



1     **Probabilistic seasonal outlook for the rainy season over India by monitoring**  
2             **the onset dates using GPM IMERG satellite-based precipitation**

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9

10                             **Abstract**

11

12     We utilized the Integrated Multi-Satellite Retrievals for Global Precipitation Mission version 6  
13     (IMERG) rainfall observation (available in real time) over India to determine the onset and demise  
14     of the rainy season. The annual mean climatology derived from IMERG observations over India  
15     aligned closely with the rain gauge-based India Meteorological Department observation. The  
16     IMERG rainfall time series was randomly perturbed to generate 101 ensemble members at every  
17     grid point of the rainfall analysis to obtain a corresponding ensemble of the onset and demise dates  
18     of the rainy season. The perturbations were designed to sample the uncertainty due to random  
19     synoptic or mesoscale rain events influencing the diagnosis of the onset/demise dates at the  
20     granularity of the IMERG observations (at 10 km grid). Following earlier studies, we find from  
21     the IMERG dataset that seasons with an earlier onset date are strongly related to a lengthier and  
22     wetter season, whereas seasons with a later onset date correspond to a shorter and drier season. In  
23     contrast, the connections between the onset, demise, seasonal length, and rainfall with ENSO and  
24     IOD were comparatively weaker over most of India. The generation of ensembles in this study  
25     underscores the potential for real-time application of generating reliable, probabilistic seasonal  
26     outlooks of the rainy season over India by leveraging the local links amongst onset date, seasonal  
27     length, and seasonal rainfall anomalies. This potential is further confirmed by the high probabilistic  
28     skill scores of the seasonal outlooks using the area under the relative operating characteristic curve  
29     method.

30



31 **1. Introduction**

32

33 India's water and agriculture sectors rely heavily on copious summer monsoon rainfall,  
34 emphasizing its critical role in defining the country's agrarian economy and water resource  
35 management (Gadgil and Gadgil 2006). The seasonal progression of the Indian Summer Monsoon  
36 (ISM) season has an impact not only on agricultural outputs but also on other sectors such as  
37 economy and ecology (Lal 2000). Based on rainfall patterns and wind conditions, the India  
38 Meteorological Department (IMD) officially declares the date of monsoon onset over Kerala  
39 (MoK) each year. In a normal year, the ISM season begins in southern peninsular India on June 1<sup>st</sup>  
40 (with MoK), spreads throughout the country by mid-July, and then begins to retreat on September  
41 1<sup>st</sup> (Pai et al. 2020).

42

43 There are many different definitions for the monsoon onset; however, it is typically considered as  
44 a quick, substantial, and prolonged increase in rainfall after May 10th (Pai and Rajeevan 2009). In  
45 addition to the rainfall-based definitions (e.g., Ananthakrishnan and Soman 1988; Noska and Misra  
46 2016; Misra et al. 2017b), several other atmospheric dynamical and thermodynamical variables  
47 (winds, outgoing longwave radiation, temperature, moisture flux convergence, and precipitable  
48 water) were utilized to identify the onset of summer monsoon rainfall (Fasullo and Webster 2003;  
49 Zeng and Lu 2004; Prasad and Hayashi 2005; Joseph et al. 2006; Wang et al. 2009; Walker and  
50 Bordoni 2016; Stolbova et al. 2016). These variables provide a comprehensive understanding of  
51 the atmospheric conditions and dynamics that influence the onset and seasonal total rainfall over  
52 India. All these approaches produce somewhat identical onset dates, but their connections with the  
53 local-scale onset of the rainfall during the ISM differ (Moron and Robertson 2014; Noska and  
54 Misra 2016).

55

56 Owing to variations in the onset and demise date of the monsoon season there are considerable  
57 spatial and temporal variations in the availability of the rainwater and length of the rainy season  
58 over India (Joseph et al. 1994; Lal 2000; Wang et al. 2002; Misra et al. 2017a; Misra et al. 2018).  
59 Preenu et al. (2017) indicate from IMD archive that the earliest start of the ISM was May 11, 1918,  
60 and the most delayed onset was Jun 18, 1972. Several studies discuss the interannual variability of  
61 onset dates in India and its teleconnection with El Niño and the Southern Oscillation (ENSO) and



62 the Indian Ocean Dipole (IOD, Xavier et al. 2007; Sankar et al. 2010; Misra et al. 2017a; Pradhan  
63 et al. 2017; Choudhury et al. 2021). In ENSO and IOD years, the monsoon onset is altered by the  
64 modulation of the teleconnections with SST anomalies in the tropical oceans, which affect the  
65 Walker and Hadley circulations, respectively (Pradhan et al. 2017). Significant changes in the  
66 large-scale atmospheric patterns over the monsoon areas are identified during the onset of the  
67 monsoon over India (Joseph et al. 1994). According to Wang et al. (2013), the Interannual  
68 variations in ocean-atmosphere interaction processes significantly influence the association  
69 between the monsoon onset and ENSO, which is driven by the meridional SST gradient across the  
70 Indian Ocean. Noska and Misra (2016) show that the variations in the onset and demise date of the  
71 rainy season over India that largely overlaps with ISM are linked to the variability of the cross-  
72 equatorial upper-ocean heat transport in the Indian Ocean, variations in large-scale atmospheric  
73 and oceanic circulations, and regional ocean-atmosphere thermal gradients.

