Multiscale Analysis of Drought Teleconnections of West Central India using Wavelet Coherence

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ABSTRACT

Drought is a natural climate variability that emerged as a result of the prolonged decrease in precipitation. This study used Standardized Precipitation Index (SPI) to evaluate the drought variability over West Central India (WCI) and its association with various climatic oscillations (COs) like Pacific Decadal Oscillation (PDO), El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO) and Indian Ocean Dipole (IOD). The dominant periodicities of the drought index and climatic oscillations were analyzed using Continuous Wavelet Transform (CWT). Partial Wavelet Coherence (PWC) was used to understand the standalone effect of a specific CO on drought, excluding the role of other climatic oscillations. The study investigated the individual and combined influences of the large-scale climatic oscillations at different time scales using Bivariate Wavelet Coherence (BWC) and Multiple Wavelet Coherence (MWC). To identify the most influential climatic driver for the meteorological and hydrological drought of WCI, various multi-factor combinations were considered. The ENSO-PDO combination gave maximum coherence in the case of a two-factor combination for short-term and long-term drought. The maximum coherence value was obtained for the three-factor combination of ENSO-PDO-IOD for all drought conditions. In short, PDO was found to be the most influencing driver in the drought experienced in WCI.

Keywords: Drought, Teleconnection, Standardized Precipitation Index

1 Introduction

Precipitation is a weather element which has the potential to create a flood or drought in an area. Insufficient precipitation for a longer duration result in an imbalance in the hydrological cycle and this is known as drought. A drought is a slow-onset natural hazard which can be classified into meteorological, hydrological and agricultural drought based on the various hydrological components that are affected. The analysis of a natural hazard means quantifying its behaviour. Zargar *et al.* [1] describe the various drought indices like Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI) etc commonly used for quantifying drought events in a region. Since precipitation deficiency is an indicator of drought, most of the studies make use of the precipitation-based drought index Standardized Precipitation Index (SPI). The SPI computed at different aggregation time scales like 1-month, 3-month, 6-month etc. accounts for the meteorological, hydrological and agricultural droughts.

India, an agricultural country depends on precipitation, and the drought events witnessed in the country have badly affected its economy. Indian Summer Monsoon Rainfall (ISMR) contributes the major portion of precipitation in India. Researchers illustrated the effect of climate oscillations like the El Nino Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), North Atlantic Oscillation (NAO) etc in modulating the ISMR [2]. Rainfall being a major indicator of meteorological drought, it is important to investigate the teleconnections of droughts in multiple time scales, for improving drought forecasting. In this context, understanding the teleconnections of hydrological variables with climatic oscillations in diverse

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time scales is highly important. Wavelet-based techniques are a powerful spectral tool to perform the multi-scale teleconnection analysis [3], [4], most such attempts considered only one of the oscillations at a time. However, as different oscillations play a dominant role in precipitation and such oscillations are interrelated, it is advisable to examine their concurrent and standalone role in hydro-climatic teleconnection studies. Some of the improvisations on wavelet coherence (WC) considered these aspects and the Multiple and Partial variants of WCs were proposed [5]–[7]. Some of the researchers investigated the teleconnections of global streamflow with multiple oscillations [8]. Das *et al.* [9] analyzed the teleconnections of COs with monthly precipitations over India, and Rathinasamy *et al.* [10] investigated the partial role of oscillations on Indian precipitation. The present study simultaneously considers, bi-, multiple- and partial effects in the investigations of the drought-teleconnections of West Central India, a drought-prone homogeneous monsoon region in India.

2 Study Area and Database

Based on the rainfall homogeneity, the 36 meteorological subdivisions in India are again classified into 5 homogeneous monsoon regions: Northwest, West Central, Northeast, Central Northeast, and Peninsular region by the Indian Institute of Tropical Meteorology (IITM) Pune. The present study focuses on the homogeneous region, West Central India (WCI) which comprises 9 meteorological sub-divisions: Madhya Maharashtra, Marathwada West Madhya Pradesh, East Madhya Pradesh, Konkan and Goa, Vidarbha, Chattisgarh, Telangana and North Interior Karnataka as shown in Fig 1.

