

1 **Climate-Catchment-Soil Control on Hydrological Droughts in Peninsular India**

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27 **Abstract**

28 Most land surface system models and observational assessments ignore detailed soil characteristics
29 while describing the drought attributes such as growth, duration, recovery, and the termination rate
30 of the event. With the national-scale digital soil maps available for India, we assessed the climate-
31 catchment-soil nexus using daily observed streamflow records from 98 sites in tropical rain-
32 dominated catchments of peninsular India (8 - 25° N, 72 - 86° E). Results indicated that climate-
33 catchment-soil properties may control hydrological drought attributes to the tune of 14-70%. While
34 terrain features are dominant drivers for drought growth, contributing around 50% variability, soil
35 attributes contribute ~71.5% variability in drought duration. Finally, soil and climatic factors
36 together control the resilience and termination rate. The most relevant climate characteristics are
37 potential evapotranspiration, soil moisture, rainfall, and temperature; temperature and soil
38 moisture are dominant controls for streamflow drought resilience. Among different soil properties,
39 soil organic carbon (SOC) stock could resist drought propagation, despite low-carbon soils across
40 the Indian subcontinent. The findings highlight the need for accounting feedback among climate,
41 soil, and topographical properties in catchment-scale drought propagations.

42 Introduction

43 Peninsular River Basins (PRB) of India (8-25° N, 72-86° E) are facing increasingly severe
44 droughts and water scarcity¹⁻³. Climate change and an ever-growing population further strain
45 locally-available surface water⁴ gradually push the region towards a ‘day-zero’ situation⁵. Krishna
46 and Godavari are the two major rivers in PRB and both are rain-fed. Failures and delays in
47 southwest (June to September) or northeastern (October – December) monsoon⁶⁻⁸ in this region
48 trigger below-normal streamflow and hydrological droughts⁹ in varying intensities. Even with
49 decades of catchment-scale drought propagation studies^{2,8,12,11,12}, it is not clear how a given river
50 basin develops into a “drought-rich” or “drought-poor” region. Climate and catchment control on
51 hydrological droughts are more or less known¹³⁻¹⁷; however, no studies have attempted to examine
52 how varying soil conditions influence these controls. With the availability of a national-scale
53 digital soil map¹⁸, here we explore the climate-catchment-soil control on hydrological droughts
54 and identify key drought drivers (KDD) for drought propagation.

55
56 We used daily observed streamflow records of past 50 years (1965 – 2019) from 98 stream gauges
57 over PRB in a multi-stage framework^{19,20} (**Fig. 1**) to quantify the contiguity in locations and time
58 of occurrence of hydrologic droughts (the space-time clustering²¹ or synchronicity in drought
59 properties) and identify potential KDDs from a wide range of climate, soil, and terrain attributes
60 (**Fig. 1**, Supplementary **Fig. S1**, **Table S1**). We applied a daily variable threshold approach to
61 derive streamflow droughts by developing 366 (additional for leap year) flow duration curves
62 using continuous streamflow records²² (Methods). While we obtain meteorological and catchment-
63 specific geospatial attributes from the archived database²³⁻²⁷, the soil attributes are derived from a
64 recently developed digital soil database of India¹⁸ (see Data and Method section). We show the
65 extent to which climate, catchment and soil attributes influences and co-vary with catchment-scale
66 drought characteristics (Methods), such as growth, persistence (duration and frequency or number
67 of events), recovery, and drought termination rate (DTR). Specifically, we investigate how soil
68 organic carbon (SOC) influence the growth, persistence, and recovery of droughts over PRB given
69 that the Indian soils are typically low in SOC contents^{18,28}.

71 Space-Time Synchronicity in Drought Responses

72 Previous studies^{10-13,29} have used gridded hydrometeorological forcing with a coarser temporal
73 resolution to identify drought clusters over PRB. Here, we identify the temporal evolution of
74 drought characteristics using continuous daily streamflow records, namely, drought growth,
75 persistence, recovery and the DTR (See Methods; **Fig. 1b-c**). Then, we identify drought regimes
76 by applying a clustering algorithm to 98 gauges across PRB based on 9 catchment-scale drought
77 attributes (see Methods): (i) latitude and longitude of the stream gauges; (ii) drought properties,
78 *i.e.*, mean and maximum drought duration, and mean and maximum deficit volume; (iii) catchment

79 properties, such as the baseflow index (BFI)³⁰ and catchment area, and (iv) seasonality³¹ in drought
80 termination. We show the temporal evolution of drought characteristics and identify the presence
81 of “drought rich” and “drought poor” periods over the past five decades using the Hovmöller
82 diagram (**Fig. S2**). The decadal pattern of events (during the time-window 1979-80, 1989-90,
83 2001-02, 2008-10) shows over 30% of the areas are drought-affected. Further, we identify spatial
84 clustering of persistent droughts over several regions, primarily concentrated between latitudinal
85 belts 13° and 20°N latitudes between 2001 to 2005, including two major historical hydrological
86 drought events spanning the periods, 2000-01 and 2003-04 (ref. ¹⁰). The drought in 2000 is mainly
87 attributed to warmer Sea Surface Temperature (SST) conditions that drive warm El Niño
88 conditions in the Pacific and Indian oceans¹⁰. An earlier study³² reported a decrease in precipitation
89 and low seasonal streamflow variability over PRB is associated with the warm El Niño Southern
90 Oscillation (ENSO) episode. On the other hand, drought in July 2002 was typically associated with
91 the lack of monsoon rainfall, which led to droughts in a large part of the western peninsula³³.

92

93 To explore the nature of hydrological drought responses on a regional scale, we delineate the
94 collection of sites based on fuzzy c-means clustering^{34,35} (see Methods and the Supplementary
95 Information SI 1.2). A study by Ahmadi et al.²⁰ showed characterizing droughts into different
96 stages or properties provide better understanding of temporal and spatial coherence of localized
97 drought events. Further, Yaeger *et al.*³⁶ showed that only accounting geomorphological features
98 and drought attributes may not provide a credible estimate of the homogenous region. Hence, we
99 introduce the seasonality of drought termination month, represented by the mean date of drought
100 termination, to identify homogenous regions (see Methods). The regionalization of hydrological
101 droughts based on drought properties involves the Principal Component Analysis (PCA) followed
102 by fuzzy c-means clustering method³⁷ (See SI 1.2). Based on PCA and fuzzy clustering, we identify
103 the optimal number of drought regimes (*i.e.*, represented by a cluster of sites based on drought-
104 specific attributes) as 4. We find that collectively the first six principal components (PCs) explain
105 the ≈94% variability of the streamflow droughts characteristics (**Fig. S3a**); therefore, only the first
106 six PCs are used for identifying drought clusters. The biplot of the top two PCs of the selected
107 attributes shows (**Fig. S3b**) that the maximum and mean drought durations have notable
108 contribution to the first PC. On the other hand, for the second PC, the seasonality of drought
109 termination, showed the significant contribution. The mean deficit volume and the catchment area
110 did not significantly contribute to the first two PCs. The BFI showed a negative correlation with
111 both these PCs. Geospatial locations and drought durations significantly contributed to the spatial
112 variations in clusters 1 and 4 and the mean termination date contributed to the spatial variations
113 in cluster 2. Finally, the BFI that inherently embeds the effect of geology and soil permeability is
114 the major contributor for variations in cluster 3.

