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Key Points:

- We examine Indian summer monsoon rainfall interannual variability and teleconnections 1901–2020
- All-India Rainfall Index (AIRI) closely tracks spatial and temporal extent of wet anomalies
- El Niño-Southern Oscillation teleconnection projects onto AIRI but Indian Ocean Dipole onto a known tripole pattern

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On the All-India Rainfall Index and Sub-India Rainfall Heterogeneity

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Abstract We revisit longstanding controversies regarding summer-mean relationships among the all-India rainfall index (AIRI), sub-India rainfall, El Niño-Southern Oscillation (ENSO), and the Indian Ocean dipole (IOD) using 120-year sea surface temperature and high-resolution rainfall datasets. AIRI closely tracks with the spatial extent of wet anomalies and with the average across grid points in rainy day count. The leading rainfall variability mode is a monopole associated primarily with rainy day count and ENSO. The second mode is a tripole with same-signed loadings in the high-rainfall Western Ghats and Central Monsoon Zone regions and opposite-signed loadings in Southeastern India between. The IOD projects onto this tripole and, as such, is weakly correlated with AIRI. However, when the linear influence of ENSO is removed, the IOD rainfall regressions become quasi-homogeneously more positive, making the ENSO-residual IOD and AIRI time series significantly correlated.

Plain Language Summary The Indian summer monsoon generates copious rainfall each June through September, but more in some years than others, and more in some Indian sub-regions than others. We use observational datasets spanning 1901–2020 to reconcile past disagreements about these fluctuations. There has long been concern that the rainfall rate averaged over the whole summer and whole of India—the all-India rainfall index—doesn't necessarily track with the spatial extent of wet or dry anomalies within India which is more relevant for many societal purposes, but we show that the two measures vary closely with one another. There has been disagreement about how the all-India average relates to rainfall in fixed sub-regions of India, and we show using high-resolution rainfall data that the issue stems in part from the use of coarse datasets in the past. Finally, we reconcile disagreements about whether or not the Indian Ocean dipole (IOD) teleconnection influences all-India rainfall by showing that, when the El Niño-Southern Oscillation signal that influences both the IOD and the monsoon rains is removed, the IOD significantly influences the all-India average and with a distinct sub-India spatial pattern.

1. Introduction

Rainfall averaged across India and over June-July-August-September (JJAS)—the All-India Rainfall index (AIRI)—is a widely used, physically intuitive, and societally relevant (Gadgil, 1995; Gadgil & Gadgil, 2006; Mooley et al., 1981; Parthasarathy et al., 1988) bulk indicator of the summer monsoon. But its use is controversial, largely owing to summer monsoon rainfall's pronounced sub-India and sub-seasonal heterogeneity. Summer rainfall is high within a broadband of northern-central India, higher still within a narrow band in the southwest between the Arabian Sea and the Western Ghats (WG) mountains, and much lower in southeastern India (SEI) between these two bands. And throughout the subcontinent JJAS rainfall variability is much higher on daily than interannual timescales (Krishnamurthy & Shukla, 2000). In this study, we address three long-running controversies regarding AIRI's interpretation in light of this spatiotemporal variability, attempting to synthesize and reconcile past arguments made with differing and often short and/or coarse datasets by using state-of-the-art, 120-year datasets of Indian rainfall at high resolution and of sea surface temperature (SST).

First is the relationship between AIRI and the overall spatiotemporal extent of wetting or drying across India. Spatially, in most summers there are parts of India that experience drought and others excess rainfall, and for rain-fed agriculture for example, quite plausibly the spatial extent of drought relative to local rainfall normals is more relevant than the average rainfall anomaly in mm day $^{-1}$ across India (Parthasarathy et al., 1993). This has motivated attempts to define bulk indices in terms of the fraction of the Indian surface area experiencing rainfall anomalies exceeding specified thresholds (Mooley et al., 1981; Parthasarathy et al., 1987). Temporally, a recent

© 2022. American Geophysical Union. All Rights Reserved. series of studies (Moron et al., 2012, 2017; Robertson et al., 2019) employ a useful decomposition of JJAS-mean rainfall at any given point into the product of the frequency of rainy days and the mean rainfall intensity on rainy days, arguing that rainy day frequency tends to be more spatially coherent across India and thus potentially predictable. We will make use of this decomposition to construct and compare alternative indices to AIRI.

