



Predicting tipping points of vegetation resilience as a response to precipitation: Implications for understanding impacts of climate change in India

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Abstract

Although the impacts of climate change are long-term in nature, the transformation in climate regime can lead to an ecosystem change from one stable to another stable state through intermediate bistable or metastable states. Such state transition or resilience to change in ecosystems is seldom sharp and therefore difficult to quantify with a single tipping point. Rather, the change can be understood through a tipping point range (tipping zone) across hysteresis loop(s). This study uses a satellite data-derived actual vegetation cover map of India and categorizes it into different vegetation types: forest, scrubland, grassland, and vegetation-less. We used high-resolution long-term average precipitation data to develop moisture-driven hysteresis curves and predict various tipping point ranges for vegetation-type regime shifts. Our results reveal that the forest and vegetation-less states could have one-way, while scrubland and grassland have two-way transition probabilities with a probable shift in precipitation regime. In the dry conditions, the precipitation tipping zone predicted between 154 and 452 mm for the forest to scrubland transitions, while the reverse transition (from scrubland to forest) could occur in wet conditions between 1080 and 1400 mm. Similarly, the transition between scrubland and grassland, between grassland and vegetation-less state, may occur in contrasting dry and wet conditions, creating a hysteresis loop. The results indicate that the reversal of state change requires differential energy spent during the onward and reverse transitions. The study proposes a novel characteristic curve demonstrating the varied precipitation tipping points/zones, precipitation overlaps and distribution of the various vegetation types, and co-existence zones, which has huge implications for understanding the climate change impacts.

Keywords Binary logistic regression · Hysteresis loops · Regime shift · Sigmoid curve · Gamma distribution

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Introduction

The interactions between ecosystem and environmental conditions and feedback are coupled via biogeophysical and biogeochemical processes regulated through complex and non-linear mechanisms (Bonan 2008). Forest ecosystems exhibit a long-term stability pattern in response to local and regional environmental conditions and stochastic disturbances (Scanlan 2002; Davidson et al. 2012). On the other hand, terrestrial ecosystems are one of the major carbon sinks and regulate the carbon cycle and global warming. The seasonality of water and energy availability and nutrient concentration drive biological activities, define vegetation distributions, and influence biodiversity. The moist and humid tropical region facilitates the prevalence of tree-dominant forests compared to the hot and cold deserts in a hyper-arid and temperate region, while shrub-dominated scrubland and herb-dominated grassland in the intermediate climatic conditions. The hydro-climatic settings determine the vegetation types by regulating the water-holding capacity and percolation mechanisms. Forest dominance directly relates to precipitation and moisture availability, indicating a prevalence of forests in the wetter region and vice versa. The higher rooting depth of trees allows access to water at greater depth and sustains the dry periods when the grassland becomes dormant, demonstrating the larger capacity of the forest ecosystem to survive longer drought spells compared to scrubland and grassland (Davidson et al. 2012), whereas scrubland and grassland are more adaptive to hot- and cold-arid climate. Various studies have demonstrated that significant changes in precipitation and temperature can modify the biogeochemical processes and plant functioning (le Houérou 1996; Cusack et al. 2016; Kooperman et al. 2018), while the role of water availability is more prominent in the tropical region (Fernandez-Illescas and Rodriguez-Iturbe 2004; Wiegand et al. 2006).

Ecosystem resilience refers to the capacity of an ecosystem to absorb external disturbances and undergo change while maintaining its function and structure (Walker et al. 2004). The ecosystem response to climate stress conditions can be explained based on elasticity principles. For instance, when stress is applied to a material, it leads to strain or temporary deformation within the elastic limit or tipping point, and the material experiences a permanent change if the applied stress is beyond its elastic limit. Within the elastic limit, once the applied stress is reversed, the system returns to its original state, and sometimes it can follow an alternative pathway. This creates a hysteresis loop, and the area of the loop is considered as the energy dissipated through the process. Similarly, the vegetation's self-adaptation capacity or resilience can respond to external disturbance up to a threshold limit (tipping point), beyond which any small disturbance can cause significant changes, leading to vegetation type change or regime shift (Folke et al. 2004; Groffman et al. 2006). Such changes introduce some degree of irreversibility, which indicates that differential energy is required for an unstable state to return to its initial stable state (Kinzig et al. 2006; Beisner and Cuddington 2010). The transition of ecosystem structure or vegetation type from one stable to another stable state is experienced through an intermediate bistable or metastable state. Moreover, the threshold conditions or tipping point for such transitions varies based on the local environmental conditions and feedback mechanisms. Therefore, vegetation-type transitions can never be sharp or denoted by a single tipping point; rather, they should be understood through a range of tipping points (tipping zone).

In fact, various natural and anthropogenic disturbances, including climate change, forest fire, deforestation, and land use change, are modifying biodiversity and ecosystem struc-

