

Chapter 5

Modeling Landscape Level Forest Disturbance-Conservation Implications



Mukunda Dev Behera

Abstract Increasingly forest land is diverted to different land uses leading to various levels of disturbances in a landscape. Any disturbance could affect the structure and functions of a landscape, their inherent properties and interactions, thereby could lead to temporal or irreversible changes. In this chapter, the spatial distribution of various forests and non-forest patches were combined with road and settlement proximity zones using remote sensing and GIS tools to generate disturbance index (DI) of a landscape, by adopting landscape ecological principles. Various landscape ecological matrices such as forest fragmentation, interspersions, juxtaposition patchiness, and porosity, were analyzed using spatial analysis. Field sampling data on species richness from 862 plots (nested quadrats of $20 \times 20 \text{ m}^2$) were analyzed to adjudicate the correlation between different DI levels and their diversity content, and interestingly, higher species richness was observed for lower DI levels. The study was selected in the northeastern India of the eastern Himalaya accommodating Arunachal Pradesh, Assam, and Meghalaya states. DI demonstrated progressive disturbance in the forest structure and composition. Meghalaya state has better reflected the decreasing pattern of DI with species richness and its endemic subset. Disturbance Index, a landscape-based model proved to have well captured the patterns and processes, thereby advocating wider application and replication for conservation planning.

5.1 Introduction

Disturbance is responsible for triggering forest fragmentation, edge-interactions, and species migration in a landscape. The landscape level disturbance can be perceived with respect to natural and anthropogenic disturbances. Understanding the spatial configuration and the forces prevailing over a landscape helps study the possible

M. D. Behera (✉)

Spatial Analysis and Modeling Lab., Centre for Oceans, Rivers, Atmosphere and Land Sciences (CORAL), Indian Institute of Technology Kharagpur, Kharagpur, India
e-mail: mdbehera@coral.iitkgp.ac.in

impacts (Moloney and Levin 1996). The human being has been altering the frequency and extent of various disturbances at a faster pace and greater extent (Barik and Behera 2020). In absence of strict land use and land cover policy enforcement, the settlements and transportation networks such as roads and rails add to the existing sources of biotic disturbances. The disturbances can be visualized across multiple scales and geographical space and can be studied using patchiness or interspersed matrices (Murthy et al. 2016).

Disturbances could change the homogeneity or heterogeneity of elementary patches in a landscape, thereby defining renewed or new functionalities. Any disturbance may alter the homo- or heterogeneous structural organization of patches. Individual-level disturbances may lead to homogeneous conditions at higher scale, while at lower scale multiple disturbances lead to patch heterogeneity. Any alternation in the spatial configuration of a landscape, therefore could be a reflection of the influencing disturbances itself (Das et al. 2017). Further, continuous or periodic disturbances could lead to propagation of the impacts or changes across the landscapes (Behera et al. 2018), thereby posing cascading challenges for management (Das et al. 2021). Therefore, the landscape disturbances must be studied in terms of their nature and sources including periodicity of occurrence and scale, for appropriate management and restoration.

The response of biological diversity to landscape disturbance could vary from individual species to community across a changing disturbance regime (Chitale et al. 2020). The response of species assemblages to any disturbance may demonstrate varied time-lag and reorganization periods. This may lead to alternation of established and matured ecosystems or creation of new ecosystems with renewed species assemblages with tendency of accommodating more invasive and faster growing species. Therefore, the disturbances alter the species assemblage pattern, either by loss or establishment of new species owing to the suitability of the changing environment. Alternations in disturbance regimes and their impact on biotic interactions could modify or redefine the structure and function of biodiversity in a landscape (Behera et al. 2018). However, it may be hard to estimate any quantitative or qualitative change in lieu of complexity and cascading effects of the interactions. Changes in the types, intensity, and frequency of disturbances could affect the composition of biodiversity and primary production within an ecosystem (Mahanand et al. 2021). The impact of climate change with respect to increased extreme weather events also has greater impact on landscape.

Landscape is often regarded as the best spatial scale to assess the responses as it can reflect ecosystem level alternations where the patches are the individual units. A landscape accommodates different homogeneous patches that can be studied to understand their spatial arrangement, shape and size, and neighborhood effect using various landscape matrices (Turner et al. 1989). The arrangement of patches over space such as the number of a particular patch in an area, the shape, and size of the patches, the configuration of patches, can be considered to understand different communities and species level interactions in a natural landscape (Lidicker 1995). The landscape matrices adopt a geographical window approach that could be overlapping or non-overlapping in nature (Dillworth et al. 1994). Fragmentation risks patch

level disturbance having implications such as edge effects and alternations in energy balance in a landscape (Nilsson and Grelsson 1995). Therefore, disturbance induces alternations in spatial arrangement of patches and their functional characteristics including biodiversity and primary productivity.