115 **Fig. 2a** shows the delineated hydrological drought regimes, a large fraction of stream gauges
116 located across the central part of PRB is under regime 1 with 35% spatial extent; whereas regimes
117 2-4 contain 20-24% of gauges. **Figs. 2b-f** shows the spatial distribution of drought characteristics
118 during 1965-2018 time window. Most catchments located in Central (*i.e.*, catchments of Godavari,
119 and Narmada) and a few of eastern (Subarnarekha and Mahanadi) river basins (**Fig. S1**) reported
120 a large growth period, often more than a week (**Fig. 2b**) with frequent drought (**Fig. 2f**) events.
121 The average drought duration in the catchments of Godavari and Narmada from regimes 1 and 2
122 ranges more than 50 to 100 days. In particular, the catchments in regime 1 show a large variation
123 in DTR often exceeding 250 mm/day (**Fig. 2d**) with a recovery length more than a month (**Fig.**
124 **2e**). The spatial distribution of seasonality in drought termination (**Fig. S4**) shows high regularity
125 in drought termination for regimes 1 and 2 with average seasonality of more than 0.5. The
126 catchments in regime 1, which includes 74% sub-basins from Narmada, and the Godavari in
127 Central India and remaining from Krishna, and Mahanadi basins contains large watershed area and
128 show persistently longer drought episodes with average termination period during mid-monsoon
129 season during the month of September. Temporal evolution of drought characteristics during 2000
130 – 2005 time window for rivers in Central India (regime 1) shows (**Fig. S5**) the growth of droughts
131 initiated during the month of August in 2000, which lasted until early 2001; subsequently, the
132 majority of stations showed recovery in the monsoon season of the same year (*i.e.*, in June 2001).
133 During the year 2003 – 05, we note the presence of multi-season persistent droughts, especially
134 towards the South of 20°N, which lasted for more than a year (from March 2004 to July 2005) in
135 this region. The rivers in this region contains low BFI with a median value around 0.3. Further,
136 this region often accompanied by strong local heating of the black soils with high PET³⁸, which
137 could lead to low baseflow yield in this region³⁹. The low BFI, indicates a flashy flow regime with
138 less permeable soil that may generate more minor drought events that have short duration.

139
140 The sub-basins in Regime 2 shows relatively fewer drought events than other regions with
141 relatively low average drought duration (less than 100 days; **Fig. 2c**) and is associated with the
142 lowest average recovery period (average recovery less than a month; **Fig. 2e**). This regime includes
143 70% of sub-basins from Krishna, Tapi, and the Godavari River basins (**Fig. S1**) with moderately
144 large catchments areas. The most severe drought that occurred in Regime 2 lasted around 250 days
145 (August 2003 to April 2004; **Fig. S5**). For gauges located in this regime, the drought terminations
146 ranges between August and December months with median termination during post-monsoon
147 season in October (**Fig. S4**). The values of BFI tend to be the lowest for this regime as compared
148 to others, with a median BFI value of 0.25 (**Fig. S4**). Interestingly, the rivers in this regime shows
149 a strong seasonality in the mean timing of drought termination with the strength of seasonality
150 close to 0.8 indicating high persistence in drought termination, *i.e.*, all streamflow droughts at a
151 particular site occur on the same day of the years during the analysis time window⁴⁰.

152 Regime 3, comprising nearly 60% of sub-basins from Cauvery and Krishna and the rest from the
153 southern peninsula region (*e.g.*, Pampa, Periyar, Vaigai), experience the lowest number of
154 droughts (on an average, 15-20 events; **Fig. 2f**) followed by a minimum variation in the DTR (<
155 15 mm/day; **Fig. 2d**). In general, the drought termination pattern in regime 3 does not show any
156 specific trend with termination period scattered throughout the year with a large variation in
157 seasonality strength; however, August is detected as the median termination month (**Fig. S4**). The
158 rivers in this regime show the highest BFI (with BFI > 0.5), which may be due to the presence of
159 large reservoirs (the Krishnaraj Sagara reservoir over Cauvery River) and wet lands^{41,42}. The
160 catchments with high BFI sustain the recharge and groundwater storage³⁹, which results in large
161 variation in drought termination months (or low seasonality in drought termination; **Fig. S4**). The
162 analysis of 2000-05 time window for regime 3 shows (**Fig. S5**) the “drought-rich” periods exist
163 after 2002, which persists between 2003 and 2005. By early 2003, the catchments of Cauvery and
164 a few catchments in southern India (*e.g.*, Pampa and Ponnaiyar) were also affected and remained
165 under drought throughout the year, which recovered later in April-May 2004.

166
167 Finally, regime 4, comprising a majority of catchments across eastern peninsular India (87% of
168 sub-basins from Mahanadi, Subarnarekha, and Brahmani and the rest from Baitarni and Godavari;
169 **Fig. S1**) reported an average drought duration of more than two months with a large variability in
170 drought frequency (15-30 events) (**Fig. 2f**). The average drought recovery length in this regime is
171 relatively larger (**Fig. 2e**) and a large number of sites show recovery period more than 40 days.
172 The most severe drought in regime 4 occurred in August 1979 which lasted until July 1980 (**Fig.**
173 **S2**) and was considered as a severe drought in the literature^{43,44}. The average drought termination
174 period in this regime is mainly during post-monsoon period in November (**Fig. S4**) with
175 termination months varies from October to December. The catchments in this regime showed the
176 least regularity in drought termination (**Fig. S4**).

177
178 Overall, our analyses reveal the following: (i) majority of regimes (1, 2, and 4) show the average
179 termination either in the monsoon (June-September) or post-monsoon (October-December)
180 months suggesting profound roles of southwest and northeast monsoon rainfalls in the termination
181 of droughts. On the other hand, regime 3 showed no specific trend in drought termination
182 seasonality with termination periods scattered throughout the year. (ii) Large spatial heterogeneity
183 in drought responses indicates drought stages differ significantly across space and time, which
184 could be a consequence of several factors including topography and morphological attributes of
185 catchments, soil, and climatic controls^{15,16,45}.

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189 Hot and Cold Spots of Streamflow Droughts

190 To further explain the nature of synchronicity in drought responses and identify vulnerable regions,
191 we compare the maximum deficit volume and maximum duration of streamflow droughts (**Fig.**
192 **3a**). In addition, we present heat maps of drought deficit volume-recurrence interval-vs-recovery
193 duration for different regimes (**Fig. 3b**). A large fraction of gauges in Regime 1 is characterized
194 by moderately severe drought (a spatial average value of 1.7 mm); however, experiences long and
195 persistent drought episodes (more than 250 days; **Fig. 3a**). The rivers in this regime show an
196 extended drought recovery period coinciding with a short return time or recurrence interval (within
197 the range of 250 days; **Fig. 3b**).