Second is the relationship between AIRI and rainfall anomalies over geographically fixed sub-India regions. The literature on dividing India into so-called "coherent" or "homogeneous" sub-regions-i.e., over which rainfall interannual variability tends to be similar-dates to the nineteenth century (see Gadgil et al., 1993; Parthasarathy et al., 1993; Shukla, 1987 and references therein). Subseasonally, it is well established that the predominant variability mode-the so-called active-break cycle-comprises a tripole: in active periods, rainfall is enhanced over the WG and Central Monsoon Zone (henceforth CMZ) bands but suppressed over SEI (Rajeevan et al., 2010). And because the CMZ and WG anomalies are larger than the SEI anomalies in absolute terms, AIRI is enhanced (the same results hold with signs reversed for break periods). Interannually, the predominant mode is instead a quasi-uniform wetting or drying across the subcontinent that strongly projects onto AIRI (Krishnamurthy & Shukla, 2000, 2007, 2008; Mishra et al., 2012; Moron et al., 2012, 2017; Shukla, 1987; Straus & Krishnamurthy, 2007). A second seasonal-mean variability mode has been identified (Krishnamurthy & Shukla, 2008) but characterized by Mishra et al. (2012) as a north-south dipole rather than the CMZ-SEI-WG tripole, with generally same-signed anomalies across peninsular India including both the WG and SEI, and opposite-signed conditions to the north including the CMZ. This would seem consistent with the argument put forth separately that seasonal-mean rainfall anomalies in the CMZ and WG are weakly correlated, and that therefore AIRI effectively amounts to the superposition of two quasi-independent processes (Vecchi & Harrison, 2004). We will revisit both arguments using a $0.25^{\circ} \times 0.25^{\circ}$ rainfall data set that better resolves the sharp rainfall gradient between the WG and SEI regions.

Third is the relationship between both AIRI and sub-India rainfall anomalies to teleconnection modes emanating from the tropical Pacific and Indian Oceans. The link between the Indian summer monsoon and the El Niño-Southern Oscillation (ENSO) is well established, with drought more likely in El Niño summers and excess rain in La Niña summers (Pant & Parthasarathy, 1981; Rasmusson & Carpenter, 1983), both at the all-India scale and most individual points (excluding the far northeast for reasons described below). Nevertheless, ENSO indices have always left the majority of AIRI variance unexplained (Surendran et al., 2015), even before a weakening of the ENSO-AIRI lag-zero correlation in recent decades compared to the mid-twentieth century (Ashok et al., 2019; Kumar et al., 1999). The Indian Ocean dipole (IOD)-the zonally oriented oscillatory mode spanning the equatorial Indian ocean (Saji et al., 1999; Webster et al., 1999)—has been argued to modulate ENSO's influence on AIRI (Ashok et al., 2001, 2004), with the IOD-AIRI correlation relatively high in decades when the EN-SO-AIRI correlation is relatively low and vice versa. While it has been argued (Krishnamurthy & Kirtman, 2003; Stuecker et al., 2017) that the IOD is in fact largely controlled by ENSO, Ashok and Saji (2007) argue that the IOD spatial imprint on Indian summer monsoon rainfall is much more heterogeneous, concentrated roughly over the CMZ region. Meanwhile, other studies focused on the atmospheric counterpart to the IOD, the Equatorial Indian Ocean Oscillation, have argued that the correlation between the IOD and AIRI is effectively zero (Gadgil et al., 2004; Ihara et al., 2007; Surendran et al., 2015). We will attempt to reconcile these arguments by examining the spatial imprint of the IOD and ENSO on rainfall amount, rainy-day frequency, and mean rainfall intensity (cf. Moron et al., 2017) and by isolating the IOD and ENSO signals from one another (cf. Ashok & Saji, 2007).