Remote sensing images can be interpreted to define the spatial arrangement of different patches, and are therefore potentially used to analyze disturbances across time and scale. The patch or class wise information can be transferred and linked to characterize biodiversity structure and function using statistical and modeling approaches. The Geographical Information System (GIS) helps in integration of the satellite derived spatial maps such as fragmentation, patchiness, porosity, interspersion, and juxtaposition for estimating landscape disturbance, thereby useful in management decision-making. The Global Positioning System (GPS) provides information on the geographic locations of different landscape elements, thereby helpful in locating the sample plots for mapping, classification accuracy assessment, spatio-statistical analysis, and model validation (Behera et al. 2000).

Indian national level forest cover assessment is done biannually using visual and digital interpretation techniques by Forest Survey of India (FSI; SFR 2019). In a maiden attempt, Roy et al. (2015) that have prepared a nation-wide vegetation type map of India using satellite data, with 100 classes such as mixed, gregarious, locale specific, degradational and scrub formations along with plantations. Vegetation type map serves as an intermediate input for calculation of disturbance index (*DI*). Here, the vegetation type map was generated using satellite data that was further utilized for generating a *DI* image along with other information using a customized package, Bio_CAP (Behera et al. 2005).

5.2 Study Site

The Arunachal Pradesh, Assam, and Meghalaya states are located in the eastern Himalaya, and categorized under the Himalaya-East-Himalaya biogeographic zone (Rodgers and Panwar 1988), were selected as study sites (Fig. 5.2a; Table 5.1). The three states accommodate diverse tropical ecosystems comprising of mixed wet and dry evergreen, and deciduous broadleaved forests. The study site experiences very high humidity thereby supporting diverse forests with several primitive species. The three states vary as per climate and topographic conditions as well as human activities.

The state of Arunachal Pradesh accommodates a wide range of ecosystems such as grasslands, dense evergreen broadleaved and needle leaf forests, alpine scrubs, open forests adjoining to settlements, and road networks, and disturbed secondary formations (Roy and Behera 2005). The state of Meghalaya conglomerates several undulating hills in east-west orientation, thereby accommodating mosaic of valleys and hillocks. The flora of Meghalaya has been reported as the richest in India with a dominant number of angiospermic plant species. Recently large-scale deforestation have been reported from the forests of Assam and Arunachal Pradesh (Pasha et al. 2020). The driving forces for forest loss and conversion in the region are deforestation

Table 5.1 Characteristics of the study site, three states in northeastern India

Parameters	Arunachal Pradesh	Assam	Meghalaya
Total geographic area (km ²)	83,743	78,438	22,429
Forest area (km ²) (%)	68,019 (81.22)	27,827 (35.48)	16,839 (75.08)
Forest types; Champion and Seth (1968)	Tropical, sub-tropical temperate, sub-alpine alpine scrub	Tropical	Tropical, sub tropical
Altitude	50–7000 m	Up to 1000 m	Up to 1600 m
Physiognomy	Mountainous, complex terrain	Mainly plain land, partly mountainous	Mountainous, complex terrain
Dominant land use/cover	Forest	Agriculture	Forest
Single factor hitched to forest conservation	Complex terrain	Protected forests	Sacred groves ^a
Driving force for forest loss	<i>Jhumming</i> and deforestation	Deforestation	<i>Jhumming</i>
<i>Hotspot</i> category	Himalaya	Partly in Himalaya and Indo-Burma	Indo-Burma

^a The scared groves of Meghalaya are a very rich storehouse of vegetation wealth. They form isolated patches of vegetation that remain untouched due to the religious beliefs and myths of the tribal people. Many endangered species have been reported from the scared groves

and shifting cultivation activities (Table 1). In past few decades, the forest loss due to slash-and-burn agricultural practices (also called *jhumming* or shifting cultivation) has slowed down (Das et al. 2020). The *jhumming* is a process of slash-and-burn agriculture, wherein the farmers clear a patch of forest for cultivation and leave it fallow for certain number of years. Deforestation has a strong relationship with the proximity to roads and habitations. The rise in population growth, the shifting cultivation activities, and industrialization in the form of plywood factories are some of the major proximate factors responsible for deforestation and forest degradation in northeastern India (Khan et al. 1997).

5.3 Methodology

Forest fragmentation can be defined as the number of forest patches to the non-forest patches in a landscape (Monmonier 1974), whereas patchiness is estimated as the density and number of patches of all types occurring in a landscape (Romme 1982). The higher fragmentation and patchiness are indications of landscape heterogeneity, thus associated with disturbance. The measure of interspersion and juxtaposition in a landscape indicate dissimilar and proximal neighborhoods of various patches

respectively (Lyon 1983). Therefore, higher interspersions indicate greater disturbance while lower juxtaposition indicates higher disturbance in a landscape. The porosity can be calculated to realize the disturbance within a native or original vegetation type in a defined region (Forman and Godron 1986). For the northeastern region, the porosity was judged for all the primary forests. The species richness information from 862 field plots provided inputs for juxtaposition calculation and correlating between different *DI* levels and their biodiversity content (Fig. 5.1).