tures. The tropical and sub-tropical climate regions with broad precipitation ranges support diverse ecosystems and species composition. However, sizable alterations in climate conditions can modify the hydroclimatic conditions, species diversity, and ecosystem structure (Panda et al. 2017; Das et al. 2018; Chitale and Behera 2019; Tripathi et al. 2019). Studies have reported that the shift in climate regime from wet to arid conditions in the Sahara has led to the degradation of dense vegetation into a desert (Rietkerk et al. 2011; Tierney et al. 2017). Foley et al. (2003) reported that recurrent and consecutive drought events due to the overall reduction of precipitation by 25–40% from 1969 to 1997 have led to a significant change in the forest regime in Sahel, Africa. Similarly, the weakening of the Indian summer monsoon has led to arid climate conditions in India's Thar desert (Dixit et al. 2014; Pillai et al. 2018; Sarkar et al. 2020). The carbon isotope studies in the Nilgiri forest of Western Ghats, India, revealed forest to grassland state shift due to past climate change (Sukumar et al. 1993; Geeta et al., 1997). In addition to other environmental variables, precipitation alteration plays a dominant role in defining the change in ecosystem productivity and function and, thereby, causes land transformation (Bai et al. 2008). Matin et al. (2019) studied land transformation and degradation and reported reduced moisture availability and corresponding vegetative photosynthetic capacity in various parts of the Indian Ganga River basin. The response of forests to climatic stressors depends on the duration and nature of disturbances, where the short (ecosystem change) and long (succession) term changes are observed at the leaf level to ecosystem levels (Peterson et al. 1998; Drever et al. 2006; Reyner et al. 2015). Various past studies have assessed the impact of drought, fire, and heat anomalies on ecosystem resilience using satellite data-derived vegetation proxies such as leaf area index, normalized difference vegetation index, enhanced vegetation index, net primary productivity, and evapotranspiration (Ponce-Campos et al. 2013; de Keersmaecker et al. 2014; Li et al. 2018; Sharma and Goyal 2018; Wu and Liang 2020). However, identifying true tipping points through vegetation proxies is difficult, especially in tropical and sub-tropical ecosystems, where diverse plants are adapted to competitive water and energy use mechanisms to thrive and often share wide and overlapping ecological niches (Craine and Dybzinski 2013).

Various methods have been employed to investigate ecosystem resilience. The logistic regression has been used in a few studies for estimating ecosystem resilience (Bucini and Hanan 2007; Hirota et al. 2011; Das and Behera 2019). The logistic regression uses a sigmoid function and appropriately transfers the observed binary distribution into a probability space (varies between 0 and 1). The trajectories or paths traced by a probability curve based on the dependent variable are used to estimate the transition points. Bucini and Hanan (2007) studied forest resilience in response to long-term climatic conditions and suggested that dryness and disturbances may lead to low resilience. Hirota et al. (2011) observed significant changes in tree canopy cover states (forest, savanna, and treeless states derived from the satellite tree canopy cover data) with annual precipitation in the tropics and represented the alternative stable states separated by a double hysteresis curve. They employed logistic regression to estimate resilience of forest, savanna, and treeless states based on moisture availability. They have reported a higher forest resilience in wet regimes and lower resilience toward savanna under drier conditions, wherein savanna can have bidirectional transition probability towards the forest and treeless state owing to contrasting wet and dry moisture levels. Das and Behera (2019) added scrubland as another intermediate forest state and estimated the regime shift probability among the forest, scrubland, and grassland states

in India. Ratajczak and Nippert (2012) segregated the tree density data into vegetation type categories based on threshold values and found that such categorization may incorporate bias leading to the improper representation of vegetation type distribution corresponding to meta-stable states. Van Nes et al. (2014) observed a possible overestimation of tipping point values computed using satellite tree canopy cover data and reported an underestimation in the original hysteresis due to positive precipitation feedback. Further, they suggested that the forest regime shift may skip intermediate states during the transition if tree canopy density data is used instead of actual tree cover distribution data.

The forest cover of India has been estimated at $\sim 21.7\%$ of the total geographical area of the country (FSI, 2021). Among the land use change determinants, agriculture was responsible for major forest loss (about 57%) in India in the past few decades (Reddy et al. 2016). The climate change and precipitation regime shift impact on Indian forest sustainability is still poorly understood. It is also imperative to estimate the critical precipitation threshold (tipping point) for vegetation type regime shift, which has implications for the ecosystem functioning, ecosystem services and the dependent socio-economy. Predicting the terrestrial ecosystem resilience is essential to prescribe climate-adaptive national forest conservation measures and sustainable landscape management. This current study uses an actual forest state map to evaluate the moisture-determined ecosystem resilience in India. The study estimates ecosystem resilience and the probability of regime shift using vegetation distribution under different precipitation regimes employing the logistic regression. The precipitation tipping points are estimated for lower resilience (0.1 to 0.25), which provides information on forest resilience across various climate regions of India and thereby holds promise for improved understanding of precipitation-dependent ecosystem resilience and regime shift in the changing climate.

Data and methodology

The vegetation type map of India prepared using satellite data by Roy et al. (2015) contains 100 classes, including various forest types, cropland, built-up, and waterbody. The vegetation classes were regrouped into three categories: forest (tree-dominated), scrubland (shrub-dominated), and grassland (herb-dominated), beside the vegetation-less class, excluding the man-made features and waterbody (Table S1). The human-managed vegetation classes, such as agriculture has been excluded from the analysis. The vegetation type map of India was prepared at 1:50,000 scale and had 90% accuracy as validated using 15,565 field locations. The average annual precipitation data at 30" resolution was acquired from the WorldClim database from 1970 to 2010. The WorldClim precipitation data was generated using collections from several sources, including the older version of WorldClim data, global data as Climate Research Unit (CRU), Global Historic Climate Network Dataset (GHCN), World Meteorological Organization (WMO) and Climatological Normal (CLINO), Center for Tropical Agriculture (CIAT) in Colombia, and European Climate Assessment and Dataset monthly (ECAM) (Fick and Hijmans 2017). The global two-fold cross-validation indicated a high accuracy ($R^2=0.86$, Root Mean Square Error [RMSE]=49.46 mm) for most of the world, with poor correlation for regions having low station density and complex topography (Fick and Hijmans 2017). However, the precipitation map indicates good accu-

racy for most parts of India except the mountainous Himalayan region (including Northeast India) and the Western Ghats.