After describing the datasets and methods used (Section 2), we argue the following (Section 3): AIRI is an excellent indicator of the spatial extent of wet anomalies across the subcontinent; the second leading mode of interannual variability is the familiar CMZ-SEI-WG tripole; rainfall anomalies within the CMZ and WG regions are well correlated; ENSO strongly imprints on the leading monopole pattern and thus on AIRI while the IOD imprints on the tripole pattern and thus weakly on AIRI; and when the ENSO signal is linearly removed the IOD influence becomes more positive at most points such that the ENSO-residual IOD and AIRI time series are significantly correlated. We then conclude with summary and discussion (Section 4).

2. Methods

For rainfall, we use the Indian Meteorological Department (IMD) daily, gridded $0.25^{\circ} \times 0.25^{\circ}$ data set spanning 1901–2020, which is derived from a dense but time-varying network of rain gauges across India comprising 6,955 total and on average ~2,600 operational each year (Pai et al., 2014). Daily values from 1 June to 30 September each year are averaged to form a JJAS seasonal mean. No further temporal filtering is employed. We have compared the IMD data set with the TRMM 3B42v7 (Huffman et al., 2007) daily data set over the period 1998–2014. On individual days the differences between the datasets can be substantial (not shown), but the JJAS-mean AIRI time series computed with the two datasets are highly correlated (r = 0.94). We distinguish rainy days from non-rainy days using a 1 mm day ⁻¹ threshold, with results very similar if 0 mm day ⁻¹ is used instead (not shown).

As common in studies of the summer monsoon (Krishnamurthy & Shukla, 2000; Parthasarathy et al., 1988; Vecchi & Harrison, 2004), we exclude points in far north and northeast India, in our case by applying the "monsoonal India" mask of Gadgil et al. (2019). In far northern India the terrain makes rain gauges less reliable and representative, and the vicinity to the Himalayas and extratropical influences make interannual rainfall variability not clearly related to the summer monsoon circulation. For Northeast India there appear to be spurious data points in a cluster of grid cells on the border of Bangladesh, with the JJAS mean and variance jumping in 1971 to implausible values over the remainder of the record (not shown). Nonetheless, the mean JJAS rainfall time series with or without the monsoon mask are highly correlated (r = 0.95); henceforth we refer to the monsoonal-India average as AIRI.

We use standard SST-based indices of ENSO and the IOD—the NINO3.4 and Dipole Mode Index (DMI; Saji et al., 1999) respectively—computed with monthly SSTs spanning years 1901–2020 from the NOAA Extended Reconstruction SST (Huang et al., 2015) data set (ERSST) version 5. NINO3.4 is defined as the average SST anomaly spanning $120^{\circ}-170^{\circ}$ W, 5° S– 5° N, and DMI is defined as the difference between the SST anomalies averaged over a western equatorial Indian Ocean box ($50^{\circ}-70^{\circ}$ E, 10° S– 0°) and over an eastern equatorial Indian Ocean box ($90^{\circ}-110^{\circ}$ E, 10° S– 10° N). Anomalies are defined as the diviation at each grid point from the local climatology over 1901–2020 for that month, with June through September anomalies then averaged to yield JJAS values for each index. The correlation with AIRI is virtually unchanged if NINO3.4 is replaced by the NINO3 index (both r = -0.53) and moderately weakened for NINO4 (r = -0.40), and rainfall regression and correlation patterns also look very similar for each of the three NINO indexes (not shown).

The AIRI, grid point-local rainfall, ENSO, and DMI JJAS-mean, 120-year time series are each detrended by subtracting the linear trend over 1901–2020 from simple least squares regression. Trends over 1901–2020 are weak in the IMD rainfall data set at the vast majority of grid points, and all major results we present are insensitive to the detrending (not shown). For all detrended JJAS time series analyzed the interannual autocorrelations are sufficiently weak and the distributions are sufficiently normal (not shown) that a simple *t*-test yields a reasonable measure of statistical significance; in particular, using a conservative estimate of 100 degrees of freedom yields significance at the 5% level for correlations with |r| > 0.195. Though note that for spatially gridded data this pointby-point approach may overstate significance due to spatial autocorrelations (Wilks, 2016).