The landscape level disturbance Index (*DI*) was assessed as cumulative function of spatial and social attributes using a customized package Bio_CAP (Fig. 5.1). IRS LISS-III satellite data were used for classification of forest vegetation types using a pre-defined classification scheme (Roy et al. 2012). The simplified forest fragmentation map was utilized to generate a *DI* image along with a few other landscape matrices such as patchiness, porosity, juxtaposition and interspersions, and settlement and road buffers. Stratified random sampling following probability proportionate to the size (PPS) was practiced for field sampling and linking in-situ forest composition. A total of 862 field plots were laid in Arunachal Pradesh (405), Assam (324), and Meghalaya (133) respectively, those accounted for 0.002–0.005% of the natural vegetation area. The measurements for all tree and liana species (20'20 m), shrubs (5'5 m), and herbs (1'1 m) were taken within each sample plot (Roy et al. 2012). The location and extent of the natural vegetation types and their landscape matrices were integrated with the social attributes such as road and settlement buffer, by assigning proportionate weights (Behera et al. 2005) to derive *DI* (Eq. 5.1; Fig. 5.3). The *DI* was scaled at 10-levels and an area estimate was done (Fig. 5.4).

$$\text{Disturbance Index}(DI) = f \int \{ \text{disturbance buffer}(B), \text{interspersions}(I), \\ \text{juxtaposition}(J), \text{fragmentation}(F), \text{patchiness}(P), \\ \text{and porosity}(PO) \} \quad (5.1)$$

$$DI = \{Wti(F) + Wti(P) + Wti(I) + Wti(PO) + Wti(J) + Wti(B)\}$$

where, $Wti(t = 0.1 - 1.0)$ indicates proportionate weight.

For validation of *DI*, the field plots were segregated into 10-categories using their field gathered GPS coordinates (Fig. 5.1c). Each group of sample plots pertaining to different levels of *DI* were enumerated further to study the distributional pattern of the life forms such as tree, shrub, herb, and liana species, along with the endemic species and mean tree BA. The regression fitness curves were plotted to study the agreement between modeled output (i.e., *DI*) and field conditions (species diversity; Fig. 5.5).

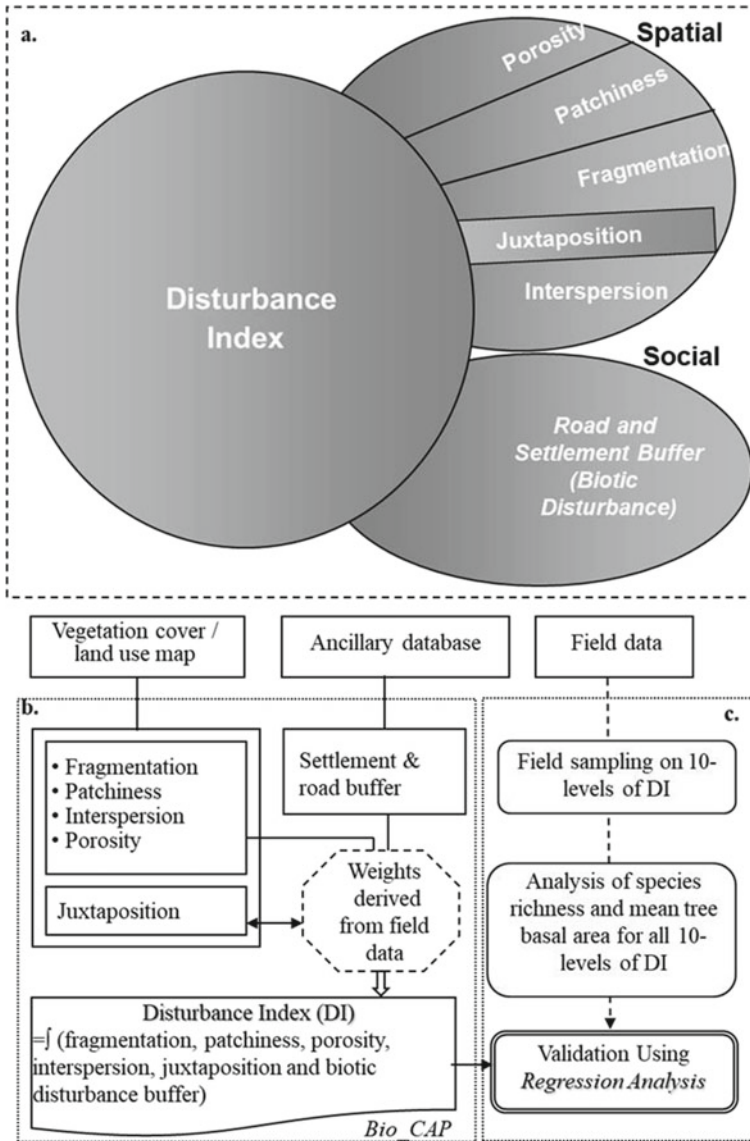


Fig. 5.1 a Disturbance index (*DI*) is estimated as a cumulative property of social and spatial attributes in a landscape; paradigm for b Assessment of forest disturbance regimes using remote sensing, GIS, and GPS tools (Modified from Behera et al. 2005) and c Validation of *DI* using field sampling plots