A grid mesh with a 5×5 km resolution was created to represent the distribution of forest based on their highest area occupancy, and precipitation was represented using the mean annual value. The outliers were removed using gamma distribution to estimate the range of precipitation experienced by forest with 90% occurrence (Kumar and Lalitha 2012; Nooghabi et al. 2010). The forest was treated as binary data in various pair-wise analyses. The probability of holding on to any forest was estimated as a function of mean annual precipitation (MAP) using binary logistic regression (Eq. 1) to understand the competitive suitability and the alternate stable states (Hirota et al. 2011).

$$\text{Logit}(Y_i) = \ln [Y_i/(1-Y_i)] \quad (1)$$

Where $Y_i=1$ and 0 represent the presence or absence of a forest; a =the intercept and b =the coefficient of the independent variable (Precipitation, x).

The forest state and vegetation-less state are found at the highest and least precipitation range, respectively, at either extreme end, thus can have only a one-way transition probability (Hirota et al. 2011). On the contrary, the intermediate scrubland and grassland states could have two-way transitions in either direction in response to variations in precipitation (Das and Behera 2019). The forest and scrubland were assigned 1 and 0 to estimate the forest resilience and transition probability towards scrubland. On the contrary, reverse states as high (1) and low (0) were assigned to scrubland and forest to estimate the scrubland resilience and transition probability towards forest. Similarly, the resilience and transition probability between scrubland and grassland were estimated by assigning alternative high (1) and low (0) states. The same approach was applied to estimate resilience and transition probability between grassland and vegetation-less states.

The probability (P_r) of a vegetation types state with respect to precipitation was computed using Eq. 2.

$$P_r = \frac{1}{1 + \exp(-(a + bx))} \quad (2)$$

The probability value (P_r) varies between 0 and 1, with 0 indicating the least probability being in the current state and high chances for transition to another state, while 1 indicates the maximum resilience to hold on to current state and least chances for transition.

Using the logistic regression, we generated a sigmoid curve which contained two saturation zones at the low and high probability ranges. The maximum curvature on the curve at the low probability range can be considered as the tipping point, below which the chances of transition to an alternative state are high. Similarly, at the high probability range, the maximum curvature indicates the point beyond which transition chances are the least, indicating higher resilience. The tipping point values significantly differ based on the probability of the maximum curvature as determined by the occurrence of various vegetation types. Thus, the MAP range for different resilience probability levels ($P_r=0.1, 0.15, 0.2$ and 0.25) around the maximum curvature was considered here. The range of tipping points corresponding to the resilience probability values from 0.1 to 0.25 (corresponding transition probability 0.9 to 0.75) could demonstrate a transition zone or tipping point ranges instead of one tipping

point. The meta-stable state where two states could co-exist can be inferred from the probability corresponding to the maximum slope of the sigmoid curve.

Results

The area of different vegetation classes included 18.44% forest, 1.80% scrubland, and 3.67% grassland, respectively, of India's total geographical area (Fig. 1a). Overlap with climate region map shows >92% of the forest were distributed in two climate regions such as (i) the warm temperate humid & winter dry region, and (ii) the equatorial humid & winter dry region (Table 1). However, the scrubland was nearly equally distributed in the warm temperate humid & winter dry region, equatorial humid & winter dry, and arid & semi-arid region. On the contrary, grassland and vegetation-less states dominate the montane region, followed by arid & semi-arid regions. Contiguous forests were seen mostly in moist areas, whereas fragmented scrublands and grasslands were found in relatively dry areas, and a decreasing pattern of precipitation was evident from forest to scrubland, grassland and vegetation-less in sequence (Fig. 1a and b). Interestingly, we observed a few patches in the Western Ghats and northeastern states in India devoid of any natural vegetation yet receiving >2000 mm of annual precipitation. The mean annual precipitation received by various vegetation types showed a wide overlap (Fig. 2). The grassland and vegetation-less states demonstrated an exponential distribution of precipitation, while a positively skewed distribution was observed for scrublands and forests (Fig. 2). The gamma distribution was fitted to remove the outliers and estimate the precipitation ranges with 90% of the occurrences, which indicated a significant p -value with low RMSE. After removing the outliers, the different vegetation types exhibited prominent differences in the precipitation

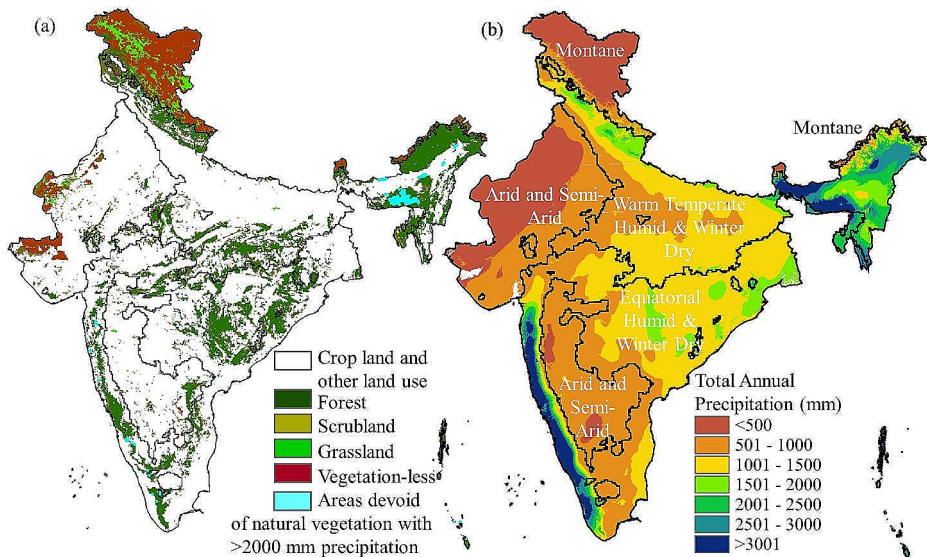


Fig. 1 (a) Vegetation types map of India (Modified from Roy et al. 2015 as per Table S1); (b) Four broad climate regions of India as per Köppen-Geiger (adapted from Kriticos et al., 2012), overlaid on annual precipitation map (Peel et al. 2007)

