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Key Points:
- Our analysis helps explain previously contradicting results of trends in ISM rainfall
- We identify regions experiencing significant rainfall-intensity changes in the extremes

Supporting Information:
- Supporting Information S1

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Spatiotemporal patterns and trends of Indian monsoonal rainfall extremes

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Abstract In this study, we provide a comprehensive analysis of trends in the extremes during the Indian summer monsoon (ISM) months (June to September) at different temporal and spatial scales. Our goal is to identify and quantify spatiotemporal patterns and trends that have emerged during the recent decades and may be associated with changing climatic conditions. Our analysis primarily relies on quantile regression that avoids making any subjective choices on spatial, temporal, or intensity pattern of extreme rainfall events. Our analysis divides the Indian monsoon region into climatic compartments that show different and partly opposing trends. These include strong trends toward intensified droughts in Northwest India, parts of Peninsular India, and Myanmar; in contrast, parts of Pakistan, Northwest Himalaya, and Central India show increased extreme daily rain intensity leading to higher flood vulnerability. Our analysis helps explain previously contradicting results of trends in average ISM rainfall.

1. Introduction

Large parts of South Asia and Southeast Asia receive more than 80% of their annual rainfall during the four summer months of June, July, August, and September (JJAS) [*Bookhagen and Burbank*, 2010] (see Figure S1 in the supporting information). The strong rainfall seasonality is caused by the Indian summer monsoon (ISM) system and is a critical climatic phenomenon for over a billion inhabitants of the South and Southeast Asian region, with significant socioeconomic impacts. Much of the cultural, economic, and agricultural life centers around the ISM season in this densely populated region of the world [*Webster et al.*, 1998a; *Gadgil and Gadgil*, 2006; *Gadgil and Kumar*, 2006].

Despite the ISM's significance, there still remain large uncertainties about rainfall extreme events, which often lead to floods or droughts. Both have been identified to exert significant impact on cultural, social, and economic life [*Schiermeier*, 2006; *Gadgil and Gadgil*, 2006; *Kshirsagar et al.*, 2006; *Sivakumar and Stefanski*, 2011; *Mirza*, 2011; *Turner and Annamalai*, 2012]. In recent years, several attempts have been made to understand and quantify the changes in the properties of extremes during the ISM in the context of global warming, e.g., *Goswami et al.* [2006], *Rajeevan et al.* [2008], *Dash et al.* [2009], *Krishnamurthy et al.* [2009], *Ghosh et al.* [2012], *Malik et al.* [2010, 2012]; *Singh et al.* [2014], and *Mishra and Liu* [2014]. Several new insights about monsoonal changes were presented in these studies. For example, *Goswami et al.* [2006] and *Rajeevan et al.* [2008] concluded that ISM extreme rain events over central India are increasing. In contrast, *Ghosh et al.* [2012] concluded that there is no uniform spatial trend in extremes over the Indian subcontinent, but rather their variability is increasing. In a recent study by *Singh et al.* [2014] it has been shown that extreme wet and dry spells during the ISM have statistically significant changes in their intensity and frequency in the period between 1951 and 2011. Also, it has been suggested that the ISM is showing two contrasting phases: a wetter early summer followed by a drier period, with a possible influence of aerosol concentrations on precipitation patterns [*Gautam et al.*, 2009; *Kharol et al.*, 2013].These changing rainfall patterns have been hypothesized to lead to an increased risk of droughts [*Mishra and Liu*, 2014]. See Text S1 in the supporting information (SI) for further detailed discussion on ISM and climate change.

In our study, we present additional insights into the emerging features of the ISM rainfall over South and Southeast Asia by carrying out an analysis of two different climatic data sets: area-averaged time series of monthly rainfall from five different regions of India from 1871 to 2012 [*Parthasarathy et al.*, 1993; *Mooley et al.*, 1981; *Parthasarathy et al.*, 1987] and gridded daily rainfall data for South and Southeast Asia from 1951 to 2007

[*Yatagai et al.*, 2009]. This research differs from previous studies in the following critical ways: (1) We rely on a distinct computational method for trend analysis, known as *quantile regression*, which does not make any subjective choices on the rainfall amounts or return periods, as in more commonly used approaches involving linear regression and extreme value theory. *Quantile regression is an entirely different method from the common practice of using least squares linear regression for estimating trends in different quantiles*. (2) The majority of the previous studies used a data set that was limited to the political boundary of India. Instead, we analyze a data set with higher spatial resolution and larger spatial coverage, including all of South and Southeast Asia. Additionally, we have analyzed area-averaged time series extending from 1871 to 2012. (3) A large number of past studies have concentrated only on rain events related to high extremes, e.g., above the 90th percentile. Our study presents a more comprehensive analysis of extremes during the ISM and includes droughts as well. (4) Our results capture the regional variations of extremes. This is important because the ISM is composed of complex spatial patterns influenced by several local geographic factors such as topography and small-scale atmospheric processes.