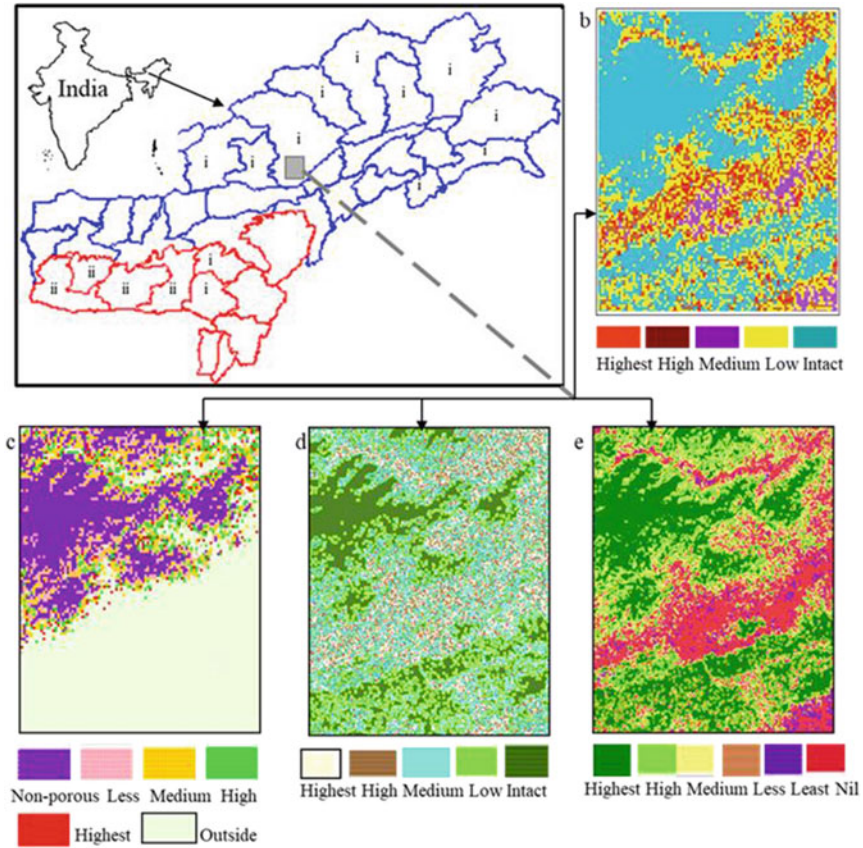


Fig. 5.2 a location map of (i) Arunachal Pradesh, (ii) Meghalaya and Assam, falling two hotspots; Arunachal Pradesh and upper part of Assam belong to Himalaya hotspot [shown in blue color]; Meghalaya and southern part of Assam belong to Indo-Burma hotspot. Depiction of **b** Fragmentation image, **c** Porosity image of sub-tropical evergreen forest, **d** Interspersion and **e** Juxtaposition image for part of the study area

5.3.1 Biodiversity Characterization Package (Bio_CAP)

Bio_CAP is a semi-expert package, developed for uniform use in the ‘Biodiversity Characterization at landscape level’ project (Roy et al. 2012). The package takes a vegetation type map as the primary input and calculates other landscape parameters as grid data. Bio_CAP was customized using pre-defined codes for different classes of vegetation type map such as for fragmentation estimate, all the class codes from 1 to 150 are automatically considered as forest, and from 151 to 255 picked as non-forest classes. This package was used for estimating the *DI* that provided 10-levels within forest vegetation patches (Behera et al. 2005). The non-forest areas and unclassified