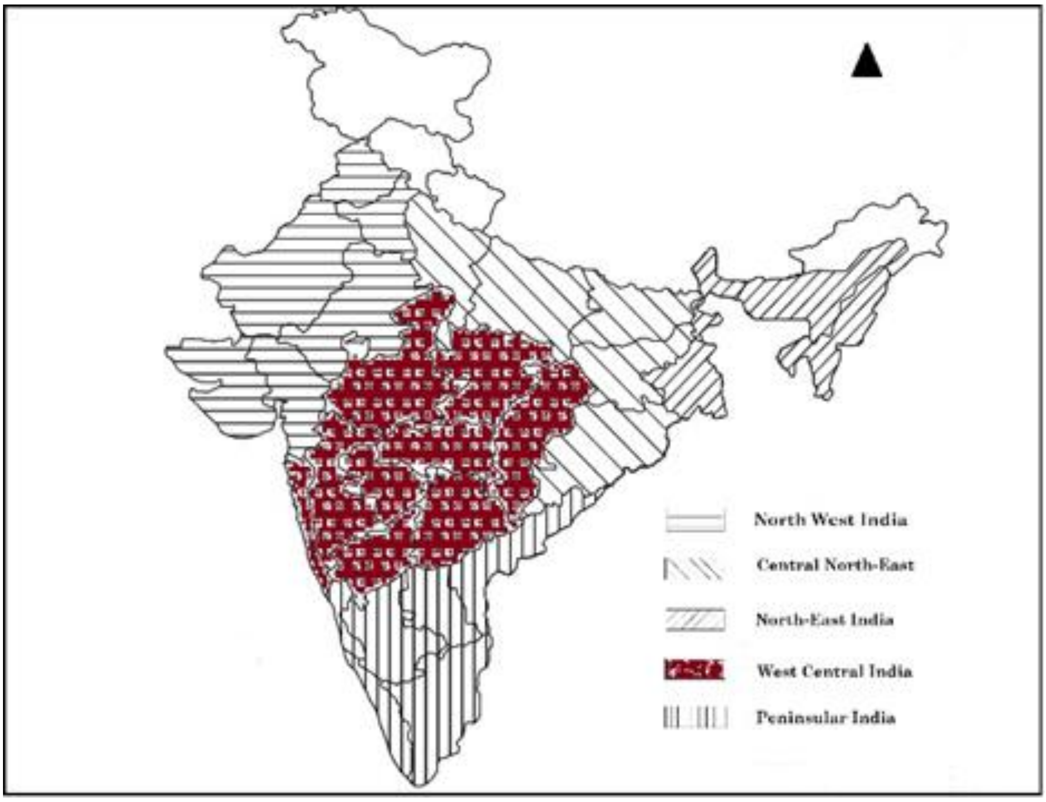

Figure 1: *West Central India*

The monthly rainfall time series of West Central India collected from the Indian Institute of Tropical Meteorology (IITM) Pune from 1950 to 2016 is used to compute the drought indices. The time series data of four climatic oscillations namely the Nino 3.4 index, PDO, NAO and IOD for the same period collected from the National Oceanic and Atmospheric Administration (NOAA) is used to perform the teleconnection study.

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3 Materials and Methods

A brief description of the Standardized Precipitation Index (SPI) and wavelet-based approaches are described in this section.

3.1 Standardized Precipitation Index (SPI)

The SPI evaluates the deficiency in observed precipitation. The SPI series representing various drought events can be computed for different accumulated timescales. Aghakouchak and Farahmand [11] recommend the use of non-parametric SPI for drought assessment in India. The computation of SPI using a non-parametric approach employs the marginal probabilities of precipitation and the SPI values are obtained using the Gringorten plotting position formula.

$$p\,(Xr) = \frac{r-0.44}{n+0.12} \tag{1}$$

Where n is the total number of years in the time series, r denotes the rank of non-zero precipitation data from the smallest, and p(Xr) is the corresponding empirical probability. The SPI can be derived as:

$$SPI = \Psi^{-1}(p) \tag{2}$$

Where Ψ is the standard normal distribution function and p is probability derived from Equation 1.

3.2 Continuous Wavelet Transform

The Morlet wavelet is commonly used in the area of hydro-climatology for wavelet functions. The wavelet power spectrum averaged over time and scale is used for interpreting the results. The time average of power at a given frequency known as the global wavelet spectrum (GWS) is an "efficient" estimator of the "true" power spectrum. GWS is used to identify the important periodic elements in the time series. The dominant periodicity is indicated by the peak of the global wavelet spectrum.