Table 1 Area estimates (in %) showing resilience of various forest cover states in different climate zones at different probability percentage [Abbreviations, SF: Scrubland to Forest, GS: Grassland to Scrubland, VG: Vegetation-less (Barren land) to Grassland, FS: Forest to Scrubland, SG: Scrubland to Grassland, GV: Grassland to Vegetation-less]

Climate Zones	Probability	FS	SF	SG	GS	GV	VG
Equatorial Humid Winter wet & dry	<0.25	-	19.53	-	2.64	-	-
	0.25–0.5	0.02	10.63	-	0.25	0.12	0.06
	0.5–0.75	5.60	-	3.01	-	0.74	-
	>0.75	40.55	-	27.15	-	2.02	-
Arid & Semi-arid	<0.25	0.02	0.10	7.98	0.37	9.93	-
	0.25–0.5	0.58	9.66	6.00	1.77	2.14	0.49
	0.5–0.75	3.78	11.32	10.57	1.40	1.07	5.42
	>0.75	-	4.53	1.05	9.77	0.16	14.17
Warm Temperate Humid Winter wet & dry	<0.25	-	23.69	-	15.37	-	0.18
	0.25–0.5	0.02	9.14	0.08	0.08	-	0.42
	0.5–0.75	4.83	0.20	2.22	-	2.22	0.12
	>0.75	41.06	-	30.73	-	13.23	-
Montane	<0.25	-	2.12	2.75	6.22	48.54	1.97
	0.25–0.5	0.53	4.89	1.23	6.35	10.59	5.24
	0.5–0.75	1.27	2.45	1.88	11.00	6.55	14.16
	>0.75	1.75	1.74	5.34	44.79	2.68	57.77

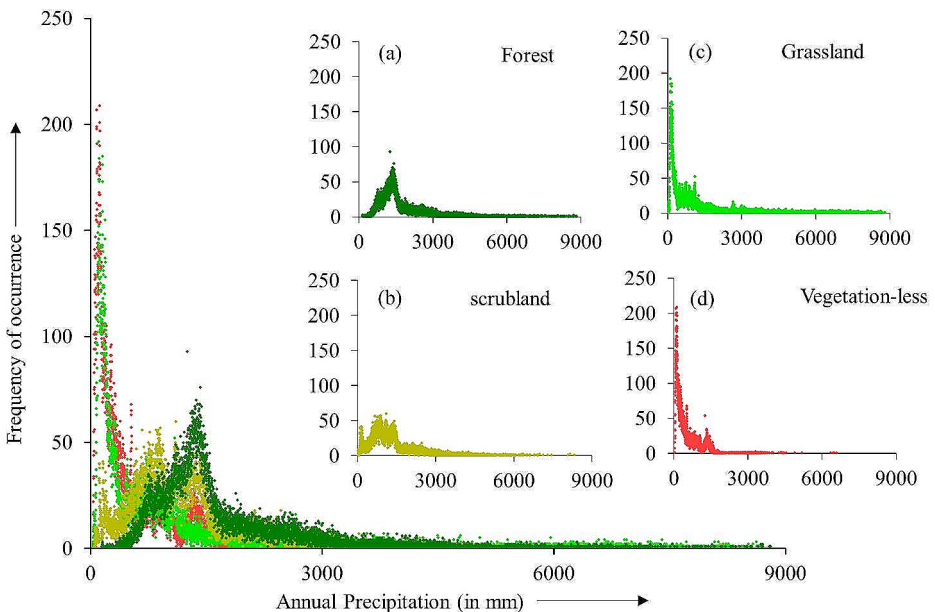


Fig. 2 Histogram showing the distribution of forest (green), scrubland (orange), grassland (light green) and vegetation-less (red) state pixels (y-axis) across receipt of mean annual precipitation (x-axis) (combined and individual representation are shown)

range and MAP (Fig. 3). The mean and range of annual precipitation experienced by forest, scrubland, and grassland states were 2190 mm (785–8650 mm), 954 mm (357–2017 mm), and 229 mm (58–1920 mm), respectively, while vegetation-less state received only 71 mm (34–615 mm). Though the range of MAP received by all vegetation types and vegetation-less states demonstrated some overlaps, their mean average values were distinctly separated from each other (Figs. 2 and 3).

More than 81% of India's forest in the wet climate regions was predicted to be highly resilient ($Pr \geq 0.75$), i.e., minor changes in precipitation in wet climate regions won't affect forests (Fig. 4; Table 1). The majority of the resilient forests were distributed in the wet equatorial humid and warm temperate humid regions. However, about 45% of the scrubland in these wet regions exhibited the least resilience toward forests, i.e., high transition probability towards forests (Fig. 4; Table 1). On the contrary, scrublands in the dry regions showed a high resilience towards forests and less towards grassland, i.e., such scrublands were less likely to be converted into forest rather than grasslands. About 10.73% of the scrublands showed less resilience ($Pr < 0.25$), i.e., high transition probability towards grassland in dry arid & semi-arid and montane regions. About 64.27% of scrublands were predicted resilient ($Pr \geq 0.75$), i.e., less change-prone towards grassland primarily found in the moderate to wet regions (Fig. 4b and c; Table 1). Similarly, 21.59% of the grasslands in the wet regions showed a high transition probability towards scrubland, whereas 58.47% of the grassland in the dry montane and arid & semi-arid region showed a high transition probability toward the vegetation-less state (Fig. 4d and e). On the contrary, the vegetation-less state in such dry regions was predicted highly resilient due to dryness, whereas it showed a high transition probability towards grassland in wet regimes (Fig. 4f).