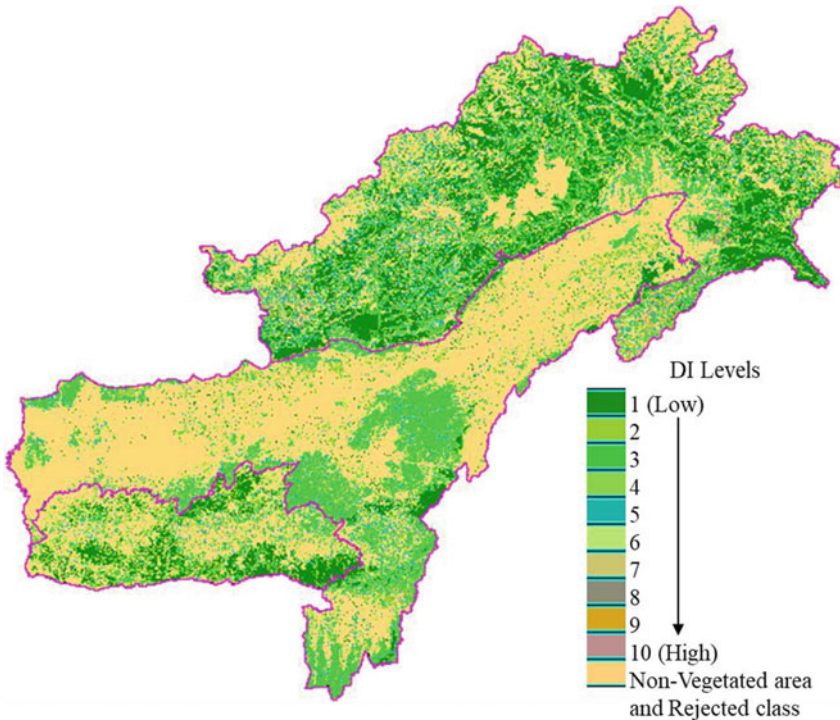


Fig. 5.3 Disturbance Index (*DI*) image of (i) Arunachal Pradesh, (ii) Assam and (iii) Meghalaya; Various *DI*-levels range from 1 to 10

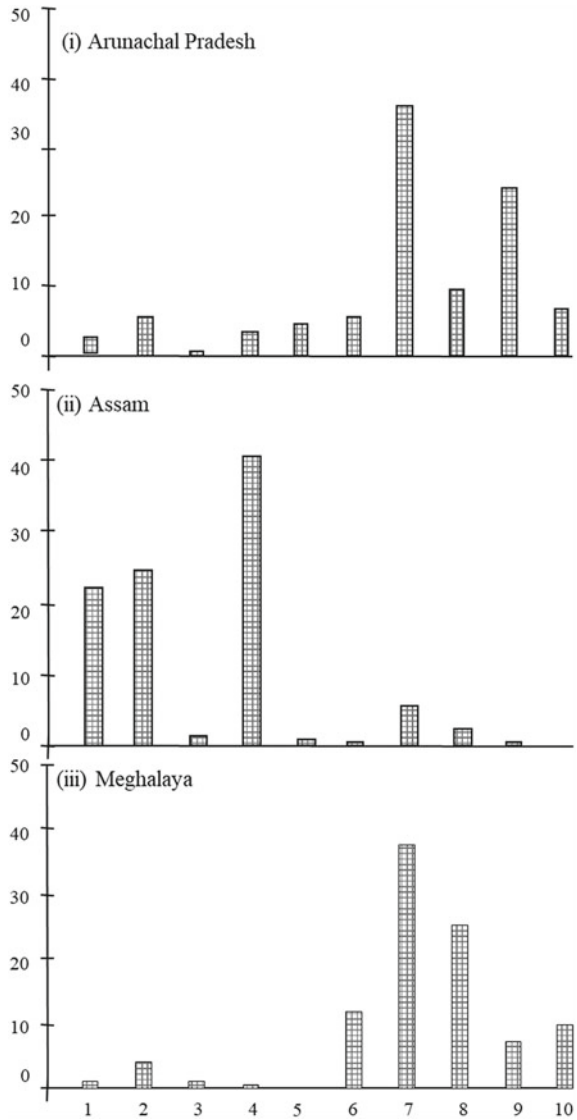
areas such as cloud, shadow, etc., were not considered for landscape analysis and *DI* estimate (Fig. 5.3).

5.4 Results

5.4.1 Landscape Analysis

The forest type map generated from satellite imagery using a hybrid classification approach offered the requisite input spatial layer for analysis of landscape indices (Roy and Behera 2005). The tropical semi-evergreen forests are distributed in the regions of Arunachal Pradesh and Assam state border areas. However, the forests are exposed to large-scale exploitation and deforestation owing to their easy accessibility with respect to adjacency to the road network and simpler topography. The sub-tropical evergreen forests are found distributed in the entire study site and are the most affected by jhumming, due to their proximity to human settlements. The degraded

Fig. 5.4 Percentage area (Y-axis) distribution in (i) Arunachal Pradesh (ii) Assam and (iii) Meghalaya; X-axis represents different *DI* levels. Note that severity of disturbance varies from level 1 to 10



forests are originated through various activities such as jhumming, landslide, fire, etc. The secondary forests or the abandoned jhum lands are found dominated by varieties of scrubs, herbs, grasses, bamboos, weeds, etc., which receive higher direct sunlight and do faster primary production. The temperate and sub-tropical evergreen forests accommodate thorny bamboos forming an impenetrable canopy.