3. Results

3.1. AIRI Relationship to Spatiotemporal Extent of Rainfall Anomalies

Figure 1a shows the climatological JJAS rainfall and its interannual standard deviation for each grid point. The standard deviation largely scales with the local climatological mean, and both are heterogeneous—high within CMZ, highest within WG, and much lower in SEI. Figure 1b shows the fraction of annual-mean rainfall that occurs in JJAS as well as surface elevation contours. The JJAS rainfall fraction exceeds 95% in parts of the far western CMZ, exceeds 80% over most of the WG and CMZ, and does not exceed 50% in most of SEI, where in the far southeast the rainy season occurs during the northeast monsoon in boreal autumn (Ramesh et al., 2021). The elevation contours highlight how southwesterly low-level summer monsoon flow largely perpendicular to the WG mountain range axis results in a concentrated rainfall band on the windward side and a much broader and drier regime on the leeward side over the Deccan Plateau (Francis & Gadgil, 2006; Flynn et al., 2017; Hunt et al., 2021). Figure 1c shows the climatological number of rainy days in JJAS and the mean rainfall rate on those rainy dates. Rain falls nearly every summer day within most of WG, most days within most of the CMZ, and less





Figure 1. (a) Climatological June-July-August-September (JJAS) rainfall mean in color shading and standard deviation in contours in the Indian Meteorological Department (IMD) $0.25^{\circ} \times 0.25^{\circ}$ gridded data set, 1901–2020. Standard deviation contours from white to black are 1, 2, 3, 4, and 5 mm day ⁻¹ (maximum standard deviation is 14.2 mm day ⁻¹). (b) Climatological fraction of annual-mean rainfall that occurs during JJAS in color shading and surface elevation in contours. Elevation contours from white to black are 100, 300, 500, 700, and 900 m (maximum elevation is 1,028 m). (c) Climatological mean number of rainy days in JJAS in color shading and mean rainfall intensity on rainy days in contours. Mean rainfall intensity contours from white to black are 10, 15, 20, 25, and 30 mm day ⁻¹ (maximum mean rainfall intensity is 44.8 mm day ⁻¹). Blue outlines in panel a and in subsequent figures show the borders of the three sub-India regions we analyze in detail, namely, the central monsoon zone in the north, Western Ghats in the southwest, and Southeastern India in the southeast.

frequently within most of SEI. Mean rainfall intensity is highest within WG directly along the coast, with a sharp gradient moving inland up the mountain slope, with smoother spatial variations elsewhere.

Given this heterogeneity, in principle AIRI need not be a useful indicator of the spatial extent of wet or dry anomalies: an average across regions with high variance and regions with low variance will depend primarily on the former and weakly on the latter. We have therefore constructed six alternative all-India measures of JJAS rainfall variability: first, the average standardized rainfall anomaly (i.e., the raw anomaly divided by the standard deviation, rather than just the raw anomaly as for AIRI); second, the number of grid points in which the local JJAS rainfall anomaly is positive; third, the average across all grid points of the number of rainy days; fourth, the average across all grid points of the rainfall anomaly is positive; and sixth, the mean rainfall anomaly restricting to those grid points for which the rainfall anomaly is negative. The first, third, and fourth variants were introduced by Moron et al. (2017).

Figure 2 provides a cross-correlation matrix of AIRI and these six alternative measures (along with numerous additional fields below the first horizontal line to be discussed below). Among AIRI and the first three variants—which characterize the spatial or temporal extent of wet anomalies—all correlation coefficients exceed 0.9. Among AIRI and the last three variants, which characterize the intensity of wet or dry anomalies, no correlation coefficient exceeds 0.77. Thus, AIRI depends more on the spatiotemporal extent of rainfall across India and JJAS than on the severity of rainfall anomalies when and where they occur. This agrees with Moron et al. (2017), who also note that this contrasts with interannual variability at the grid point scale: for most grid points of monsoonal India the JJAS rainfall amount depends more on the intensity of rain events than the number of rainy days.