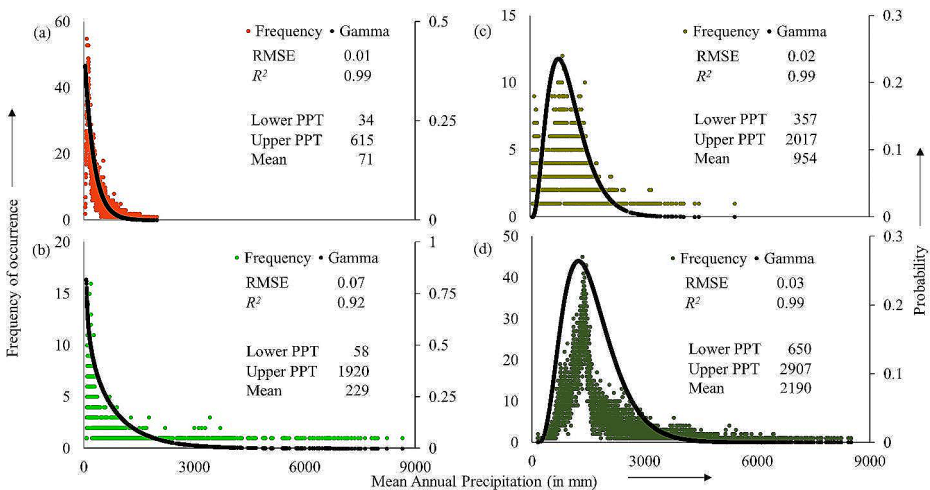


Fig. 3 Histograms showing Gamma distribution curve fittings for (a) vegetation-less, (b) grassland, (c) scrubland and (d) forest state with 90% mean annual precipitation (*PPT) values, indicate significant differences at p -value < 0.001

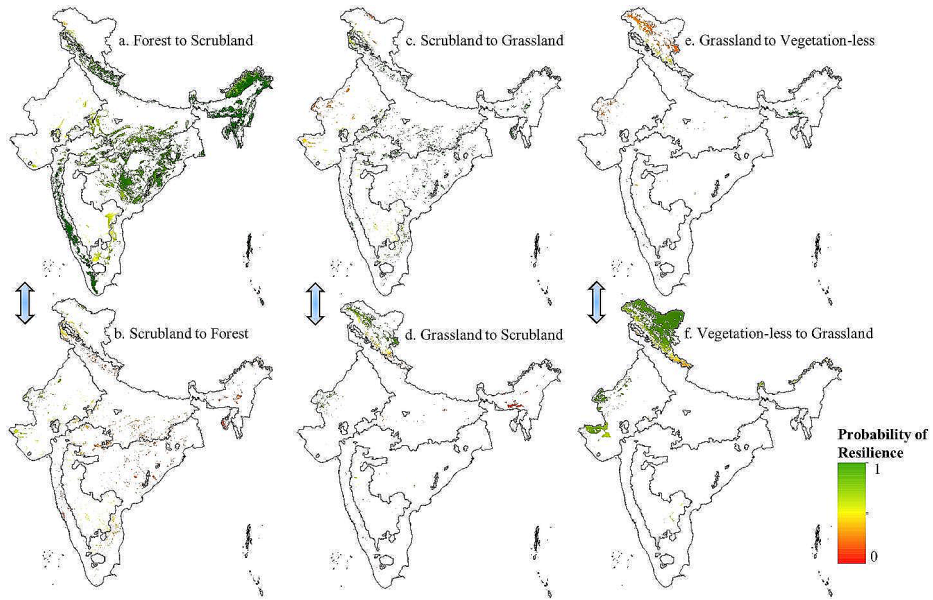


Fig. 4 Resilience probability of (a) forest, (b, c) scrubland, (d, e) grassland and (f) vegetation-less state as per mean annual precipitation

Table 2 The mean annual precipitation (in mm) values demonstrate the range of tipping points for different forest cover states at different (resilience and change prone) probability percentage (Abbreviations as mentioned in Table 1)

Resilience Probability	Change prone Probability	Life form changes towards:					
		Higher canopy density (wet regimes)			Lower canopy density (dry regimes)		
		SF	GS	VG	GV	SG	FS
0.1	0.9	1393	1020	1346	58	64	154
0.15	0.85	1263	924	1207	162	167	271
0.2	0.8	1162	849	1093	268	246	371
0.25	0.75	1080	788	1016	357	312	452

Resilience trajectory and tipping zone

The resilience probability of all the vegetation type categories was estimated based on the long-term average annual precipitation (Table 2). With the increase in precipitation, the scrubland resilience probability toward forests could decrease to 0.1 (1393 mm), 0.15 (1263 mm), 0.2 (1162 mm) and 0.25 (1080 mm). Therefore, the scrubland to forest transition could occur between 1080 and 1393 mm, denoting the tipping zone (Fig. 5a). Similarly, the grassland resilience probability towards scrublands in wet regimes decreases to 0.1 and 0.25 corresponds to 1020 mm and 788 mm precipitation, respectively, denoting the tipping zone (Fig. 5b). The transition of vegetation-less state to grassland could occur between 1346 mm and 1016 mm (tipping zone), indicating a higher tipping zone than the grassland to scrubland transition (Fig. 5c). Alternatively, the tipping zone for forests to scrublands transition (with