74

75 It may be noted that we make a subtle distinction between the ISM and rainy seasons, with the  
76 latter solely determined by rain rates (e. g., Noska and Misra 2016) while the former is additionally  
77 influenced by circulation features and other thermodynamic factors. Figure S1 highlights the  
78 difference between the variable season and fixed southwest monsoon season (June to September),  
79 which makes it evident that the variable season accumulates more rainfall in southern peninsular  
80 India and in regions east of the central monsoon region. Similarly, when compared to the fixed  
81 season, the variable season has higher total rainfall over both western and northern India. Notably,  
82 pre-monsoon rainfall and rainfall from pre-monsoon and post-monsoon tropical cyclones are also  
83 included in the rainy season defined here, and they significantly contribute to the annual rainfall.  
84 Pre- and post-monsoon tropical cyclones can contribute up to 25% of the yearly rainfall in some  
85 parts of India, even though the southwest monsoon is the main rainy season (Khouakhi et al. 2017).

86

87 The information about the arrival of the monsoon rainfall is imperative for farmers to plan their  
88 strategy for the upcoming season. There are many attempts to predict the MoK (Kung and Shariff  
89 1980; Rajeevan and Dubey 1995; Pai and Rajeevan 2007; Pradhan et al. 2017). But many studies  
90 have shown that variations of the MoK have very little influence on the seasonal rainfall anomalies  
91 of the ISM (Dhar et al. 1980; Mooley and Parthasarthy 1984; Mooley and Shukla 1987; Misra and  
92 DiNapoli 2014). Furthermore, MoK is known to have insignificant relationship with subsequent



93 progression of the onset isochrones of the ISM (Bansod et al. 1991; Fasullo and Webster 2003; Pai  
94 and Rajeevan 2007). Noska and Misra (2016) proposed an objective method to define the onset  
95 and demise of the rainy season based on area averaged all India daily rainfall, and they found that  
96 seasonal mean anomalies are closely linked with variations in the onset and demise dates. In a  
97 following study, Misra et al. (2018) obtained onset (demise) dates of the Indian rainy season at the  
98 granularity of the rainfall analysis and showed that they are negatively (positively) correlated with  
99 seasonal rainfall anomalies across the Indian region. These studies suggest that monitoring the  
100 onset date provides a good indication of the evolution of the seasonal length and rainfall of the  
101 forthcoming rainy season. Bhardwaj and Misra (2019) found that Remotely Sensed Rainfall  
102 Products such as Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation  
103 Analysis (TMPA) produce onset and demise dates similar to IMD observations. This simple  
104 rainfall-based definition was found useful for monitoring the onset in real-time and issuing the  
105 seasonal outlook over various regions such as Florida (Misra et al. 2022), and Central America  
106 (Rodgers et al. 2024).

107

108 Many studies have used the IMERG data set as one of their primary dataset for the analysis of the  
109 ISM (Bushair et al. 2019; Thakur et al. 2020; Saikrishna et al. 2021; Phadtare et al. 2023). In this  
110 study, we employ a rainfall-based objective method to define the onset and demise of the rainy  
111 season, leveraging the high-resolution IMERG dataset available since January 2001. Utilizing its  
112 12-hour latency product, we demonstrate the potential for real-time monitoring of the onset of the  
113 rainy season, which aids in anticipating the anomalies of the seasonal length and seasonal rainfall  
114 across India. Motivated from the grid-point level onset and demise dates established by Misra et  
115 al. (2018) and Bhardwaj and Misra (2019), this study advances this framework by how the IMERG  
116 12-hour latency product can be effectively used to monitor these parameters at fine spatial scales,  
117 enabling better anticipation of anomalies of the seasonal length and seasonal rainfall. In addition,  
118 the novelty of this work lies in the use of a perturbation technique applied to rainy season following  
119 Misra et al. (2023) and Rodgers et al. (2024) to generate 101 ensembles of daily rainfall data. This  
120 approach is the first of its kind over the Indian region and allows us to define the onset and demise  
121 dates, providing a probabilistic estimate of the evolution of the rainy season that accounts for  
122 observational and analysis uncertainties.

123



124 Additionally, this study explores the interannual variation of the evolution of the rainy season and  
125 its link to large-scale forcing such as ENSO and IOD and compares their viability as predictors of  
126 the rainy seasons to the local links we establish with the variations of the onset dates. We believe  
127 that the insights from this study will have significant potential applications in agricultural planning  
128 and water resource management.

129

## 130 **2. Data and Methodology**

### 131 **2.1 Data**

132 The analysis performed in this study utilized daily precipitation data from the IMERG version 6  
133 (Huffman et al. 2019). This dataset is part of the Global Precipitation Measurement (GPM)  
134 mission, which was launched in 2014 and is co-operated by NASA and the Japan Aerospace  
135 Exploration Agency (JAXA). The  $0.1^\circ$  grid resolution ( $\sim 10$  km) IMERG data are available at half-  
136 hourly intervals from June 2000 to the present. The dataset comprises early, late, and final run  
137 products, which have latencies of approximately 4 hours (Early), 12 hours (Late), and 3.5 months  
138 (Final). The IMERG late run incorporates data from multiple sources, such as satellite microwave  
139 and infrared estimations, precipitation gauge analysis, and other potential precipitation estimators.  
140 This dataset provides detailed temporal and spatial coverage for both the TRMM and GPM eras  
141 worldwide. However, in this study, we used the daily 12-hour latency product (daily averages were  
142 estimated from half-hourly products), which has great potential for monitoring the rainy season in  
143 real-time. To assess the fidelity of the IMERG product over India we have used rain gauge-based  
144 IMD gridded rainfall data for the period 2001 - 2023 at  $0.25^\circ \times 0.25^\circ$  resolution (Pai et al. 2014)  
145 as a validation dataset. Additionally, we defined the onset and demise dates and compared them  
146 with the IMERG using the daily NOAA Climate Prediction Center (CPC) precipitation data set  
147 (Xie et al. 2007).

