Unraveling the spatial diversity of Indian precipitation teleconnections via nonlinear multi-scale approach

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Abstract. A better understanding of precipitation dynamics in the Indian subcontinent is required since India's society depends heavily on reliable monsoon forecasts. We introduce a nonlinear, multiscale approach, based on wavelets and event synchronization, for unraveling teleconnection influences on precipitation. We consider those climate patterns with highest relevance for Indian precipitation. Our results suggest significant nonlinear influences which are not well captured by the wavelet coherence analysis, the state-of-the-art method in understanding linkages at multiple time scales. We find substantial variation across India and across time scales. In particular, El Niño/Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) mainly influence precipitation in the southeast at interannual and decadal scales, respectively, whereas the North Atlantic Oscillation (NAO) has a strong connection to precipitation particularly in the northern regions. The effect of PDO stretches across the whole country, whereas AMO influences precipitation particularly in the central arid and semi-arid regions. Our results provide an exciting perspective for capturing the dynamics of precipitation and improving precipitation forecasting.

Keywords. extreme rainfall, climatic patterns, teleconnections, complex network, wavelet

1 Introduction

Understanding the spatial patterns, frequency and intensity of precipitation in the Indian subcontinent is an active area of research due to its essential impact on life and property. The Indian monsoon is the pulse and lifeline of over one billion people, and the socio-economic development in this part of the world heavily depends on reliable predictions of the monsoon (Goswami and Krishnan, 2013).

Numerous studies have emphasized the importance of understanding the influence of large-scale climatic patterns on precipitation for improving forecast accuracy (Feng et al., 2016), therefore many studies have analyzed the relationship between precipitation and climatic patterns for India. This research has shown that the relevant patterns are the El Niño/Southern Os-

cillation (ENSO) (Kumar et al., 2006; Mokhov et al., 2012), the Indian Ocean Dipole (IOD) (Krishnan and Swapna, 2009; Behera et al., 1999), the North Atlantic Oscillation (NAO) (Bharath and Srinivas, 2015; Feliks et al., 2013), the Pacific Decadal Oscillation (PDO) (Dong, 2016; Krishnan and Sugi, 2003), and the Atlantic Multidecadal Oscillation (AMO) (Goswami et al., 2006; Krishnamurthy and Krishnamurthy, 2016).

5   Over the years, linkages between climatic patterns and precipitation have been investigated by a range of statistical methods, such as correlation (Abid et al., 2018), principal component analysis (Luterbacher et al., 2006), empirical orthogonal functions (Hannachi et al., 2007), regression and canonical analysis (Xoplaki et al., 2004). However, all these methods are limited in capturing the scale-specific feedbacks and interactions between the long-range climatic patterns and precipitation. Such information is very crucial since in climatic systems energy is stored and transported differently on different temporal
10 scales, resulting from interactions of intertwined sub-components across a wide range of scales (Peters et al., 2007). Multiscale interactions have therefore received extensive attention in the field of climate dynamics (Peters et al., 2007; Steinhaeuser et al., 2012) and have been proposed as a mechanism for triggering extreme events and abrupt transitions. That holds the promise of better understanding the system dynamics compared to analyzing processes at one time scale only.

    In last decades, wavelet coherence has become the state-of-the-art method for studying the influence of climatic patterns on
15 precipitation at different temporal scales. For example, Ouachani et al. (2013) investigated the multiscale linear relationship between Meditarrian region (Northen Africa) and large scale climatic patterns such as ENSO, NAO and PDO. The study reported the strong correlation between ENSO and precipitation series at lag of 2 years. The study further reported that the influence of ENSO on precipitation was stronger compared to other climatic modes considered in this particular study. Coherently, Tan et al. (2016) analyzed the relations between Canadian precipitation and different global climate indices. Similar studies using
20 wavelet coherence also reported in other parts of the world (Araghi et al., 2017; Hu and Si, 2016). Though all such studies based on wavelet coherence were illuminating and contributed significantly in our existing knowledge of climate. However, there remains a large scope of advancement, that in particular, in capturing the nonlinear scale-specific interactions between climate patterns and Indian precipitation.

    To capture such nonlinear scale specific interactions, recently event synchronization (ES) has emerged as a powerful similar-
25 ity measure (Boers et al., 2014, 2019; Malik et al., 2012; Quiroga et al., 2002; Stolbova et al., 2014; Ozturk et al., 2018, 2019) because ES automatically classifies pairs of events arising at two locations as temporally close (and, thus, possibly statistically – or even dynamically – interrelated) without the necessity of selecting an additional parameter in terms of a fixed tolerable delay between these events (Conticello et al., 2018; Rheinwalt et al., 2016; Agarwal et al., 2018a). Also, ES is a robust measure to study interrelationship between series of non-Gaussian data or data with heavy tails (Agarwal, 2019). These intrinsic
30 features of ES is advantageous in climate, in general and to quantify interactions between climatic patterns and precipitation in particular since the time delay between such patterns (for e.g. ENSO) and their effect on precipitation is tedious to quantify beforehand.

    We therefore decided to use ES to quantify the (possibly nonlinear) linkages between large-scale climatic patterns and precipitation across India. More specifically, we analyze the linkages between the 95-percentile extreme events, extracted
35 from gridded Indian precipitation data at monthly resolution, and the climate patterns ENSO, IOD, NAO, PDO, and AMO

which have been shown to be of significant relevance for precipitation in India. We combine ES with the wavelet transform, as proposed recently by (Agarwal et al., 2017). This combination, termed MSES (Multiscale Event Synchronization), allows studying nonlinear connections between times series at different temporal scales. To consider the spatial variation across India, we sub-divide India into homogeneous regions that share similar precipitation characteristics and identify a representative grid

5 cell for each region. The homogenous regions and the representative grid cells are obtained using the concept of complex networks approach (Agarwal et al., 2018c) and the resultant network is referred as climate network (Boers et al., 2019; Tsonis and Roebber, 2004).