The higher level of forest fragmentation was observed adjacent to settlement and road networks owing to resource use by the local people (Fig. 5.1b). The patchiness image demonstrated higher homogeneity for the state of Arunachal Pradesh

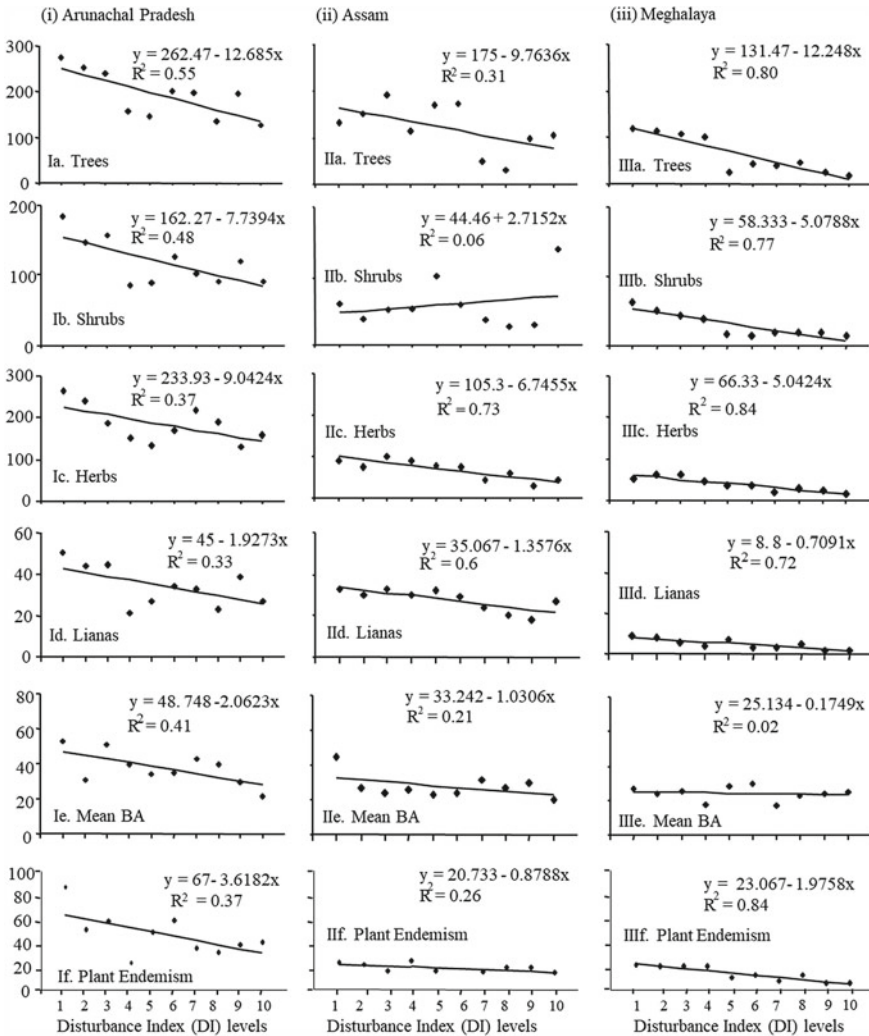


Fig. 5.5 Distribution of various life forms such as **a** tree, **b** shrub, **c** herb, **d** liana species, along with **e** mean BA and **f** plant endemism across various disturbance indexes (*DI*) levels for (I) Arunachal Pradesh, (II) Assam, and (III) Meghalaya; Y-axis represents the number of species. *DI*-level is plotted from 1 to 10 along X-axis. All the regression curves have shown decreasing trend along increased levels of *DI*, except the shrubs in Assam state

and higher heterogeneity for the state of Assam, whereas Meghalaya showed an intermediate level of patchiness. The medium level of patchiness is an indication of landscape disturbance. Porosity was calculated for both the tropical and sub-tropical forests that are semi-evergreen and evergreen in nature respectively (Fig. 5.1c). Both the forests were found to be relatively porous with very less patches in an intact state. Since any sort of disturbance start affecting the edges, intermediate level of porosity

was found across the edge transitions, which could be attributed to degradation and deforestation activities. 80% area was found under different degrees of interspersions in the landscape, pointing to low patch diversity (Fig. 5.1d). This indicated that the dispersal ability of the central class is low or reduced. The juxtaposition image using the adjacency criteria of central pixel with the neighboring pixels was regrouped under five categories (Behera et al. 2005). The juxtaposition image demonstrated greater adjacency or neighborhood effects between the tropical semi-evergreen and sub-tropical evergreen forests owing to their nature of occurrence (Fig. 5.1e). Therefore, juxtaposition is found as a critical indicator revealing the patch interactions in a landscape.

5.4.2 Disturbance Index (DI) Model

The *DI* image reflects various levels of disturbance prevailing in the states (Fig. 5.3). Overall, the *DI* image demonstrates that the forests adjoining to human settlements and road networks are highly disturbed in the northeastern landscape (Fig. 5.3). The non-forest classes, snow, and cloud were not considered for estimating disturbance as they are relatively inert from anthropogenic point of view. The highest level of disturbance was found adjoining the agricultural area and natural vegetation. The forests with low level of interspersions and higher juxtaposition demonstrated the lowest level of disturbance on the *DI* image owing to their remoteness from habitations.