2. Data and Method

In our study we rely on two data sets, the Homogeneous Indian Monthly Rainfall Data Set (1871–2012), a set of time series prepared by the Indian Institute of Tropical Meteorology hereafter referred to as IITM-HIMR [*Mooley et al.*, 1981; *Parthasarathy et al.*, 1987, 1993], and the gridded data set for the South Asia region from the APHRODITE (Asian Rainfall Highly Resolved Observational Data Integration Towards the Evaluation of Water Resources) project [*Yatagai et al.*, 2009]. The APHRODITE data set (APHRO-V01003R1) includes spatial coverage for both South and Southeast Asia (see Figure S1 for regions included in this analysis). For further details on the data set, including additional data sources, see Text S2 of the SI.

We rely on quantile regression [*Koenker and Hallock*, 1978, 2001; *Koenker*, 2005], where one estimates the relationship between a variable X and conditional quantiles of response variable Y given that $X = x$, providing a more robust analysis of the central tendency and statistical dispersion of the relationship between variables. Conditional mean-based classical (linear) regression is very sensitive to the extremes. In contrast, quantile regression is robust to the extremes of the response variable [*Koenker and Hallock*, 1978, 2001; *Koenker*, 2005], making it a much more powerful tool for studying trends of extremes in a distribution.

For a random sample of Y of size n $\{y_1, y_2, \dots, y_n\}$, in our data y_i is the rainfall on the x_ith day or year (depending on the temporal resolution of the data). We notate the cumulative distribution function by $F_Y(y) = P(Y \le y)$. The τth quantile of Y is given by $Q_Y(\tau) = \inf\{y : F_Y(y) \ge \tau\}$ where $\tau \in [0, 1]$. In this notation, $Q_Y(0.5)$ is the median of the sample Y. Whereas one can obtain the sample mean of Y by minimizing a sum of squared residuals, the median can be obtained by minimizing a sum of absolute residuals $\min_{\xi\in\mathbb{R}} \sum_{i=1}^{n} |y_i - \xi|$. In general, one can obtain any other quantile by minimizing a sum of *asymmetrically* weighted absolute residuals, i.e., $\min_{\xi\in\mathbb{R}} \sum_{i=1}^{n} \rho_\tau(y_i - \xi)$, where ρ_τ is the tilted absolute value function, more specifically $\rho_\tau(z) = z(\tau - \mathbf{1}(z < 0))$, $\mathbf{1}(.)$ denotes the indicator function. Quantile regression is specified in a form related to conditional expectation $E(Y|X = x)$, which can be estimated by $\hat{\beta} = \mathrm{argmin}_{\beta\in\mathbb{R}^p} \sum_{i=1}^{n} (y_i - \mu(x_i, \beta))^2$, where $\mu(x_i, \beta)$ is a parametric function. Instead, the conditional quantile functions are estimated by

$$\hat{\beta}(\tau) = \mathrm{argmin}_{\beta\in\mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(y_i - \xi(x_i, \beta)).$$

The function $\xi(x, \beta)$ is formulated as a linear function of the type $x_i^T \beta$. We have solved the above minimization problem by unconstrained nonlinear optimization, utilizing the *fminsearch* function available in the optimization toolbox of MATLAB® The resulting quantities $\hat{\beta}(\tau)$ are called the *regression quantiles* [*Koenker*, 2005]. For linear quantile regression we will obtain two regression parameters from the quantile regression procedure: the intercept $\hat{\beta}_0(\tau)$ (rainfall magnitude at the initial time) and the slope of the fitted line $\hat{\beta}_1(\tau)$ (change in magnitude of rainfall per unit time). Rainfall in the x_ith year or day for the τth quantile can then be estimated as $\hat{\beta}_0(\tau) + x_i\hat{\beta}_1(\tau)$.

