



1 On the regional-scale streamflow variability using flow 2 duration curve

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13 **Abstract.** As each catchment responds uniquely, even if they appear similar, formulating generalizable
14 hypotheses and using routinely used signatures of catchment similarity to examine streamflow variability can be
15 difficult. Flow Duration Curve (FDC), a concise portrayal of streamflow variability at a specific gauging station,
16 can provide insights into hydroclimatic and landscape processes occurring at a wide range of space and time scales
17 that govern flow regimes in a region. This study explores the suitability of partitioning of annual streamflow FDC
18 into seasonal FDCs, and total streamflow FDC into fast and slow flow FDCs to unravel the process controls on
19 FDCs at a regional scale, with application to low-gradient rivers flowing east from the Western Ghats of
20 Peninsular India. The focus is on investigation of the controls of common regional landscape features (in space)
21 and seasonal climatic (in time) variations on regional variations of the FDC. Findings of the study indicate that
22 bimodal rainfall seasonality and higher fraction of moderate to good groundwater potential zones explains the
23 higher contribution of slow flow to total flow across north-south gradient of the region. Shapes of fast and slow
24 FDCs are controlled by recession parameters revealing the role of climate seasonality and geologic profiles,
25 respectively. A systematic spatial variation across north-south gradient is observed– highlighting the importance
26 of coherent functioning of landscape-hydroclimate settings in imparting distinct signature of streamflow
27 variability. The framework is useful to discover the role of time and process controls on streamflow variability in
28 a region with seasonal hydroclimatology and hydro-geologic gradients.

29 1 Introduction

30 The hydrologic functioning of catchment systems in any given region is coevolved with the long-term climatology
31 and landscape features present in the region through mutual interactions operating across multiple spatial and
32 temporal scales (Wagener et al., 2013). These interactions and long-term feedbacks impart variability to
33 hydrologic processes that are characteristic of the region of interest, including runoff generation and riverine
34 transport processes, thus influencing water availability and reliability to human populations that depend on the
35 streamflow. Understanding streamflow variability in time and space across river basins in the region is therefore
36 very important for water resource management (Deshpande et al., 2016; Sinha et al., 2018) and the prediction and



37 mitigation of floods (Kale et al., 1997). The frequency of high flows, low flows, or flows within specific ranges,
38 is essential for risk assessment of water management projects involving control of streamflow variability. Correct
39 portrayal of streamflow variability at the scale of catchments and river basins is therefore an indispensable
40 component in many hydrologic applications.

41 The focus of this paper is on the flow duration curve (FDC), which is a compact description of temporal
42 streamflow variability at the catchment scale. The FDC represents (daily) streamflow values plotted against the
43 proportion of time the given flow is exceeded or equalled (Smakhtin, 2001; Vogel & Fennessey, 1994). The
44 graphical form of the FDC embeds within it the governing hydrologic processes and dominant flow characteristics
45 throughout the range of recorded streamflows at the catchment scale (Botter et al., 2008). In this sense, the FDC
46 is also an important signature of a catchment's rainfall to runoff transformation (Ghotbi et al., 2020a; Vogel &
47 Fennessey, 1994). FDC thus typifies the old proverb, "one picture is worth a thousand words" with its potential
48 to encapsulate much of the relevant information of streamflow variability in a single plot (Vogel & Fennessey,
49 1995), and has been used in many hydrologic applications. Vogel and Fennessey (1994) provide a brief history of
50 the application of flow duration curves in hydrology. Applications of FDC include waste load allocation (Searcy,
51 1959), water quality management (Searcy, 1959; Rehana & Mujumdar, 2011, 2012), reservoir and sedimentation
52 studies (Vogel & Fennessey, 1995), low-flow and flood analyses (Smakhtin, 2001), assessment of environmental
53 flow requirements (Smakhtin and Anputhas, 2006), and water availability for hydropower (Basso & Botter, 2012).

54 Streamflow observed in a river is the culmination of interacting hydrological processes of runoff generation,
55 overland and subsurface flow and evaporation, operating at multiple time and space scales, in response to climatic
56 inputs and their interactions with a range of landscape properties, all of which are highly heterogeneous. This
57 makes it challenging to decipher the process controls on streamflow variability, and their manifestation in the
58 shape of the FDC (Cheng et al., 2012; Ghotbi et al., 2020b; Yokoo & Sivapalan, 2011). Therefore, there is a need
59 for appropriate conceptual frameworks that can bring out these process controls of FDCs and generate deep
60 insights into the governing principles underpinning observed variability. Yokoo and Sivapalan (2011) presented
61 a framework for deciphering the process controls of the FDC by considering the FDC of total streamflow (TFDC)
62 as a statistical summation of a fast flow duration curve (FFDC) and a slow flow duration curve (SFDC). FFDC is
63 a filtered version of precipitation variability, with rainfall intensity patterns and surface soil characteristics as
64 controlling factors (Yokoo & Sivapalan, 2011). On the other hand, SFDC reflects a competition between
65 subsurface drainage and evapotranspiration (Yokoo & Sivapalan, 2011), in which case seasonality and regional
66 geology are stronger controlling factors. This contrast in the process controls governing quick (surface) runoff
67 and slow (subsurface) flow, supports the notion of stratifying total streamflow into these two components
68 operating at two different time scales. The distinction between the two (fast and slow) flow time scales enables
69 the conceptualization of the process controls of fast flow (surface runoff) and slow flow (subsurface streamflow
70 and groundwater flow) separately (Cheng et al., 2012; Yokoo & Sivapalan, 2011).

71 Ghotbi et al (2020a, 2020b) used this framework to explore the climatic and landscape controls of FDCs using
72 streamflow data for hundreds of catchments across the continental United States in a comparative manner. In
73 their work Ghotbi et al. (2020a) emphasized the need to consider the fast flow and slow flow time series
74 independently as stochastic responses of catchments to sequences of storm events. Intensity and frequency of
75 rainfall events and the properties of soils and topography govern the variability of fast flows, whereas climate



76 seasonality and regional geology of the aquifer system govern variability of slow flow components. More
77 specifically, Ghotbi et al. (2020b) showed the dominant process controls of FDCs as aridity index, topographic
78 slope, coefficient of variation of daily precipitation, timing of rainfall, time interval between storms, snow fraction,
79 and recession slope.

80 Due to significant differences between fast and slow process controls, each may be used to explain streamflow
81 variability independently. While recognizing the necessity to represent the hydrological processes across two
82 distinct time scales, this paper aims to develop a process-based understanding of how regional scale features
83 impact streamflow variability across Peninsular India, using the flow duration curve (FDC) as a signature of this
84 variability. For this purpose, an extension of this concept was made by including seasonal (timing) streamflow
85 variability in a regional context. To isolate the effects of the drivers on the observed FDCs and to identify the
86 controls of time and process scales on streamflow variability, a modeling framework is presented that comprises
87 partitioning streamflow in multiple ways: seasons/months in the time domain, east-west/north-south directions in
88 the space domain, fast/slow flows in the process domain. Streamflow data available from a large number of stream
89 gauges within and between the major river basins across Peninsular India is employed for this purpose. The
90 scientific novelty and methodological advancement of the paper lie in two interconnected aspects, which have not
91 been adopted in the literature to date: (i) the timescale partitioning framework is used to study the relative
92 contributions of different seasons to the FDC (repeated for fast and slow flow components), exploring how the
93 relative contributions holistically vary across the whole region and using the framework to reconstruct the annual
94 flow duration curve using seasonal flow duration curves, (ii) the Wegenerian approach in connecting the spatial
95 variability of streamflow at a regional scale using flow duration curve. Thus, the main goal of this paper is to
96 reconstruct the flow duration curves at different scales to unravel the regional scale streamflow variability by
97 extending the process partitioning (Ghotbi et al., 2020a) with the time partitioning. Studies that use simultaneous
98 partitioning of flow duration curves at seasonal and process scales to investigate regional streamflow variability
99 in space and seasonal climatic in time fluctuations using the Wegenerian approach are limited. The remainder of
100 the paper is structured as follows. Section 2 elaborates on the details of the study area and the daily streamflow
101 dataset used. The description of the conceptual framework employed for the analysis is presented in Section 3.
102 The results of the application of the framework to Peninsular India and the interpretation of the results are
103 presented in Sections 4 and 5, respectively. Finally, the paper is concluded in Section 6 with key insights gained
104 for the nature and controls of streamflow variability across Peninsular India.

105 **2 Study region**

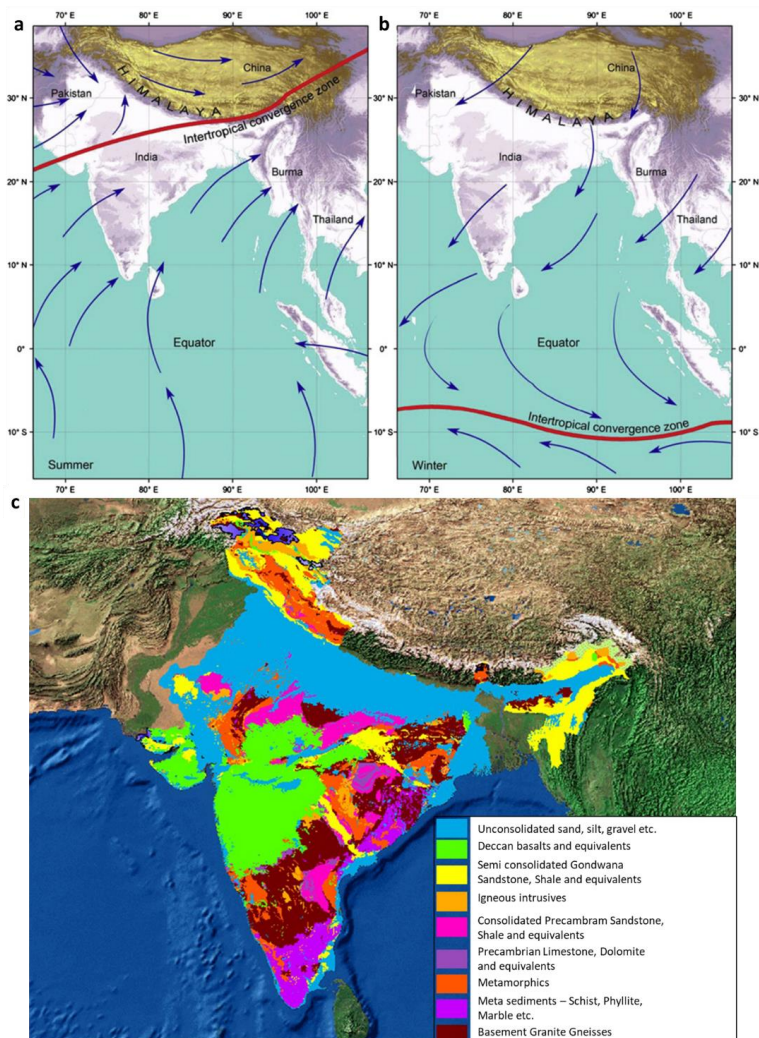
106 Peninsular India is a cratonic region with an approximate shape of a vast inverted triangle with diverse topography
107 and characteristic climatic patterns, bounded by the Arabian Sea in the west, the Bay of Bengal in the east, and
108 the Vindhya and Satpura ranges in the north. The long escarpments of the Western Ghats and the Eastern Ghats,
109 constituting the western and eastern continental fringes of India, and an asymmetric relief with eastward tilt
110 towards the floodplains of several eastward draining rivers from the 1.5 km high Western Ghats, characterize the
111 physiography of Peninsular India (Richards et al., 2016).

112 The rise of the Himalayan-Tibetan plateau has significantly contributed to the Neogene climate of Asia, favoured
113 the birth of the modern monsoon (Fig. 1.a, b) (Chatterjee et al., 2013, 2017), and triggered glaciation in the



114 Northern region. A wide variety of plateaux, open valleys, bedrock gorges, mountain ranges, inselbergs and
115 residual hills constitute the geomorphology of Peninsular India (Kale & Vaidyanadhan, 2014). The Peninsular
116 landscape is dominated by Deccan Traps (Deccan basalts) of Cretaceous-Eocene, igneous and metamorphic rocks
117 (Granite-gneisses) of Archaean-Late Precambrian along with minor consolidated sediments (Sandstone, shale) of
118 Precambrian-Jurassic (Fig. 1.c) (Kale, 2014).