We therefore conclude that AIRI is an excellent indicator of the overall spatial extent of wet or dry anomalies, as well as of the average anomaly in rainy day occurrence across India. Insofar as the latter two measures are more directly relevant to agricultural and thus economic outcomes, this helps explain the high correlations found by previous studies of AIRI itself with agricultural yields and gross domestic product on interannual timescales (Gadgil, 1995; Gadgil & Gadgil, 2006; Mooley et al., 1981; Parthasarathy et al., 1988).





Figure 2. Cross-correlation matrix showing the correlation coefficients (unitless) among all-India rainfall index (AIRI), six variants thereof as defined in the text, four principal component (PC) time series as described in the text, regional rainfall averages over each of the central monsoon zone (CMZ), southeastern India (SEI), and Western Ghats (WG) regions and a linear combination of CMZ and SEI as described in the text, and the NINO3.4 (with sign reversed) and dipole mode index (DMI) time series, all for June-July-August-September (JJAS) and over the 1901–2020 period. For the final row only, labeled "DMI, N34 resids," both the DMI time series and all target time series are the residuals after linearly removing the NINO3.4 signal. Horizontal and vertical lines separate the time series into categories: AIRI and variants thereof, PC time series, sub-region averages, and teleconnection indices, respectively from top to bottom and left to right.

3.2. Rainfall Relationships Among Fixed Sub-India Regions

We have repeated the empirical orthogonal function (EOF) analyses of Moron et al. (2017) for JJAS standardized anomalies in each of rainfall mean, rainy day frequency, and mean rainfall intensity; our calculations include more recent years and, more importantly, the second EOF for rainfall amount (cf. Mishra et al., 2012) in addition to each first EOF. Figure 3 shows these EOFs, and Figure 2 reports correlation coefficients among the corresponding principal component (PC) time series as well as AIRI. The first EOF of rainfall amount accounts for 18.2% of the total variance and consists of same-signed loadings at the vast majority of grid points (Krishnamurthy & Shukla, 2000). This resembles the first EOF of rainy day frequency, which explains 32.4% of the rainy day frequency variance and exhibits an even more homogeneous pattern, though sharing the two local minima located east of the WG mountains axis and in the far east. The PC time series corresponding to these amount and frequency first EOFs are each highly correlated with AIRI (r = 0.96 and 0.93, respectively).

Both the first EOF of mean rainfall intensity (7.2% of variance) and the second EOF of rain amount (9.3% of variance) comprise a CMZ-SEI-WG tripole pattern. The corresponding PCs are highly correlated with one another (r = 0.85) but weakly with AIRI. Unlike for rainfall amount and rainy day frequency, the first EOF for mean rainfall intensity is not well separated in variance explained from the remaining EOFs (the second EOF,





Figure 3. (a) First and (b) second empirical orthogonal function (EOF) of June-July-August-September (JJAS) rainfall amount, and first EOF of (c) rainy day frequency, and (d) rainfall intensity, each with the percentage of variance explained by that EOF printed in the top-left. EOFs were computed from standardized anomalies in each case. In each panel, values are normalized by that EOF's maximal value, and solid gray contours signify that EOF's zero contour.

not shown, accounts for 5.5%). But its physical relevance is supported by the correspondence of its pattern to the rainfall EOF2 and to the IOD teleconnection results we will present below.

We compute averages over each of the CMZ, WG, and SEI sub-regions using border definitions as follows (shown as blue contours in Figures 1a, 3, and 4). The CMZ boundaries follow Gadgil et al. (2019). We define the non-coastal borders of WG to align with the sharp rainfall gradient separating the coastal and inland peninsular regimes, and define SEI to be all grid points east thereof and south of 18°N. Pointwise correlation maps (not shown) indicate that rainfall in points within the CMZ tends to vary positively both with other CMZ points and with points within WG, but weakly or negatively with those in SEI; the region-mean JJAS rainfall correlations are r = 0.23, 0.63, and 0.33, respectively, for CMZ-SEI, CMZ-WG, and SEI-WG.