To assess statistical significance, we construct the confidence interval of $\hat{\beta}(\tau)$ using a method of bootstrapping on residuals. This is accomplished by adding randomly resampled residuals back to the model fits to obtain synthetic samples of response variables. We generate 1000 such samples and employ the above described algorithm for quantile regression to estimate $\hat{\beta}_b^\star$ $(b = 1, \dots, 1000)$ on each of these synthetic samples of response variables. Next, we order $\hat{\beta}_1^\star \le \cdots \le \hat{\beta}_{1000}^\star$, with the 95% confidence interval given by the 25th

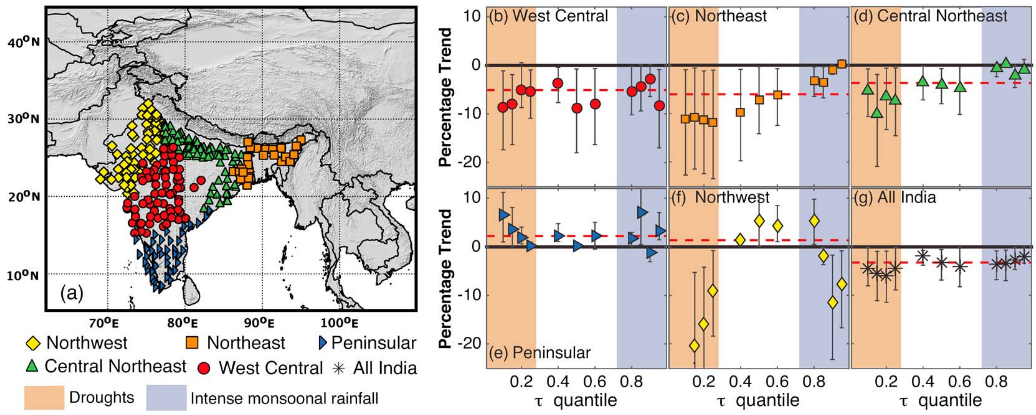

Figure 1. (a) Station locations used in the constructing of area-averaged time series of the IITM-HIMR data set (1871–2012), for different homogeneous rainfall regions. Each color represents one particular region, whereas "All India data" includes all stations. IITM-HIMR data consist of area-averaged monthly rainfall amounts from 1871 to 2012. We have built the time series of annual ISM rainfall from these data by taking the average over JJAS months for each year. (b–g) Markers are the percentage trend in each quantile over the 142 year period; marker colors and shape correspond to different geographic regions and the error bars represent the 95% confidence intervals obtained using method of bootstrapping on residuals. Red dotted lines indicate the linear trend in the mean of the respective time series over the 142 years, independent of quantiles. Black heavy lines act as a reference for no change/no trend. Quantile values are indicated by τ (horizontal axes). Brown shaded vertical bands highlight the lower quantiles, i.e., trends for $\tau \in [0.1, 0.3]$. Blue shaded vertical bands highlight the higher quantiles, i.e., trends for $\tau \in [0.75, 0.95]$. Observe the low values of the quantile trends for $\tau \in [0.1, 0.3]$ for West Central, Central Northeast, Northeast, Northwest, and All India indicating intensification of droughts in these regions. See Figures S7, S8, and S9 and Text S3.2 for additional information.

and 975th ordered elements. For significance testing, we reject the null hypothesis $H_0 : \hat{\beta} = \hat{\beta}_0$ at the 5% significance level if $\hat{\beta}_0$ lies outside the above stated confidence interval.

For our purposes, extreme events are defined as the very low and very high quantiles of a distribution, following a convention that considers the top and bottom 10% as extremes [*Field et al.*, 2014; *Solomon et al.*, 2007]. We refer the reader to Text S3 in the supporting information for details on the strength and limitations of quantile regression and Text S3.1 for interpretation of trends and units used in the analysis.

3. Results

The IITM-HIMR data set (see Text S2 of SI for the detailed description of the data set) provides area-averaged time series of monthly rainfall from 1871 to 2012 for five different regions of India: the regions are Northwest, Northeast, Peninsular, Central Northeast, West Central, and a sixth time series that is a composite of all regions, and is referred to as All India (see Figure 1a). We have analyzed the time series individually to identify and compare trends in the annual JJAS rainfall in different regions of India. In Figures 1b–1g we show trends for different quantiles for all six time series, using quantile regression.