119 The region is strongly impacted by monsoons, major seasonal winds which are a manifestation of the seasonal
120 movement of the Intertropical Convergence Zone (ICTZ in Fig. 1.a and Fig. 1.b), which contribute largely to the
121 annual rainfall variability in much of the Indian subcontinent (Gadgil, 2003). The monsoons have two components
122 – South-West monsoon and North-East monsoon, which arrive during June – September (JJAS) and October –
123 December (OND), respectively. South-West monsoon season contributes more than 75% of annual rainfall over
124 majority of the regions of the country (Saha et al., 1979). However, the Southern Peninsula receives a significant
125 portion (30-60%) of its annual rainfall during the North-East monsoon, which contributes only 11% of the rainfall
126 annually to India as a whole (Rajeevan et al., 2012). The maximum extent of rainfall over the Southern Peninsula
127 during the North-East Monsoon is due to the reversal of lower-level winds over South Asia from the South-West
128 to the North-East during the retreating phase of the South-West monsoon (Rajeevan et al., 2012). In Peninsular
129 India, there is a spatial variability of the South-West monsoon in the south-north direction. For example, the
130 Western Ghats, located at the western edges of Krishna and Cauvery basins, obstruct the incoming South-West
131 monsoon winds causing heavy rainfall on the mountains. After crossing the Western Ghats, the monsoon winds
132 have less moisture, causing a sharp decline in rainfall amounts towards the central and the north-eastern part of
133 the Peninsula (Fig S2.a in Supplementary Material). The North-East monsoon occurs during winter, and mostly
134 influence the rainfall in the Cauvery and some parts of the Krishna basins. Vegetation on the long escarpment of
135 Western Ghats is primarily tropical evergreen forest, which plays an important role in intercepting the South-West
136 monsoon winds (Ramachandra, 2018). Ramachandra (2018) portrayed the profile of vegetation across the west-
137 east gradient as it varies from tropical-evergreen to semi-evergreen and then moist to dry deciduous forests
138 towards the rain-shadow region just east of the Western Ghats. The topography map for the Peninsular region and
139 a selected point in the region is depicted in Fig. S1.a and Fig. S1.b in Supplementary Material, respectively. The
140 western margin of Peninsular India experiences heavy rainfall due to the presence of Western Ghats, whereas the
141 rain shadow region witnesses deficient rainfall (Fig. S2.c). It can thus be seen that the long geological, tectonic
142 history and the onset of monsoon climate events have made an imprint in the shaping the present landform of the
143 Indian Peninsula (Kale, 2014).



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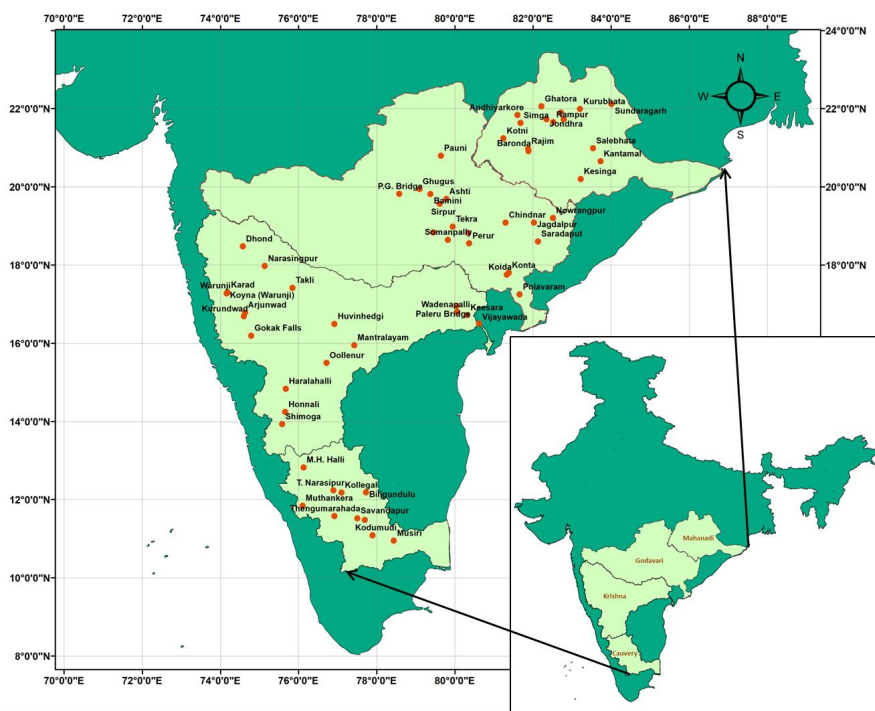
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146 **Figure 1.** (a) The relation of uplift of Himalaya-Tibetan Plateau and monsoon initiation in India. Monsoon winds
147 blow from the Indian Ocean towards land in the summer (b) during the winter, the Himalaya prevents cold air
148 from passing into the subcontinent and causes the reversal of wind direction and monsoon blow from land toward
149 sea [Reprinted from (Chatterjee et al., 2013)] (c) geology of Peninsular India [Reprinted from: Central Ground
150 Water Board(<https://www.aims-cgwb.org/general-background.php>)].



151 The region shown in Fig. 2 is selected as the study area in the Deccan Plateau of Peninsular India. The escarpment
152 of Western Ghats forms the western margin of the Deccan Plateau which serves as the main water divide for the
153 Peninsular River systems. The gentle slope from west to east causes Peninsular rivers such as the Mahanadi,
154 Godavari, Krishna, and Cauvery (Fig. 2) to flow eastwards. Three of these rivers (Godavari, Krishna and Cauvery)
155 originate from the Western Ghats, spread across the area from the Deccan Plateau, flow eastwards, and drain into
156 the Bay of Bengal. The Mahanadi River rises in the mountains of Siwaha bounded by the Eastern Ghats in the
157 south and east, and drain eastwards into the Bay of Bengal. The Mahanadi basin constitutes a total catchment area
158 of about 141,600 km² with an average annual rainfall of 1,360 mm and a mean annual river flow of 66,640 million
159 m³ (Rao et al., 2017). With an annual average rainfall of 1096 mm, the Godavari, the largest of all Peninsular
160 rivers, receives nearly 84 percent of its annual rainfall on average during the South-West monsoon (Koneti et al.,
161 2018). The Godavari basin's challenges include frequent flooding in its deltaic lower reaches, given the area's
162 proximity to the coastal zone, which is prone to cyclones, and frequent drying up during the drier months (Koneti
163 et al., 2018). Krishna is Peninsular India's second-largest river, with a total catchment area of 2,60,000 km², and
164 is susceptible to floods and droughts in some specific regions (Chanapathi & Thatikonda, 2020). The South-West
165 monsoon is the most significant contributor to rainfall in the Krishna basin, accounting for about 90% of its total
166 rainfall; the Krishna Basin, however, has a non-uniform rainfall distribution caused by climate variability, with
167 an average annual rainfall bout of 770 mm (Chanapathi & Thatikonda, 2020). Annual rainfall in the Cauvery
168 varies from 621 mm in the lower reaches to 4137 mm in the mountainous uplands, exhibiting considerable
169 variation across the basin (Kumar Raju & Nandagiri, 2017). The river Krishna, with a mean annual runoff of less
170 than 100 mm, is designated as an arid river (Milliman JD, 2011; Gupta et al., 2022), Cauvery as a semiarid river
171 (100–250 mm), Mahanadi and Godavari as humid rivers (250–750 mm). The higher baseflow index occurs within
172 0.5 and 0.7 in catchments in the Godavari and Mahanadi basins, whereas the lower baseflow index is noted from
173 0.25 and 0.45 in the Cauvery and Krishna basins (Bhardwaj et al., 2020). For agricultural purposes, the semiarid
174 regions of the Cauvery basin rely more on groundwater than surface water when compared to the other three
175 basins (Sreelash et al., 2020).

176 In this study, daily streamflow data between 1965 to 2012 for 62 stream gauges (Fig. 2) are selected from Water
177 Resources Information System database (WRIS) and located across the four river basins. The daily gridded rainfall
178 product at spatial resolution of 0.25° × 0.25° from India Meteorological Department (IMD) is also employed for
179 the analysis (Pai et al., 2014).



180

181 **Figure 2.** Location map of four Peninsular River Basins. Stream gauges considered in this study are marked with
182 red circles.

183

184 3 Conceptual framework for stratification of streamflow variability using time scale

185 In this section, we check the suitability of a framework to stratify observed streamflow time series in the time
186 domain into distinct time scales to better understand the physical controls of streamflow variability across the
187 region. Partitioning of streamflow across seasonal and monthly time scales is able to bring out the role of climate
188 seasonality on streamflow variability. Moreover, the progression of the seasons spatially imparts signatures on
189 streamflow variability regionally as a whole. Time scale partitioning thus offers an opportunity to understand
190 these climatic and landscape controls on streamflow variability through quantifying the relative contributions of
191 seasonal streamflow on annual streamflow variability and how they vary regionally.

192 The streamflow hydrograph is the response of a physical, deterministic system (catchment) to a sequence of
193 rainfall events. Given that the rainfall events are very much random in all their properties, equivalently, the
194 streamflow hydrograph can also be seen as a stochastic time series, with streamflow considered a random variable.
195 Therefore, it is amenable to a stochastic treatment in terms of distribution functions (e.g., cumulative distribution
196 function, CDF). A major advantage of the CDF is that it enables us to make a concise statement of streamflow
197 variability across a population of events. They have diagnostic value in that they can explain or interpret a
198 catchment's streamflow response and compare it across many catchments and they help to classify catchments
199 based on the flow regimes. They also have practical value in engineering design and environmental monitoring



200 that require a probabilistic treatment of streamflow. The cumulative distribution function of a random variable
201 (the random variable of interest to us is daily streamflow; Q) expresses the probability that a realization (i.e.,
202 observation) of Q does not exceed a specific value q :

203 Cumulative Distribution Function (CDF):

$$F(q) = P[Q \leq q] \quad (1)$$

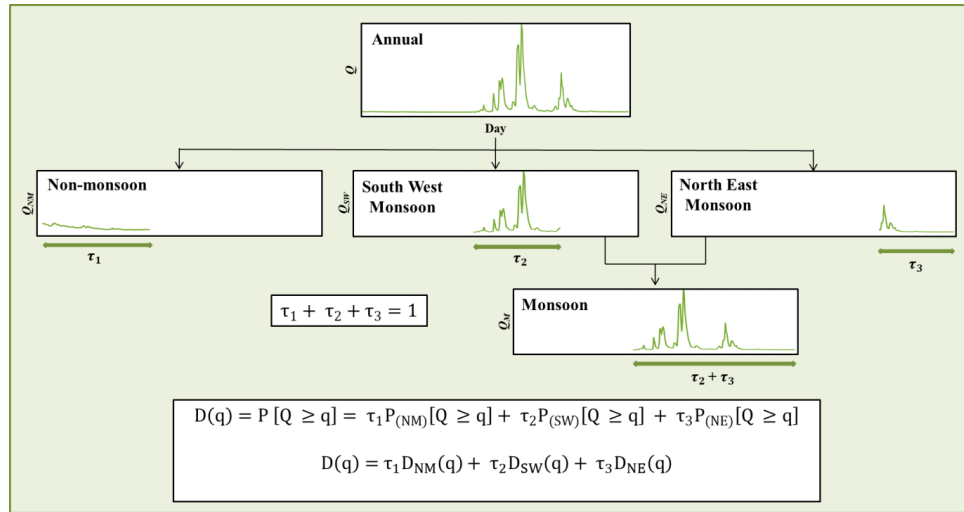
204 The flow duration curve is an alternative, but equivalent, measure of the streamflow variability that is widely used
205 in hydrology. The flow duration curve is a plot that shows the fraction of time (D) that the streamflow is likely to
206 equal or exceed some specified value of interest. Mathematically, D can be expressed as,

$$D(q) = P[Q \geq q] = 1 - F(q) \quad (2)$$

207 Despite its probabilistic definition given above, in hydrological applications, the flow duration curve is plotted in
208 terms of $q(D)$ i.e., q (in the vertical axis) as a function of D (in the horizontal axis).

209 ***Time scale partitioning of streamflow variability***

210 The streamflow time series can be equivalently divided into temporal segments of distinct seasons as well as
211 distinct months. In this case, by joining observed time series over multiple years, FDCs for each time segment can
212 be reconstructed. Assuming independence (as an approximation), these can then be combined to generate annual
213 FDCs. The theory for the time scale partitioning is illustrated in Fig. 3. The year is divided into three distinct (non-
214 overlapping) seasons, viz. Non-monsoon, South-West, and North-East seasons (for Peninsular India) of relative
215 durations τ_1 , τ_2 , and τ_3 (with $\tau_1 + \tau_2 + \tau_3 = 1$) respectively. These seasons can be assumed to have distinct
216 characteristics in terms of rainfall variability and how they translate to streamflow variability. The daily
217 streamflow time series is used to construct the seasonal as well as annual FDCs. For example, the FDC of Non-
218 monsoon season is constructed by using the daily streamflow during the period of January – May over the years.
219 Similarly, FDCs for South-West and North-East monsoons are constructed using the daily streamflow during June
220 – September and October – December months over the years respectively and the annual FDC is constructed using
221 daily streamflow values for 365/366 days over the years. The FDCs at monthly time scales are obtained using the
222 daily values of streamflow in a month over the years. The FDCs for the three distinct seasons, i.e., Non-monsoon,
223 South-West monsoon, North-East monsoon, are denoted as $D_{NM}(q)$, $D_{SW}(q)$, and $D_{NE}(q)$ respectively. Initially,
224 the FDCs for each season can be constructed separately (Fig. 3).