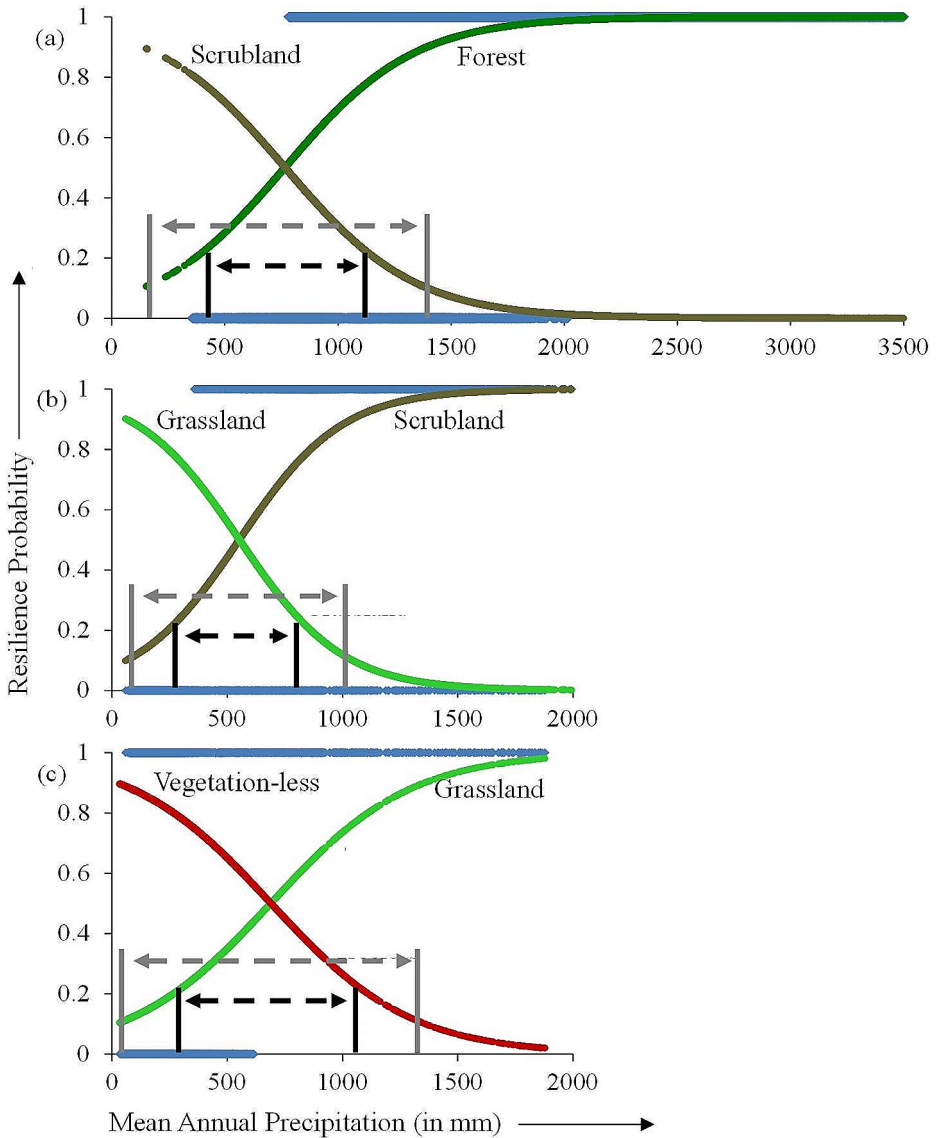


Fig. 5 Curves showing resilience probabilities (y-axis) for transitions between two vegetation types across the mean annual precipitation (x-axis) between 0.1 and 0.25 levels. The grey and black vertical lines (x-axis) indicate resilience probability, while the corresponding horizontal arrows indicate co-existence ranges between any two vegetation types

a resilience probability of 0.1 to 0.25) was estimated between 154 and 452 mm precipitation. The tipping zone for scrublands to grasslands transition was estimated between 64 and 310 mm, whereas the tipping zone for grassland to vegetation-less was estimated between 58 and 162 mm (Table 2). In other words, the scrubland to forest transition may occur in wet conditions (1080 – 1393 mm), whereas the reverse transition (forest to scrubland) may occur in much drier conditions (452 mm – 154 mm). Similarly, the tipping zone for grass-

land to scrubland transition was estimated in wet conditions (788 – 1020 mm) compared to reverse transition in dry conditions (64 – 312 mm). The tipping zone for vegetation-less to grassland transition may occur in wet conditions (1016 – 1346 mm) compared to reverse transition in dry conditions (58 – 162 mm). The contrasting precipitation ranges for different vegetation types transition in the wet and dry conditions are demonstrated through resilience probability curves (Fig. 5). The tipping points range for each resilience probability of 0.1 to 0.25 (alternatively, transition probabilities between 0.75 and 0.9) is shown between the vertical grey and black lines on the x-axis. The precipitation ranges (horizontal dotted lines) between the grey and black lines show the co-existence zones for the various vegetation type categories (Fig. 5).

Discussion

The majority of the forests of India distributed in humid regions of the Western Ghats, Eastern Ghats, Indian Himalayan region, and wet regions of the Deccan Peninsula were predicted to be highly resilient. However, <1% of the total forest was predicted to be the least resilient found in the drier montane, arid & semi-arid regions. About 45.44% of the scrublands in wet regions were estimated to change-prone towards the forest, while only 10.73% towards grassland in the dry regimes. The grasslands exhibited a higher transition probability towards scrubland and vegetation-less state in the contrasting wet and dry regimes.