The threshold we have used for defining droughts is $\tau \in [0.1, 0.3]$, i.e., the bottom 10% ($\tau = 0.1$) to 30% ($\tau = 0.3$) annual rainfall amounts. These thresholds, highlighted by brown vertical bands in Figures 1b–1g, are sufficiently low that they have the potential to cause drought conditions irrespective of other environmental conditions. Except Peninsular India, we observe intensification of droughts, i.e., decrease in rainfall intensity in $\tau \in [0.1, 0.3]$ quantiles in all of the other time series (West Central, Northeast, Central Northeast, Northwest, and All India). In the four time series Northeast, Central Northeast, West Central, and All India, we observe a decrease in the mean of the annual JJAS rainfall of $3 - 5$% (see red dotted line in Figures 1b–1g).

In Figures 1b–1g we have highlighted higher quantiles, i.e., trends for $\tau \in [0.75, 0.95]$ by blue shaded vertical bands. Increase in these quantiles can indicate intensification of annual monsoonal rainfall. We observe that for the Northeast, Central Northeast, and All India time series the rainfall appears to be mostly stable in these quantiles. Meanwhile, West Central and Northwest show some decrease in rainfall intensity in these quantiles. Although for some extremely low quantiles ($\tau < 0.1$) all regions except the Central Northeast show an increase in rainfall, it is difficult to draw definitive conclusions from these features as very few data points are available for such low quantiles in the 142 year annual time series.

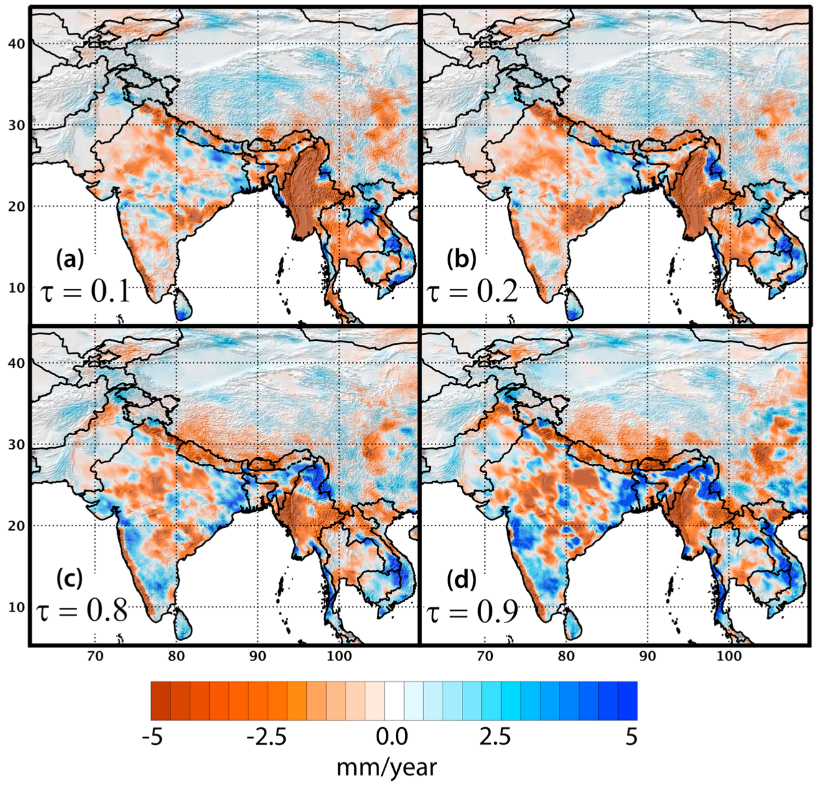

Figure 2. Trends in the *annual* JJAS rainfall based on the analysis of the spatial gridded APHRO–V1003R1 data set (1951–2007). Annual JJAS rainfall amounts (in mm) at a grid point were calculated by summing daily rainfall amounts of 122 JJAS days. Trend in the (a) 10th and (b) 20th percentile of the annual JJAS rainfall. A negative trend indicates a decrease in rainfall for these quantiles and can be associated with an intensification of droughts. Trend in the (c) 80th and (d) 90th percentile of the annual JJAS rainfall. A positive trend indicates an increase in rainfall for these quantiles which may be associated with a higher frequency and/or greater strength of intense rainfall events. To obtain net increase in mm over the entire time period of the data set (1951–2007), multiply the value given above in mm/year by 56. For further details about converting and interpreting above units for trends see Text S3.1. For comparison with other τ thresholds and data sets see Figures S3 and S4.