198
199 On the other hand, regime 2 shows droughts with relatively longer recurrence interval
200 accompanied by more than a month of recovery period. Droughts in this regime have the lowest
201 deficit volume with average deficit volume ~0.74 mm (**Fig. 3a and b**). This could be because
202 catchments in this region show the lowest BFI values than others (**Fig. S4**), suggesting a minimum
203 contribution towards groundwater recharge owing to relatively impermeable geology^{16, 46-47}.
204 Regime 3 shows the largest average recovery length (**Fig. 2e**) with considerable variability in
205 deficit volume – a few outlying events even led to deficit volume of more than 200 mm (See
206 whisker length of the box plot in **Fig. 3a**). This region also shows considerable variability in
207 drought seasonality (**Fig S4**). Interestingly, more than 50% of sites show a recovery period of less
208 than a month (shades of the pixels in **Fig. 3b**) with an average recurrence interval of 350 days (**Fig.**
209 **3b**), which is the largest among all regimes. A relatively small recovery period compounded by a
210 large recurrence interval could be due to the largest baseflow indices of catchments in this region
211 (**Fig. S4**), which indicate relatively permeable geology with substantial groundwater recharge.

212
213 Finally, regime 4 shows a contrasting pattern to regime 1, where droughts with relatively less
214 deficit volume (< 1 mm) are coincided with a recovery period of more than a month. Further, a
215 rare event characterized by a high deficit volume of more than 10 mm and a prolonged recurrence
216 interval of more than 100 days often witnesses a low recovery period (typically less than a month;
217 **Fig. 3b, bottom right corner**). A relatively long recovery period could be because of low baseflow
218 indices for gauges in this region with a median value of less than 0.5 (**Fig. S4**), indicating a flashy
219 river basin^{47,49} analogous to regime 2.

220
221 Overall, our analysis shows the following: (i) catchments in central peninsular India (13-23°N and
222 73-84°E) is exposed to frequent droughts compounded by a long recovery period, making it one
223 of the most vulnerable regions where a chronic state may be reached when an incomplete recovery
224 would coincide with another severe drought episode leading to an adverse consequence to land-
225 carbon sink. Interestingly, this region contains relatively low SOC contents as may be seen in the

226 newly developed national SOC map¹⁸. (ii) In contrast, catchments in regime 2 are characterized by
227 relatively less severe droughts with a larger recovery period despite having the lowest BFI in
228 regime 2. We hypothesize that streamflow drought resiliency in regime 2 could be partially linked
229 to the high SOC content of the soil in the Western Ghat area of the PRB¹⁸ - a high SOC may lead
230 to an increase in soil water storage capacity resulting in a slowdown in severe drought occurrences.
231 On the other hand, the low BFI at region 2 could be associated with climate, soil and
232 geomorphologic properties. While soil controls the infiltration of water, the underlying aquifer
233 properties control the storage and release of water to streams. Recently, Naveena *et al.*³⁸ have
234 detected emergence of a “hot blob” during the pre-monsoon season (end of March – May) over
235 the south-central parts of the PRB, which promotes the accumulation of high temperature in this
236 region. High clay content of black soils (region 2) further abets the sustenance of the “hot blob”
237 resulting in higher frequencies of hot days, which could lead to low baseflow yields in this region³⁹.

238

239 **Key Drought Drivers (KDD's) Influencing Drought Vulnerability**

240 To provide a causal attribution of drought responses, we investigate the influence of several
241 covariates, such as meteorological variables, soil properties, and catchment-specific terrain
242 attributes (**Table S1**), totaling 89 hydrometeorological and morphological features. The Shapiro-
243 Wilk test of drought variables as well as the covariates reveal that 85% of variables (*i.e.*, 79 out of
244 93) show a strong deviation from normality assumption at a 10% significance level. The skewness
245 and kurtosis values of covariates further confirm that the covariates exhibit a strong asymmetry
246 (**Fig. S7**). The nonparametric dependence analysis (Kendall's τ test) suggests that the drought
247 growth strongly depends on (significant positive dependence) terrain features in regime 1, from
248 which topographic wetness index (TWI) shows the highest correlation value of Kendall's $\tau = 0.39$.
249 This could be because the TWI^{50,51}, which is a function of the local slope with the upslope
250 contributing area per contour length, will be more likely in wet and relatively shallow soils with
251 moderate slopes, where soil permeability increases with saturation. On the other hand, drought
252 duration and recovery show (significant) negative dependence on SOC and stock (Kendall's $\tau < -$
253 0.21). This may be due to moderately low SOC content in this region^{18,28}.

254

255 In regime 2, the drought growth shows positive dependence to both soil and meteorological
256 attributes, such as the mean temperature of April-July (Kendall's $\tau > 0.48$) followed by pH and
257 cation exchange capacity (CEC) values at 0.3 and 1 m soil depths (Kendall's $\tau > 0.47$),
258 respectively, whereas a negative dependence was observed for SOC content and SOC stock
259 (Kendall's $\tau < -0.35$). In contrast, the recovery stage in this region shows more dependence on
260 terrain features. In regime 3, the growth shows a strong positive dependence on different soil
261 moisture covariates (**Fig. S7**). Further, there is high variability among factors influencing drought
262 duration and recovery – in general, sub-basins show a strong negative dependence on soil organic

263 content (Kendall's $\tau < -0.44$). In contrast, DTR fails to show any conclusive evidence of
264 significantly strong dependence on any of the covariates. Finally, in regime 4, recovery and DTR
265 show a moderately strong dependence with meteorological and terrain features, which is in the
266 order of ± 0.4 (*i.e.*, terrain feature slope show a significant negative dependence with drought
267 recovery, Kendall's $\tau_{\text{recovery}} = -0.4$ and a significant positive correlation with DTR, Kendall's τ_{DTR}
268 $= 0.38$).

269

270 Our analyses reveal a large proportion of gauges in regimes 2 and 3 that show a strong dependence
271 on covariates. For example, in regime 2, 51% of catchments show strong dependence with
272 covariates during growth phases. Likewise, drought persistency in regime 3 is largely controlled
273 by 65% of covariates. Further, the drought resilience or recovery phase in regime 3 is more strongly
274 influenced by terrain features as reflected by the largest BFI values followed by meteorological
275 attributes. On the other hand, in regime 2 recovery phase shows a strong positive correlation,
276 associated with terrain features. As noted earlier, the sub-basins in regime 2 show the lowest BFI
277 indicating a minimum baseflow contribution or groundwater replenishment, which results in a
278 relatively long recovery period in this region. Our results corroborate with an earlier studies^{48,49,52},
279 which showed low flows are often controlled by the soil and geology of the catchment.