The novelty of this study is the integration of (1) the nonlinear method for quantifying the linkages between large-scale climate patterns and climate network (precipitation) in India at (2) multiple time scales, considering (3) the spatial variation

10 of these linkages. To our knowledge, this combination (nonlinear – multiple time scales – spatial variation) has not yet been implemented, neither for India nor for any other region. We argue that it allows unraveling the spatio-temporal diversity of Indian precipitation teleconnections, offering a compelling perspective for capturing the dynamics of precipitation and improving precipitation forecasting.

2 Study area and data

15 ### 2.1 Study area

Our study area is the Indian subcontinent which shows a significant variation in climate characteristics. India extends over an area of $3,287,263\ km^2$. Its climate regimes are classified as arid (northwestern India), semi-arid (northern lowlands and central peninsular India), humid (coastal lowlands, southwestern and northeastern highlands) and alpine (Himalayan mountains in the north). The spatio-temporal variation of precipitation, as well as temperature, is significant over the country (Bharath and

20 Srinivas, 2015; Shukla et al., 2018). The entire country receives 80% of its total precipitation during the southwest monsoon, from June to September (Bharath and Srinivas, 2015). During the northeast monsoon (October to December), the precipitation is considerable but confined to the southeastern part of the country.

2.2 Gridded precipitation data

We use the high-resolution $(0.25° \times 0.25°)$ daily gridded precipitation data set for the period 1901–2013, developed by the

25 Indian Meteorological Department (IMD) for the spatial domain of $66.5°E$ to $100°E$ and $6.5°N$ to $38.5°N$, covering the mainland region of India (Pai et al., 2014). The gridded data has been generated from the observations of 6995 gauging stations across India (Pai et al., 2014). The dataset captures well the spatial distribution of precipitation over the country. For our study, out of 17415 grid cells, 4631 cells lying inside the boundaries of India were identified.

2.3 Time series of global and regional climate indices

For understanding the linkages between climate patterns and precipitation, we use time series of global and regional climate indices for the same period, i.e., 1951–2013. We have selected those indices for which earlier studies have shown a relation to Indian precipitation. The selected climate indices and the respective studies are: ENSO (Mokhov et al., 2012), IOD (**?**), NAO (Kakade and Dugam, 2000), PDO (Dong, 2016; Krishnan and Sugi, 2003) and, AMO (**?**). For detailed information on these climate indices and the data sources, we refer to https://www.esrl.noaa.gov/.

3 Methodology

To investigate the nonlinear, multi-scale linkages between climate patterns and precipitation we propose the methodology shown in Fig.1. First, we construct a precipitation network of 4631 grid cells of the precipitation dataset using event synchronization. We further pool grid cells with similar precipitation characteristics into homogenous regions and identify a representative grid cell for each region as proposed by Agarwal et al. (2018b). The linkages between the precipitation time series of the representative cells and the teleconnection indices are analyzed by the Multi-scale Event Synchronization (MSES) method developed by Agarwal et al. (2017). Finally, the proposed methodology is compared to the state-of-the-art method in multi-scale time series analysis, the wavelet coherence analysis (WC).

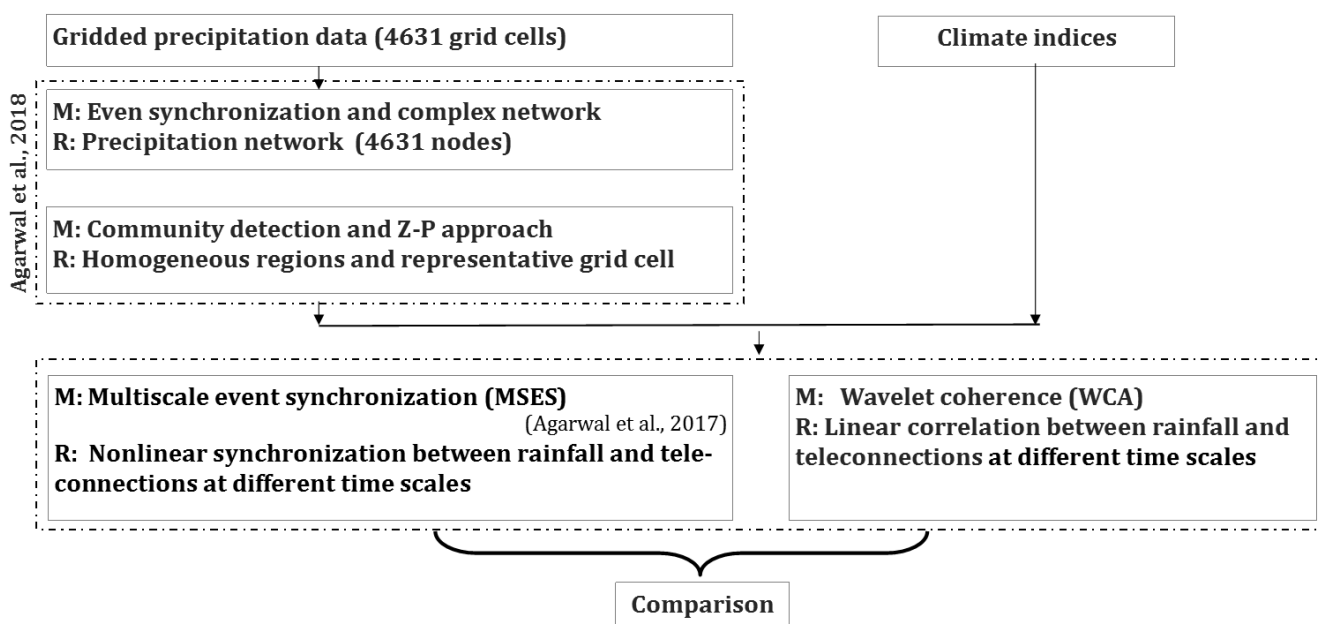



Figure 1. Schematic of the methodology to investigate the linkages between climate patterns and precipitation (M stands for method and R for result). Methods such as community detection and Z-P approach has been discussed in Appendix A.