For the Northwest region, we observe high variability in the trends for different quantiles (Figure 1f). Lower quantiles show a massive decrease of up to 20%, while the moderate quantiles show an increase and higher quantiles show a decrease as well. The Peninsular region (Figure 1e) shows a different trend compared to all the other regions, and it appears that rainfall is either increasing or stable across all quantiles. The All India time series also shows a decrease across all quantiles, close to the decrease in the mean rainfall. The two main results of our analyses are (1) rainfall is decreasing or stable to different degrees in all the regions except peninsular India where it has increased and (2) there is an intensification of droughts in the Northwest, Central Northeast, West Central, and the Northeast.

To ascertain whether trends have shown any alterations over time, we have carried out further analysis of the six IITM-HIMR time series by estimating trends over moving time windows. We divide the time series into windows consisting of data points for 72 years with 67 year overlap between neighboring time windows (the total temporal range of each time series is 142 years) and estimate trends in two different quantiles ($\tau = 0.25$ characterizing droughts and $\tau = 0.85$ characterizing heavy rainfall) for each of these windows separately. Using this method of windowing, we lose the ability to identify any alterations in trends before 1943 (the first window's end point). To quantify any gradual temporal shifts in trends of these quantiles, we estimate slopes of linear regression line fitted to data points from years before and after 1970. Negative (positive) signs of these slopes indicate gradual decrease (increase) in percentage trend for these two quantiles (see Figure S2b). Although visual comparison gives the impression of a change point in 1970, a change-point analysis documents that none of these time series undergo a statistically significant change point (Figure S2c and explanation in the SI).

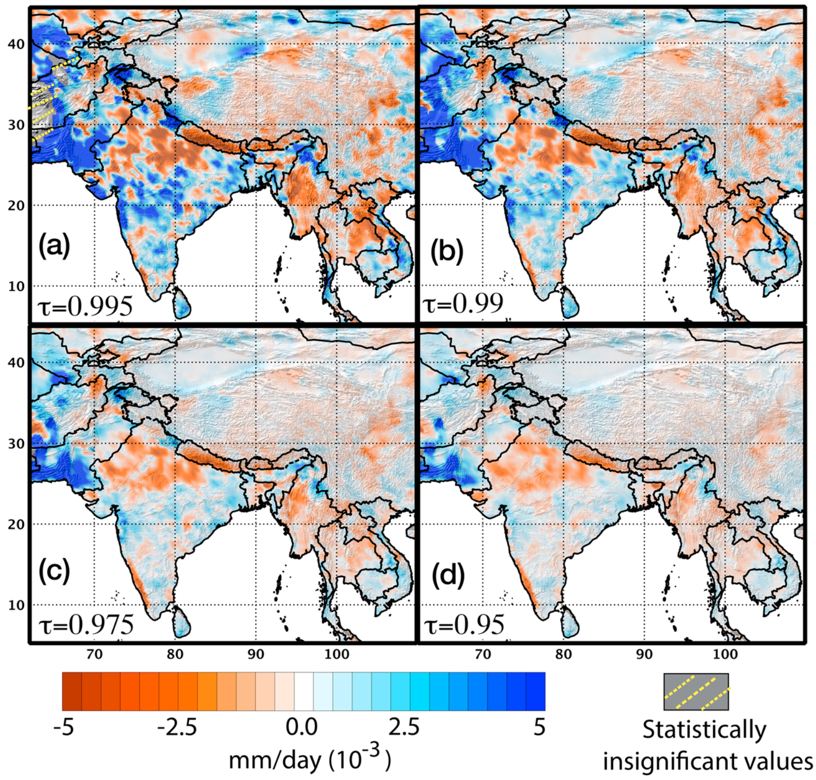

Figure 3. Trends in the extreme *daily* JJAS rainfall events based on the analysis of the spatial gridded APHRO−V1003R1 data set (1951−2007). The unit of daily rainfall in this data set is mm, and for the analysis we have used all the JJAS days (6954) available in the data set. Trend in the (a) 99.5th, (b) 99th, (c) 97.5th, and (d) 95th percentile of the daily rain events during JJAS. An increase of intense rainfall events has the potential to lead to flash floods and associated hazards. Observe the increasing trend over parts of south Pakistan, and the Northwest and Karakoram Himalaya. Trend increases can also be seen in central and eastern India and the northeast Himalaya. Baseline magnitudes (intercepts of the fitted lines) for these thresholds are available in Figure S14. To obtain net increase in mm over the entire time period of the data set (1951−2007), multiply the value given above in mm/day by 6953, i.e., one less than the total number of JJAS days in the data. See Text S3.1 for converting and interpreting above units for trends.