148

### 149 **2.2 Methodology**

#### 150 **2.2.1 Onset and Retreat**

151 This study uses a simple objective definition to identify the onset and cessation dates of the wet  
152 season over India which are determined by finding the minima and maxima of the cumulative  
153 rainfall anomaly curve (Liebmann and Marengo 2001). For a year  $i$ , the cumulative anomaly of  
154 the daily rainfall at a day  $j$  (*i.e.*,  $C_i(j)$ ) at each grid point is estimated as;



155

156

$$C_i(j) = \sum_{j=1}^J (R_i(j) - \bar{R}) \text{ ----- (1)}$$

157

158 where  $R_i(j)$  is the rainfall for the day  $j$ ,  $\bar{R}$  is the climatology of the annual mean rainfall. The  $C_i(j)$   
 159 for 365/366 days in a year represents the cumulative rainfall anomaly curve. After the onset and  
 160 demise dates of the season are determined, we estimate the number of days between them to define  
 161 the seasonal length. Seasonal rainfall refers to the daily rainfall that accumulates from the day of  
 162 onset date to the demise date.

163

164 **2.2.2 Perturbation**

165 The motivation to perturb the timeseries is to account for the uncertainty of random synoptic or  
 166 mesoscale events that is potentially unrelated to the seasonal cycle, which could affect the  
 167 diagnosis of the onset/demise date of the rainy season. The threat of false diagnosis of onset/demise  
 168 dates of the rainy season is acute from the proposed methodology since this diagnosis is computed  
 169 at the granularity of the rainfall analysis. Therefore, generating an ensemble of onset/demise dates  
 170 of the rainy season that accounts for this uncertainty is essential. The perturbations are generated  
 171 randomly by replacing the rainfall of each day in the original timeseries for a given grid point by  
 172 rainfall in the range of  $\pm 3$  days. The range of  $\pm 3$  days used in the generation of the perturbed  
 173 timeseries covers the uncertainty in the occurrence of the synoptic (1 to 7 days) to meso-scale (1  
 174 to 3 days) rain features of the rainy season. In this manner, an ensemble of 101 (100 perturbations  
 175 + 1 original) timeseries are generated. The diagnosis of the onset/demise date of the rainy season  
 176 will converge or diverge amongst the ensemble members if it is found to be insensitive or sensitive  
 177 to these random rain events, respectively.

178

179 **2.2.3 Signal-to-noise Ratio**

180 We estimated the signal-to-noise ratio of the four quantities by utilizing the 101 ensemble  
 181 members.

182

$$S_{noise}^2 = \frac{1}{A(B-1)} \sum_{a=1}^A \sum_{b=1}^B (X_{ab} - \bar{X}_b)^2 \text{ ----- (2)}$$

183

$$S_{signal}^2 = S_{em}^2 - \frac{1}{b} S_{noise}^2 \text{ ----- (3)}$$



184 Where,  $X$  belongs to any of the four quantities such as onset date, demise date, seasonal length,  
185 and seasonal rainfall anomalies,  $a$  and  $b$  are indices for  $A$  years and  $B$  ensemble members,  
186 respectively.

$$187 \quad S_{em}^2 = \frac{1}{(A-1)} \sum_{a=1}^A (\bar{X}_a - \bar{\bar{X}})^2,$$

$$188 \quad \text{And } \bar{X}_a = \frac{1}{(B-1)} \sum_{b=1}^B X_{ab}, \quad \bar{\bar{X}} = \frac{1}{(A-1)} \sum_{a=1}^A \bar{X}_a,$$

189 The signal-to-noise ratio is then given by:

$$190 \quad ratio = \frac{S_{signal}^2}{S_{noise}^2}$$

191 When  $ratio < 1$  then it indicates that noise (or chaotic variations) is dominant, and the signal  
192 dominates when  $ratio > 1$ . A strong signal indicates that perturbing the rainfall time series will  
193 not substantially influence the diagnostics of the onset date, demise date, seasonal length, and  
194 seasonal rainfall anomalies.

195

#### 196 **2.2.4 Significance test**

197 In this study, we first estimate the two-tailed p-values of the correlation coefficients using the t-  
198 statistic. Further, following Benjamini and Hochberg (1995), we conduct a test for false rejection  
199 on all temporal correlations to assess its robustness, which is necessary because of the large number  
200 of simultaneous statistical significance tests conducted across all grid points of the domain. This  
201 process involves adjusting the p-value (Benjamini and Hochberg 1995) to control the false  
202 rejection of the null hypothesis, also known as the false discovery rate. By controlling the false  
203 discovery rate, we enhance the confidence in the significance of the findings.