3.1 Event synchronization and network construction

Event synchronization (ES) measures the nonlinear synchronization for point processes (Quiroga et al., 2002). Each grid cell of the precipitation data set serves as a network node, while the daily precipitation estimates at each cell provide the time series for that node. Following Agarwal et al. (2018b), we define heavy precipitation events at each node as those days with precipitation

5   larger the $95th$ percentile at that grid cell. Then ES is used to calculate the strength of synchronization (Q) between all possible pairs of grid cells. A link between two grid cells is set up if their heavy precipitation occurrence is strongly synchronized, which we define as having a Q value greater than the $95th$ percentile (for more details see Agarwal et al. (2018b)). We repeat the procedure for all possible pair of nodes to construct a precipitation network which is mathematically represented as (Agarwal et al., 2018b)

$$A_{i,j} = \begin{cases} 1, & \text{if } Q_{i,j} \geq \theta_{i,j}^{Q}. \\ 0, & \text{otherwise.} \end{cases} \qquad (1)$$

Here, $\theta_{i,j}^{Q} = 95th$ percentile is a chosen threshold, and $A_{i,j} = 1$ denotes a link between the ith and j^{th} nodes and 0 denotes otherwise.

3.2 Community detection and Z-P approach

The linkages between climate indices and precipitation are evaluated on a regional scale. The study area is subdivided into

15   homogeneous regions with similar characteristics of heavy precipitation events using the concept of complex networks, as proposed by Agarwal et al. (2018b). Several studies have reported superior performance of complex networks in identifying homogeneous regions compared to more traditional methods, such as the hierarchical clustering algorithm or the information-theoretic algorithm (Harenberg et al., 2014).

    Further, for each community, we identify a representative grid cell using Z-P space approach as proposed by Agarwal et al.

20   (2018b). The cell with the highest number of intracommunity links is considered as representative (Halverson and Fleming, 2015), based on the argument that this cell shows the strongest synchronization within the community. We expect its climatological properties, such as the linkage to large-scale climate patterns, to have the highest similarity to the properties of the other cells in the community. We could also use a composite, e.g., by normalizing the grid cell time series and defining the time series of the mean of the normalized series as representative. However, this definition would reduce the variability and could

25   mask existing connections to climatic patterns.

3.3 Multi-scale Event Synchronization

In this study, we use the multi-scale event synchronization (MSES) measure (Agarwal et al., 2017) to quantify the relationship between precipitation and climate indices. MSES combines the wavelet transform and event synchronization. The MSES values between precipitation and climate indices are estimated in the following manner:

1. The climate indices and precipitation values at monthly resolution are decomposed using the maximum overlap discrete wavelet transformation (MODWT; supplementary information) to obtain the scalewise detail components. These components represent the features of the signal at the different time scales.

2. After fixing a 95% threshold for each of the components of precipitation and climate indices, the event synchronization values are estimated. The 95% threshold values are estimated for each scale component separately, ensuring a reliable estimation of the synchronization between the events. Since the time series of the climate indices represent anomalies, both strongly positive and strongly negative values are considered in the derivation of event time series.

3. The estimated ES values are considered significant if they are higher than the ones obtained from a significance test (Agarwal et al., 2017).

4. These steps (a-c) are repeated for all combinations of climate indices and precipitation for the different regions.

3.4 Wavelet coherence

We benchmark the MSES results against the wavelet coherence (WC) analysis, because wavelet coherence is the state-of-the-art method in evaluating linkages between hydroclimatological variables at multiple time scales (Peters et al., 2004; Tan et al., 2016). We use the Grinsted Toolbox (Grinsted et al., 2004) for calculating the WC between precipitation of the representative grid cells and the climatic indices (supplementary information). It is important to note that WC uses the complete, continuous time series for quantifying the linkages between precipitation and climate patterns, whereas MSES first derives events at the different time scales, and then uses the synchronization between these events to identify the linkages.

4 Results and Discussion

4.1 Homogeneous regions and representative grid cells

To reduce the number of pairs of precipitation and climate index time series for finding mutual associations, we pool precipitation grid cells with similar heavy precipitation event characteristics into homogeneous regions. These regions and their main physical characteristics are given in Fig.2. A more detailed discussion of these regions is provided in Agarwal et al. (2018b). For each community, we identify a representative grid cell (black dots in Fig.2) using the Z-P space approach. Next, we investigate the nonlinear linkages between the precipitation time series of the representative cells and the climate indices.

4.2 Linkages between precipitation and climatic patterns at multiple time scales

Figs.4(a-e) and 3(a-e) show the nonlinear synchronization, in terms of MSES values, and the linear coherence, in terms of WC values, between precipitation and the climatic patterns, respectively. MSES and WC are given for the five most relevant climatic patterns for the Indian subcontinent and precipitation in each of the representative grid cells of the seven homogeneous regions. We limit the analysis to scale 7, i.e., 16 years, due to the distortion created by the boundary effects of the wavelet