Characteristic curves for different vegetation types transitions

The results show contrasting precipitation thresholds or tipping zones corresponding to various vegetation type transitions during the wet and dry conditions, indicating that the reversal of state change requires differential energy for the onward and reverse transitions. Our study has developed a unique characteristic curve on vegetation type resilience and regime shift in response to moisture conditions (Fig. 6). The figure shows the precipitation tipping points (at 0.1 resilience or 0.9 transition probability) of various transitions in wet and dry conditions and the intermediate co-existence zone (indicated by the precipitation overlap). The black dotted line could be typically called a characteristics curve that connects

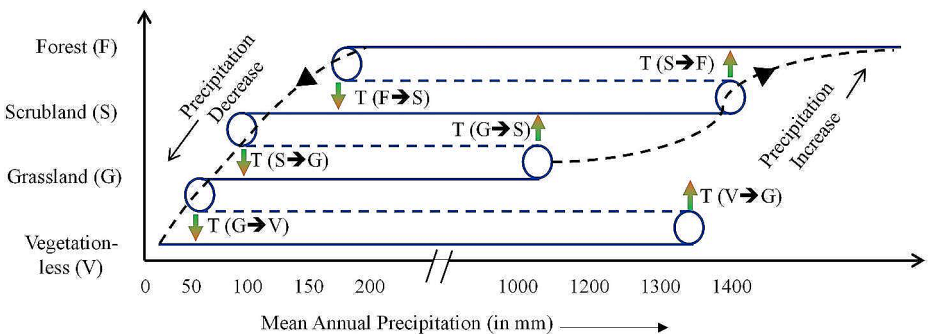


Fig. 6 Characteristic curves (hysteresis loop; black dotted curve) due to contrasting dry and moist conditions denoting tipping points [$T(\dots)$] (transition probability 0.9) and the dotted blue lines represent the precipitation overlap or 'co-existence zone' among the vegetation types classes

the various transition points. The hysteresis loop area denotes the precipitation overlap and co-existence of multiple vegetation type categories, which has been shown through a conceptual diagram as Fig. 7. Moreover, it could be noted that the large and small hysteresis loops shown in Fig. 7 denote the characteristics curve for the tipping points with 0.1 and 0.25 resilience probabilities, respectively. The larger hysteresis loop area indicates wider precipitation ranges and overlaps with higher contrasting tipping zones and *vice-versa*. The distribution of various vegetation type categories showed a wider co-existence range and overlap between forest – scrubland, vegetation-less – grassland compared to scrubland – grassland (Figs. 2, 5 and 6). The comparative assessment at 0.1 probability indicated the highest co-existence zones between grassland and vegetation-less states (~1288 mm), followed by forest and scrubland (~1239 mm), and scrubland and grassland (~956 mm), which could be signifying nature of distribution overlap (Fig. 6). Interestingly, the tipping zone for vegetation-less to grassland transition exceeds that for grassland to scrubland transition. This could support the hypothesis postulated by van Nes et al. (2014), wherein vegetation-less to scrubland transition can occur, skipping the intermediate grassland. However, such hypothesis requires further analysis, including various other environmental conditions and anthropogenic activities. The identified precipitation threshold for various vegetation types

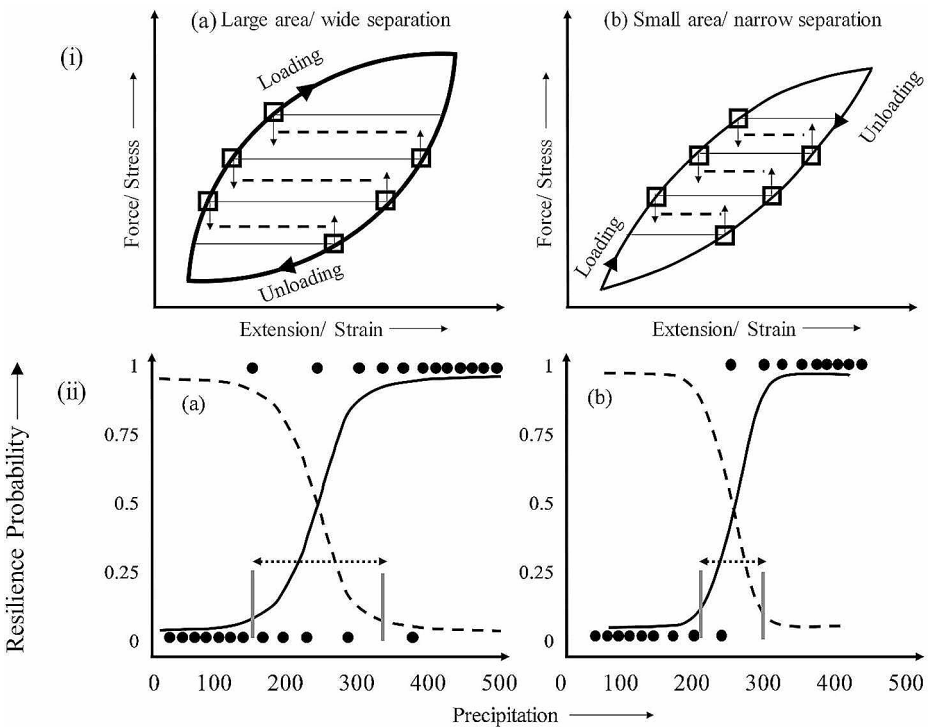


Fig. 7 (i) Conceptual diagram on comparative (a) large and (b) small hysteresis loop area corresponding to wide and narrow separation (solid horizontal lines and boxes to resemble vegetation types and tipping points, respectively, and the dotted line indicates the co-existence zone). (ii) Conceptual diagram of (a) flattened and (b) steep resilience curve with the co-existence zone (dotted line with arrow). The range between reverse transitions (co-existence zone) is higher for the flattened curve (high overlap) corresponds to a large hysteresis area; and shorter for the steep curve (less overlap) corresponds to a small hysteresis area

exhibited that deep-rooted plants can survive in a regions of large precipitation changes due to their adaptability to drought in wet regions (van Nes et al. 2014), wherein scrubland and grassland are more adapted to dry regions.

