (ω). Traditionally, the basin characteristics parameter is assumed to be dependent on land cover and human activities (Saha et al., 2020). However, the basin characteristics parameter is more influenced by aridity index, particularly intraseasonal variability of rainfall and other climate variables (Saha et al., 2020). Therefore, instead of a constant basin characteristics parameter as adopted in the present study, a dynamic basin characteristics parameter, which can account for the intra-seasonal rainfall and other climate variability, can be implemented in the drought estimation.

Moreover, it can also be noted that the study has used one of the most widely used state-of-the-art remote sensing based AET data to formulate SPAEI. However, the study can be extendable to analyze the sensitivity of various remote sensing based AET data (e.g., Moderate Resolution Imaging Spectroradiometer, MODIS) on drought characterization. In the present study, the main emphasis was given to study the impact of PET and AET on the water and energy-limited zones of India, where both the data sets are from one particular source, such as GLEAM. Also, GLEAM data is available for sufficiently long time periods, which allowed to study the possible trends in drought characteristics as demonstrated in the present study. Furthermore, it can be noted that all uncertainties, limitations of the PET and AET data source of remote sensing will be accumulated in the drought assessment. Further studies could improve the drought assessment framework presented here with better AET and PET estimates, which are most difficult variables to measure and deserve more attention toward water resources management.

The limitation of SPEI to capture the seasonality of precipitation has been addressed by adopting water availability deficit ($(P - PET/AET) - \overline{P - PET/AET}$). The newly formulated drought index $\text{SPAEI}_{\text{Seasonal}}$ was able to capture the drought intensities for water-limited zones during drought years compared to the original formulation of SPEI. The study compared one water-limited zone of Western and one energy-limited zone of Northeast for the comparison of drought intensities.

The AET-based drought index was consistent with conventional PET-based drought index in identifying the historical droughts for the seven meteorological homogeneous zones of India, which are characterized as water- and energy-limited zones. The Central, South, West, North, and J&K are identified as water-limited, whereas NE and NE hills as energy-limited zones. Considerable difference in extreme drought affected area was noticed between SPEI and SPAEI for all water-limited zones, while such differences were not observed for energy-limited zones. Further, higher percentage of area was categorized under extreme/severe conditions with SPEI, which was identified as severe/moderate otherwise with SPAEI for all water-limited zones. Drought areal extents were increased in recent years under changes in climate, land, and vegetation consequent pronounced impacts on water availability and management all over India.

Evapotranspiration has emerged as an essential element in the drought assessment in the context of increasing temperatures under global warming in recent periods. However, most of the focus of earlier studies have been on the application of potential evapotranspiration which represents the climatic evaporative demand only, without including the actual water budget available for evaporative demand. The study demonstrated how water- and energy-limited regions drought characterization can vary according to the use of PET and AET with a case study of India. The use of AET in the place of PET in the drought estimation is a valuable proposition by itself, provided accurate measurements of AET. The drought index proposed based on AET estimates using remote sensing data and using Budyko frame work with basic structure of SPEI was found to be a valuable tool for characterizing the droughts for water-limited zones. The proposed drought index can be easily extendable with sufficiently accurate estimates of AET as the AET is one of the most complex hydrological variables and estimates of which needs to be carefully validated. The basic water balance approach as the difference between P and R (runoff) can be implemented for any such extensions of the proposed drought index for other case studies. However, as the current study was not at the catchment scale, the study was not able to validate with the empirical estimates. However, given that remote-sensing based data as the most dependable and accurate estimates, the current study has found a reasonable comparison between empirical estimates of AET and remote sensing-based AET data.

6. Conclusions

The study emphasized on use of AET in the drought assessment instead of PET. The study restructured the SPEI to account for both water and energy based evaporative demand (P-PET/AET) in drought characterization. For this, AET estimated based on nonparametric formulation of Budyko framework and remote sensing-based AET data has been used. The limitation of SPEI to capture the seasonality of precipitation has been overcome by adopting water availability deficit $((P - PET/AET) - \overline{P - PET/AET})$ rather than the actual atmospheric water demand (P-PET/AET). The newly formulated drought index has been named as SPAEI ($SPAEI_{Seasonal}$), which has been applied on the water and energy-limited regions of India.

The following conclusions are derived from this study:

1. Extreme drought areal extents were identified as more sensitive to the use of PET and AET compared to moderate and severe drought categories. Considerable difference in extreme drought affected area was noticed between SPEI and SPAEI for all water-limited zones, while such differences were not observed for energy-limited zones.
2. AET has been identified as suitable variable and provides more insight toward the drought intensity, extreme drought areal extents, shorter-time scale drought frequencies, and longer-time scale drought durations for water-limited zones.
3. Higher percentage of area was categorized under extreme/severe conditions with SPEI, which was identified as severe/moderate respectively otherwise with SPAEI for all water-limited zones.
4. Given the spatial and temporal heterogeneity of P, PET, and AET all over India, the drought assessment at water- and energy-limited zones as presented in the study is important. The AET-based drought index was consistent with conventional PET-based drought index in identifying the historical droughts.
5. Both PET- and AET-based drought indices have shown increasing trends of drought areal extents, frequencies, and durations over India in recent years of 1980 to 2014 indicating notable changes of climate along with land and vegetation in recent years.
6. The drought indices developed by including AET based on remote sensing data can be robust for the drought assessment under both water energy along with land and vegetation variability and promising for water-limited regions.

Data Availability Statement

We sincerely acknowledge the India Meteorological Department (IMD) for providing the gridded observations of precipitation and temperatures over India and details of data are given in the website (https://iridl.ldeo.columbia.edu/SOURCES/.IMD/index.html?Set-Language=en). We also appreciate the Global Land Evaporation Amsterdam Model (GLEAM), satellite-based land evapotranspiration data used in this study available at https://www.gleam.eu/ website. The data used in this research can be downloaded from the Mendeley data repository (https://doi.org/10.17632/8jt8cshzsx.2) (https://data.mendeley.com/datasets/8jt8cshzsx/draft?a=4ed90e88-b5ba-4c9d-8d99-570c19ffb208).

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