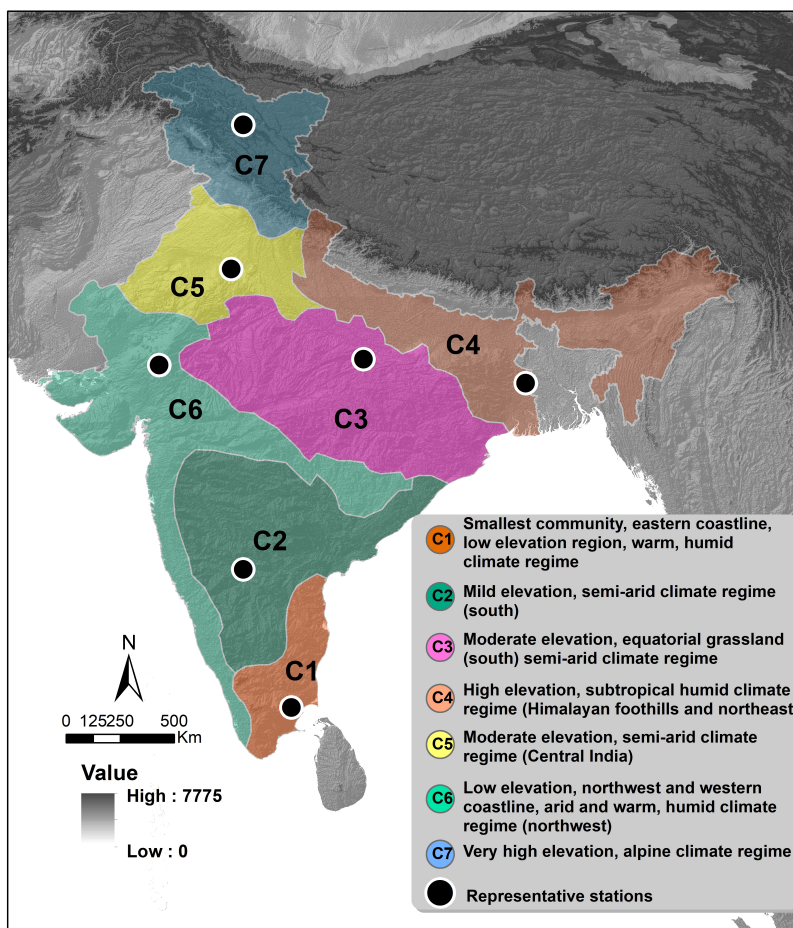
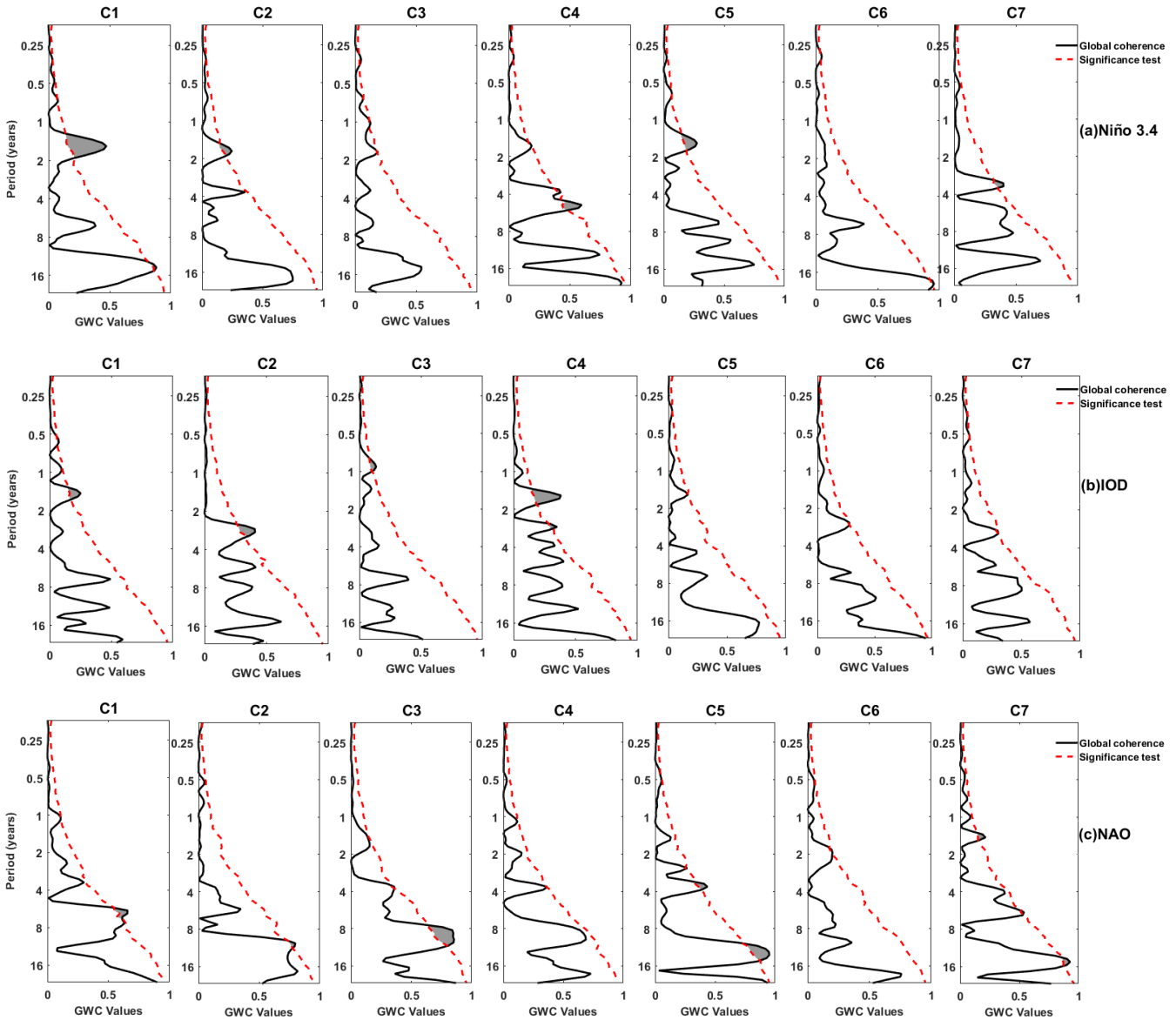



Figure 2. Spatial distribution/ extent of the seven regions, or communities, with similar heavy precipitation event characteristics across India. Black dots indicate representative grid cells for each of the community identified using the Z-P space. Terrain characteristics of the Indian subcontinent is shown using the SRTM DEM (in background).

decomposition (Percival and Walden, 2000). Fig.4a shows a significant association between El Niño/Southern Oscillation (ENSO) and precipitation in all regions of India at the interannual scale. Its strength varies in space and with temporal scale. It is stronger for the southeastern peninsular ($C1, C2, C3$ and $C4$) and decreases notably in the northwestern Himalayan ($C5, C6$ and $C7$) regions. In the southeastern peninsula, the highest synchronization for the low ($C1$), mild ($C2$) and moderate ($C3$) elevation regions occurs at the 4-year scale, and at the 2-year scale for the high elevation ($C4$) region. For the southeast regions of India, we observe a significant synchronization at the decadal scale ($8 - 16$ years) which is counterintuitive given