225

226 **Figure 3.** Scale partitioning into seasonal and monthly time scales. The conceptual framework illustrates the time
 227 scale partitioning of streamflow time series into various seasonal components considering patterns of rainfall
 228 variability. The annual streamflow time series is decomposed into three components: (1) Non-monsoon flow, (2)
 229 South-West monsoon flow, and (3) North-East monsoon flow.

230

231 The annual FDC with exceedance probability $P [Q \geq q]$ refers to the probability of flow in annual scale being
 232 greater than or equal to q , and is expressed as

$$D(q) = P [Q \geq q] = \tau_1 P_{(NM)} [Q \geq q] + \tau_2 P_{(SW)} [Q \geq q] + \tau_3 P_{(NE)} [Q \geq q] \quad (3)$$

$$\text{or, } D(q) = \tau_1 D_{NM}(q) + \tau_2 D_{SW}(q) + \tau_3 D_{NE}(q) \quad (4)$$

233 where, $P_{(NM)} [Q \geq q]$, $P_{(SW)} [Q \geq q]$ and $P_{(NE)} [Q \geq q]$ refer to, respectively, the probability of flow in Non-
 234 monsoon, South-West monsoon and North-East monsoon being greater than q . As the seasons are non-
 235 overlapping, the probability of flow being greater than q at annual scale (i.e., $P [Q \geq q]$) can be expressed as the
 236 sum of the weighted probabilities of flow being greater than q in the three seasons.

237 In general, the FDC at the annual scale can be constructed as follows:

$$D(q) = \tau_1 D_1(q) + \tau_2 D_2(q) + \dots + \tau_n D_n(q) \quad (5)$$

238 where n is the number of distinct seasons considered for the analysis and, $\tau_1 + \tau_2 + \dots + \tau_n = 1$. The validity of
 239 the above depends on the assumption that there is no carryover of flows from one season to the next season (which



240 is an approximation). In this study, the assumption of independence between flows across three seasons is checked
 241 using multivariate Hoeffding's test (see details in Text S1 of Supplementary Information).

242 If $F_A(\cdot)$, $F_{NM}(\cdot)$, $F_{SW}(\cdot)$ and $F_{NE}(\cdot)$ represent cumulative distribution function of daily flows during annual, Non-
 243 monsoon, South-West monsoon and North-East monsoon, respectively, then using equation (2), equation (6) can
 244 be written as:

$$1 - F_A(q) = \tau_1[1 - F_{NM}(q)] + \tau_2[1 - F_{SW}(q)] + \tau_3[1 - F_{NE}(q)] \quad (6)$$

245 Differentiating the above equation with respect to q ,

$$f_A(q) = \tau_1 f_{NM}(q) + \tau_2 f_{SW}(q) + \tau_3 f_{NE}(q) \quad (7)$$

246 where $f_A(\cdot)$, $f_{NM}(\cdot)$, $f_{SW}(\cdot)$ and $f_{NE}(\cdot)$ represent probability density functions of annual, Non-monsoon, South-
 247 West monsoon and North-East monsoon flows respectively.

248 If Q , Q_{NM} , Q_{SW} and Q_{NE} represent random variables comprising of daily streamflow at annual, Non-monsoon,
 249 South-West monsoon and North-East monsoon time scales respectively, the expectation $E(Q)$ and variance $V(Q)$
 250 of annual flow in terms of seasonal flows can be expressed as

$$E(Q) = \tau_1 E(Q_{NM}) + \tau_2 E(Q_{SW}) + \tau_3 E(Q_{NE}) \quad (8)$$

$$V(Q) = \tau_1 E(Q_{NM}^2) + \tau_2 E(Q_{SW}^2) + \tau_3 E(Q_{NE}^2) - (E(Q))^2 \quad (9)$$

251 The magnitudes of τ_1 , τ_2 and τ_3 are $\frac{5}{12}$, $\frac{4}{12}$ and $\frac{3}{12}$ based on the annual proportions of Non-monsoon, South-West
 252 monsoon and North-East monsoon respectively.

253 The same concept can be continued by combining the flows in different months, in which case the way to combine
 254 monthly FDCs into an annual FDC is given by:

$$D(q) = \frac{1}{12} \sum_{m=1}^{12} D_m(q) \quad (10)$$

255 where $m = 1, \dots, 12$.

256 If Q_m represents the random variable daily streamflow over m^{th} month, then the expectation $E(Q)$ and variance
 257 $V(Q)$ of annual flow in terms of monthly flows can be expressed as



$$E(Q) = \frac{1}{12} \sum_{m=1}^{12} E(Q_m) \quad (11)$$

$$V(Q) = \frac{1}{12} \sum_{m=1}^{12} E(Q_m^2) - (E(Q_A))^2 \quad (12)$$

258 The relative contributions of Non-monsoon ($C_{NM \rightarrow AN}$), South-West monsoon ($C_{SW \rightarrow AN}$) and North-East monsoon
 259 ($C_{NE \rightarrow AN}$) flows to annual flow can be approximated through following expressions:

$$C_{NM \rightarrow AN} = \frac{\tau_1 E(Q_{NM})}{\tau_1 E(Q_{NM}) + \tau_2 E(Q_{SW}) + \tau_3 E(Q_{NE})} \quad (13)$$

$$C_{SW \rightarrow AN} = \frac{\tau_2 E(Q_{SW})}{\tau_1 E(Q_{NM}) + \tau_2 E(Q_{SW}) + \tau_3 E(Q_{NE})} \quad (14)$$

$$C_{NE \rightarrow AN} = \frac{\tau_3 E(Q_{NE})}{\tau_1 E(Q_{NM}) + \tau_2 E(Q_{SW}) + \tau_3 E(Q_{NE})} \quad (15)$$

260 Similarly, the relative contributions of monthly flows to annual flow can be expressed as:

$$C_{m \rightarrow AN} = \frac{\frac{1}{12} E(Q_m)}{\frac{1}{12} \sum_{m=1}^{12} E(Q_m)} \quad (16)$$

261 where, $m = 1, 2, \dots, 12$, represents the index for months.

262 Note, as before, these relative contributions to total flow effectively also measure the relative contributions of the
 263 seasonal/monthly flows to the mean of the annual flow duration curve.

264 The methodology for constructing annual FDC using seasonal FDC is as follows:

265 1. The empirical PDFs – $f_{NM}(q)$, $f_{SW}(q)$ and $f_{NE}(q)$ are derived for daily streamflow time series for Non-
 266 monsoon, South-West monsoon and North-East monsoon seasons respectively.

267 2. These PDFs are then multiplied by scaling factors, τ_1 , τ_2 and τ_3 in equation 9. The scaling factors represent
 268 relative durations of the three seasons considered. For example, $\tau_1 = 5/12$, as the duration of duration of non-
 269 monsoon season is 5 months.

270 3. The PDF of annual flow is estimated as the weighted sum of three scaled density functions corresponding to
 271 three seasons (see Eq. 7). The annual flow consists of the daily streamflow for Non-monsoon, South-West
 272 monsoon and North-East monsoon seasons.

273 The performance of the time scale partitioning framework is assessed using the metric, root mean square error
 274 (RMSE). The method of estimation of q_{sim} is shown in Fig. S3.



$$275 \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (q_{actual} - q_{sim})^2} \quad (17)$$

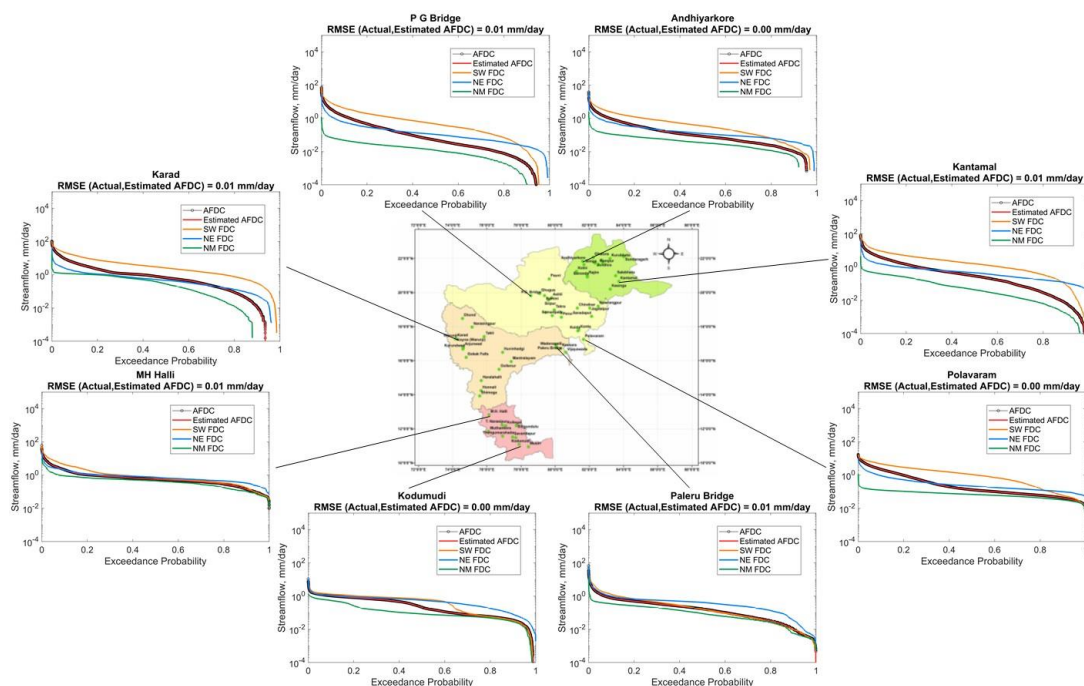
276 **4 Results**

277 **4.1 Time scale partitioning**

278 We initially investigated the spatial variations in seasonal and annual flow duration curves across Peninsular India
279 employing the partitioning framework. The annual flow duration curve and seasonal flow duration curves for
280 Non-monsoon, South-West monsoon, and North-East monsoon are shown in Fig. 4 for eight representative
281 gauges, one at the upstream and one at the downstream of each of the four river basins. The estimated annual flow
282 duration curve (red curve) using the equation 7 is also shown in Fig. 4. Daily streamflow time series is normalized
283 by catchment area before plotting (on a semi-log paper) the flow duration curve for comparison across the gauging
284 stations. In particular, the annual flow duration curve (black scatter) is reproduced well by the partitioning of both
285 seasonal (red curve in Fig. 4) and monthly flows (red curve in Fig. S4). The mean and variance of annual flows
286 are also reproduced well by the time scale partitioning framework (Fig. S5). This confirms the efficacy of the time
287 scale partitioning approach of seasonal/monthly flows in approximating the annual flow duration curve (see also
288 Fig. S4, Fig. S5.a and Fig. S5.d in Supplementary Material).

289 Another feature that can be observed in Fig. 4 is that in gauging stations located in the northern part of the
290 peninsular region, flow duration curves (FDCs) of South-West monsoon flows (orange curve) are relatively higher
291 than other seasonal FDCs. Given the logarithmic scale used to plot of the flows, this dominance is significant. In
292 sites located in the southern part of the region, the dominance of South-West monsoon is not as strong and North-
293 East monsoon flows (blue curve) are also significant.