280

281 We employed a hybrid feature selection procedure consisting of filtering and wrapping through
282 Boruta algorithm⁵³ (see Methods) using all 89 covariates. The average sand contents at 1 m depth
283 in the western part of the peninsula is relatively low as compared to the eastern and southern part
284 of the peninsula, which influences the drought growth for gauges in this region (**Fig. S8a**), whereas
285 a relatively high clay content in this region affects average drought termination rate (**Fig. S8d**).
286 The SOC content and SOC stock at 1 m depth over a large portion of the landmass is consistently
287 low (**Fig. S8b-c**). Among three KDD categories (soil, hydro-meteorological and terrain), drought
288 growth appears to be most influenced by $\sim 17\%$ (15 out of 89) attributes (see **Fig. 4a**), *e.g.*, the
289 cross-sectional (Kendall's $\tau = -0.23$) and longitudinal (Kendall's $\tau = 0.22$) curvatures, slope
290 (Kendall's $\tau = -0.23$), and terrain roughness index (Kendall's $\tau = -0.23$) in addition to sand content
291 (Kendall's $\tau = -0.14$), CEC (Kendall's $\tau = 0.20$), and soil moisture for the months of January
292 (Kendall's $\tau = -0.18$), April (Kendall's $\tau = -0.19$), and May (Kendall's $\tau = -0.21$), denoting the
293 influence of soil moisture on drought growth in the transition months from winter to spring and
294 spring to summer. Drought growth shows a strong dependence on hydro-meteorological factors,
295 such as average potential evapotranspiration (PET) at the onset (Kendall's $\tau = 0.14$ for June) and
296 retrieval (Kendall's $\tau = 0.17$ for September) months of monsoon. This could be because of
297 feedback between soil moisture and surface water availability (precipitation minus
298 evapotranspiration, $P-E$). In water-limited regions, the soil moisture is shown to modulate
299 evapotranspiration, which positively feedbacks precipitation via moisture recycling^{54,55}. The

300 drought duration showed strong dependence on soil properties, primarily SOC and SOC stock and
301 mean monthly winter (November - December) soil moisture and temperature regimes. However,
302 no terrain features are found to be critical in influencing drought duration. In general, soils with
303 low SOC contents and moisture deficits during post-monsoon seasons will have a longer drought
304 duration. Likewise, drought recovery appears to be largely dependent on mean monthly soil
305 moisture contents during February and March (Kendall's $\tau = 0.12$), mean temperature of February
306 (Kendall's $\tau = -0.17$) and January (Kendall's $\tau = -0.18$), SOC contents, and SOC stocks of top 1
307 m soil profile (Kendall's $\tau = -0.21$). This agrees qualitatively with findings from an earlier study⁵⁶,
308 which showed that temperature strongly influences streamflow-based drought characteristics such
309 as spatial extent and duration. Further, SOC controls the soil moisture levels and, in turn, drought
310 development and termination stages (**Fig. S8**)^{28,57}.

311
312 Interestingly, **Fig. 4b** confirms that the early monsoon (June-July) soil moisture conditions and
313 winter (primarily between November and December) temperature notably impact on drought
314 duration. On the other hand, drought recovery heavily depends on the soil moisture regime during
315 the spring (February-March) and the temperature conditions during the winter (November-
316 January) until the end of the spring (March-end) season. Likewise, the DTR is typically influenced
317 by only 12% (11 out of 89) attributes (**Fig. 4d**). An apparent positive dependence between PET
318 (Kendall's $\tau = 0.17$), clay content (Kendall's $\tau = 0.16$), and CEC (Kendall's $\tau = 0.14$) with DTR
319 suggests the inherent ability of soils coupled with hydro-meteorological factors to accelerate or
320 cease prevailing desiccation. These are further aided by terrain factors such as flow accumulation
321 (Kendall's $\tau = 0.22$) and relative slope (Kendall's $\tau = 0.18$) in the governing rate of drought
322 termination. Overall, our results show that drought growth is largely controlled by terrain attributes
323 ~50% of total covariates; drought persistently is mostly controlled by soil attributes accounting for
324 more than 70% of all three covariates. Interestingly, drought recovery is equally controlled by
325 hydroclimatic and soil properties with little or no role of terrain attributes, whereas DTR is
326 primarily controlled by hydroclimatic (~51% share) and soil (~35% share) factors together.

327
328 Our analyses suggest the following: (i) Considering peninsular catchments as a whole, terrain
329 features largely control drought growth; soil attributes contribute more than 70% in drought
330 persistency; whereas DTR is largely controlled by meteorological attributes. In addition, drought
331 resiliency is equally impacted by soil and meteorological attributes. (ii) Considering homogeneous
332 drought regimes, a large proportion of gauges in regimes 2 and 3 show a strong dependence on
333 growth (for regime 2) and persistent (for regime 3) phase, respectively. Further, drought recovery
334 in regime 3 shows a strong anticorrelation with soil and terrain features, whereas a strong positive
335 dependence on meteorological attributes, primarily with PET. The relatively small recovery period
336 (less than a month) of most of the gauges compounded by a large recurrence interval at regime 3

337 could be attributed to the largest baseflow yields of catchments, which is largely controlled by
338 geology, land use, catchment and terrain characteristics^{16,48,49}. In addition, the meteorological
339 factors, such as high evapotranspiration-induced moisture surplus accelerates a swift recovery.
340 This clearly shows that soil, hydro-meteorological, and terrain features play distinct roles in the
341 propagation of catchment-scale hydrological droughts.

342

343 **Discussion and Conclusions**

344 The observational evidence indicates strong support that heterogeneity in hydrological drought
345 responses is controlled by feedback between climate-catchment-and-soil attributes (**Fig. 4** and **Fig.**
346 **S7**). Previous studies^{15,16,58,59} conducted on catchment-scale droughts provide important yet
347 incomplete insights into the role of potential drivers in hydrological drought propagation. Based
348 on an earlier study⁶⁰ that establishes structural control on catchment sensitivity, our approach
349 further expanded on geomorphological features by exploring additional covariates, a range of
350 terrain, and soil characteristics influencing various drought characteristics, which have not been
351 investigated so far - neither in observational assessments nor in land surface model-based
352 simulation^{10,61}. The sources of uncertainty in the analyses stem from the quality of available
353 records. Climate change may impart nonstationarity in low flow series, which may account for
354 additional uncertainty in the analysis. However, we compensated this by considering average (or
355 median) relationships, which is commonly applied in low flow regionalization studies and
356 followed elsewhere¹⁶ as a robust measure in presence of weak nonstationarity. Further, accounting
357 nonstationarity in records would require longer hydroclimatic time series, which is limited for the
358 area being considered here.

359

360 Our findings have direct implications for catchment-scale drought mitigation. The identified
361 dynamic covariates, such as climate and soil moisture level could be utilized for monitoring
362 drought stages one to two seasons advance and to support drought warning effort by developing a
363 multivariate forecast model, enabling seasonal-to-sub-seasonal (S2S) prediction^{62,63}. While
364 meteorological to hydrological drought is forecasted at a monthly to the seasonal time scale in
365 practice⁶⁴, timely issuance of targeted drought early warning systems (DEWS)⁶⁵ and a dynamical
366 low flow forecast at a higher temporal resolution involving primary drought attributes, such as
367 growth, persistence and recovery pattern, could be effective in mitigating impacts. Further, for
368 climatologically heterogeneous regions of India, developing an improved probabilistic S2S low
369 flow forecast integrating the static and dynamic controls could be of great interest in aiding
370 economic resilience to droughts⁶⁶.

371

372 The obtained insights from this study highlight soil management plays a crucial role in desiccation
373 and its resilience. Since climate variability and change have exacerbated the concurrence of warm-

374 and-dry conditions⁶⁷, the persistence of carbon loss (the “legacy effect”)⁶⁸ a few years after
375 extreme and persistent droughts, may have long-term effects on the carbon-budget of the tropical
376 rain-dominated ecosystem of the Indian peninsula. While soil carbon stocks for peninsular India
377 are relatively low than that of the global average²⁸, efficient soil and water conservation measures
378 can improve soil carbon sequestration^{69,70} and enhance drought resilience, ensuring water-and-
379 food security of the country⁵⁷.