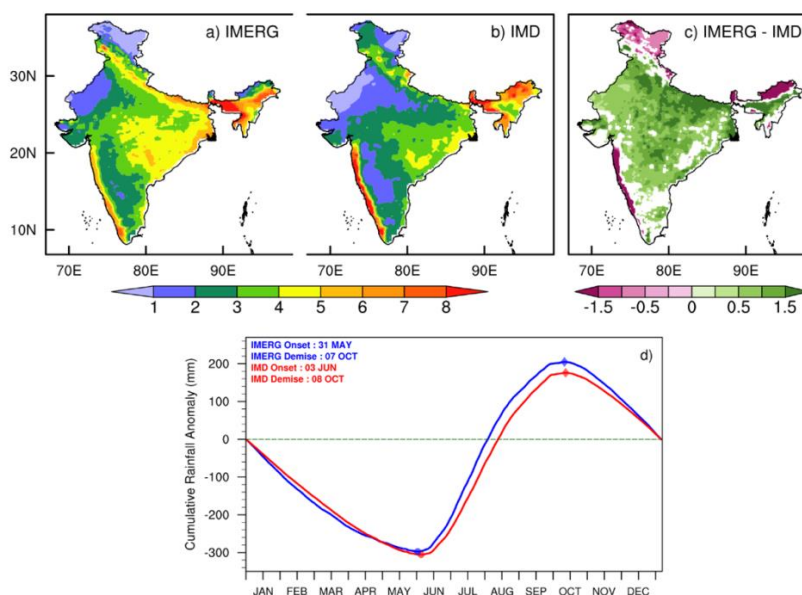
204

### 205 **3. Results**

206 The seasonal mean rainfall over India observed from IMERG is found to be comparable with IMD  
207 observation and superior to other satellite products over the region (Saikrishna et al., 2021). This  
208 is further confirmed in Figs. 1a-c which compares the 23-year annual mean rainfall climatology  
209 between IMERG observations and the corresponding IMD rainfall dataset. It may be noted that in  
210 Equation (1), the annual mean rainfall climatology ( $\bar{R}$ ) at each grid point is used to determine  
211 onset dates and demise dates of the rainy season over India (e.g., Misra et al., 2018). Overall, the



212 annual mean rainfall climatology from IMERG compares well with the IMD rain gauge dataset.  
213 However, the overestimation of rainfall in the Indo-Gangetic plains and parts of northeast India  
214 and underestimation of rainfall over the northern Western Ghats, northern sections of northeast  
215 India, and the bulk of Jammu and Kashmir by IMERG relative to IMD dataset is apparent (Fig. 1).  
216 Bushair et al., (2019) noted that IMERG underestimates the rainfall over high-altitude regions  
217 compared to IMD observations, which are rain gauge based. Further, Fig. 1d shows the cumulative  
218 rainfall anomaly curve generated from the 23-year (2001 - 2023) daily rainfall climatology area  
219 averaged over all of India for IMERG (blue) and IMD (red) observations. The onset (inflection at  
220 the nadir of the cumulative anomaly curve) and demise (inflection at the zenith of the cumulative  
221 anomaly curve) dates estimated from IMERG and IMD closely match each other, with the onset  
222 dates being 31<sup>st</sup> May and 3<sup>rd</sup> June, and the demise dates being 7<sup>th</sup> October and 8<sup>th</sup> October,  
223 respectively.  
224



225  
226 **Figure 1:** Spatial pattern of the 23-year climatology of the mean annual rainfall during the period  
227 2001-2023 from a) IMERG observation, b) IMD observation, and c) the difference between the  
228 IMERG and IMD (only differences significant at 5% percentile level on t-test is shaded). d) The  
229 cumulative rainfall anomaly curve generated from the 23-year daily rainfall climatology of

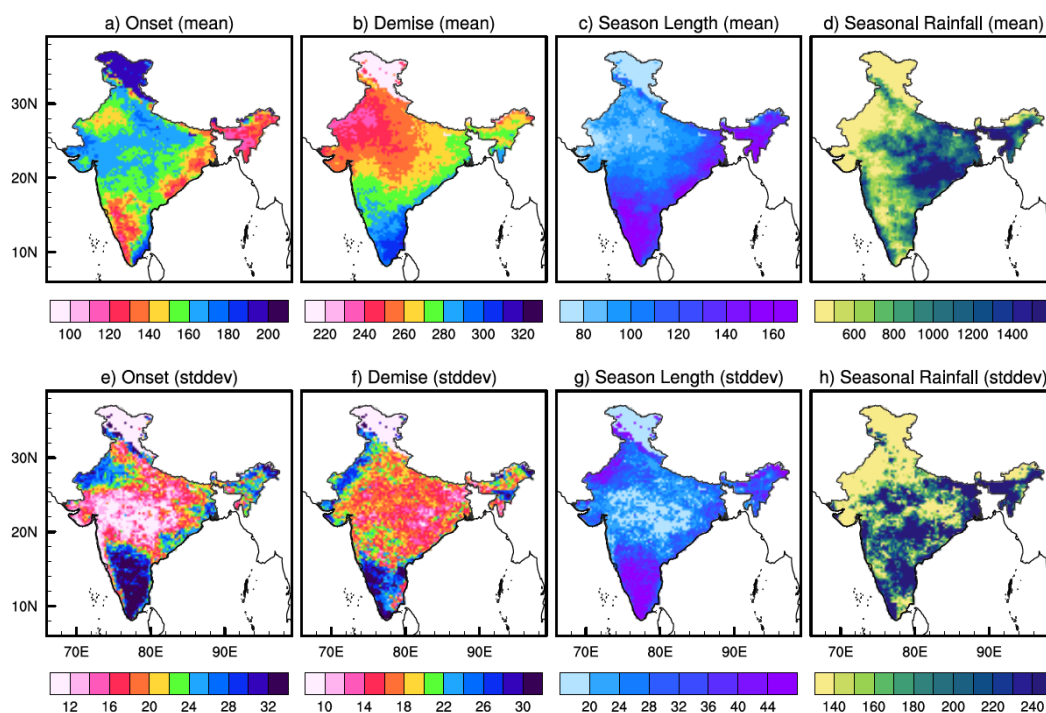




230 *IMERG (blue) and IMD (red) observations. The onset dates (filled circles) and demise dates (filled*  
231 *diamonds) obtained from both datasets are marked.*