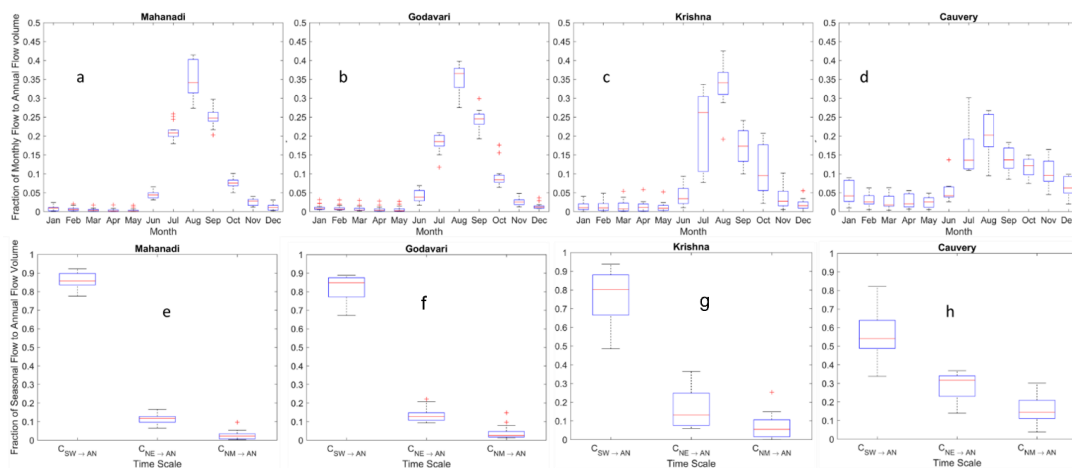
294 Motivated by these observations, we extracted seasonal and monthly streamflow time series from the entire dataset
295 across all gauging stations to compute the relative contributions of seasonal and monthly flows to the annual flow
296 duration curve. The results are presented in Fig. 5. At the monthly scale (top panel, Fig. 5), the contributions of
297 flows during the months of June to September are much higher than in other months in northern Peninsular basins
298 (Mahanadi and Godavari, Krishna to a less extent). This can be explained by the contribution of monthly rainfall
299 to annual rainfall, which is higher during these months as shown in Fig. 6. On the other hand, in the southernmost
300 Cauvery basin, the dominance of June to September months is relatively not as strong, and there is also a
301 significant contribution during the months of October to December, higher than in northern basins (Fig. 5.d). This
302 can be attributed to the slightly more equal dominance of both South-West (June - September) and North-East
303 (October - December) monsoons over the Cauvery basin (Fig. 6.d) than in the northern basins. This pattern is also
304 reflected at the seasonal scale (bottom panel, Fig. 5), with the contribution of South-West monsoon flow to annual
305 flow being slightly higher than that during the other seasons, and much higher in northern basins. However, the
306 contribution of South-West monsoon to annual flow decreases in southern basins, while the contribution of North-
307 East monsoon increases, as can be seen clearly in Fig. 5.h for the Cauvery basin. The contribution of Non-monsoon
308 to annual flow is also higher in southern basins relative to northern basins. This can be attributed to carry over
309 flows from winter rains during the North-East monsoon, which is more pronounced in the southern part of the
310 region.



311

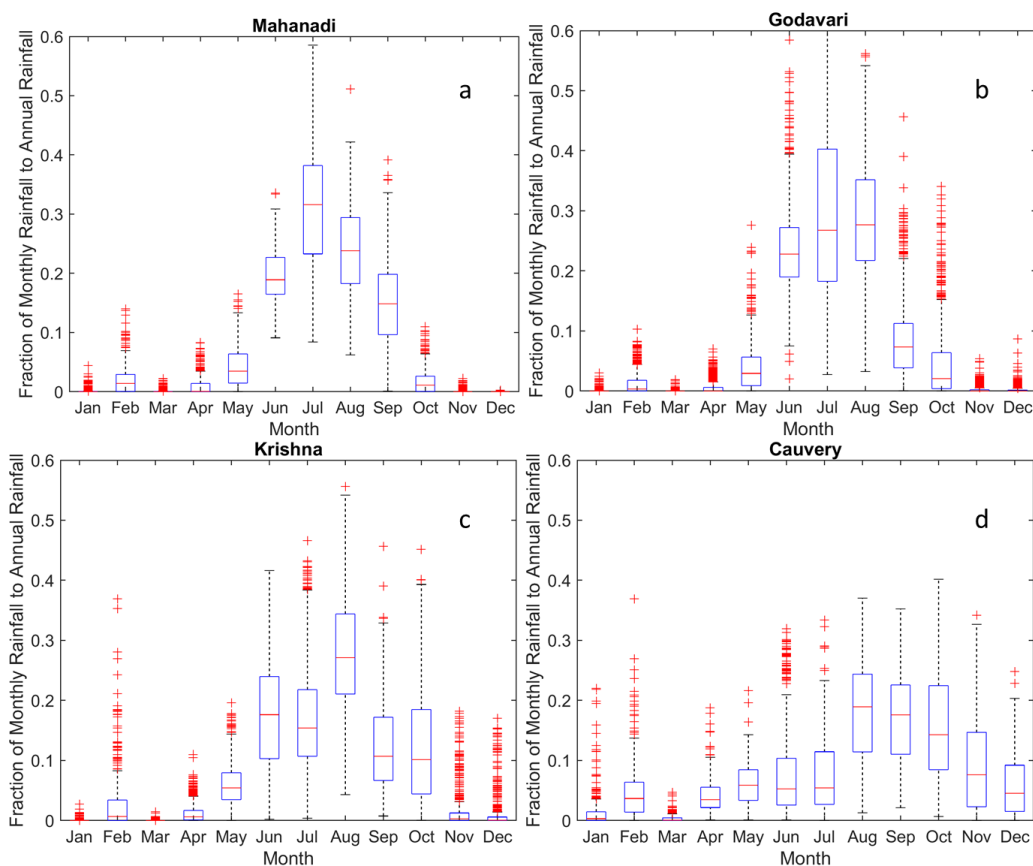
312 **Figure 4.** Spatial variations in seasonal and annual flow duration curves across Peninsular India. The time scale
 313 partitioning framework of seasonal flows in approximating annual flow duration curves works reasonably well.

314



315

316 **Figure 5.** The relative contributions of monthly and seasonal flows to annual flow at basin scale. The contributions
 317 of South-West monsoon flow to annual flow increases in northern basins whereas it decreases in southern basins.
 318 However, the contributions of North-East monsoon flow to annual flow increases towards southern basins.



319

320 **Figure 6.** Long-term (1951-2010) fractional contribution of monthly rainfall across Peninsular
321 basins.

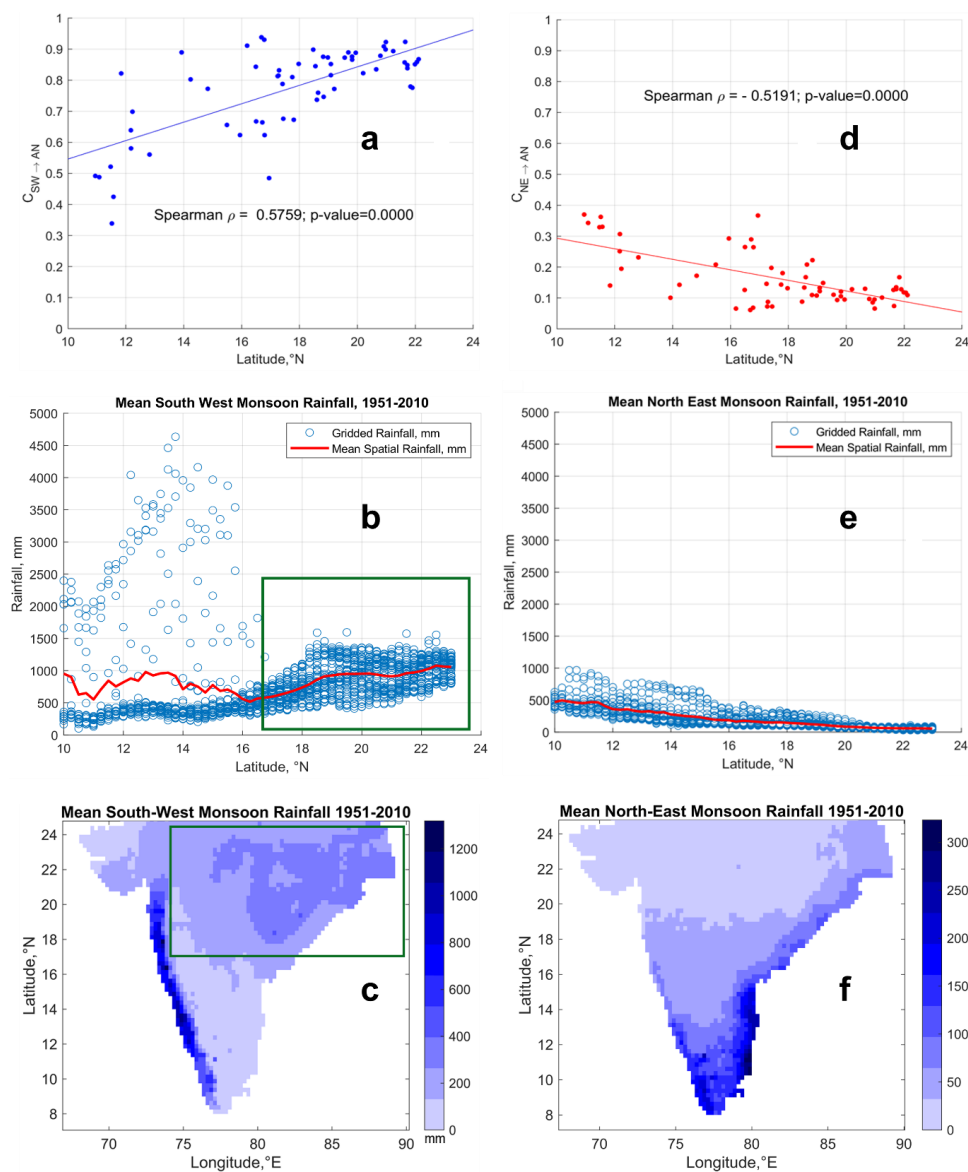


322 We next carried out regional scale analysis by considering streamflow time series of all the gauging stations across
323 all four river basins. Similar to basin scale analysis presented before, the relative contributions of seasonal and
324 monthly flows to annual flow are now estimated at the regional scale (Fig. 7). The spatial patterns of South-West
325 and North-East monsoon rainfall across the Peninsular region are plotted for comparison using IMD gridded
326 rainfall product (Fig. 7.b and Fig. 7.e).

327 The contribution of South-West monsoon flows to annual flow increases in the northerly direction (Fig. 7.a). The
328 mountainous region of the southern Peninsula (western part of Krishna basin and north-western part of Cauvery
329 basin) receives high rainfall during the South-West monsoon season (Fig. 7.b – extended till 17° N latitude). The
330 streamflow produced in the headwater regions of southern basins in response to high rainfall, contributes at least
331 70% of the annual flow (Fig. 7.a). Yet, the areal fraction of these high rainfall, headwater regions within the four
332 river basins is quite small and their contributions to the average precipitation or flow at the basin scale is much
333 smaller. There is also considerable variability in the contributions of South-West monsoon flows to annual flow
334 in the sub-basins located at the eastern and south-eastern parts of Krishna and Cauvery basins (represented by the
335 scatter below the regression line till 17° N latitude in Fig. 7.a) due to declining rainfall (Fig. 7c). This considerable
336 variability, on average, reduces the overall contributions of South-West monsoon to annual flow in southern
337 Peninsula with respect to the basins in the northern part.

338 The northern part of the Peninsular region receives comparatively higher rainfall than the southern part without
339 considering the Western Ghats. This increased rainfall is attributed to the movement of low-pressure systems that
340 develop over the Bay of Bengal towards central India (Krishnamurthy & Ajayamohan, 2010; Prakash et al., 2015).
341 The low-pressure systems are a regular feature of South-West monsoon, which brings significant amount of
342 rainfall in the northern part of the Peninsular region (Krishnamurthy & Ajayamohan, 2010). The increased rainfall
343 (Fig. 7.b – after 16° N latitude) is responsible for higher contribution of South-West monsoon flows to annual
344 flow in the northern basins. As the spatial variability of this rainfall is comparatively less than in the southern
345 Peninsular region, there is less variability in the contribution of South-West monsoon flows to annual flow. The
346 spatial variability in South-West monsoon along the south-north direction across Peninsular region can explain
347 the gradient in the contribution of South-West monsoon flows to annual flow in the same direction.

348 On the other hand, the contribution of North-East monsoon flows to annual flow increases in the southerly
349 direction (Fig. 7.d and Fig. 7.e). This can be explained by the fact that the southern part of the Peninsular region
350 receives higher rainfall during North-East monsoon than the rest of the Peninsular region (Fig. 7.f).



351

352 **Figure 7.** Contribution of seasonal flows to annual flow at regional scale. The spatial variability of South-West
 353 and North-East monsoons can explain the variation in contributions of seasonal flows to annual flow across south-
 354 north gradient. The green box in (b) indicates the northern part of peninsular region which receives higher rainfall
 355 than the southern part. The green box in (c) indicates the spatial extent of the rainfall grids which was considered
 356 in figure (b). The red line in figure (b) indicates the mean rainfall – obtained by averaging the rainfall values at a
 357 specific latitude (°N).



358 The application of the analysis framework used here is based on the critical assumption of independence of flows
359 between different seasons (months), which needs to be critically evaluated. Moisture carry-over across seasons is
360 a confounding issue in the case of strongly seasonal catchments (i.e., exhibiting sharp transition from wet season
361 to dry season in terms of rainfall climatology), specifically when the initial wetness condition at the onset of the
362 dry season depends on the final wetness at the end of wet season and vice-versa. Although most of the rainfall
363 (58-90%) is concentrated during South-West monsoon months (i.e., June – September, red bar in Fig. S6) in
364 Peninsular basins, more than 10% of the annual rainfall is received during North-East monsoon months (i.e.,
365 October – December, yellow bar for Cauvery and Krishna in Fig. S6). In addition, more than 8% of annual rainfall
366 occurs in non-monsoon season (i.e., January – May, blue bar in Fig. S6). This highlights that rainfall received
367 during non-monsoon and North-East monsoon seasons are comparable, and thus it is difficult to distinguish the
368 rainfall climatology across these seasons. Therefore, it is challenging to declare these are catchments with
369 seasonally dry climates. In order to justify our assumption in the reconstruction of annual FDC from seasonal
370 flows, we have now conducted a multivariate Hoeffding test (Gaißer et al., 2010) to check the independence
371 between three random variables representing Non-monsoon, South-West Monsoon and North-East Monsoon
372 flows respectively. A value of test statistic – φ^2 – close to zero indicates independence between three random
373 variables. It is observed that except for two stations in Krishna basin, 60 out of 62 stations show independence
374 between flows across the seasons (Fig. S7). This supports appropriateness of the assumption of no carry-over that
375 had been used in this study to construct annual FDC based on seasonal FDCs.