We observe a gradual change toward the intensification of droughts for all regions since 1970 (Figure S2). Except for the Central Northeast, every region has experienced a gradual shift from less intense to more intense droughts. For the Northwest, the Central Northeast, the West Central, and All India we also observe decreasing strength of heavy monsoonal rainfall years since 1970 (Figure S2a). These observations are indicative of some form of rainfall reduction over multiple parts of India. It has been hypothesized by *Bollasina et al.* [2011] that monsoonal precipitation over south Asia has decreased in the second half of the twentieth century, due to the slowdown of the tropical meridional overturning circulation caused by increasing aerosol emissions over the region.

In order to enhance the spatial and temporal resolution of our analysis, we present the results of our analysis of the APHRO−V1003R1 data set (see Text S2 of SI for the detailed description of the data set). This analysis is carried out at two different temporal resolutions: (i) total seasonal JJAS rainfall and (ii) daily rainfall during the JJAS season.

A decreasing trend in the lower quantiles ($\tau \leq 0.25$) of the seasonal JJAS rainfall documents intensification of drought situations at a grid point. The maximum intensification of droughts or strongest decrease in the lower quantiles of the annual JJAS rainfall are observed over parts of Myanmar, parts of Northwest India, and adjoining parts of Central India (see Figures 2a, 2b, and S1). Other notable areas showing sharp intensification of droughts are the Northwest Himalaya and the high ISM rainfall zone west of the western Ghats (west coast of India along the Arabian Sea). Some parts of Eastern and Central India also show signs of intensification of droughts. An increasing trend in the higher quantiles ($\tau \geq 0.80$) of the annual JJAS rainfall will amount to

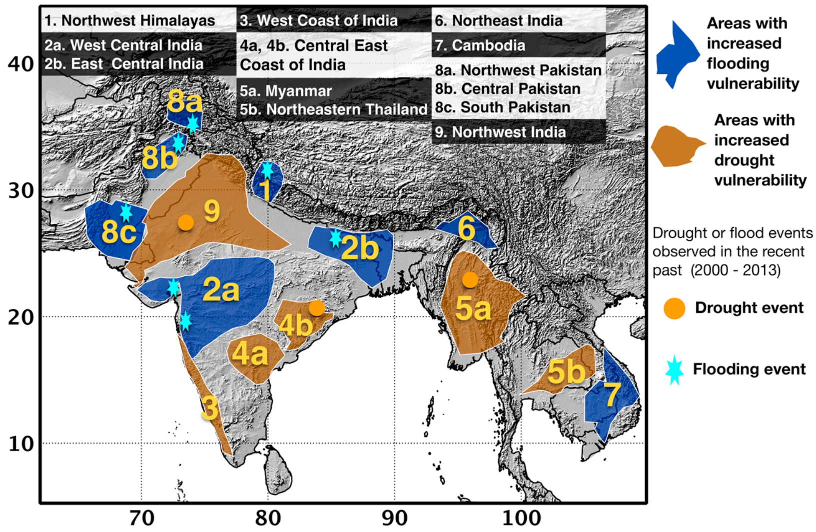

Figure 4. Synthesis showing spatial patterns of strongest rainfall trends in the extremes during the ISM season over the past 57 years. Brown regions indicate increasing trends in lower quantiles, often associated with drought conditions, while blue regions indicate areas with increasing rainfall at the higher percentiles, generally characterized by an increase in flooding. Region numbers and associated geographic regions are shown on the right. The demarcation of drought regions has also been corroborated by our observed trends (Figure 1). We use light blue (flood) stars and orange (droughts) dots to indicate particular events during the recent past (between the years 2000 and 2013). These events were either extensively studied by the scientific community or have been reported by international media coverage (see SI Table S1, Figures S12, S13, and Text S5 for additional information).

above average ISM rainfall for a grid point if the rainfall is evenly spread across four months of the JJAS season. If JJAS rainfall is not evenly distributed over the four ISM months then an increase may be associated with heavy rainfall events and related destruction of life and property. We observe an interesting pattern over parts of peninsular India with an increase in the higher quantiles of JJAS rainfall over almost the entire Indian peninsular, except over the western Ghats mountain range and regions west of them (a very high annual seasonal JJAS rainfall zone) (Figures 2c and 2d). A similar increase can be observed over Eastern and Northeast India, Northern Myanmar. There is a general decrease in annual ISM strength in the Himalaya and parts of Tibet, central Myanmar, and parts of Central and Northwest India.