3.3 Bivariate (BWC) and Multiple Wavelet Coherence (MWC)

The wavelet coherence estimates the connection between two-time series within the time-frequency space by measuring the correlation between the data. The value varies from 0 to 1. This technique reveals the dynamic behaviour of hydro-climatological variables by analyzing the hydrological components. Following Torrence and Compo [3] , the wavelet coherence of two-time series is defined as

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}|W_n^X(s)|^2\right).S\left(s^{-1}|W_n^Y(s)|^2\right)} \tag{3}$$

Where,$R_n^2(s)$ denotes the coherence coefficient with maximum coherence at 1 and no coherence at 0, $W_n^{XY}(s)$ represents the cross wavelet transform of two-time series,$W_n^X(s)$ and $W_n^Y(s)$ are the continuous wavelet transform of each time series, s^{-1} is used to convert to energy density and S denotes the smoothing operator.

Hu and Si [6] used the Multiple Wavelet Coherence (MWC) analysis based on auto- and cross-wavelet power spectra among the analyzed variables. In this study, the response variable is the SPI.

3.4 Partial Wavelet Coherence (PWC)

The wavelet coherence method developed to estimate the partial correlation between two-time series y and x_1 after eliminating the influence of the time series x_2 is known as Partial Wavelet Coherence (PWC). The PWC can be squared (after the removal of the effect of x_2) and can be defined by an equation similar to the partial correlation squared as

$$R^2(y, x_1, x_2) = \frac{|R(y,x_1)-R(y,x_2).R(y,x_1)^*|^2}{[1-R(y,x_2)]^2[1-R(x_2,x_1)]^2} \quad (4)$$

This squared value, like the simple BWC, ranges from 0 to 1 and $R(y, x_1)$, $R(y, x_2)$, $R(x_2, x_1)$ is given by equations 5, 6 and 7 respectively as

$$R(y, x_1) = \frac{s[W(y,x_1)]}{\sqrt{s[W(y)].s\{W(x_1)]}} \quad (5)$$

$$R(y, x_2) = \frac{s[W(y,x_2)]}{\sqrt{s[W(y)].s\{W(x_2)]}} \quad (6)$$

$$R(x_1, x_2) = \frac{s[W(x_1,x_2)]}{\sqrt{s[W(x_1)].s\{W(x_2)]}} \quad (7)$$

In this study, two statistical coherence measures Average Power of Wavelet Coherence (AWC) and Percentage of Significant Coherence (PoSC) developed by Nalley *et al.* [8] are used to quantify the results of Bivariate (BWC), Partial (PWC) and Multiple wavelet coherences (MWC). The average of the wavelet coherence produced over all scales to the coherence values produced is represented as the Average Power of Wavelet Coherence (AWC). The percentage of Significant Coherence (PoSC) is estimated by calculating the ratio of the number of significant values of power over the total number of values of the power produced in the MWC computation. The significant power arises when the ratio of the power over the significance level is greater than 1. Higher overall AWC and PoSC values indicate more dominance. Nalley *et al.* [8] recommend an increase in PoSC value by at least 5% before concluding the practical significance of an additional teleconnection variable.

4 Results and Discussion

The results and discussions of the various wavelet approaches are provided in this section.

4.1 Continuous Wavelet Transform

The wavelet transform analysis on climate oscillations (Fig 2.a.) revealed interannual periodicity for ENSO (16-64 months), PDO (8-16 months) and NAO (8-32 months). For NAO, a decadal periodicity of 128 months is also visible while no significant periodicity is observed for the case of IOD.