232

233 Figures 2a-d depict the 23-year local climatological onset date, demise date, seasonal length, and  
234 seasonal accumulated rainfall from IMERG, with the associated standard deviation displayed in  
235 Figs. 2e-h. The spatial distribution of the climatology of the onset dates (Fig. 2a) shows the earliest  
236 onset occurs over northeast regions of India followed by southern Kerala, and then it gradually  
237 advances to the other parts of the country and looks like the typical isochrone evolution of the ISM  
238 (Ramage 1971; Rao 1976; Janowiak and Xie 2003). The delayed onset occurs over the east coast  
239 of Tamil Nadu followed by Jammu and Kashmir. The onset dates over Kerala and adjacent regions  
240 mostly start from early May and do not coincide with the MoK, and this is because this  
241 methodology probably detects the onset dates early due to strong and continuous spells of pre-  
242 monsoon rainfall. Similarly, the earliest withdrawal (Fig. 2b) of the ISM occurs over northwestern  
243 India such as Rajasthan, Punjab, Haryana, and Himachal Pradesh. The demise date is delayed over  
244 southern peninsular India, with the most delayed demise occurring over the southeast coast of  
245 Tamil Nadu. The seasonal length (Fig. 2c) is shorter in the west and northwest regions of India,  
246 with the shortest season in Jammu and Kashmir. The longer season over the peninsular India, as  
247 well as the coastal regions of Odisha and West Bengal, is linked to the season's earlier start date.  
248 The spatial distribution of the seasonal accumulated rainfall (Fig. 2d) closely follows the typical  
249 seasonal mean ISM distribution. The standard deviation patterns of the onset dates show central  
250 parts of India have less variability than other regions, such as southern peninsular India, northeast,  
251 and northwest regions. Similar patterns of variability are observed in the demise dates and seasonal  
252 length with the largest variations found over southern peninsular India and northwest India and  
253 least over central India. On the other hand, the seasonal rainfall exhibits a significant range of  
254 variability across most of India, whereas comparatively less variability is observed over Rajasthan  
255 and Jammu and Kashmir.



256

257 **Figure 2:** The climatological a) onset date (Julian day), b) demise date (Julian day), c) seasonal  
258 length, and d) seasonal accumulated rainfall (mm) of the rainy season from IMERG. The  
259 corresponding standard deviation of e) onset date (days), b) demise date (days), c) seasonal length  
260 (days), and d) seasonal accumulated rainfall (mm).

261

262 The IMERG dataset, with its 23-year record, was compared to the IMD and CPC datasets spanning  
263 1979–2023 (limited to this period in order for CPC and IMD to have a common period) to evaluate  
264 onset and demise dates, seasonal length, and seasonal accumulated rainfall of the rainy season over  
265 India (Fig. S2). The motivation to carry out this comparison is to establish that a 23-year record of  
266 IMERG is comparable to a longer record of dataset available from the other two sources besides  
267 examining its fidelity.

268

269 It is apparent from Fig. S2 that the spatial patterns of the climatological onset and demise dates,  
270 seasonal length and rainfall in IMERG is comparable to corresponding climatologies from IMD  
271 and CPC datasets. There is however a tendency for IMERG to have a bias of a slightly earlier onset  
272 of the rainy season compared to IMD and CPC, particularly over southern peninsular India,



273 including Kerala and Tamil Nadu (Fig. S2a-c). Similar inference is observed in Rajasthan, coastal  
274 Odisha and West Bengal, and few isolated grid points over other regions. In contrast, over Jammu  
275 and Kashmir, IMERG exhibits a noticeably delayed onset, which makes us unsure about the results  
276 over this area. Similarly, IMERG display a systematic bias of slightly later demise dates along the  
277 Western Ghats, but overall, the rainy season demise dates are consistent across datasets (Fig. S2d-  
278 f). As a result, IMERG's rainy season seems to last longer than the other two datasets in some of  
279 these locations (Fig. S2g-i). Again, in terms of seasonal accumulated rainfall (Fig. S2j-l), IMERG  
280 overestimates precipitation compared to IMD and CPC in some of these locations. However,  
281 rainfall over the Western Ghats exhibits stronger gradients and is underestimated in IMERG while  
282 it exhibits more rainfall over western central India and Tamil Nadu than the other two datasets.

283

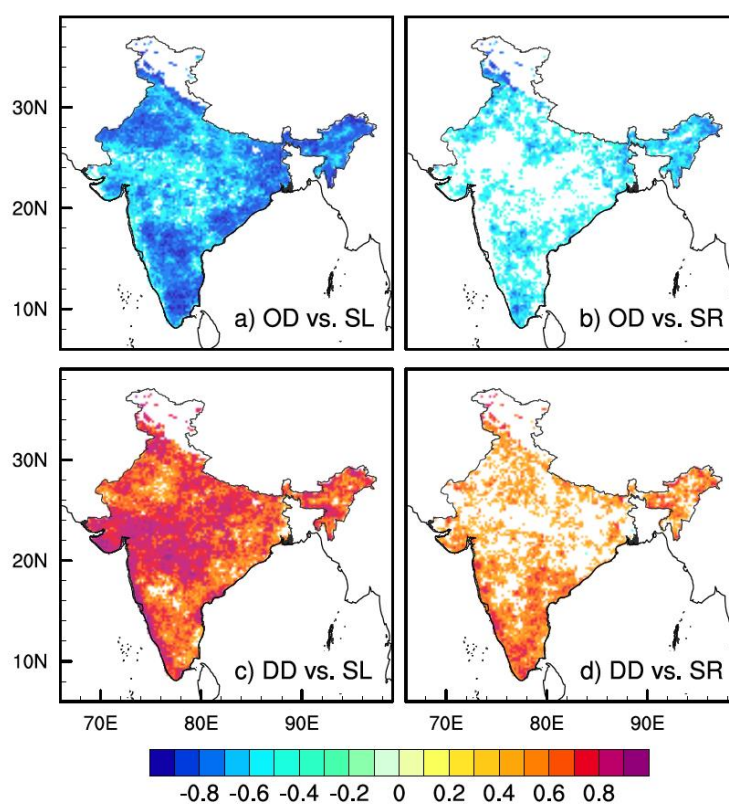
284 The interannual variability of these variables in IMERG also appear to be comparable to the other  
285 two datasets, especially in their spatial gradients (Fig. S3). There are however instances of some  
286 differences in the datasets. For example, over central India, the standard deviation of seasonal  
287 rainfall is significantly overestimated in IMERG compared to IMD (Fig. S3j-l), even though the  
288 demise dates (Fig. S3d-f) and seasonal length (Fig. S3g-i) exhibit less variability in IMERG. The  
289 discrepancies observed in IMERG can likely be attributed to the choice of the 12-hour latency  
290 product, which is an early version with limited calibration against ground-based observations, its  
291 shorter temporal coverage of 23 years, compared to the 45 years of data used for IMD and CPC.  
292 Despite these limitations, which seem to be tolerable for the applications of this study (compare  
293 Figs. 1, S2, and S3) we are inclined to used IMERG because of the potential for real-time  
294 applications.