380

381 **Methods**

382 **Hydro-Meteorological Forcing Data Set**

383 We obtain the observed daily streamflow time series from the nationwide water resources
384 information system (India-WRIS; <https://indiawris.gov.in/wris/>). The observed streamflow
385 records are obtained for the stations that are not considerably affected by major reservoirs and
386 dams with an average ~16% (ranges from 3 – 33%) area under irrigations considering both surface
387 and groundwater (*e.g.*, tube wells and dug wells) sources⁷¹. To ensure adequate spatial coverage
388 as well as the completeness of records, we selected the catchments based on the following criteria:
389 (1) The stations with a minimum of 20 years of continuous streamflow record availability during
390 the analysis period (1965-2019); (2) The catchment area of the sub-basin to be at least 1000 km²
391 or more. Based on this criteria, we selected 98 stream gauges with catchment area range between
392 1200 and 307,800 km² from 18 different river basins across PRB (**Fig. 1; Fig. S1**). Following the
393 earlier literature^{72,73}, we infill the missing gaps in daily streamflow time series using the time series
394 interpolation technique.

395

396 To examine meteorological control on drought stages, we use the observed gridded meteorological
397 datasets with a spatial resolution of 0.5° available at a monthly time scale. The meteorological
398 variables are precipitation²³, soil moisture (1.6 m depth)²⁶, mean air temperature (at a height 2 m
399 above surface)²⁴, PET²⁵ estimated using the Penman-Monteith method. To identify potential KDDs
400 for catchment-scale drought propagation processes, we obtain catchment boundaries from the
401 Global Streamflow Indices and Metadata (GSIM) archive²⁷. To ensure data compatibility, we kept
402 the record lengths of hydrometeorological variables same as the streamflow record lengths for
403 each catchment. Further, the baseflow index for each catchment is calculated following the WMO
404 manual on low-flow estimation procedure⁷⁴.

405

406 **Delineation of Drought Characteristics**

407 We identify hydrological droughts by applying a variable threshold approach to the daily
408 streamflow time series^{15,19,22}. The advantage of using the variable threshold method of drought
409 delineation over the constant threshold is two folds: (1) Ability to capture the seasonal variability
410 that prevents the natural low flow season to be detected under drought (2) enables detections of

411 various drought characteristics rather than instantaneous drought onset and termination points as
412 followed in the standardized index-based drought detection approach (*e.g.*, standardized indices of
413 precipitation⁷⁵ and streamflow⁷⁶). For the threshold determination, 366 (an additional day for leap
414 year) flow duration curves are developed using continuous time series of streamflow records.
415 Following the literature^{15,16,77,78}, an 20th percentile threshold (flow equaled or exceeded 80% of the
416 flow record) is selected for each day of the year forming the variable threshold time series. Since
417 the daily threshold time series appeared to be a jagged curve resulting in several short deficit
418 periods, a centered moving average of 30 days is applied as a smoothing filter^{19,22}. A drought
419 episode is detected when the daily streamflow time series falls below the variable threshold.

420
421 After identifying drought events, next, we further categorize streamflow-based droughts into
422 several characteristics^{19,79} (see **Fig. 1b**). Drought duration is the period in which streamflow is
423 lower than the threshold continuously for 30 days or more (this phase is shown from t_{sp} to t_{ep} in
424 **Fig. 1b**, where ‘*s*’ denotes initiation, ‘*e*’ is the termination point and ‘*p*’ indicates persistence
425 phase). Following Ahmadi and Moradkhani (2018)¹⁹, we select the threshold time window of 30
426 days based on the consideration of the natural variation and long enough to filter out the inter-
427 seasonal anomalies. Following the refs.^{19,20,79} we detect the drought growth as moving 60 days
428 back from the drought termination, when the streamflow falls above the threshold for less than 15
429 days, *i.e.*, the occurrence of short deficits interrupted by less than 15 days of above-normal
430 streamflow (in **Fig. 1b**: t_{sg} to t_{eg} , where ‘*s*’ is the initiation, ‘*e*’ is the termination, and ‘*g*’ denotes
431 the growth). We detect the recovery period as moving 60 days forward from the end of the
432 persistence phase, when the streamflow falls below the threshold for less than 15 days (in **Fig. 1b**:
433 t_{sr} to t_{er} where ‘*s*’ is the initiation, ‘*e*’ denotes the termination and ‘*r*’ shows the recovery phase).
434 If the streamflow time series persistently remains below the threshold for more than 15 days then
435 we mark ‘no recovery’ and the following episode is then considered as a part of a multi-season
436 drought event. Finally, we quantify DTR as the magnitude of change in flow from the Maximum
437 Drought Deficit volume (MDD, the day with the largest negative departure from normal
438 streamflow between the time of the start of drought development and the time of the end of drought
439 termination in **Fig. 1b** - for details please see last but one paragraph in page 4267 in Parry et al⁷⁹)
440 to the peak surplus flow (PS, **Fig. 1b**), divided by the time taken for this transition.

441
442 We determine the seasonality in drought termination using directional (or circular) statistics. The
443 termination date is used as a directional variable³¹ (**SI 1.1**), in which the position of the mean
444 termination date can be determined using angles (Eq. 1.3 in **SI 1.1**). Following the ref.⁸⁰, we
445 calculate the mean termination day (*i.e.*, mean direction of the day of drought termination as
446 described by the circular data) and its variance by weighing the deficit volume (see **SI 1.1**),
447 ensuring the events are given importance as per the persistency of the event.

448 **Digital Soil Mapping (DSM)**

449 We develop Digital soil maps primarily for nine different soil parameters, *e.g.*, sand and clay
450 contents; SOC contents, SOC stock; pH; CEC; moisture contents at field capacity and permanent
451 wilting point; and available water capacity for the Indian subcontinent at six standard depths (0-5,
452 5-15, 15-30, 30-60, 60-100, and 100-200 cm respectively) according to the GlobalSoilMap
453 specifications⁸¹. We develop DSMs using an Indian soil legacy database that utilized archived data
454 from various sources, such as the National Bureau of Soil Survey and Land Use Planning
455 (NBSS&LUP) and other institution publications¹⁸. The newly developed, digital soil map follows
456 *scorpan* model⁸², in which a soil property at an unknown location is estimated as a function of
457 environmental covariates. The environmental covariates used in generating the current maps
458 include terrain attributes derived from the 90 m shuttle radar topographic mission (SRTM) digital
459 elevation model (DEM) data⁸³ and climate covariates, which includes mean monthly temperature
460 and precipitation¹⁸. Soil parameters (**Table S1**) for top 30 (weighted average of depths 0-5, 5-15,
461 15-30 cm) and 100 cm (weighted average of depths 0-5, 5-15, 15-30, 30-60, 60-100 cm) soil layers
462 are extracted over the selected catchments of PRB.