376 4.2 Combined influence of time scale and process scale partitioning

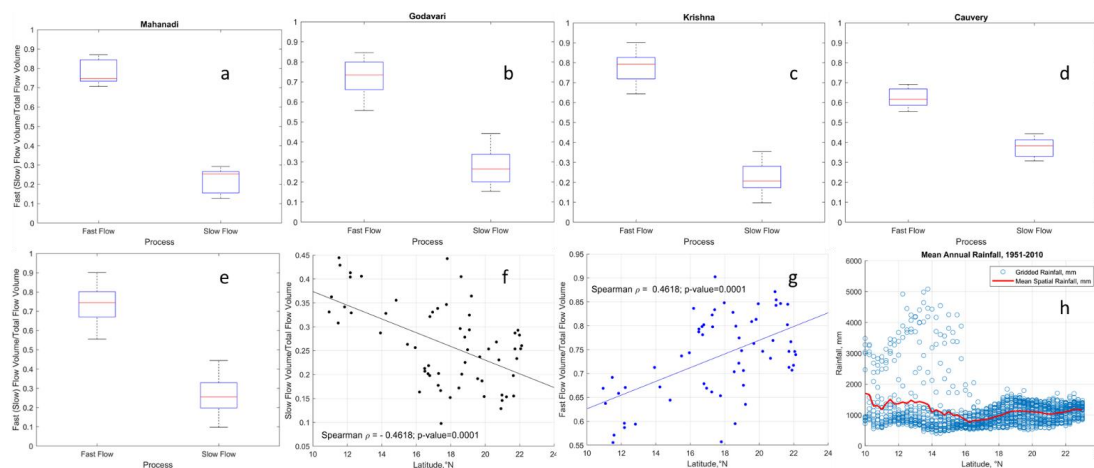
377 In order to further explore the climatic and landscape controls of streamflow variability regionally, we next
378 partition streamflow into fast and slow flow components, notionally representing surface runoff, and a
379 combination of subsurface and groundwater flow respectively (Ghotbi et al., 2020a, b) (see details in Text S2 and
380 Fig. S8 in Supplementary Material). Fast flow is controlled by event scale runoff generation processes and its
381 variability is characterized by topography, land use, soil and rainfall characteristics. On the other hand, climate
382 seasonality and geologic formations of the subsurface are primary controllers of slow flow variability (Ghotbi et
383 al., 2020a, b). The slow flow component is extracted from observed streamflow by using a recursive digital filter
384 (see details in Appendix A1). The fast flow component is obtained by then subtracting the slow flow from
385 observed streamflow. The relative contributions of fast flow and slow flow to total flow (and hence also mean
386 annual flow) are estimated using equations S2 and S3 respectively, for all the gauging stations across all four
387 basins. The relative contributions of fast and slow flows to total flow at the basin and regional scales (combining
388 all the gauging stations) are shown in Fig. 8. In addition, the long-term mean annual rainfall across the Peninsular
389 region is also presented for comparison and to possibly explain the contributions of fast flow (Fig. 8.h).

390 The contributions of fast and slow flows to total flow in each of the four river basins is presented in Fig. 8.a to
391 Fig. 8.d, indicating a strong dominance of fast flow in the northern basins (close to 80% in Mahanadi, Godavari
392 and Krishna), and relatively less dominance (around 60%) in the southern Cauvery basin. This dominance of fast
393 flow also shows up at the regional scale (Fig. 8.e). The regional variations of the relative contributions of slow
394 and fast flows to total flow can also be seen in the results for individual gauges presented in Fig. 8.f and Fig. 8.g,
395 respectively. On average, the contribution of slow flow decreases in the northerly direction, while the contribution
396 of fast flow increases in a corresponding way.



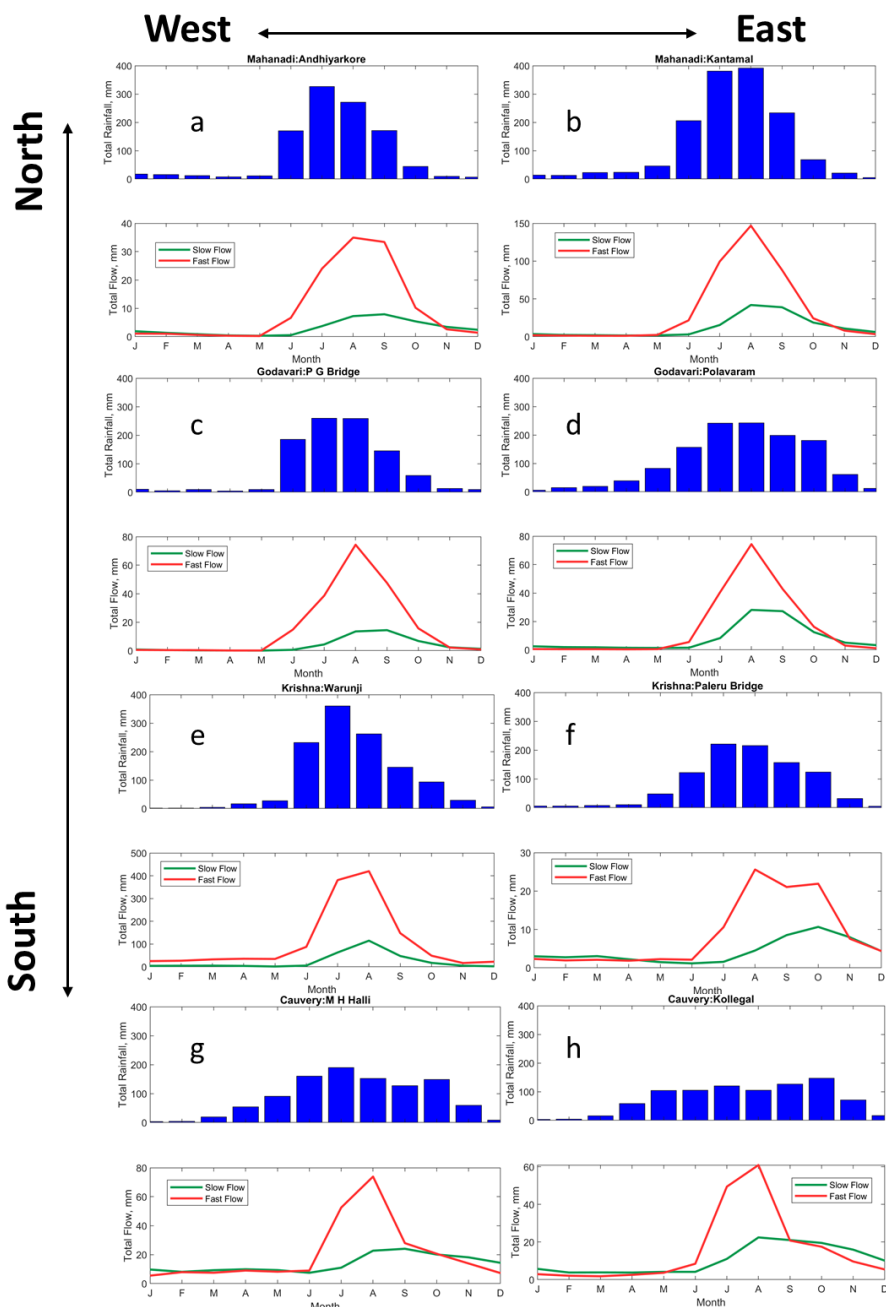
397 The contribution of fast flow to total flow increases in the northern direction of the Peninsular region (Fig. 8.g).
398 The fast flow component of streamflow is generally more responsive to the characteristics of rainfall intensity.
399 The southern part of the region receives high rainfall over Western Ghats along the western edge of Krishna basin
400 and Cauvery basin (Fig. 8.h). In Cauvery basin, the headwater catchments (namely, MH Halli, Muthankera and
401 Thengumarahada in Fig. 6) contribute 57 – 65 % of fast flow to total flow locally. The subbasins located at the
402 western edges of Krishna basin contribute 80% of the fast flow to total flow (between 13° N and 18°N latitudes
403 in Fig. 8.g) locally. However, there is a wide range of variability in the contributions of fast flow to total flow for
404 subbasins located in the eastern part of Krishna basin. The spatial mean rainfall increases and variability decreases
405 after 16° N latitude (Fig. 8.h), which dictate the increased contribution fast flow to total flow. Therefore, the
406 spatial characteristics (mean and variability) of annual rainfall control the south-north gradient in fast flow
407 contributions to total flow. In order to explain the variability in slow flow fraction of total flow, a multivariate
408 regression analysis is performed (details are provided in S3 section of Supplementary Information). It is observed
409 that the location of the gauges is an important predictor of the slow flow fraction of total flow in Peninsular region,
410 revealing the existence of regional groundwater gradient in the region.

411 The contributions of slow flow to total flow increases in the southerly direction over the Peninsular region (Fig.
412 8.f). This can be explained by two major factors. Firstly, the Peninsular region is mostly dominated by hard rock
413 geologic formations, where the subsurface flows are controlled by secondary porosities due to weathering and
414 fracturing (Chandra, 2018; Das, 2019). The distribution of these formations is highly heterogenous (Fig. 1.c) and
415 is responsible for baseflow (slow flow) contribution to total flow (Collins et al., 2020; Narasimhan, 2006). For
416 example, 84% of the total area of Cauvery basin is classified as moderate and good groundwater potential zone
417 (Arulbalaji et al., 2019). The influence of such potential regions of Cauvery basin is reflected on the presence of
418 significant amount of slow flow even in the Non-monsoon season (Fig. 9.g and Fig. 9.h). Likewise, 63% of the
419 total area of Krishna basin is classified under same category (Harini et al., 2018). However, the slow flow regime
420 becomes much more seasonal (Fig. 9) in the northern part of the Peninsular region due to limited capability of
421 geologic formations in transmitting slow flow (Patil et al., 2017) as well as strong seasonality in rainfall patterns
422 (Fig. 9). Secondly, the southern part of the Peninsula receives rainfall almost equally during both South-West and
423 North-East monsoons, which is reflected in the bimodal pattern of rainfall seasonality (Fig. 9.g and Fig. 9.h). The
424 compounding effect of bimodal rainfall seasonality and higher fraction of moderate to good groundwater potential
425 zones explains the higher contribution of slow flow to total flow in southern part of the Peninsular region.



426

427 **Figure 8.** Relative contributions of fast and slow flow to total flow. Consistent higher contribution of fast flow
428 and lower contribution of slow flow to total flow are observed in Peninsular India (a – d) at basin scale. At regional
429 scale, a systematic gradient in fast and slow flow contributions is observed (f and g). The spatial patterns of rainfall
430 (h) can explain the gradient in fast flow contributions. The high scatter of rainfall in the low latitudes represents
431 the heavy rainfall with high variability occurring in the Western Ghats.