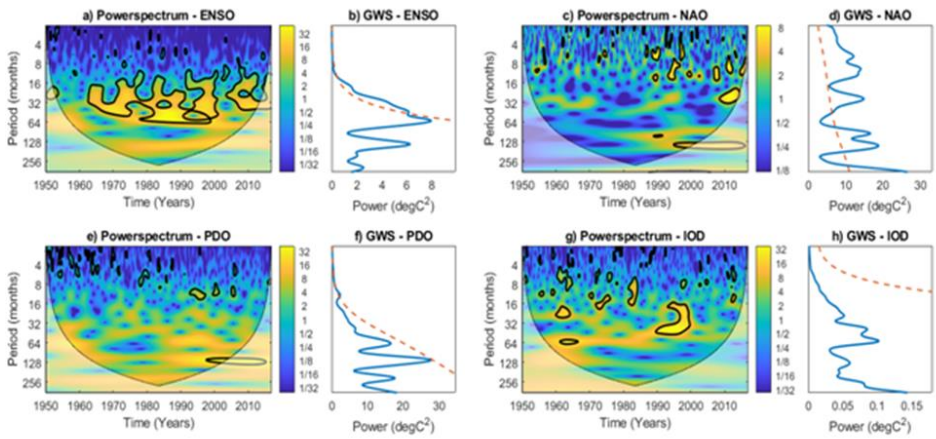

Figure 2 (a): *Climate oscillations*

SPI-3 and SPI-6 have an annual periodicity of 8-16 months whereas SPI-12 has an interannual periodicity of 16-64 months (fig 2.b).

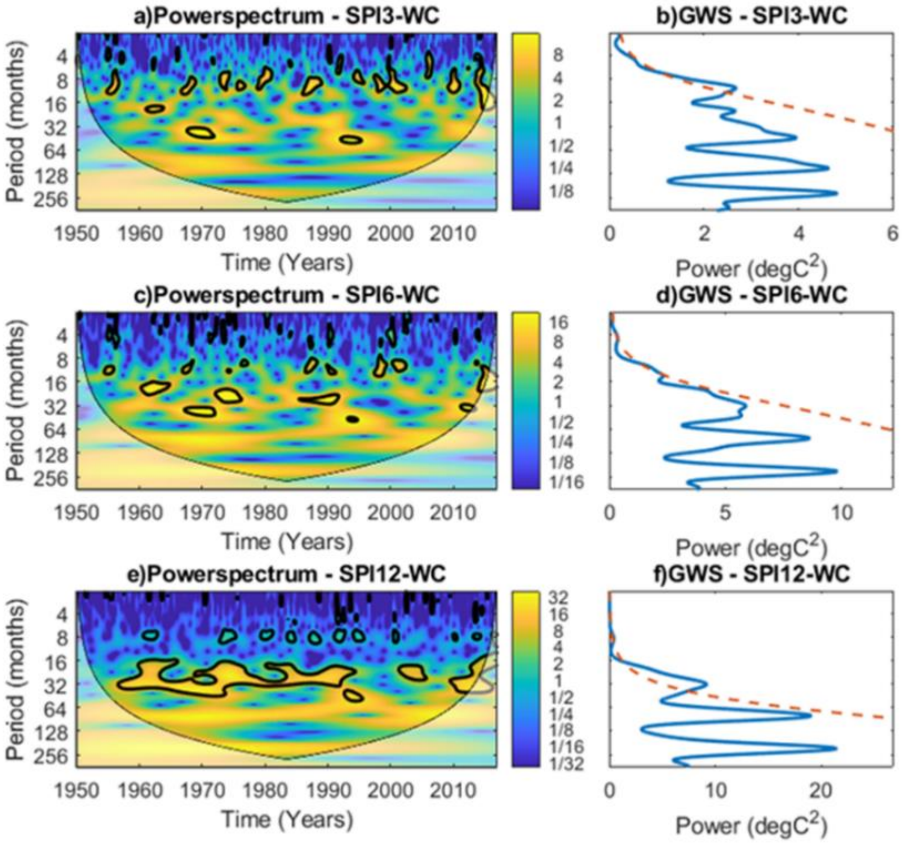

Figure 2 (b): *SPI of WCI*

Figure 2: *Power Spectrum and Global Wavelet Spectrum (GWS)*

4.2 Wavelet Coherence Analysis

The statistical parameters of wavelet coherence analysis - average wavelet coherence and percentage of significant coherence obtained are shown in table 1.