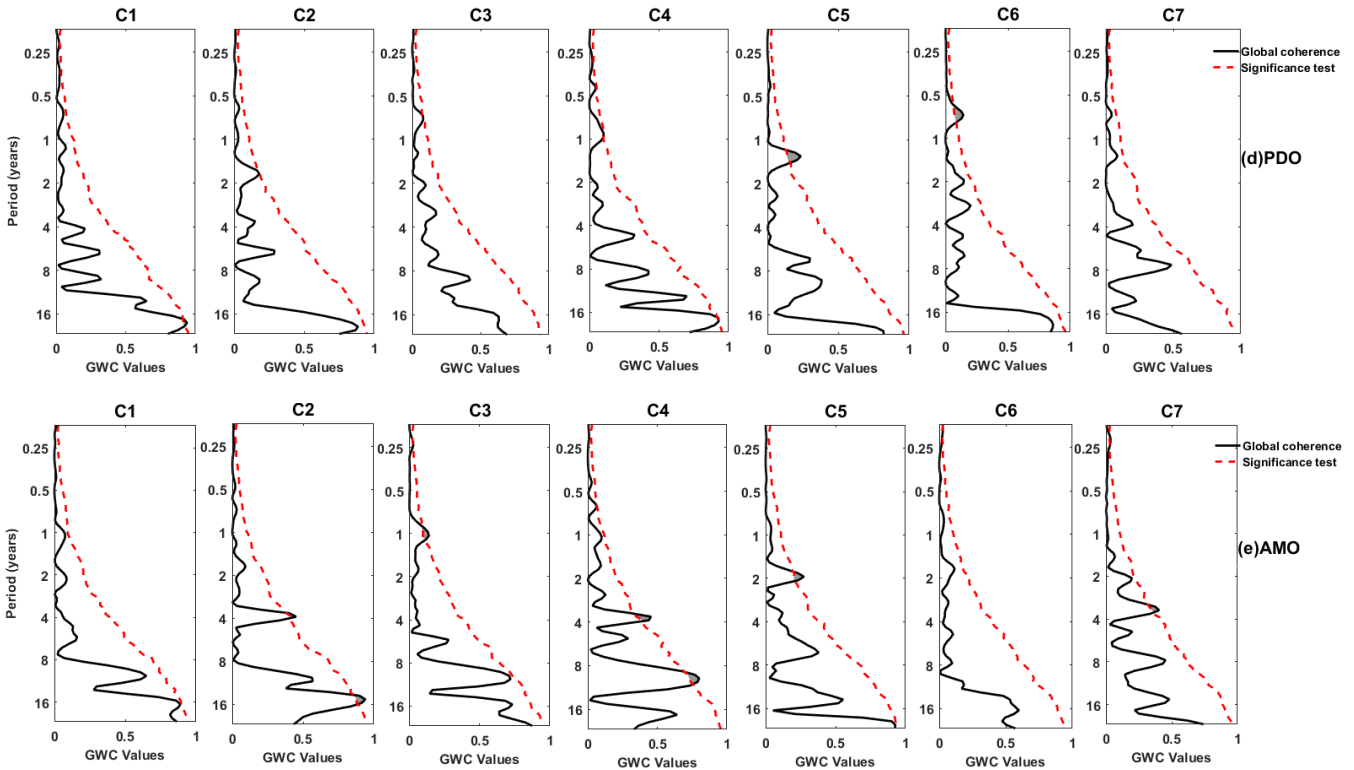



Figure 3. Global Wavelet Coherence (GWC) between precipitation and climate indices. [Top to bottom]: Nino3.4, IOD, NAO, PDO, and AMO. From left to right: Community 1 to community 7. WC values are shown as solid lines, and significant connections (at the 95% significance level) are marked in grey.

the interannual time scale of ENSO (D'Arrigo, 2005; McGregor et al., 2013). The analysis based on WC (Fig.3a) shows substantially less correlation between precipitation and ENSO in all regions.

Overall, the association between ENSO and precipitation at the interannual scale is coherent with the general understanding that extreme precipitation and in India are associated with ENSO (Rajeevan and Pai, 2007). However, the variation of this

5 linkage across India has not been reported. We find stronger linkages for the regions close to the ocean (southeastern peninsular comprising $C1$ to $C4$) compared to the inland regions with higher elevation (northwestern India comprising $C5$, $C7$). The results mentioned above are in congruence with the findings by Guhathakurta et al. (2017); Mishra et al. (2012). The spatial heterogeneity in the strength of the relationship between ENSO and precipitation may be a result of the tropical convection during the ESNO events (Bansod, 2011). Other studies have confirmed that there is a decrease in the strength of the relationship

10 between precipitation and ENSO events with distance from the ocean. A similar pattern observed in Mexico where the Nino3.4 teleconnection is weaker, if not opposite in sign, in northern versus southern Mexico (Hu and Feng, 2002). This observation leads us to the understanding that the ENSO teleconnection is strong in regions of climatologically strong convection.

Interestingly, an association between ENSO and precipitation at the decadal scale has not been reported for India so far. This association might be a consequence of the interdependencies between ENSO and IOD at the decadal scale (Luo et al., 2010). Recently, Izumo et al. (2010) demonstrated that IOD events tend not only to co-occur with ENSO events but also to lead them through tropospheric biennial oscillation (Pillai and Mohankumar, 2010). These interdependencies are vital for enhancing

5   prediction skills. MSES has the potential to capture such interdependencies when applied directly to such indices. However, this is beyond the scope of the study.