463

464 **Linking Drought Stages with Climate-Catchment-Soil Controls**

465 To identify the potential KDDs in influencing drought dynamics, first we perform a non-
466 parametric correlation analysis. Table S1 lists all 89 covariates that are chosen to identify key
467 drought drivers (KDD). Among climatological attributes, we also consider several hydro-
468 meteorological indices, especially for extremes calculated from monthly time series of
469 precipitation (Rainfall_20p), temperature (TX90p), PET (PETX_20p), and soil moisture
470 (SMX_20p), which are widely used for analysing climatic extremes at the regional and global
471 scales^{84,85}. These extreme indices are calculated by calculating the median of the values greater (or
472 lower) than equal to the n^{th} percentile (where, $n = 20$ for deficit and 90 for surplus as adopted here)
473 of each meteorological variable. Next, we perform dependency analysis between each KDD and
474 catchment-wise median drought stages using Kendall's τ , which is robust to the small number of
475 outliers (unlike Pearson's correlation coefficient) and discrepancies in the data⁸⁶. We check the
476 statistical significance of dependence at 10% significance level with p -value < 0.1 .

477

478 Finally, to select KDDs influencing the drought stages, we implement a hybrid feature selection
479 procedure consisting of filtering and wrapping through Boruta algorithm⁵³, which is built around
480 the random forest classification algorithm. For filtering, we retain the covariates exhibiting
481 significant (p -value < 0.1) association with drought stages in the Kendall's rank correlation.
482 Subsequently, we apply Boruta on the reduced set of significant variables to obtain the key drought
483 drivers (KDDs) by fixing the number of iterations as 1000 (**Fig. 1c**). This was achieved by creating
484 'shadow' attributes for each original attribute from shuffling the corresponding values of original

485 covariates across stations. Finally, we perform feature selection by using the random forest
486 classification algorithm and compute the importance of all attributes of this extended system with
487 reference to maximum Z-score of shadow attributes (MZSA). We mark the variables significant
488 when they have ‘importance’⁵³ significantly higher than that of MZSA and discard the variables
489 that show ‘importance’ lower than that of MZSA.

490 **Data Availability**

491 All the data used in this study are publicly available. The precipitation data is obtained from
492 Global Precipitation Climatology Centre
493 (https://opendata.dwd.de/climate_environment/GPCC/html/fulldata_v7_doi_download.html).
494 The monthly soil moisture data is obtained from the Climate Prediction Center (CPC;
495 <https://psl.noaa.gov/data/gridded/data.cpcsoil.html>). The monthly mean surface air temperature is
496 obtained from the CPC Global land surface air temperature data
497 (<https://ual.geoplatform.gov/api/items/ff4f9af65d322c28a421cf569471d216.html>). The PET time
498 series is obtained from the Climate Research Unit’s (CRU) version 4.04 database
499 (<https://crudata.uea.ac.uk/cru/data/hrg/>). All data are available at a 0.5° spatial resolution in a
500 monthly time scale. The shapefiles for the Indian river basins are obtained from the Global
501 Streamflow Indices and Metadata Archive (<https://doi.pangaea.de/10.1594/PANGAEA.887477>).
502 The digital elevation map to develop terrain features are derived from the 90 m SRTM DEM
503 database (<https://cgiarcsi.community/data/srtm-90m-digital-elevation-database-v4-1/>). The
504 digital soil mapping for India was developed using an Indian soil legacy database that utilized
505 archived data from various sources, such as the National Bureau of Soil Survey and Land Use
506 Planning (NBSS&LUP; <https://www.nbsslup.in/>) and other institution publications¹⁸.

507

508 **Code Availability**

509 The MATLAB Codes used for drought characteristics and delineation of drought regimes have
510 been archived by the authors and are available on request from P.G., pganguli@agfe.iitkgp.ac.in.
511 The source codes for Digital Soil Map of India codes are available from authors through personal
512 request.

513

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517

518 **Contributions**

519 PG contributed to overall concept development, writing, prepared initial data processing scripts in
520 MATLAB for hydrological droughts and final edits; BJS and AR performed data collection and

521 screening of the time series; BJS performed drought data analysis and prepared the first draft; NNR
522 performed digital soil mapping and prepared corresponding write-up; AR analyzed rainfall data
523 and land-use pattern and contributed to writing; DM carried out feature selection analyses and
524 performed the data interpretation with the help of BSD and PG and wrote feature selection part;
525 BSD conceived soil control concept and performed final edits. All co-authors discussed the results,
526 reviewed and approved the final manuscript.

527

528 **Competing Interests**

529 The authors declare no competing interests.

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551 **References**

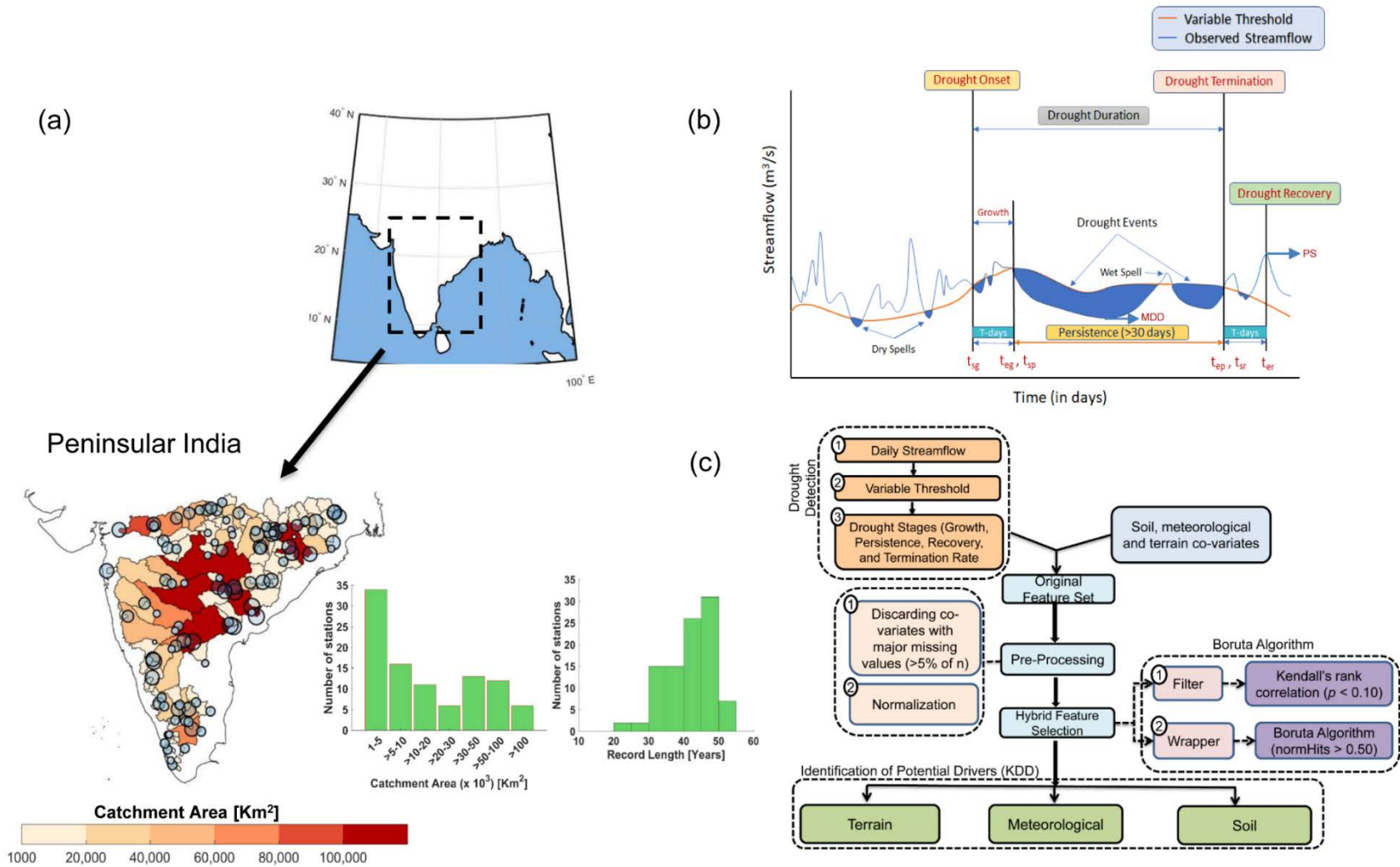
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741 **Fig. 1 Distribution of stream gauges, drought characteristics and conceptual diagram illustrating KDD detection.** (a) Location of stream gauges within
 742 each catchment. The size of bubbles shows the record length which is proportional to the sample length (in years). Histograms show the distribution of
 743 catchment area (in km²), and available record lengths (in years). (b) Identification of drought characteristics using daily variable threshold approach. The
 744 blue shaded region depicts streamflow deficit. The t_{sg} and t_{eg} represent the start and end of the growth period. Likewise, t_{sp} and t_{ep} indicate the initiation
 745 and termination of the drought persistence stage. t_{sr} and t_{er} denote the initiation and termination of the drought recovery, MDD and PS indicate maximum
 746 drought deficit volume during the persistence stage and peak surplus flow after drought termination. (c) Detection of Key Drought Drivers (KDD's)
 747 using random forest-based feature selection algorithm. The threshold criterion, normHits > 0.50 indicates only those features are selected that show higher
 748 'importance' than their shadow attributes (obtained by random permutation of features) for more than 50% of total iterations.