Using the CMZ, SEI, and WG regional averages, we have constructed one, two, and three-region linear regression models for AIRI and for the tripole mode, the latter defined by the rain amount PC2 (results are similar if the intensity PC1 is used instead; not shown). For AIRI, at r = 0.93 the CMZ alone explains most of the variance as shown by Gadgil et al. (2019), leaving little additional skill to be gained by including either of the other regions. For the tripole mode, by contrast, the highest-magnitude single-region correlation is with SEI at r = -0.70. The CMZ-SEI two-region model, whose relative weights are 0.6 and -1, respectively, and whose time series is included in Figure 2 along with the three individual region averages, yields r = 0.92 with the tripole mode. This is effectively unchanged by including the WG as well.



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Figure 4. Top row, correlation coefficient between June-July-August-September (JJAS) $-1 \times NINO3.4$ and grid point local (a) rainfall amount, (b) frequency of rainy days, and (c) mean rainfall intensity. Overlain in thin gray are the -0.2 and +0.2 contours, which give a reasonable estimate of statistical significance as described in Section 2. Bottom row, panels (d–f) repeat (a–c) but with the NINO3.4 index replaced by the DMI, and with the linear influence of NINO3.4 on both rainfall and DMI removed via a partial correlation calculation. Dashed box in (d) shows the WG region border used by Vecchi and Harrison (2004).

Thus, despite WG being home to the highest JJAS-mean rainfall variances throughout monsoonal India, it adds little predictive power to CMZ and SEI for these bulk measures, due to it being well correlated with CMZ (r = 0.63). This is considerably higher than two similar-but-different regions ($r \approx 0.2$) reported by Vecchi and Harrison (2004). That study's WG region (borders overlain in Figure 4d), based on coarser $2.5^{\circ} \times 2.5^{\circ}$ grid-ded CMAP rainfall data, spans into peninsular India and thus includes points for which rainfall anomalies are anti-correlated with those along the coast. The correspondence between WG and CMZ rainfall anomalies has also been established through cluster analysis of seasonal-mean rainfall anomalies by Moron et al. (2017) using $0.25^{\circ} \times 0.25^{\circ}$ data.

We conclude that the sharp rainfall gradients in the southwest—which have dictated the border definitions of subdivisions of the IMD station network since the nineteenth century (Kelkar & Sreejith, 2020)—are insufficiently resolved in gridded datasets with resolutions of 1° or more. With higher resolution the second interannual variability mode after the quasi-uniform first mode is a CMZ-SEI-WG tripole (a semblance of the tripole is visible in Figure 1 of Mishra et al. (2012) based on $0.5^{\circ} \times 0.5^{\circ}$ data, but it is described in their text as a north-south dipole). As such, the CMZ and WG mean rainfall anomalies cannot be considered quasi-independent (Vecchi & Harrison, 2004).

3.3. ENSO and IOD Teleconnections

Figure 2 includes the $-1 \times NINO3.4$ and DMI time series, the sign of NINO3.4 flipped so that positive values correspond to positive AIRI anomalies. The correlation between $-1 \times NINO3.4$ and AIRI is r = 0.54, between $-1 \times NINO3.4$ and DMI is r = -0.29, and between DMI and AIRI nearly zero, r = 0.01, all broadly consistent with past studies. Using partial correlation analysis to remove the linear NINO3.4 signal from both rainfall and the DMI time series, the resulting DMI and AIRI residual time series become significantly positively correlated,

r = 0.21. In El Niño years removing the NINO3.4 signal increases AIRI and makes the DMI more positive, and similarly with signs reversed for La Niña years, and this is why the AIRI-DMI correlation becomes more positive. Conversely, removing the DMI signal hardly affects the ENSO-AIRI relationship (r = 0.56), and mechanisms through which ENSO influences the IOD are well documented (Stuecker et al., 2017). We therefore now analyze the spatial imprints of ENSO and the IOD on the Indian summer monsoon via the rainfall frequency-intensity decomposition, in the case of the IOD focusing on the NINO3.4 residuals (cf. last row of Figure 2).