295

296 The primary motivation to monitor the local onset and demise of the ISM is its significant  
297 interannual variations and spatial variability. Both the variation in seasonal length and seasonal  
298 rainfall are crucial in determining the nature of the ISM (Xavier et al. 2007; Sperber and  
299 Annamalai 2014). The correlation of the onset date with the seasonal length shows a significant  
300 negative correlation across India except in some parts of central India and Jammu and Kashmir  
301 (Fig. 3a). This negative correlation suggests that an early or later onset date is likely to be  
302 associated with a longer or a shorter rainy season, respectively. Only the correlations significant  
303 at a 5% level are shaded in Fig. 3. Similarly, early onset is associated with a wetter season, while



304 a delayed onset is linked with a drier season (Fig. 3b). However, the grid points showing significant  
305 correlation are fewer in Fig. 3b compared to Fig. 3a. The correlations of the demise date with  
306 seasonal length (Fig. 3c) and seasonal rainfall anomalies (Fig. 3d) show that later or early demise  
307 of the wet season corresponds to a longer and wetter season, whereas an earlier demise corresponds  
308 to shorter and drier seasons. However, the demise date may not be a useful predictor for the rainy  
309 season because it occurs when the rainy season ends. Figure 3e shows that onset and demise dates  
310 are largely uncorrelated, implying that their variations are independent of each other. These  
311 outcomes imply that the onset date alone can be a useful predictor for the outlook of the seasonal  
312 length and the seasonal rainfall anomaly of the forthcoming season.  
313

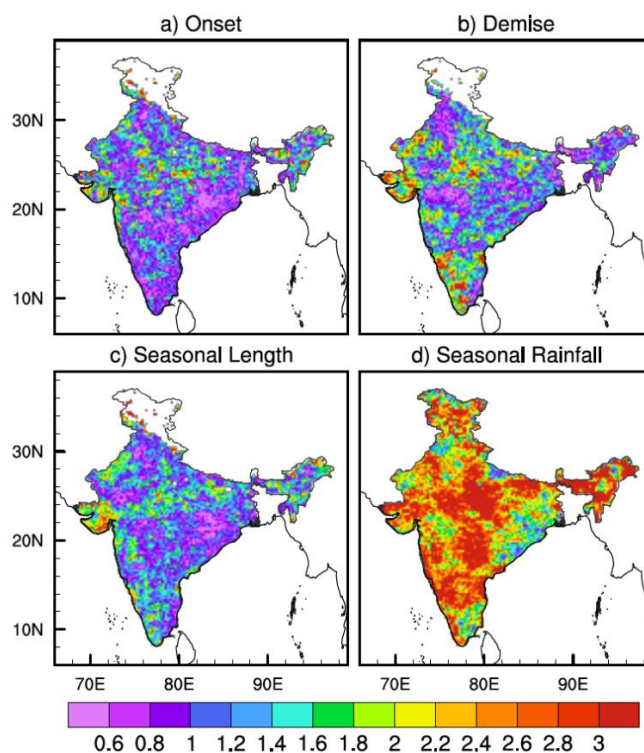


314  
315 **Figure 3:** The correlation coefficients of the onset date (OD) with a) seasonal length (SL), and b)  
316 seasonal rain (SR). Similarly, the correlations of DD with c) SL and d) SR. The shading indicates  
317 statistical significance at a 5% significance level according to the t-statistic, following false  
318 discovery rate testing as described by Benjamini and Hochberg (1995).



319

320 We estimated the signal-to-noise ratio on the four variables of onset and demise dates, seasonal  
321 length, and rainfall by utilizing the 101-member ensemble of time-series data. This analysis  
322 examines the spread across ensemble members and informs on the uncertainty of the diagnosis to  
323 random rain events. The signal-to-noise ratio for onset dates (Fig. 4a) shows that noise dominates  
324 in many places, particularly in peninsular India and the eastern half of central India. These low  
325 signal-to-noise ratio regions suggests that onset dates of the rainy season are not very strongly tied  
326 to the seasonal cycle and predicting the onset dates in these places becomes challenging and less  
327 reliable. In contrast, the signal-to-noise ratios for demise dates (Fig. 4b) are typically more than  
328 one over most grid points. This indicates greater certainty for demise dates, particularly in areas  
329 like Kerala, coastal Karnataka, and Gujarat, where the ratios are comparatively higher than one. In  
330 the case of the seasonal length, signal dominates over noise with a signal-to-noise ratio above 1  
331 over most areas (Fig. 4c). Compared to the other variables, seasonal rainfall generally shows much  
332 higher signal-to-noise ratios ( $> 1$ ) across most of the grid points. This result is obvious given the  
333 fact that seasonal rainfall is an aggregate of the daily rainfall over the entire rainy season, while  
334 the onset and demise dates are single days of the season when they are diagnosed. Therefore, there  
335 is a tendency for the cancellation of the noise in the aggregation of the daily rainfall to seasonal  
336 rainfall, which yields a higher signal-to-noise ratio.