Tipping points range for different vegetation types

The forests in India show high resilience beyond 1400 mm precipitation, similar to other national assessments (Das and Behera 2019) and slightly lower than previous global estimates of 1500 mm (Hirota et al. 2011; Staver et al. 2011; Verbesselt et al. 2016). Van Nes et al. (2014) reported a similar precipitation threshold for savanna grasslands to forest transition (~1500 mm) and the reverse transition at much higher precipitation (<1100 mm) compared to the current study. Pemadasa (2008) reported that the dominant grassland landscape in the Vindhyan Hills in Chandraprabha Sanctuary, India, receives 1050 mm of precipitation, which could become change-prone to scrublands. Khan et al. (1994) reported about 57.6% forest loss in the dry arid region of Rajasthan state, India and attributed it to the reduction in precipitation by 200–456 mm in 1987 compared to the long-term mean precipitation of 800–1000 mm. This could indicate the least resilient forests in the dry climate, leading to significant forest loss in a single-year drought.

Resilience of different vegetation types

Evidence of degradation and succession in attributing to forest resilience necessitates long-term observations. In the absence of such data, the human-assisted forest changes observed over a relatively long span can be linked as early evidence. The scrubland in the humid parts of northeastern India indicated very low resilience and high chances of a regime shift towards forests (Das et al. 2019). It is relevant to mention that the majority of the scrubs in northeastern India are regrowth on abandoned shifting cultivation lands (Behera et al. 2018; Das et al. 2021). Field visits in this region also indicated that the wide-scale rubber plantations that successfully adapted to the climatic conditions could be explained by the low resilience of scrubland to the forest. In comparison to the tree canopy density-based data used in previous studies (Hirota et al. 2011; Das and Behera 2019), this study utilized the actual vegetation type map that could incorporate human knowledge into a classification which otherwise gets ignored in automatic classification approaches (Behera et al., 2001).

The current study identifies regions where forest enrichment or degradation may occur due to significant precipitation alteration. The results could be useful in various other scientific studies, including ecosystem productivity, functioning, services, and land degradation. The identified precipitation threshold for vegetation type regime shift could help identify suitable forest conservation and management measures under climate change threats and develop spatially explicit policies for different landscapes or climate regimes. The resilience maps will benefit the ecosystem restoration processes and identify suitable areas for improving tree and vegetation cover to achieve India's nationally determined contribution (NDC) targets. The study's findings could be used to help prescribe various nature-based solutions (NbS) to protect, manage, and restore degraded ecosystems, maintain biodiversity, and improve the benefit of ecosystem services. Appropriate landscape management could help forests adapt to future climate changes, for example, by introducing suitable silvi-

culture practices, increasing climate-tolerant species heterogeneity, and diversity in forest stand structure and age.

The unavailability of long-term vegetation types and change data records is one of the major limitations in validating the impact of climate change and tipping point. Future studies may include long-term proxy indicators such as species regeneration or vegetation type dominance to validate the study outcome. The high-resolution vegetation type map used here was generated using a visual image interpretation technique and well-validated with a large number of ground data points (Roy et al. 2015). Moreover, the high-resolution (30 arcsec) global climate data were generated using coarse-resolution climate and multiple proxy indicators applying geostatistical and interpolation approaches. Such global data may include regional or local biases, most importantly in mountainous terrain (Fick and Hijmans 2017). The inaccuracies in the input data might influence the precipitation tipping points. The vegetation types in the study included various forest types such as tropical, sub-tropical, and temperate. Although such an approach avoids the regional biases in estimating the tipping points, various forest types may exhibit variable tipping points due to the local environmental conditions, which could be studied using multiple environmental variables and non-linear statistical approaches.

Conclusions

The impact of climate change on the terrestrial ecosystems may be influenced by the past long-term local and regional hydrological settings. The ecosystem response to climate changes influences biological activities via water use efficiency, photosynthetic capacity, and productivity and alike, in the long run, modifies functionality through ecosystem structure and vegetation type. This study demonstrates a novel attempt to predict ecosystem resilience using an actual vegetation type map compared to previous studies where mostly tree canopy density data were used. High precipitation overlaps among the vegetation types suggest two-way transition probabilities of the scrubland and grassland at the same instance, where the resultant probability decides the final state. The higher precipitation overlaps and similarity in distribution pattern among the vegetation types lead to higher co-existence zone and greater difference in transition in precipitation during contrasting dry and wet conditions. The study suggests a precipitation tipping zone better representing the transition or regime shifts among the vegetation types. The novel characteristic curve connects multiple components of precipitation-dependent regime shift and directs the nature of vegetation types transition and resiliency for India. Future studies on inter-comparison in the characteristic curves and hysteresis loop area regionally or globally may articulate the nature of ecosystem regime shifts in different climate regions. The identified precipitation tipping zones for various vegetation type transitions would be essential in assessing the ecosystem structure, biodiversity loss and ecological processes, including ecosystem productivity. The characteristic curve offers valuable inputs to explain vegetation type transition and identify regions where forest enrichment and degradation may occur due to climate regime shifts. Such a spatially explicit database could provide vital inputs for planning forest restoration and management activities and mitigate the impacts of climate change.

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Author contributions PD and MDB conceived the ideas and designed the methodology; PD, MDB and PSR collected the data; PD and MDB analyzed the data; PD and MDB led the writing of the manuscript; MDB and SKB supervised the research. All authors contributed critically to the drafts and gave final approval for publication.

Data Availability Data available on request from the authors.

Declarations

Conflict of interest The authors declare that they have no known conflict of interest.

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