Figures 4a–4c shows the correlation of each of JJAS rainfall amount, rainy day frequency, and mean rainfall intensity with $-1 \times \text{NINO3.4}$. For rainfall amount, the correlation is positive at most grid points, most positive within SEI and the central portion of CMZ, and least positive (including some slightly negative values) in the far east of the CMZ and along the WG mountain axis. The rainy day frequency correlation is more homogeneously positive and with higher magnitudes in most areas, especially along the Arabian Sea coast within WG and the central and western CMZ. The mean rainfall intensity correlation is noisier and has generally weaker magnitudes, with a considerable fraction of grid points below the approximate statistical significance threshold of $|r| \gtrsim 0.2$ described in Section 2. It takes the reverse sign over an appreciable fraction of grid points including much of the CMZ, and of the three sub-regions it is most consistently positive over SEI. These three spatial patterns are broadly comparable to the corresponding first EOFs for JJAS rainfall amount (mostly same-signed), frequency (more homogeneous than amount), and intensity (heterogeneous with a CMZ-SEI-WG tripole, the modest statistical significance notwithstanding).

Figures 4d–4f show the correlations between the NINO3.4-residual time series of DMI and JJAS rainfall amount, rainy day frequency, and mean rainfall intensity at each grid point. For amount and frequency, the predominant signal is a WG-SEI-CMZ tripole, with positive IOD events moderately correlated with excess rain over most of the WG and CMZ and deficient rain over SEI. Unlike for NINO3.4, the patterns in rainfall amount, rainy day frequency, and mean rainfall intensity are all grossly similar—to first order, all three are CMZ-SEI-WG tripoles, just with more positive values overall for rainy day frequency and more negative values overall for mean rainfall intensity. Though the values over most grid points for all three are insignificant on statistical grounds, the correspondence of all three patterns to the physically well-grounded tripole mode argues against them being purely artifacts. Moreover, the tripole structure helps explain why the full, non-residual DMI time series correlation with AIRI is very small (r = 0.01) but significantly larger for the tripole indicators (r = 0.31 for amount PC2, r = 0.34 for intensity PC1).

We conclude that, while it is the case that DMI is weakly correlated with AIRI, the IOD imprints a familiar spatial pattern, the WG-SEI-CMZ tripole. Moreover, when the quasi-uniform drying influence of ENSO is linearly removed, the DMI correlations become quasi-uniformly more positive, and as such the component of AIRI interannual variance not associated with ENSO is significantly related to the IOD.

4. Conclusions

We have used observational datasets of SST and high-resolution gridded rainfall spanning 1901–2020 to revisit three controversies in the literature involving relationships among the JJAS seasonal averages of the AIRI, the sub-India spatial distribution of rainfall variability, ENSO, and the IOD. The first is the extent to which AIRI is representative of the spatiotemporal extent of rainfall anomalies. Despite past concerns raised to the contrary, AIRI is found to be an excellent indicator of the spatial extent of wet anomalies across monsoonal India, and additionally of the average anomalous number of rainy days. It is less closely related to the severity of rainfall anomalies when and where they occur.

The second is how AIRI variability relates to rainfall in fixed sub-India regions, and the third is how variability in AIRI and the subregions relate to ENSO and the IOD. We confirm prior analyses of the leading variability mode via EOF analysis: it is a quasi-homogeneous wetting or drying that results primarily from an even more homogeneous and stronger signal in rainy day frequency, and it is strongly influenced by ENSO. The second mode is a tripole with same-signed loadings in the high-rainfall CMZ and WG regions and opposite loadings in SEI between. This mode is associated more with rainfall intensity than with rainy day frequency and is effectively unrelated to ENSO. The IOD imprints appreciably on the tripole mode and, with respect to the residual fields with the ENSO signal removed, imprints significantly on AIRI as well.



Data Availability Statement

IMD rainfall data used is available at https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Down-load.html. ERSST data is available at (https://www.ncei.noaa.gov/pub/data/cmb/ersst/v5/netcdf/).

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