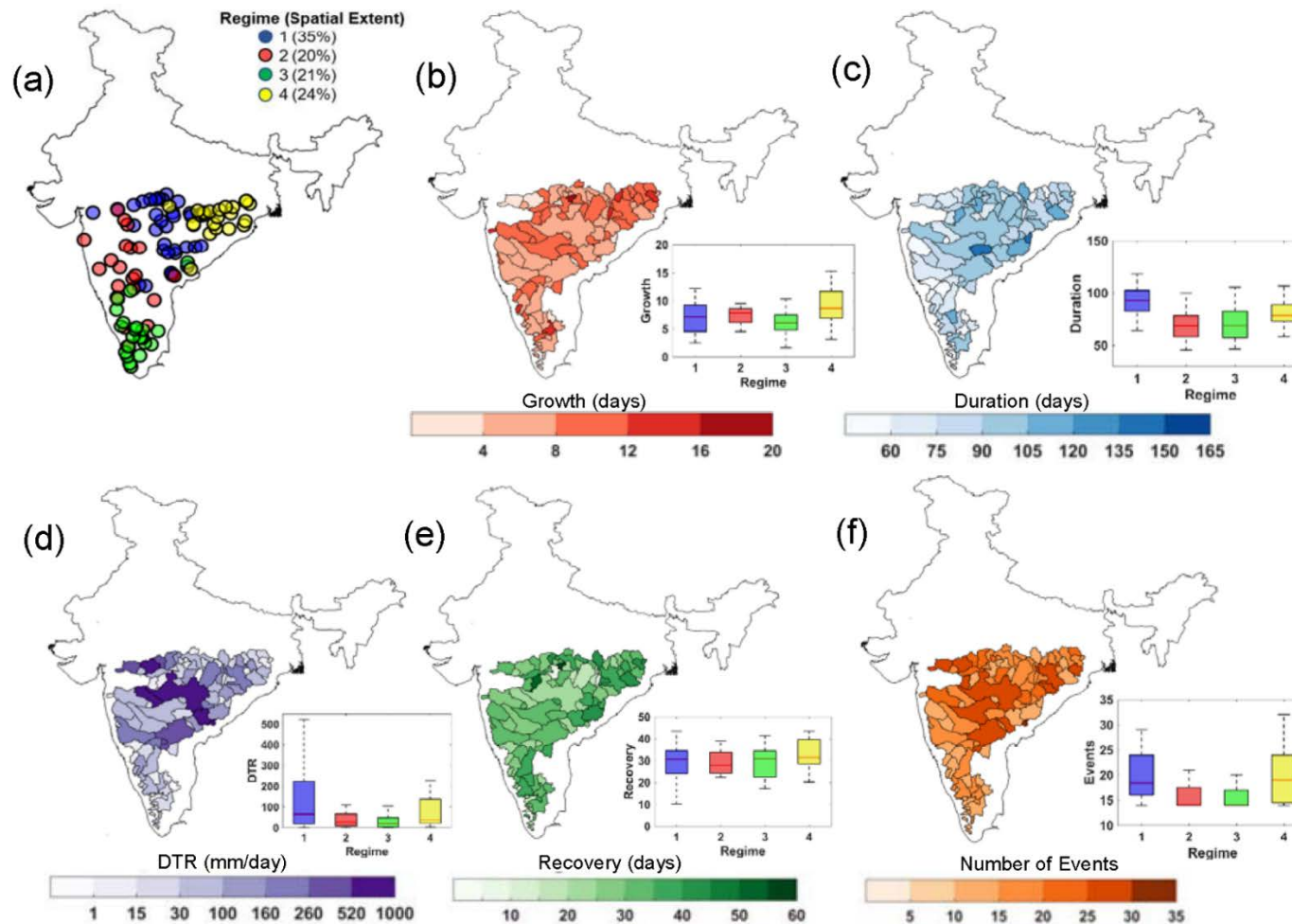
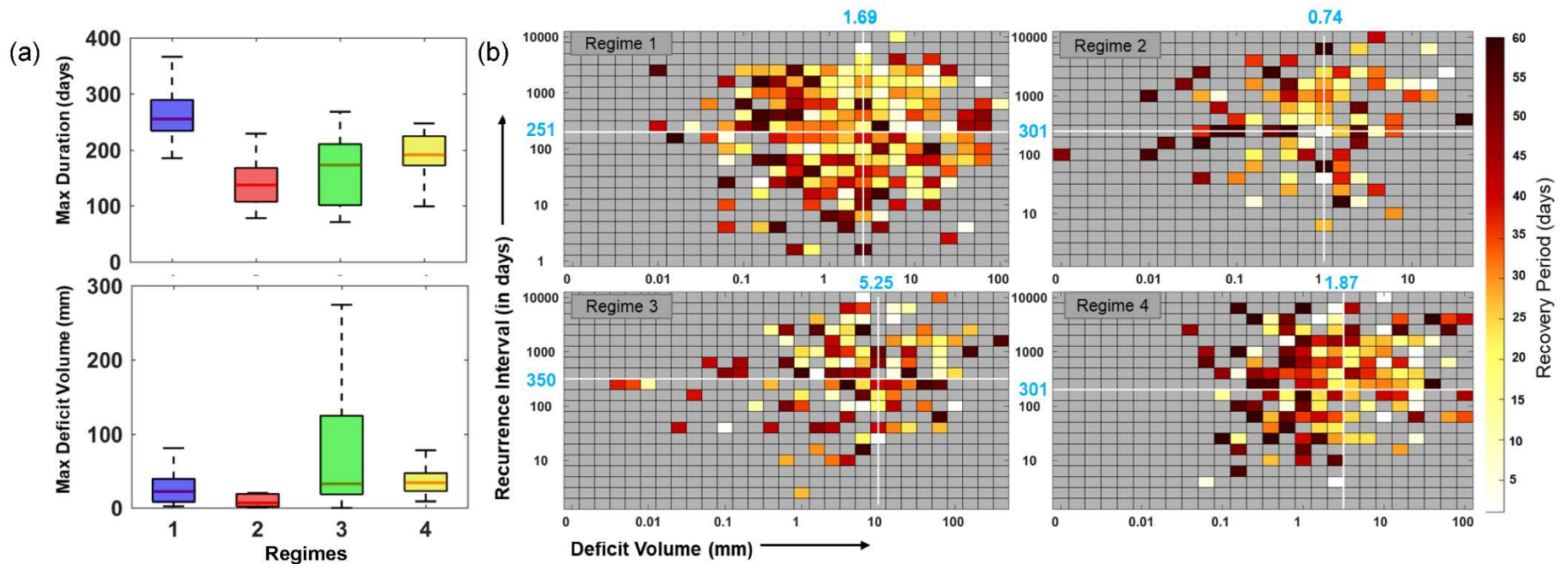
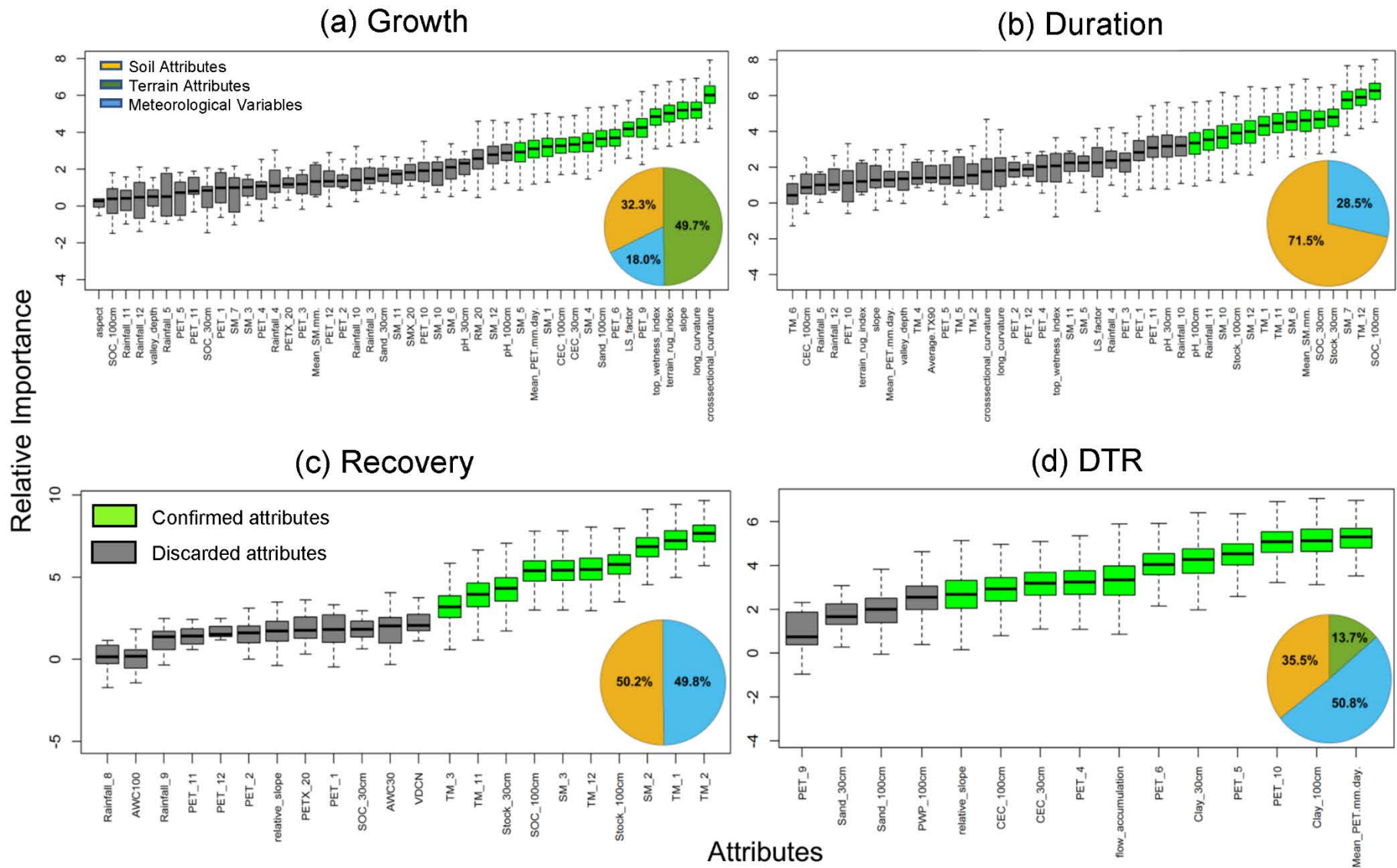