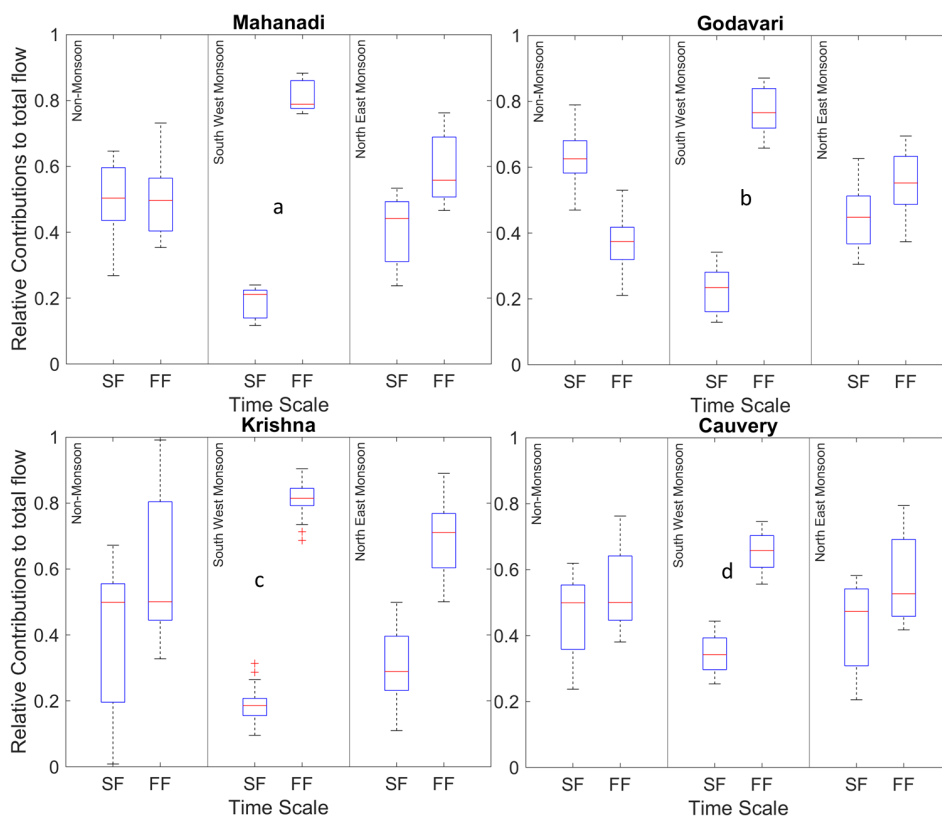
432

433 **Figure 9.** Spatial variation of long-term monthly fast and slow flow components of streamflow at selected gauges
 434 in Peninsular region. The blue bar plots represent the long-term monthly rainfall averaged over the sub-basins
 435 corresponding to the gauging stations. The seasonality in rainfall patterns changes (unimodal to bimodal) across
 436 north-south direction of the Peninsular region.



437 Further, an investigation of the combined influence of climatic time scales and process time scales is therefore
438 pertinent to fully understand the controls of streamflow variability in this region. To address this question, we
439 extracted the fast and slow flow components for each of the Non-monsoon, South-West monsoon and North-East
440 monsoon seasons. These components are then used to estimate their relative contributions to total flow for the
441 three seasons across all the gauging stations.

442 The relative contributions of fast and slow flow to total flow at basin scale are shown in Fig. 10. It is observed
443 that during the Non-monsoon period, the median contributions of fast and slow flow for Mahanadi, Krishna and
444 Cauvery basins are similar, although there exists considerable variability in their distribution. With the onset of
445 the South-West monsoon, the contribution of fast flow to total flow increases markedly for all the basins, although
446 relatively much less in the Cauvery basin. During the subsequent North-East monsoon season, the contribution of
447 fast flow decreases whereas slow flow contribution increases. The fluctuations in the fast flow contributions can
448 be explained by the onset and withdrawal of the monsoon seasons, which are major contributors to fast flow
449 generation. The fluctuations in the fast flow contributions across seasons can be explained by the differences in
450 the rainfall amount during South-West and North-East monsoons (Fig. 7.c and Fig. 7.f). Among all four basins,
451 the difference in median contributions of fast and slow flow is minimum. These can be attributed to the presence
452 of higher fraction of moderate and good groundwater potential zones (Arulbalaji et al., 2019) which promotes
453 baseflow even in dry periods (Fig. 9.g and Fig. 9.h). The presence of bimodal pattern in rainfall seasonality due
454 to both South-West and North-East monsoons minimizes the difference between the relative contributions of fast
455 and slow flow to total flow.



456

457 **Figure 10.** Seasonal contributions of fast (FF) and slow flow (SF) to total flow at basin scale.

458

459 5. Validation of stratification of streamflow variability

460 5.1 Understanding physical controls and spatial variation of flow duration curve by fitting statistical 461 distributions

462 So far in this paper, in order to understand the physical controls on regional streamflow variability across
463 Peninsular India we have partitioned observed streamflows in two ways: (i) seasonal/monthly flows, and (ii) slow
464 and fast flows. We looked at the relative contributions of these components to mean annual streamflow, looked at
465 how the relative contributions varied regionally, and attributed these to the relative strengths of the monsoons and
466 spatial variations of geological formations. We now return to the FDCs of the flow components, especially the
467 shapes of the FDCs (as reflected in the parameters of the fitted distribution) and look at how they themselves vary
468 regionally.

469 In our study the fast and slow flow time series are scaled by their respective long-term mean values to remove the
470 influence of mean climate and geology, thus providing an opportunity to identify the secondary controls on the
471 variation of shapes of FDCs. The scaled fast and slow flow time series are now used to fit the mixed gamma
472 distribution (MGD, (see details in Appendix A4). The parameters of mixed gamma distribution control the shape

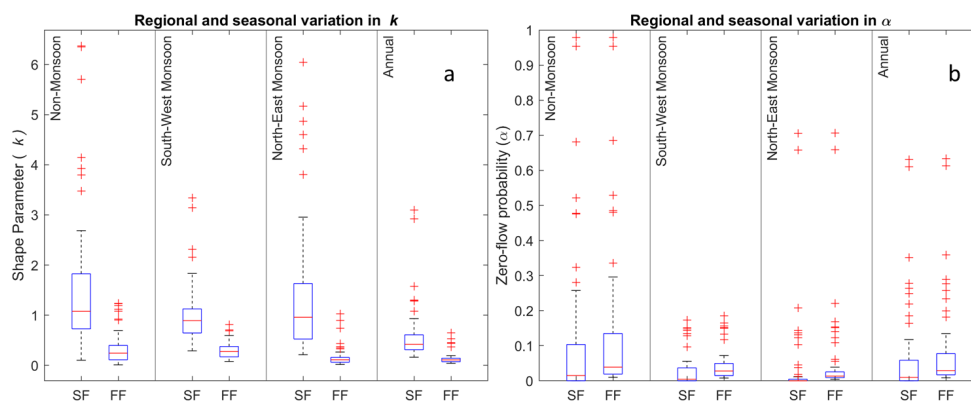


473 and orientation of the FDC. For example, the shape parameter k controls the slope of the FDC whereas α controls
474 the zero-flow part of the FDC. However, the parameter θ affects the vertical shift of the FDC. In addition, these
475 parameters are also linked with the mean and variance of the streamflow time series. For example, the scale
476 parameter θ is directly proportional to the mean of the time series whereas, the shape parameter k is inversely
477 proportional to the variance of the time series.

478 As the fast and slow flow time series are scaled with their respective long-term means, the scale parameter (θ) is
479 approximately found to be inversely proportional to shape parameter (k) through the relationship, $k\theta = \frac{1}{1-\alpha}$
480 (Cheng et al., 2012). Therefore, the variations of only k and α – zero-flow probability, are presented in this section.
481 The variation of k can be related to the steepness of the FDC, i.e., smaller values of k will have steeper slopes.

482 The Nash-Sutcliffe efficiency (NS) and coefficient of determination (R^2) goodness of fit of fast/slow flows to
483 MGD is shown in Fig. S10 (in Supplementary Information). In addition, the observed and simulated fast and slow
484 flow FDCs are compared in Fig. S8 (in Supplementary Information). It is observed that the slow flow component
485 fits well to mixed gamma distribution than fast flow component, as slow flow is most stable component and MGD
486 satisfactorily captured the shape of slow flow FDC. However, MGD adequately captures the shape of fast flow
487 FDCs at upper tail (high flow segment), except for the lower tail (low flow segment). The fast flow processes are
488 governed by more complex processes (for example, infiltration and saturation excess runoff generation, runoff
489 routing, stochastic nature of storm events, properties of soil and topography etc.) than slow flow (for example,
490 climate seasonality and underlying geology of aquifer system).

491 The seasonal variation of parameters of the mixed gamma distribution at regional scale (comprising of all the
492 gauging stations) is presented in Fig. 11. The mixed gamma distribution performed well in fitting the flow duration
493 curves of two flow components across different seasons (Fig. S10). In Fig. 11.a, it is observed that the shape
494 parameter of slow flow is consistently higher than that of fast flow. The shape parameter is inversely proportional
495 to the variance of streamflow. The slow flow exhibits lower variance due to its longer time of residence in the
496 subsurface formations. Moreover, the subsurface formations in Cauvery River basin are more favourable to slow
497 flow in comparison to the other three basins (Fig. 9.g and Fig. 9.h). In addition, the bimodal seasonal pattern of
498 rainfall is also responsible for occurrence of slow flow even in the Non-monsoon period for the southern basins
499 (Fig. 9).



500

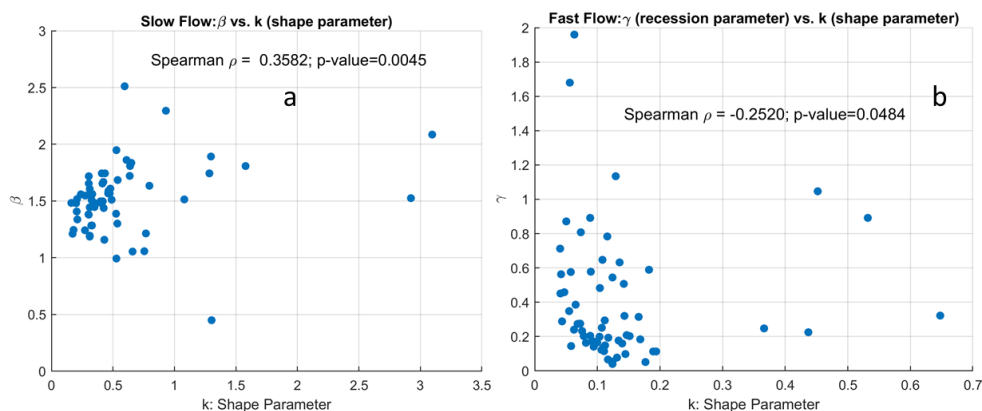
501 **Figure 11.** Regional and seasonal variation of k and α parameter of mixed gamma distribution.

502 The fast flow component exhibits higher variance than the slow flow component. The median shape parameter of
503 fast flow is highest during South-West monsoon season and lowest during North-East monsoon (Fig. 11.a). This
504 can be explained by the lower variance of fast flow during South-West monsoon as the rainfall amount is higher
505 during the season compared to the North-East monsoon (Fig. 7.c and Fig. 7.f). The dominance of both South-
506 West and North-East monsoons in Cauvery basin results in lower variance of fast flow compared to the northern
507 basins. The fast flow duration curves are steeper than the slow flow duration curves for all seasons, as the
508 magnitudes of k for fast flow are smaller than that of slow flow (Fig. 11.a).

509 The parameter α controls the zero-flow part of the flow duration curve. It is observed that the mean α for slow
510 flow is minimum during South-West monsoon and maximum for Non-monsoon season (Fig. 11.b) on a regional
511 scale. This can be attributed to the combined influence of rainfall during South-West monsoon and the
512 connectivity between underlying geologic formations in the Peninsular region. For the fast flow, the mean α is
513 minimum during the South-West monsoon and maximum during Non-monsoon as the South-West monsoon is
514 the dominating rainfall season in Peninsular India.

515 The shape parameters (k) of MGD for slow and fast flow components are linked with landscape properties through
516 recession analysis, where the parameters γ & β of power-law relationship are estimated using streamflow data
517 (details in Appendix A.2). It is observed that shape parameter (inversely proportional to variability) of slow flow
518 is positively correlated with β . The parameter β is influenced by aquifer geometry and water table elevation
519 profile defining early and late stages of recession (Tashie et al., 2020a; Tashie et al., 2020b). Higher values of β
520 indicate slow late recessions which is characterized by low variability in slow flow (Fig. 12.a).

521 The shape parameter of fast flow is negatively correlated with the parameter γ of the power-law relationship (Fig.
522 12.b). The parameter γ strongly related with the seasonality of catchment wetness and evapotranspiration which
523 are primary governing factors for runoff generation (Dralle et al., 2015; Gnann et al., 2021). In addition, the spatial
524 variation of rainfall also influences the variability of γ (Biswal & Kumar, 2014) which reflects the variability of
525 fast flow.