Table 1: *AWC and PoSC values of wavelet analysis of West Central India*

Indices		SPI-3		SPI-6		SPI-12	
		AWC	PoSC (%)	AWC	PoSC (%)	AWC	PoSC (%)
BWC	Var-ENSO	0.37	11.41	0.38	11.67	0.37	11.83
	Var-NAO	0.34	5.94	0.33	5.46	0.32	4.92
	Var-PDO	**0.44**	**16.79**	**0.43**	**14.74**	**0.42**	**13.72**
	Var-IOD	0.39	17.72	0.39	15.75	0.35	11.00
PWC	Var-ENSO-NAO	0.28	7.12	0.28	8.12	0.28	8.55
	Var-ENSO-PDO	0.23	3.20	0.23	4.77	0.22	4.64
	Var-ENSO-IOD	0.26	5.38	0.28	7.03	0.28	7.50
	Var-NAO-ENSO	0.22	2.90	0.22	3.24	0.21	3.98
	Var-NAO-PDO	0.22	3.74	0.20	3.51	0.21	3.45

	Var-NAO-IOD	0.23	3.14	0.23	2.49	0.23	2.35
	Var-PDO-ENSO	0.29	8.09	0.27	4.43	0.25	4.45
	Var-PDO-NAO	**0.34**	**12.94**	**0.31**	**9.85**	**0.31**	**10.03**
	Var-PDO-IOD	0.28	11.44	0.28	13.54	0.26	11.49
	Var-IOD-ENSO	0.31	16.26	0.30	12.53	0.27	9.53
	Var-IOD-NAO	0.27	10.97	0.27	10.03	0.24	8.18
	Var-IOD-PDO	0.33	10.34	0.30	8.49	0.30	8.16
MWC	Var-ENSO-NAO	0.64	21.56	0.64	23.94	0.63	21.79
	Var-ENSO-PDO	**0.69**	**22.60**	0.67	20.82	**0.65**	**19.16**
	Var-ENSO-IOD	0.64	23.62	0.65	22.81	0.64	19.10
	Var-NAO-PDO	0.66	16.55	0.65	14.01	0.64	13.87
	Var-NAO-IOD	0.61	16.15	0.60	14.50	0.57	12.06
	Var-PDO-IOD	0.67	26.43	**0.67**	**23.88**	0.64	20.57
	Var-ENSO-NAO-PDO	0.83	27.60	0.82	27.82	0.80	27.18
	Var-ENSO-NAO-IOD	0.80	23.35	0.80	25.52	0.78	25.66
	Var-ENSO-PDO-IOD	**0.83**	**29.41**	**0.82**	**31.04**	**0.81**	**29.17**
	Var-NAO-PDO-IOD	0.81	26.67	0.80	24.80	0.79	25.04
	Var-ENSO-NAO-PDO-IOD	0.91	30.22	0.90	32.37	0.90	33.10

Note: Significant coherence values are highlighted.

4.2.1 Bivariate Wavelet Coherence Analysis

The wavelet coherence analysis between SPI and each of the climatic oscillations is performed and the wavelet power spectrum obtained from the analysis is shown in Fig 3. For PDO, the values are 0.4431, 0.4327 and 0.4181 with the significant contours being present around 4, 8, 16 and 32 months, between 16 and 32 months and between 32 and 64 months. Contours are also present around 64 months, 128 months and 256 months for all scales of SPI. Indian Ocean Dipole (IOD) plays the next significant influence in the drought values of the region. 0.3937, 0.3852 and 0.3531 are the AWC values obtained for the coherence of different SPI with IOD. The contours are present around 4, 8, 16 and 32 months. In addition to this, a contour is also observed around 128 months for SPI-3 and SPI-6. A significant contour is observed between 16 and 64 months, in the case of ENSO with all drought variables. The maximum coherence is observed for the case of PDO for all cases of SPI.