Many of the reserve forests are found having very low *DI* value that owes to the protection effort by the state forest departments. In Arunachal Pradesh, maximum area was found under low levels *DI* since most of the forest fragmentation, patchiness, porosity, and interspersions values were low too. The *DI* image of Assam shows highly disturbed patches in North Cachar district (Fig. 5.3). The evergreen and semi-evergreen forest belts of Karbi Anglong and North Cachar hill districts are found the worst affected. 20.87% area was disturbance-free and the man-made landscapes comprising of 52.11% area was not considered for *DI* analysis in Assam state. The disturbance in Meghalaya state was the highest in Garo hills followed by Khasi and Jaintia hills. It was observed that the level of disturbance was high in the areas accessible to human beings. The inaccessible areas with complex topography demonstrated lower *DI* values for the state of Meghalaya.

The percentage area for different levels of *DI* was plotted in Fig. 5.4. 36.6% forest area of the state of Arunachal Pradesh demonstrated medium (level-6) *DI* (Fig. 5.4a). In Assam, 40.73% forest area demonstrated intermediate (level-4) level of disturbance (Fig. 5.5b). Similarly, the state of Meghalaya accommodates 38.06% forest area under medium level of *DI* (level-6). These figures clearly indicate that more of the forest areas in Arunachal Pradesh and Meghalaya states suffer from low degree of disturbance (Fig. 5.4). However, for Assam, more of the forest areas experience high degree of disturbance.

5.4.3 Validation of DI Model

All the 405, 324, and 133 plots were splitted into 10-levels corresponding to their locations on *DI* image for Arunachal Pradesh, Assam, and Meghalaya respectively (Table 5.2). The species richness demonstrated S-shaped pattern across the *DI* levels and R^2 value decreases gradually from trees to lianas (i.e., 0.55, 0.48, 0.37, and 0.33, whereas the mean tree BA resulted average R^2 value of 0.41 (Fig. 5.5). In Assam state, the trees, herbs, lianas, and mean tree BA showed an overall decrease in species richness; whereas the shrubs demonstrated a reverse trend across *DI* levels ($R^2 = 0.06$; Fig. 5.5). The deviation in case of shrubs could be explained by new formations of weed species at intermediate levels of disturbances. Herbs demonstrated a very good fit with $R^2 = 0.73$, followed by lianas with ($R^2 = 0.6$; Fig. 5.5).

The state of Meghalaya has shown a significant decrease in species richness for all life forms with high degree of correlation (i.e., trees, $R^2 = 0.80$; shrubs, $R^2 = 0.77$; herbs, $R^2 = 0.84$ and lianas, $R^2 = 0.73$). Plant endemism demonstrated a decreasing pattern along *DI*, with the highest regression fitness for the state of Meghalaya, followed by Arunachal Pradesh and Assam states (Fig. 5.5f). The mean tree BA demonstrated an S-shaped curve with maxima at intermediate level of *DI*.

5.5 Discussion and Conclusions

Satellite images provided forest vegetation cover map for the states with reasonably good accuracy for generating the disturbance index (*DI*). The distribution of various forest types across elevation was first attempted by Kaul and Haridasan (1987) in the state of Arunachal Pradesh. Of the 16 major forest types classified by Champion and Seth (1968), 13 types and 54-ecologically stable formations were observed in northeastern India (Roy et al. 2012). Landscape level patch analysis very well revealed the ecological patterns and processes and thereby is important in determining diversity and distribution of species assemblages. The increase in the level of forest fragmentation leads to reduction of patch size and the edge effect. The forest fragmentation, patchiness, and porosity images uniformly demonstrated lower values for dense and intact forests that are mostly located on difficult topography, remotely from the settlements and road networks. 41% area reported under intact or low levels of interspersion, well implies medium level of interaction among and between the patches. Juxtaposition, which is based on the relative adjacency of patches, demonstrates low *DI* values for intact patches in the landscape. The *DI* image reflects high disturbance level for the areas having more biotic access and vice versa, indicating that the *DI* has efficiently incorporated the spatial phenomena. The juxtaposition image has relevance in wildlife studies as some fauna just needs one habitat type in contrast to many by other groups. Therefore, patches with low forest fragmentation and high juxtaposition may be given prior attention for management.