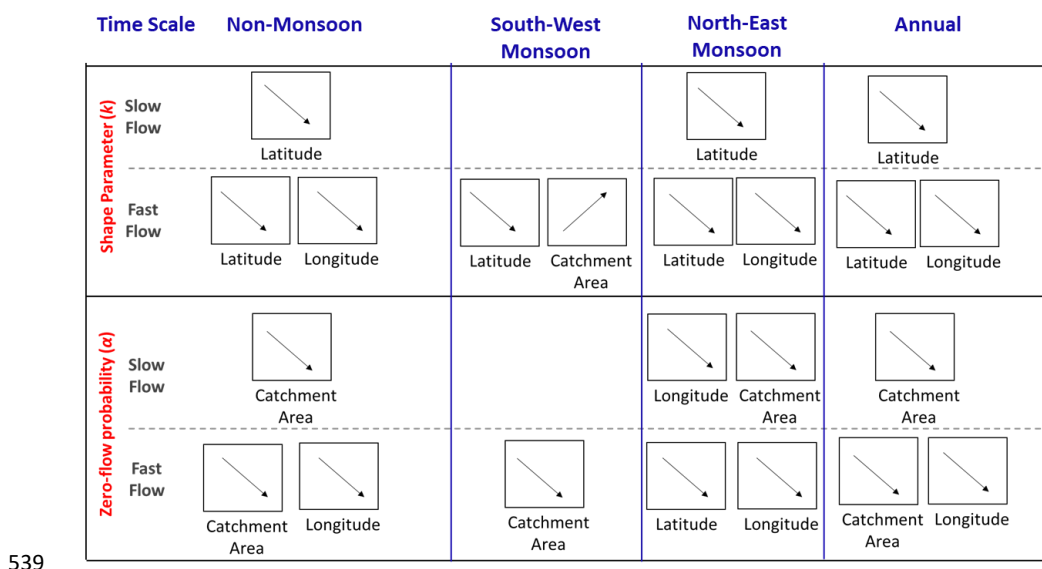


526

527 **Figure 12.** Relationship between flow variability (related inversely to shape parameter, k of mixed gamma
528 distribution) and recession parameters.

529 The variation of the parameters, k and α was also studied using spatial descriptors (latitude and longitude) as
530 explanatory variables to understand the spatial variation of FDCs across south-north, west-east gradients. In
531 addition, the behaviour of these parameters is also assessed using catchment area as another explanatory variable.
532 The regional parameter sets comprising of k and α are next constructed for slow and fast flow processes by
533 including these parameters for all the time series across different gauging stations across the Peninsular region.
534 The Spearman correlation coefficients between these parameters and explanatory variables (i.e., catchment area
535 and spatial descriptors – latitude and longitude) for slow and fast flow processes at seasonal scales are computed.
536 The schematic representation of significant directions (positive/negative correlations) in Spearman coefficient is
537 shown in Fig. 13.

538



540 **Figure 13.** Schematic representation of spatial and temporal variation of parameters of mixed gamma distribution
 541 across Peninsular India. The direction of significant Spearman correlation coefficient between model parameters
 542 and descriptors (catchment area and spatial descriptors – latitude and longitude) for fast and slow flow across
 543 multiple time scale is presented.

544 The shape parameter of fast flow is found to be positively correlated with catchment area (Fig. 13, top panel),
 545 implying lower variability of fast flow in large catchments. This can be attributed to increased smoothing effect
 546 of incoming rainfall in larger catchments through various storages, thus reducing the variability of fast flow.
 547 Moreover, the shape parameters for fast flow are negatively correlated with spatial descriptors, indicating
 548 increased variability of fast flow along south-north and west-east gradients. This can be partly explained by the
 549 bimodal seasonal pattern of rainfall due to dominance of South-West and North-East monsoons, thus reducing the
 550 variability of fast flow in the southern part of the region. The rainfall pattern becomes more seasonal (primarily
 551 due to South-West monsoon) in the northern part of region which can contribute to increased variability of fast
 552 flow. The presence of numerous water retention structures for supporting irrigation in these regions (54 – 75% of
 553 Peninsular basins are crop land) can modify the variability of the flow, although we have not analysed this
 554 separately in this study.

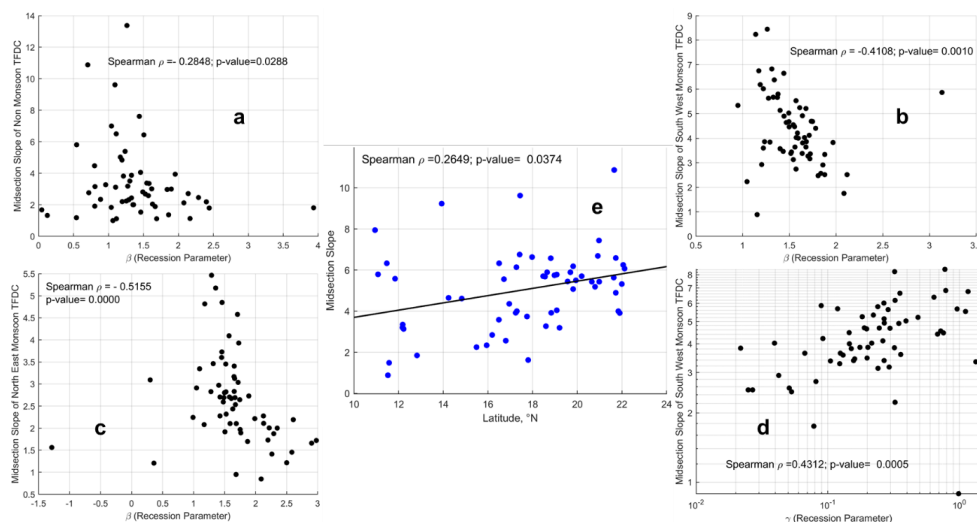
555 The shape parameter of slow flow is found to be negatively correlated with latitude, implying that slow flow
 556 becomes highly variable in the northern part of the region. This can be explained by the nature of geologic
 557 formations in the Cauvery basin that promotes slow flow even during the Non-monsoon period. However, in the
 558 northern part of the region, the slow flow tends to become more seasonal and has very limited flow during non-
 559 rainy seasons. In addition to the geology, the bimodal seasonal rainfall patterns due to monsoons can play an
 560 important role in the variability of slow flow. Apart from the spatial descriptors, the slow flow variability is
 561 inversely proportional to catchment area, implying larger catchments have lower slow flow variability than
 562 smaller catchments. This can be explained by the proportional increase in area of contribution to slow flow with
 563 increase in catchment size, thus reducing the variability in slow flow for larger catchments.



564 The parameter α is found to be negatively correlated with catchment area (Fig. 13, bottom panel) for fast and slow
565 processes, implying zero-flow probabilities are lower for larger catchments. The higher residence time of water
566 in larger catchment due to various kinds of storages facilitates flow in river even in Non-monsoon season, thus
567 reducing the zero-flow probabilities. In addition, the parameter α of both slow and fast flow are negatively
568 correlated with longitude, implying lower zero-flow probabilities along west-east direction. This can be attributed
569 to natural declining elevation (Fig. S1.b) which promotes both fast and slow flow towards eastern direction.

570 5.2 Understanding physical controls and spatial variation of seasonal flow duration curve using mid-section 571 slope

572 Apart from mean, variance and no-flow frequency, the midsection slope of the FDC – estimated using
573 $\frac{\ln(Q_{33p}) - \ln(Q_{66p})}{0.66 - 0.33}$, where Q_{33p} and Q_{66p} represent the streamflow values at 33rd and 66th percentiles respectively –
574 is connected to the average flow regime of the catchment, which is controlled by both surface and subsurface
575 processes (Yokoo & Sivapalan, 2011; Chouaib et al., 2018). The association of the slope of FDC with the
576 parameters pertaining to recession analysis is presented in Fig. 14.



577

578 **Figure 14.** Association between streamflow variability and recession parameters.

579 During Non-monsoon and North East monsoon seasons (Fig. 14a and Fig. 14c) – when rainfall is comparatively
580 less than South West monsoon – a significant association between flow variability and β highlights the importance
581 of slow flow and recession characteristics controlled by aquifer geometry and water table elevation profile. In
582 addition to significant association with β during South West monsoon (Fig. 14b), the midsection slope of FDC is
583 positively correlated with γ – the parameter which is strongly related with the seasonality of catchment wetness,
584 evapotranspiration and spatial variation in rainfall – revealing the importance of land surface processes in
585 variability of streamflow variability.



586 A coherent pattern in variability of streamflow (via. Midsection slope of FDC) is observed across South – North
587 gradient of the Peninsular region (Fig. 14e). This systematic pattern in streamflow variability reflects the influence
588 of combined functioning of subsurface and land surface processes on regional hydrologic signatures of Peninsular
589 India.

590 6. Conclusions

591 Being a signature of a catchment's hydrological behavior and a concise graphical summary of streamflow
592 variability at a specific gauging station, FDC relates the frequency and magnitude of observed streamflows and
593 helps explain flooding mechanisms and low flow conditions at the referred location. Furthermore, at the catchment
594 scale, FDCs incorporate the forcing mechanisms of the water cycle and the physical and morphological properties
595 of the river basin that influence the water partition between surface runoff and baseflow and, thus, control flow
596 regimes (Costa & Fernandes, 2021). Motivated by this fact, in this study we outlined a framework and its
597 suitability for understanding process controls of FDCs, which involved separating annual streamflow into seasonal
598 flow components and constructing annual FDC using seasonal FDCs. The goal of this study was to demonstrate
599 the efficacy of the framework to explore the process controls on streamflow variability across Peninsular India.
600 The study followed a data-based approach using streamflow data taken from 62 stream gauges distributed within
601 four major river basins in Peninsular India. The probability density functions are initially derived for daily
602 streamflow time series for Non-monsoon, South-West monsoon, and North-East monsoon seasons. These PDFs
603 are then multiplied by scaling factors that represent relative durations of the seasons considered. The probability
604 density function of annual flow is then estimated as the weighted sum of three scaled density functions
605 corresponding to three seasons. The performance of the time scale partitioning framework is then further assessed
606 using the metric root mean square error.

607 Analysis and interpretation of the results of the study revealed that the main drivers of regional variability of
608 streamflow across Peninsular India include (1) major mountain ranges – the Western and Eastern Ghats – which
609 govern regional atmospheric circulation and precipitation variability; (2) the South-West and North-East
610 monsoons that occur in different times of the year and come from different directions; and (3) east-west and north-
611 south gradients of geology. The combined influence of seasonal rainfall patterns, catchment size and the ability
612 of the subsurface formations to transmit slow flow controls the shape of flow duration curves of the flow
613 components along south-north and west-east directions in Peninsular region.

614 To summarize, the major findings of the study are outlined below:

615 I. Spatial variations of seasonal and annual flow duration curves across Peninsular India are initially
616 investigated by approximating the annual flow duration curve via partitioned seasonal and monthly flow
617 duration curves. FDCs of South-West monsoon flows are relatively dominant to other seasonal FDCs at
618 stations in the northern portion of the peninsula. From June to September, flow contributions in northern
619 Peninsular basins are significantly higher than in other months (Mahanadi and Godavari, Krishna to a
620 lesser extent). However, the contribution from June to September is not as substantial in the southernmost
621 Cauvery basin; there is also a major contribution from October to December. This is attributable to the
622 fact that the South-West and North-East monsoons both impact the Cauvery basin. It is further noticed
623 that the contribution of the North-East monsoon to annual flow is larger in southern basins than in



624 northern basins. The contribution of the Non-monsoon to annual flow is also stronger in the southern
625 basin and is attributed to winter rains from the North-East monsoon, which are more evident in the
626 southern part of the peninsula, creating carryover flows.

627 II. The streamflow produced in the headwater regions of southern basins, which extends until 17° N latitude
628 and contributes at least 70% of the annual flow, is a result of high rainfall during the South-West monsoon
629 season in the mountainous region of the southern Peninsula (western part of Krishna basin and north-
630 western part of Cauvery basin). The northern part of the Peninsular region experiences notably higher
631 rainfall than the southern part, not considering the Western Ghats region. The low-pressure system, which
632 is a regular feature of the South-West monsoon that brings significant rainfall in the northern part of the
633 Peninsular region, attributes the increased rainfall (after 16° N latitude) and is responsible for the higher
634 contribution of South-West monsoon flows to annual flow in the northern basins. The spatial variation in
635 the contribution of South-West monsoon flows to annual flow in the south-north direction is thus
636 explained by the spatial variability of the South-West monsoon in the same direction over the Peninsular
637 region. The contribution of North-East monsoon flows to annual flow, on the other hand, increases in a
638 southerly direction, which can be explained by the fact that the southern part of the Peninsular region
639 receives more rainfall during the North-East monsoon than the rest of the Peninsular region.

640 III. Spatial variations of fast/slow and total flow duration curves across Peninsular India are then explored
641 by approximating the total flow duration curve by partitioned flow duration curves. Relative
642 contributions of fast and slow flows to total flow in each of the four river basins show a significant
643 dominance of fast flow in the northern basins, close to 80% in Mahanadi, Godavari, and Krishna river
644 basins.

645 IV. The Western Ghats, which run along the western boundary of the Krishna and Cauvery basins, bring a
646 lot of rain to the southern part of the region. As a result, the western margins of the sub-basins along the
647 Krishna basin contribute 80 percent of the fast flow to total flow (between 13° N and 18°N latitudes).
648 However, the south-north gradient in fast flow contributions to total flow is governed by increasing
649 spatial mean characteristics of annual rainfall after 16° N latitude, which dictates an increased
650 contribution of fast flow to total flow.

651 V. The greater contribution of slow flow to total flow in the southern Peninsular region, particularly Cauvery
652 and Krishna, is characterized by bimodal rainfall seasonality and the presence of a higher fraction of
653 moderate to good groundwater potential zones and is responsible for the spatial variation of
654 increased relative contributions of slow flow to total flow in the southerly direction over the Peninsular
655 region.