Fig. 2 Identification of drought regimes and illustration of Catchment-scale Drought Properties. (a) Regionalization of droughts based on drought characteristics using fuzzy c means clustering algorithm (see Methods); n indicates the number of sites detected within each cluster. (b – f) Spatial distributions of drought characteristics during 1965-2018 time window: (b) drought growth (in days) (c) duration (days) (d) drought termination rate or DTR (mm/day) (e) recovery period (in days) (f) drought frequency or number of events. The boxplots in inset show the variability in drought properties among the identified clusters. Box center marks (red lines) are medians; box bottom and top edges show 25th and 75th percentiles respectively, whereas the spread of the boxes indicates interquartile range; whiskers indicate $q_{75} + 1.5(q_{75} - q_{25})$ and $q_{25} - 1.5(q_{75} - q_{25})$, where q is the quantiles of variables. The shades of boxes in purple, red, green and yellow indicate streamflow drought regimes 1 – 4, based on selected drought attributes.



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 759 **Fig. 3 Variations in drought properties, maximum severity, maximum duration, and recovery times among the detected clusters.** (a) The
 760 boxplots showing interquartile range of selected drought attributes, the (maximum) duration and the deficit volume. (b) The recovery period
 761 as a function of deficit volume and recurrence interval (*i.e.*, the time interval between two successive droughts but neglecting the first drought
 762 event) for the identified regimes. The shades of each pixel show the drought recovery period. The cells in grey indicate no observation. The
 763 straight lines in white perpendicular to the axes show the median deficit volume and the median recurrence interval for each region.



766
 767 **Fig. 4 Potential Key Drought Drivers.** The relative importance of key drought drivers is shown using box plots for various drought characteristics.
 768 The pie charts at the lower bottom corner show relative contribution of soil, terrain and meteorological variables in influencing drought
 769 stages. The x-axes show the soil-climate and topographical attributes; details of each of these attributes are described in **Table S1**. The
 770 legends applies to all figure panels.