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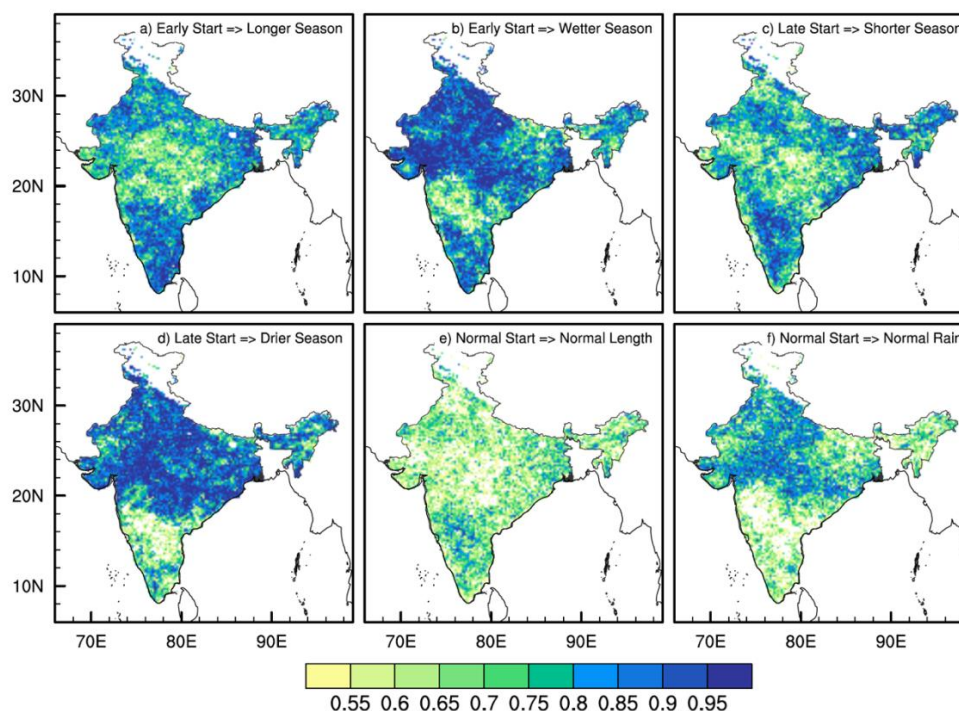
338 **Figure 4:** The 23-year climatology of the signal-to-noise ratio of a) onset date, b) demise date, c)  
339 seasonal length, and d) seasonal rainfall estimated based on the 101 ensemble members.

340 Further, we examined the probabilistic skill of the seasonal outlook by using the Area Under the  
341 relative operating characteristic (ROC) Curve (AUC) method. The AUC method is widely used to  
342 assess the skill of seasonal climate predictions (Mason and Graham 2002; Misra 2004; Narotsky  
343 and Misra 2021). Previous studies have shown that this method is useful for evaluating the  
344 probabilistic skill of predicting anomalous seasons based on anomalous onset dates of the rainy  
345 season (e.g. Rodgers et al 2024). We categorized the onset date, seasonal length, and seasonal  
346 rainfall into terciles (23-years divided into three groups): the lower tercile represents an early onset,  
347 shorter season, and drier conditions; the upper tercile signifies a delayed onset, longer season, and  
348 wetter conditions; and the middle tercile indicates normal onset, length, and seasonal rainfall. We  
349 then created a contingency table (Table S1) to assess the probability of categorical forecasts. This  
350 table evaluates how often an early or late onset is linked with a shorter or longer season and with





351 drier or wetter conditions, respectively. In addition, we also consider the effects of normal onset  
352 on normal length and seasonal rainfall.



353  
354 **Figure 5:** The probabilistic skill score as measured by the Area Under the relative operating  
355 characteristic Curve (AUC) for early start (lowest tercile) season associated with a) longer  
356 (highest tercile) and b) wetter (highest tercile) season, late start (highest tercile) season associated  
357 with c) shorter (lowest tercile) and d) drier (lowest tercile) season, and normal (middle tercile)  
358 start season associated with e) normal (middle tercile) seasonal length and f) normal (middle  
359 tercile) seasonal rain. The AUC above 0.5 is shaded.

360

361 The probabilistic skill scores derived from the AUC method are shown in Fig. 5. Here, only grid  
362 points with AUC values  $\geq 0.5$  are shaded, as these points indicate skillful seasonal outlooks that  
363 outperform random predictions (Mason and Graham, 2002). The seasons with an early start and  
364 longer season (Fig. 5a) show the most skill ( $>0.9$ ) over peninsular India, northwest India, and some  
365 parts of northeast India. Similarly, the early start of the season, along with the wetter season (Fig.  
366 5b), results in high skill levels across most parts of India except the majority of Maharashtra and