The synchronization and coherence between the Indian Ocean Dipole (IOD) and precipitation are given in Fig.4b and Fig.3b, respectively. The nonlinear dependence measure points to a significant synchronization at time scales of $8 - 16$ years in the southeastern regions $C1 - C4$. The rest of the country seems to be unaffected by IOD. The WC analysis obtains a similar

10   spatial pattern, however, the significant associations occur at shorter time scales ($1 - 4$ years, Fig.3b). Interestingly, with both methods, we cannot find any coupling in the Himalayan region ($C7$). The results obtained by MSES are in accordance with the general understanding that IOD plays a vital role in the Indian monsoon system in the southeast regions, i.e., in close proximity to the Indian Ocean, at interannual and decadal scales (Krishnan and Swapna, 2009). This result can be explained by the fact that one of the general conditions for Indian precipitation is the Tropical Easterly Jet and Tropical Westerly Jet (Rai

15   and Dimri, 2017). In case of occurrence of IOD, the pressure dipole generated between the Tibetan plateau and the Madagascar Island either strengthens the southeastern Indian monsoon (positive IOD) or weakens it (negative IOD, Jiang and Ting (2017)). However, the reason for the association at the decadal scale is not apparent and needs further investigation.

Unlike IOD, North Atlantic Oscillation (NAO) demonstrates significant synchronization with precipitation across the entire subcontinent (Fig.4c). The association in the northern regions $C4, C5$ and $C7$ are strong and significant at interannual and

20   decadal scales, whereas the southern regions $C1, C2, C3$ and $C6$ show weaker linkages. Overall, the strength of synchronization is higher at the decadal scale than at the interannual scales. The comparison of the results obtained by MSES (Fig.4c) and WC (Fig.3c) reveals that the nonlinear method shows an increase in the association particularly in the northeastern Himalayan foothill region ($C4$). For some regions, MSES detects linkages which are not found by WC. For example, in the Himalayan region ($C7$), MSES shows a significant association at time scales of $4 - 16$ years, whereas WC shows only a signal just at the

25   significance level at the scale of 16 years.

The overall MSES results are in congruence with other studies (Bhatla et al., 2016; Feliks et al., 2013; ?), but so far space and scale variation in the associations between NAO and Indian precipitation has not gained attention. The linkages between precipitation and NAO in the northern part of the country might be due to westerly influences from the Eurasian region which are, in turn, strongly affected by NAO. Another explanation by Goswami et al. (2006) suggests that the linkage of NAO and

30   Indian precipitation at higher scales (decadal and beyond) in the northern part of India results from the interdependency of NAO and AMO.

In the case of Pacific Decadal Oscillation (PDO), we infer a robust decadal synchronization across the entire subcontinent (Fig.4d). The strength of synchronization varies in space, and reaches values of around 0.7 for several regions. On the contrary, WC (Fig.3d) does not reveal significant associations at the decadal scale except for the eastern coastline ($C1$) and Himalayan

35   foothills ($C4$), where values at the boundary to significance are found. The MSES results agree with Krishnan and Sugi (2003)

who demonstrate a strong relationship between PDO and precipitation across the country. The interannual synchronization might be a pseudo influence because of the interdependency of PDO and ENSO (Krishnan and Sugi, 2003; Rathinasamy et al., 2017).

Fig.4e shows the coupling between Atlantic Multidecadal Oscillation (AMO) and Indian precipitation. The highest strength
5 of synchronization is observed in the northwestern and central regions ($C3 - C6$). Weaker associations are detected in the south ($C1, C2$), whereas no significant synchronization is found for the Himalayan alpine region ($C7$). The linkages are most prominent at the decadal scale; in some regions also significant synchronization at interannual scales is found. In contrast, WC shows only weak associations (Fig.3e).

Our MSES results confirm the assertion given by Zhang and Delworth (2006, 2005) who found an in-phase relationship
10 between Indian precipitation and AMO. A study by Goswami et al. (2006) also unravel a link between AMO and multidecadal variability of Indian precipitation. However, our study is the first to observe that the strength of the coupling between AMO and precipitation varies according to the different climate regions and is strongest at the decadal scale.

In summary, our findings re-confirm known physics-based associations, thus implicitly affirming the validity of our approach, but also provide new insights into Indian precipitation teleconnections. We find substantial variation in the significant linkages
15 across India and for different time scales (Fig.5). MSES reveals an appreciable increase in the association between climate patterns and precipitation in most regions when compared to WC. In some regions, the values increase by $40 - 50\%$. The much higher skill of MSES in detecting associations suggests the presence of nonlinear and threshold relationships which can not be captured by WC which is limited to linear, Gaussian processes.

5 Conclusions

20 A novel nonlinear, multiscale approach (MSES) based on wavelets and event synchronization is used for unraveling teleconnection influences on Indian climate network at multiple time scales. The analysis considers those climate patterns with highest relevance for Indian precipitation. To understand the spatial heterogeneity, India is sub-divided into homogeneous regions using complex networks. The comparison with wavelet coherence analysis (WCA), the state-of-the-art method in understanding linkages at different time scales, shows a much higher skill for MSES in detecting linkages between climate indices and pre-
25 cipitation. This suggests that there are significant nonlinear linkages which are not well captured by linear approaches such as WCA.

The application of MSES to the homogeneous regions, obtained using complex network approach, allows unraveling the spatial diversity in the teleconnection patterns over India. ENSO has a strong influence on precipitation in the southeastern parts of the country. These regions are also affected by IOD, however, the IOD influence is much weaker compared to ENSO. NAO
30 has a strong connection to extreme precipitation particularly in the northern regions. The effect of PDO stretches across the whole country, whereas AMO influences precipitation particularly in the arid and semi-arid regions. The substantial variation of precipitation teleconnections across India and across time scales that is unraveled by the proposed method provides an exciting perspective for rainfall forecasting for India and for making better sense of its weather.