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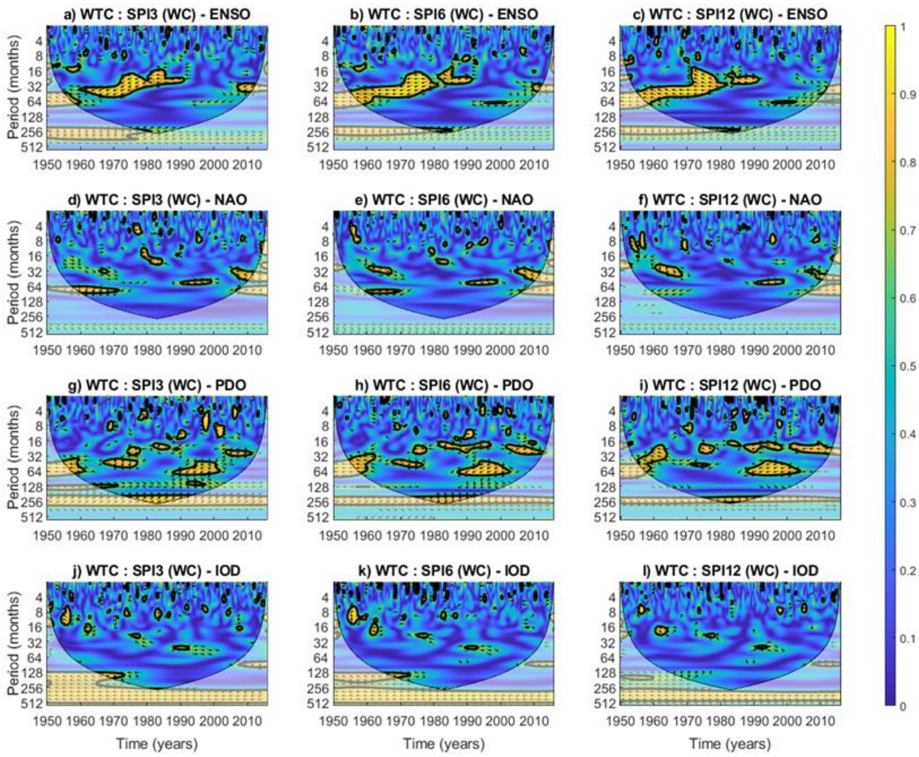

Figure 3: *Power Spectrum of bi-variate wavelet coherence analysis of SPI of West Central India with climate oscillations*

4.2.2 Partial Wavelet Coherence Analysis

The role of multiple climate drivers contributing to the drought events of a region can't be ignored. The PWC analysis is used for excluding the effects of other oscillations from a typical SPI-CO combination. The AWC values obtained from PWC analysis were found to be less than that of the wavelet coherence for all cases of SPI. The maximum AWC is detected for the case of PDO with NAO as excluding variable with AWC and PoSC values 0.3350 (12.9426%), 0.3131 (9.8549%) and 0.3068 (10.034 %) respectively for SPI-3, SPI-6 and SPI-12. The significant contours are observed as small bands around 16-32, 32-64 and 64-128 for SPI-3 and SPI-12 while for SPI-6, it is seen around 16-32, 32-64 and 256 months. The maximum decrease in AWC of all cases of SPI was for ENSO upon excluding the possible influence of PDO, compared with the individual ENSO contribution. The decrease in AWC values is observed to be 0.1487, 0.1577 and 0.1653 respectively for SPI-3, SPI-6 and SPI-12. It is observed that the influence of ENSO on all SPI around the scales 16-32 and 32-64 was due to the influence of PDO. Also, the contours around 256 are removed for SPI-3 and SPI-6 while those around 64-128 are removed for SPI-6 and SPI-12.

4.2.3 Multiple Wavelet Coherence Analysis

The MWC analysis is performed to study the influence of multiple climatic drivers. Here, two-factor, three factor and all-factor combinations are considered. In MWC analysis, for all cases, the AWC values are found to be much higher than the BWC analysis (0.57- 0.9) and PoSC ranges from 12.06 - 33.1%. The maximum AWC for two oscillation combinations is observed for the combination of ENSO-PDO with values 0.6876, 0.6699 and 0.6472 for SPI-3, SPI-6 and SPI-12 respectively. For three oscillation combinations, maximum coherence is observed for the combination of ENSO-PDO-IOD.

5 Conclusions

The present study investigated the teleconnections between climatic oscillations (ENSO, NAO, PDO and IOD) with SPI values of West Central India. Bivariate WC analysis indicated that PDO is the most influential driver on drought indices. The maximum coherence is obtained for the combination of ENSO-PDO (two-oscillations) for short-term and long-term drought. The intermediate drought is influenced by the combined effect of PDO and IOD. For the case of three-factor combinations, the effect of ENSO-PDO-IOD resulted in maximum coherence values for West Central India. The maximum AWC values are observed for the case of PDO with NAO as the excluding variable. PDO indices may better explain the relationships between drought indices over the region. The findings from the study can be used to improve drought characterization, management and drought risk analysis in West Central India.

6 Publisher's Note

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