Table 5.2 Distribution of life forms along various levels of *DI* (increases from 1 to 10) for Arunachal Pradesh, Assam, and Meghalaya

<i>A. Arunachal Pradesh</i>					
Levels	Trees	Shrubs	Herbs	Lianas	Endemism
1	275	185	265	51	87
2	254	147	240	44	51
3	240	157	188	45	58
4	157	86	152	21	23
5	146	90	133	27	48
6	201	127	168	34	59
7	197	103	219	33	35
8	134	91	189	23	32
9	196	120	130	39	38
10	127	91	158	27	40
<i>B. Assam</i>					
1	133	60	91	33	22
2	151	39	76	30	20
3	191	50	101	33	14
4	114	53	88	30	24
5	169	100	79	32	14
6	172	58	74	29	7
7	49	37	43	24	13
8	30	28	60	20	17
9	98	30	28	18	17
10	106	139	43	27	11
<i>C. Meghalaya</i>					
1	120	64	53	9	20
2	114	51	63	8	19
3	107	43	63	6	19
4	102	39	44	4	19
5	26	18	35	7	9
6	44	15	36	3	11
7	39	20	22	3	6
8	47	19	29	5	11
9	25	20	24	2	4
10	17	15	17	2	4

Disturbance regimes could vary across a given landscape as a function of biotic interactions, proximity to settlement and transport networks, and complex topography (Turner 1989). The landscape level disturbance offers fundamental inputs to the understanding of changes in various ecological structures and functions (Pickett and White 1985). It was found that the pattern of disturbance in the landscape has influenced the species diversity of the region (Pickett and Thompson 1978). These disturbance activities such as jhumming and deforestation have changed the disturbance regimes and altered the ecosystem processes through habitat loss and forest fragmentation in northeastern India.

The deforestation level was found higher in low elevation regions of Arunachal Pradesh that have a direct relationship with settlement and transport networks (Khan et al. 1997). Shukla and Rao (1993) have attributed to jhum cultivation and industrial activities as the dominant proximate factors for landscape disturbance in Arunachal Pradesh. Assam is located in the Brahmaputra valley that is dominated with permanent cultivation, while the border regions with Arunachal Pradesh has lot of tea gardens owing to sloppy terrain. The shifting cultivation practices primarily attribute to biodiversity decline in Meghalaya (Roy and Tomar 2000). In spatial context, any pixel in *DI* model is the resultant function of fragmentation, patchiness, porosity, interspersion, juxtaposition, and road and settlement buffer (Roy and Tomar 2000). Few studies were done in India that establish relationships between the landscape level disturbance and the biological richness (Pandey and Shukla 1999), which could be the next step forward.

In general, the regression fitness curves demonstrated clear decreasing trend among the field-derived species richness, mean tree BA, and endemism with *DI* (Fig. 5.5). The tree species richness pattern across *DI* levels decreased prominently from the state of Meghalaya with greater degree of regression fitness ($R^2 = 0.80$), followed by Arunachal Pradesh ($R^2 = 0.55$) and Assam ($R^2 = 0.31$). Shrub richness pattern along *DI*-levels also showed greater agreement in Meghalaya ($R^2 = 0.77$), followed by Arunachal Pradesh ($R^2 = 0.48$) and a reverse trend was seen for the state of Assam ($R^2 = 0.06$). Greater degree of agreement was observed in Meghalaya for herbs and lianas, followed by Assam and Arunachal Pradesh (Fig. 5.5). The endemic subsets of plant species demonstrated the highest fit ($R^2 = 0.84$) for Meghalaya followed by Arunachal Pradesh and Assam (Fig. 5.5). In contrast, Arunachal Pradesh has demonstrated good agreement of mean tree BA with high R^2 value (0.42), followed by Assam ($R^2 = 0.21$) and Meghalaya ($R^2 = 0.02$; Fig. 5.5). Each field sample plot represents different spatial and ecological properties that are reflections of fine scale local variations. The regression fitness curves well demonstrate the relationship between various landscape structural indices and their species diversity content. Such regression fitness gives the first-hand assurance that intact patches with lower *DI* values hold higher species richness in a landscape.

The states of Arunachal Pradesh and Meghalaya accommodate higher of species endemism, while the state of Assam has more agricultural lands (Table 5.1). Almost all of the forests are found in difficult terrain, and therefore Assam state has less forest land than Arunachal Pradesh and Meghalaya states.

Therefore, utilization of field data forms an absolute basis to validate *DI* model. Here, the statistical tests depend very much on the types of data used; and therefore are simple and preferred for first-hand correlation studies. The models of ecological and biological systems facilitate understanding the possible consequences of human action, that might not be possible otherwise. Similarly, the Ganga River basin that accommodates 40% of India's population is experiencing expansions at the periphery of agricultural and forest lands due to a significant increase in built-up area (Patidar and Keshari 2020).

The rate of plant endemism declined from tropics to alpine region in northeastern India owing to greater variation in microclimates with complex terrain and remoteness from biotic interferences (Heywood and Watson 1995). These findings partially agree with Myers's (1988) reporting that tropics could harbor higher number of endemic species than non-tropics. Behera and Kushwaha (2007) reported a decrease in species richness and an increase in species endemism across the elevation gradients in Arunachal Pradesh. Further, Behera et al. (2002) reported higher endemism in tropics than other regions that may be explained with higher plant functional activities. This study clearly indicated that species endemism decreases along the disturbance regimes in the eastern Himalaya. The potential of satellite remote sensing along with the kindred technologies such as GIS and GPS, for landscape level patch characterization, is well demonstrated in the study.

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