367 north interior Karnataka. The late start and associated shorter seasons shown in Fig. 5c exhibit the  
368 highest skill score over some parts of peninsular India. The late start with the drier season also  
369 resulted in high skill scores across most of the areas except Kerala, Tamil Nadu, Karnataka and  
370 Andhra Pradesh. The anomalous seasons (Fig. 5a-d) demonstrate higher skill levels across India  
371 compared to the normal seasons (Fig. 5e-f). This is due to the leveraging of the linear relationships  
372 of the onset date variations with the rainy season variations (Figs. 3a and b). In contrast, seasons  
373 with a normal start of the rainy season exhibit lower AUC skill scores (Figs. 5e and f) across most  
374 grid points relative to the anomalous start of the rainy seasons (Figs. 5a-d). However, the skill  
375 scores for a normal start with normal rainfall (Fig. 5f) are slightly better than those for a normal  
376 start with normal length (Fig. 5e). In summary, the behavior of the forthcoming season is more  
377 predictable if the onset date is early or delayed than the normal. It is easy to adopt this methodology  
378 for real-time applications. The evolution of the daily cumulative anomaly curve of rainfall could  
379 be monitored in real-time to find the minima in the curve as the onset date. However, to avoid  
380 misdiagnosing the onset date of the rainy season, one could wait for a period of time after this  
381 diagnosis (typically a week) to confirm that the minima were indeed reached to declare the onset  
382 date. Once the onset date is diagnosed then one could use the linear relationships shown in Fig. 3  
383 to develop a seasonal outlook for the rainy season. This is done routinely in Florida (Misra et al.  
384 2022). With the availability of the merged IMERG estimates with the rain-gauge based IMD  
385 rainfall following Mitra et al., (2009) our proposed methodology could be adopted for real-time  
386 applications over India.

387

388 Further, we investigated the interannual variability of the onset dates over India and its association  
389 with ENSO (Figure S4) and the Indian Ocean Dipole (IOD) variations (Figure S5). In comparison  
390 to Figure 3, Figures S4 and S5 failed the BH test suggesting the lack of robustness in the  
391 teleconnections of the rainy season variations with either ENSO or IOD. In light of these results,  
392 the significance of the reliability of the seasonal outlook shown in Figure 5 assumes greater  
393 significance. Furthermore, the monitoring of the observations of the evolution of the rainy season  
394 to diagnose the onset dates seems an attractive approach with the relatively lower signal-to-noise  
395 ratio of the onset date of the rainy season shown in Figure 4a relative to the seasonal length in  
396 Figure 4c or seasonal rainfall in Figure 4d. We are then able to leverage a low signal-to-noise ratio





397 quantity like the onset date of the rainy season to provide a seasonal outlook of relatively higher  
398 signal-to-noise ratio quantities of seasonal length and rainfall.

399

#### 400 **4. Summary and Concluding Remarks**

401 The seasonal prediction of the Indian rainy season is a considerable challenge given its complex  
402 spatio-temporal variations. In this study, we offer a simple and reliable technique for seasonal  
403 outlook of the rainy season, which is viable for real-time applications as well. Using precipitation  
404 estimates of IMERG version 6 over India at 10km grid, we generate an ensemble of 101 members  
405 from randomly perturbing the series to assess the uncertainty of the diagnosed onset/demise dates  
406 of the rainy season to random synoptic-meso scale rain events unconnected to the seasonal cycle.

407

408 We verified the IMERG rainfall observations against gauge-based IMD observations. The mean  
409 annual rainfall climatology of IMERG closely matches that of the IMD. However, IMERG tends  
410 to underestimate mean annual rainfall in high-altitude regions and overestimate it in the Indo-  
411 Gangetic plains. Further, we examined the relationships between the onset and demise dates with  
412 seasonal length and rainfall and discovered that variations in onset and demise dates of the rainy  
413 season across India have a significant impact on the seasonal length and the seasonal rainfall  
414 variations of the rainy season. It is found that an earlier onset date of the rainy season is strongly  
415 related to a longer and wetter season, whereas a later onset date corresponds to a shorter and drier  
416 season. However, the relationship between the onset, demise, seasonal length, and rainfall with  
417 large-scale climate drivers such as ENSO and IOD is comparatively weaker in major parts of India.  
418 This study shows that by estimating the onset date of the rainy season alone we can effectively  
419 provide a reliable seasonal outlook for both the seasonal length and total rainfall of the upcoming  
420 season by exploiting the existing local relationships. The probabilistic skill scores presented in this  
421 study also demonstrate that this method has a high potential for providing seasonal outlooks for  
422 the forthcoming season. These seasonal outlooks have numerous potential applications, and many  
423 local communities could greatly benefit from them. The proposed methodology for the seasonal  
424 outlook of the rainy season over India could be easily adapted for real-time applications with the  
425 current availability of IMERG rainfall products in real-time.

426

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429

#### 430 **Code/Data Availability**

431 The IMERG rainfall dataset is available from the NASA GES DISC

432 ([https://gpm1.gesdisc.eosdis.nasa.gov/data/GPM\\_L3/GPM\\_3IMERGDL.06/](https://gpm1.gesdisc.eosdis.nasa.gov/data/GPM_L3/GPM_3IMERGDL.06/)). The India

433 Meteorological Department rainfall data set used for the analysis in this study is available at

434 [https://www.imdpune.gov.in/cmpg/Griddata/Rainfall\\_25\\_NetCDF.html](https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html). The daily CPC data is

435 obtained from <https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html>. The Python and NCL

436 codes used for the analysis can be provided by the corresponding authors upon request.

437

#### 438 **Author contribution**

439 The study was conceptualized by CBJ and VM. CBJ carried out the analysis and validation and

440 prepared the original manuscript. VM supervised the work, acquired funding, and reviewed and

441 edited the manuscript.

442

#### 443 **Competing interests**

444 The authors declare that they have no conflict of interest.

445

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