656 VI. A coherent pattern in streamflow variability across the South-North gradient of the Peninsular region is
657 observed via the midsection slope of FDC. These similar spatial variation in streamflow variability
658 demonstrate the impact of combined subsurface and land surface processes on Peninsular India's regional
659 hydrologic signatures.

660 Previous data-based explorations of process controls on the FDC have typically followed a Darwinian (Harman
661 and Troch, 2014) comparative hydrology approach. They have looked at between-catchment and regional
662 variations of the FDC (or of parameters of statistical distributions fitted to empirical FDCs), their attribution to
663 climatic and landscape properties, and their interpretation in terms of their underlying process controls (fast flow



664 and slow flow etc). In the Darwinian approach, each catchment is deemed a particular but statistically independent
665 realization of the coevolution of climate and landscape properties, with the hydrologic response being both a cause
666 and effect in this coevolution (Wagener et al., 2013). The novelty of the data-based exploration of process controls
667 on the FDC adopted in this study is that here we have followed a Wegenerian (cf. Alfred Wegener, Sivapalan,
668 2018) comparative hydrology approach, in which the focus was on exploration of the controls of common regional
669 landscape features (in space) and seasonal climatic variations (in time) features on regional variations of the FDC.
670 We interpret the imprints of the regional variations streamflow variability of the FDCs outlined as findings across
671 Peninsular India as the consequence of several episodes of tectonic, geological, and volcanic activities in the
672 Indian subcontinent ever since the breakup of Gondwana and its collision with Asia during the Jurassic age,
673 resulting in the uplift of mountain ranges, including the Himalayas, and their role in the establishment of India's
674 monsoon climate.

675 We acknowledge, however, that in recent times streamflow variability in Peninsular India has been significantly
676 impacted by anthropogenic activities, including significant land use and land cover changes, and other human
677 interferences such as the building of dams and the extraction of water from both rivers and from groundwater
678 aquifers for human use. The present study has not explored the effects of human impacts: their impacts on both
679 temporal (inter-decadal) and spatial (regional) variations of the FDCs is left for future work. Further work is also
680 needed to understand in more detail the causes and the relative contributions of regional patterns precipitation and
681 geological formations on streamflow partitioning.

682 On the methodological front, there is opportunity to refine the analysis used here to incorporate the statistical
683 cross-correlation between fast and slow flows in the reconstruction of the FDC for total streamflow, by adopting
684 generalized approaches (e.g., copulas). In the exploration of the relative contributions of the monsoons, there is
685 scope to extend the analysis framework to partition the streamflow variability guided by the actual breakdown
686 into the seasons each year in a more flexible way, as opposed to the static way. This is likely to make the results
687 of the analysis more robust and less uncertain. Finally, in the process domain, the filter-based separation of total
688 streamflow into fast and slow flow can be variably impacted by catchment size, introducing some uncertainty into
689 the partitioning of the FDC of total streamflow into its fast flow and slow flow components. Future work in this
690 area should explore ways to overcome these methodological shortcomings.

691

692 **Appendix**

693 **A.1 Baseflow decomposition (Recursive Digital Filter)**

694 The partitioning of total flow (Q) into slow flow (Q_s) is performed using recursive digital filter technique as
695 described in Arnold & Allen (1999) and Arnold et al. (1995). Based on the study by Nathan and McMahon (1990),
696 they found that a coefficient range between 0.9 and 0.95 yielded most acceptable baseflow separation. Therefore,
697 we have taken the value 0.95 as a coefficient value for this analysis. This filter is applied to daily streamflow
698 timeseries data for all the gauging stations across the Peninsular region.

699 The equation of the filter is

$$700 \quad q_t = \varepsilon q_{t-1} + \frac{(1+\varepsilon)}{2} (Q_t - Q_{t-1}) \quad (\text{A.1})$$



701 where q_t is the filtered surface runoff (quick response) at the t time step, Q is the original streamflow (total flow),
702 and ε is the filter parameter (which is assumed to be 0.95). Slow flow, Q_s , is calculated with the equation:

$$703 \quad Q_s = Q - q_t \quad (\text{A.2})$$

704 After obtaining the slow flow component, the fast flow (Q_f) is obtained by subtracting Q_s from Q .

$$705 \quad Q_f = Q - Q_s \quad (\text{A.3})$$

706 A.2 Recession Analysis

707 In recession analysis, it is often assumed that rate of change of streamflow $\frac{dQ}{dt}$ and streamflow (Q) follows a
708 power law in the form:

$$709 \quad -\frac{dQ}{dt} = \gamma Q^\beta \quad (\text{A.4})$$

710 The parameter γ is function of static watershed properties (i.e., hydrological conductivity, drainable porosity,
711 aquifer depth, aquifer breadth, impermeable layer slope and length of stream) (Tashie et al., 2020a). The parameter
712 β represents the geometry of the contributing aquifer and water table elevation profile that defines the early and
713 late periods of recession (Tashie et al., 2020b). $\frac{dQ}{dt}$ is estimated using exponential time stepping scheme (Roques
714 et al., 2017). Strictly decreasing recession segments ($\frac{dQ}{dt} < 0$) with recession segments more than 5 days are
715 considered for the estimation of the parameters (γ and β) (Jachens et al., 2020). A weighted least square
716 regression is used to fit a line in log-log space to recession segments (Roques et al., 2017). The median of the
717 parameters is used to describe catchment-average recession behaviour (Gnann et al., 2021).

718 A.3 Absolute contributions of fast and slow flow to total flow

719 The absolute contributions of fast and slow flow to total flow are determined using the coefficient of determination
720 (R^2) of simple linear regression models, that measures the reduction in variability of total flow due to fast and
721 slow flow components. The details are given below:

$$722 \quad \text{Model 1: } Q = \varphi_1 \cdot Q_f + \varepsilon_1 \quad (\text{A.5})$$

$$723 \quad \text{Model 2: } Q = \varphi_2 \cdot Q_s + \varepsilon_2 \quad (\text{A.6})$$

724 The coefficient of determination measures the effect of slow/fast flow in reducing the variation in total flow
725 based on Model1(Model2). Higher the value of this coefficient, higher the contribution of slow/fast flow in
726 reducing the variation in total flow.

727 The coefficient of determinations for two models can be estimated as:

$$728 \quad R_{(1)}^2 = \frac{SSR^{(1)}}{SSTO} \quad (\text{A.7})$$

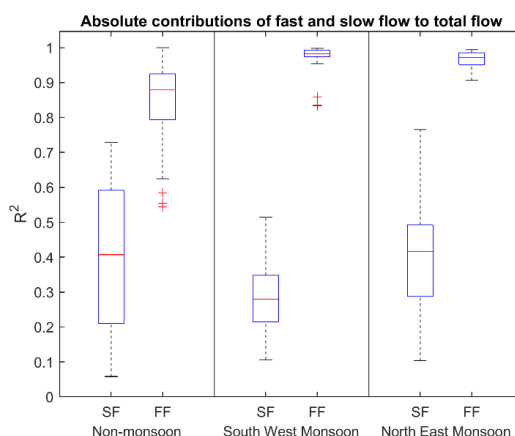
$$729 \quad R_{(2)}^2 = \frac{SSR^{(2)}}{SSTO} \quad (\text{A.8})$$



730 where, $SSR^{(1)}$ and $SSR^{(2)}$ represent the regression sum of squares for Model 1 and Model 2 respectively, and
 731 $SSTO$ represents the total sum of squared deviations from mean, i.e., $SSTO = \sum(Q_i - \bar{Q})^2$. The sum of squares
 732 due to the models are expressed as:

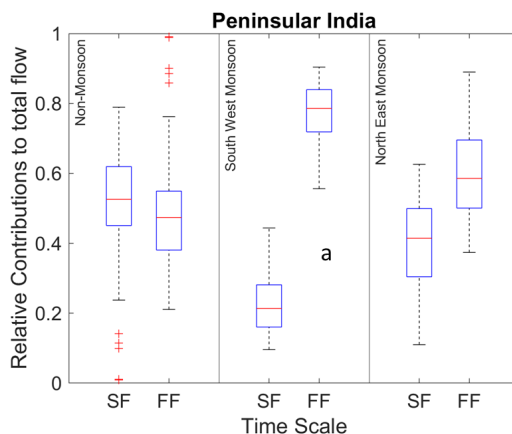
733 $SSR^{(1)} = \sum(\widehat{Q}_{(1)} - \bar{Q})^2$ and $SSR^{(2)} = \sum(\widehat{Q}_{(2)} - \bar{Q})^2$ where $\widehat{Q}_{(1)}$ and $\widehat{Q}_{(2)}$ are the fitted values of total flow using
 734 Model 1 and Model 2 respectively.

735 The values of coefficient of determination (R^2) for three seasons are shown in Fig. A1.



736

737 **Figure A1.** Coefficient of determination representing the absolute contribution of fast/slow flow in reducing the
 738 variation in total flow across seasons.



739

740 **Figure A2.** Relative contributions of fast (FF) and slow flow (SF) to total flow at regional and seasonal scales
 741 (NM – Non-monsoon, SW – South-West monsoon and NE – North-East monsoon).



742 It can be shown that the pattern of absolute contribution remains similar (in terms of phase relationship between
743 slow and fast flow contributions to total flow) with that of relative contribution as reported in Fig A2. However,
744 there are differences in the magnitudes of the absolute contributions and relative contributions of the flow
745 components to total flow. The major difference between relative and absolute contribution analyses is that the
746 contribution of the fast flow is significantly higher than the slow flow for non-monsoon season, which can be
747 attributed to rainfall during the non-monsoon period (Fig 6).

748 A.4 Fitting statistical distributions

749 A simple statistical distribution, the mixed gamma distribution, is employed here to characterize the FDC in
750 Peninsular River system. The choice of the mixed gamma distribution is made to take care of the flow regimes of
751 the selected basins (i.e., to accommodate the presence of zero flow values) (Cheng et al., 2012). The classic gamma
752 distribution is a two-parameter, continuous distribution with a shape parameter, k , and a scale parameter, θ . In
753 addition, the probability of zero flows, α , is defined as the ratio of the number of zero flow days to the total number
754 of days within the data record. The mixed gamma distribution (Cheng et al., 2012) employed to model FDC is as
755 follows:

$$f(q, k, \theta, \alpha) = \begin{cases} \alpha, & q = 0 \\ (1 - \alpha) \cdot g(q, k, \theta), & q > 0 \end{cases} \quad (\text{A.9})$$

756 where $g(q, k, \theta)$ is the probability density function of the gamma distribution. The probability density function of
757 the gamma distribution is assumed to take the form of (Cheng et al., 2012):

$$g(q, k, \theta) = \frac{1}{|\theta| \Gamma(k)} \left(\frac{q}{\theta}\right)^{k-1} \exp\left(-\frac{q}{\theta}\right) \quad (\text{A.10})$$

758 where k and θ are the shape and scale parameters, respectively. The parameters k and θ can be estimated by the
759 method of moments. The mean, μ , and variance, v , of the gamma distribution are evaluated from the $q > 0$ time
760 series. The parameters are related to μ and v as follows:

$$\mu = k \cdot \theta \quad (\text{A.11})$$

$$v = k \cdot \theta^2 \quad (\text{A.12})$$

761 The following formulation is used to obtain the flow given a probability of exceedance, p (Cheng et al., 2012):

$$q(p, k, \theta, \alpha) = \begin{cases} G^{-1}\left(1 - \frac{p}{1 - \alpha}, k, \theta\right), & 0 \leq p \leq 1 - \alpha \\ 0, & 1 - \alpha < p \leq 1 \end{cases} \quad (\text{A.13})$$

762 where G^{-1} is the inverse of the CDF of the mixed gamma distribution.

763 In this case, given that we have already looked at the climatic and landscape controls on the mean annual flows,
764 we instead work with the normalized daily streamflow time series (i.e., daily streamflow divided by long-term
765 mean daily streamflow), which is then used to estimate the parameters of the mixed gamma distribution. The
766 parameters estimated from the normalized streamflow series can thus be used to infer secondary controls on the
767 shape of flow duration curves.

768 *Data availability.* The streamflow datasets used for the analysis are accessible from
769 <https://indiawris.gov.in/wris/#/>. The daily India Meteorological Department (IMD) gridded rainfall product at



770 spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$
771 (https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html) from Pai et al., (2014) is
772 used. The function baseflow, used for partitioning total flow to slow flow is downloaded from
773 [https://in.mathworks.com/matlabcentral/fileexchange/58525-baseflow-filter-using-the-recursive-digital-filter-](https://in.mathworks.com/matlabcentral/fileexchange/58525-baseflow-filter-using-the-recursive-digital-filter-technique)
774 [technique](https://in.mathworks.com/matlabcentral/fileexchange/58525-baseflow-filter-using-the-recursive-digital-filter-technique).

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783

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