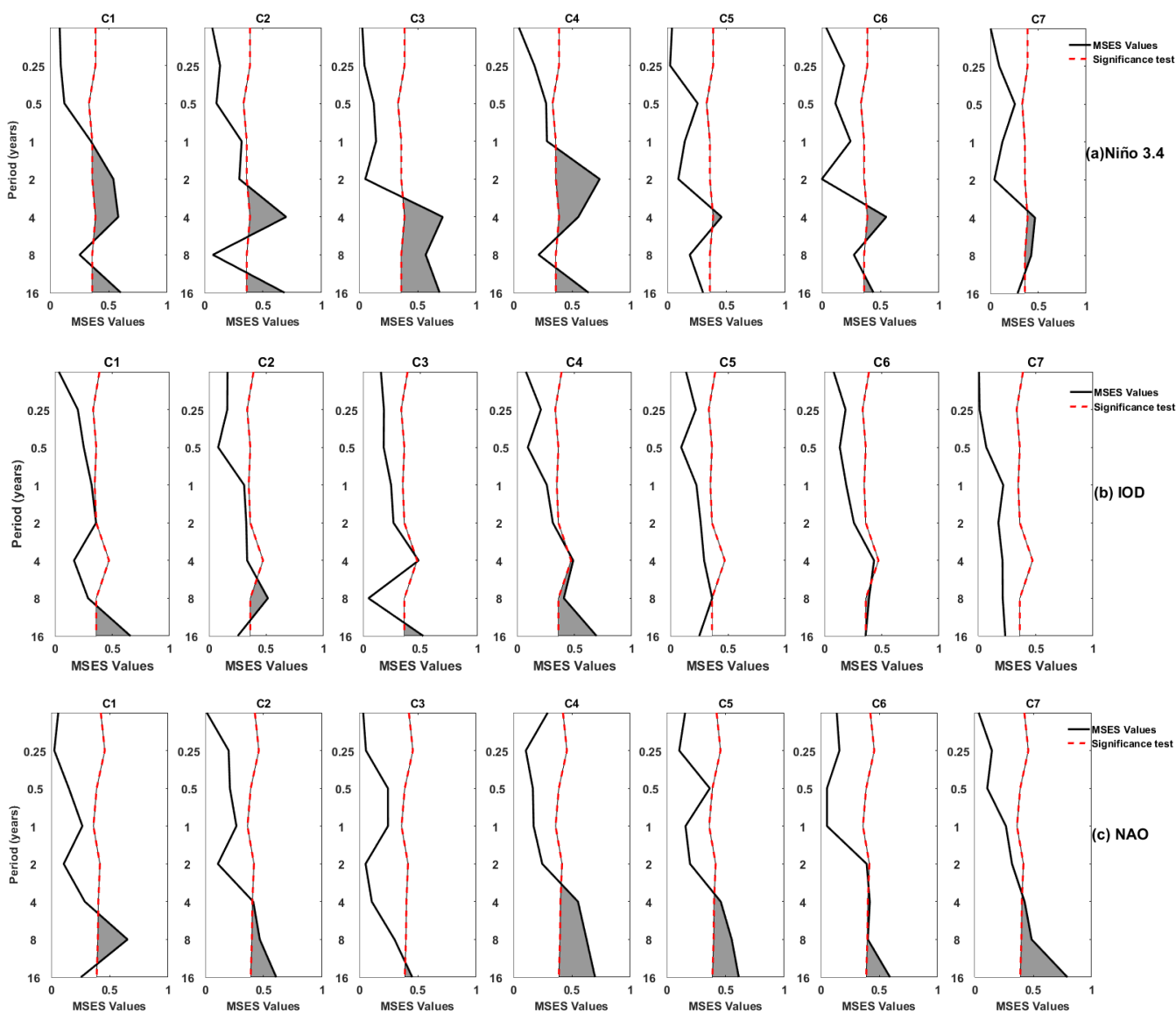
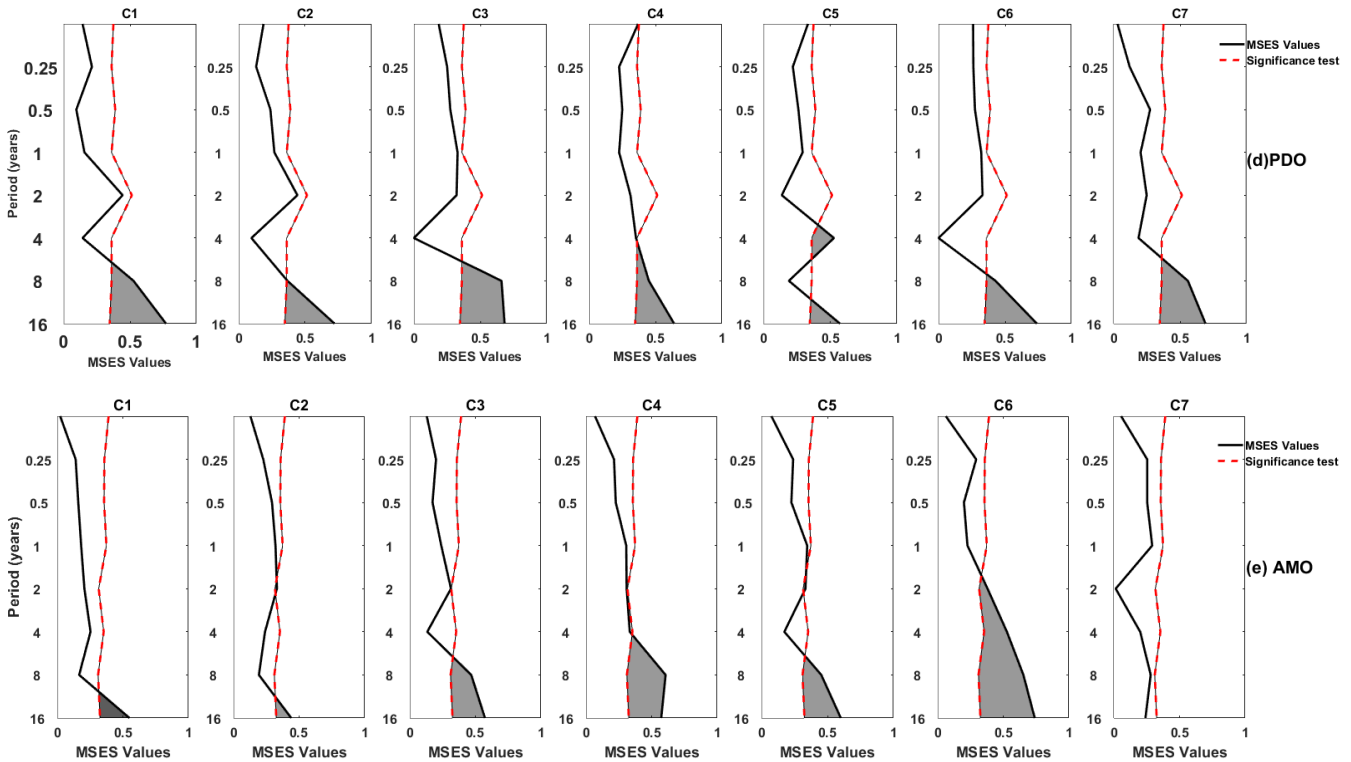