To detect changes in daily intense rainfall events in the APHRO–V1003R1 data set, we analyze trends of the 0.995, 0.99, 0.975, and 0.95 quantiles (Figures 3a–3d). These quantiles represent the top 0.5%, 1.0%, 2.5%, and 5% of daily rain events, an increase in their intensity has the potential to cause large-scale flooding and may have large socioeconomic impacts. These thresholds are chosen so that a particular extreme rain event (e.g., storm) does not make a trend, but rather a trend is estimated over multiple daily rainfall events across time. We observe a sharp increasing trend in Central India, parts of South India, South and Central Pakistan, parts of Northwest Himalaya, and adjacent regions of Tibet for all of the above mentioned quantiles. In contrast, parts of Northwest India, Myanmar, Thailand, and Cambodia show a rather strong decreasing trend in such events.

In an attempt to synthesize all of our findings, we have identified regions; with the most pronounced changes in extremes during the ISM season (Figure 4). Through visual inspection of all our results (Figures 1–3, S3, and S4), we have grouped spatially contiguous grid points with approximately similar trends into regions. We have delineated regions into two groups—regions with increase in the intensity of extreme daily rainfall and regions with intensification of droughts—because these will have the largest socioeconomic impacts, as increasing strength of extreme rain events will increase chances of flash floods and increasing intensity of droughts can cause severe shortage of fresh water (additional details about steps followed in constructing Figure 4 are provided in the SI Text S5). We have also listed some of the events (droughts or floods) within the identified regions, details about these events with corresponding references are provided in Table S1. Further discussion of results is provided in Text S4.

4. Conclusion

Our study builds on previous analyses but has added important methodological advantages, leading to the following key findings:

1. Decreasing trends in lower quantiles, generally associated with an intensification of droughts, is temporally the most stable and spatially the most extensive trend observed. Both data sets used in the analysis indicate that most of continental India shows a trend toward intensification of droughts. The regions of special concern in this context are Northwest India, parts of peninsular India and Himalaya, and all of Myanmar and some other parts of Southeast Asia (see a list of drought years in Table S2).
2. Analysis of the area-averaged monthly rainfall time series from 1871 to 2012 suggests that intensity of droughts has gradually increased since 1970. This drying could be related with increasing aerosol concentration over the region [*Bollasina et al.*, 2011].
3. We have delineated regions which are most likely to be highly vulnerable to heavy rainfall events and related natural disasters, either due to increase in the higher quantiles of annual JJAS rainfall or due to increase in the intensity of extreme rainfall events. Large parts of peninsular India and parts of eastern and central India show increasing trends in the higher quantiles of annual JJAS rainfall (top 20% years of JJAS rainfall). Also, there is a significant increase in extreme rain events especially at the top 1% over central India, Pakistan, parts of south and eastern India, and parts of Northwest Himalaya.
4. Apart from spatial inhomogeneity, we also observe dissimilarity in trends in different quantiles. For example, parts of peninsular, central, and eastern India show trends toward decreasing rainfall in lower quantiles but also show increasing rainfall in the higher quantiles.
5. A spatially homogeneous trend of decreasing strength of moderate rainfall events (strongest 40% to 25% of rain events (Figure S5 and S6)) seems to be emerging in the ISM area, even on time scales of just 6 decades. Similar observations have also been reported in previous studies [*Goswami et al.*, 2006; *Rajeevan et al.*, 2008; *Dash et al.*, 2009; *Ghosh et al.*, 2012]. In this study, we further unravel the spatial scale of this trend and show that it extends beyond continental India and covers almost all of South Asia. Furthermore, we found that this trend is more prominent in the regions of higher rainfall (wetter regions).

Our study suggests that the Indian summer monsoon region is a patchwork of trends with significant local and regional differences. Some regions are characterized by an increase in ISM rainfall, while other adjacent areas show an increase of droughts. The lack of a spatially coherent trend of the Indian monsoon will require reassessment of the vulnerability and mitigation projections for this region. This study also demonstrates that the Indian monsoon system is responding in a complex fashion to global climatic forcing and that we do not anticipate to see homogeneous changes throughout the Indian monsoon domain.

Acknowledgments

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