Figure 4. Multi-scale event synchronization (MSES) between precipitation and climate indices. From top to bottom: Nino3.4, IOD, NAO, PDO, and AMO. From left to right: community 1 to community 7. MSES values are shown as solid lines, and significant connections (at the 95% significance level) are marked in grey.

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5 Conflict of interest

The authors declare that they have no conflict of interest.

Author contributions

AA devised the project, the main conceptual ideas, and proof outline. AA & RM jointly developed the theoretical framework. AA took lead and implemented the method on real dataset and performs the analysis and tests. AA arranged, preprocessed the
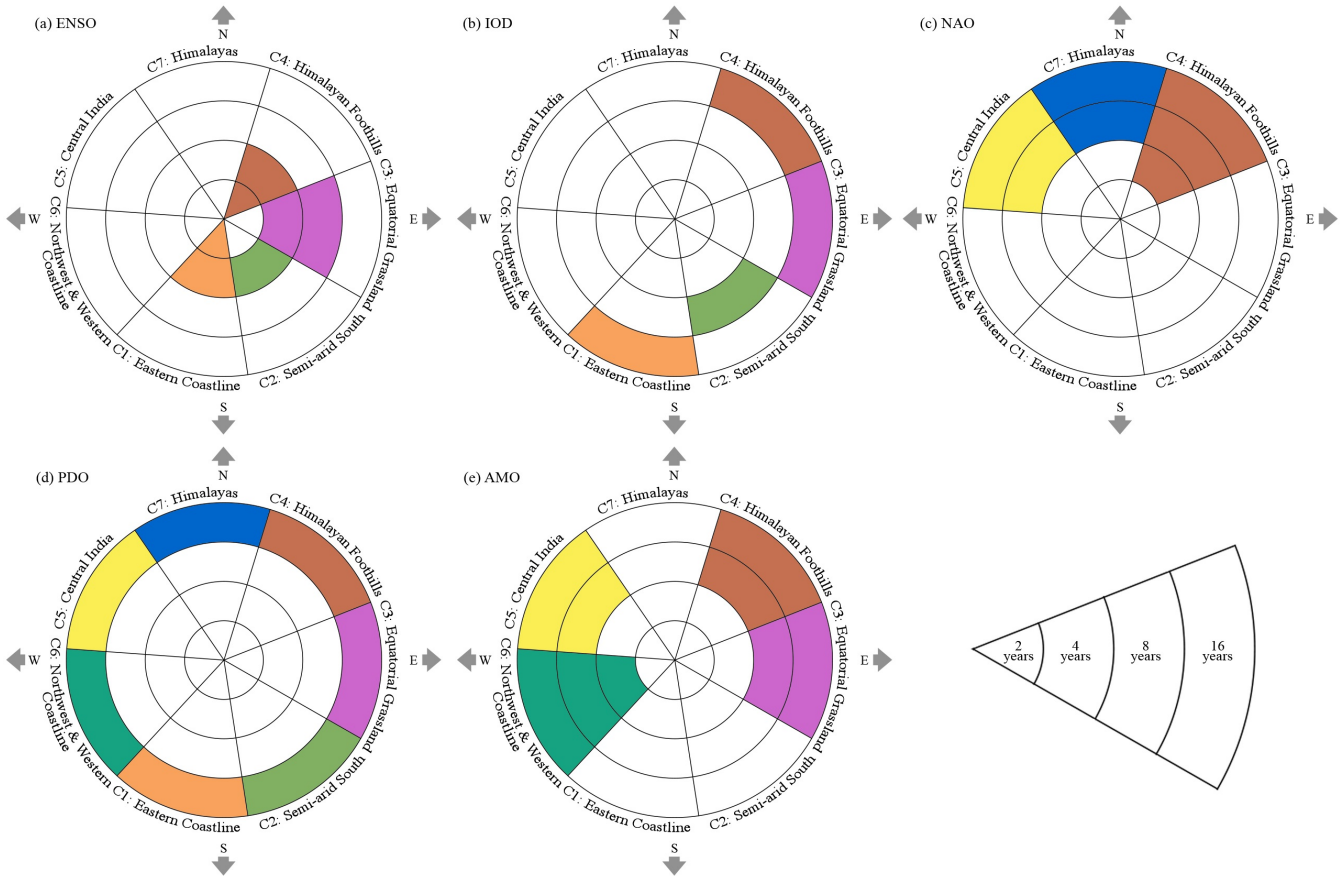
Figure 5. Schematic map of spatial diversity of Indian precipitation teleconnections at different time scales. (a) Nino3.4, (b) IOD, (c) NAO, (d PDO, and (e) AMO. Color are consistent with the community shown in the Fig.2. Presence of color (irrespective of magnitude of synchronization) in community segment indicates significant synchronization between teleconnection and Indian precipitation. Every single segment of circle shows the temporal scale. Cardinal direction have been projected in the background of each circle.

dataset, prepared all the figures and wrote the main test. BM closely supervised the work, helped extensively in rewriting the text for journal submission and helped to improve the figures. Intense discussion with NM & JK helped to reach to appropriate conclusion relevant for the climatological interpretation. RK provided the additional help to draw a meaningful conclusion in term of climatological interpretations.AA and JK equally share the first authorship.

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