

The relationship between central Indian terrestrial vegetation and monsoon rainfall distributions in different hydroclimatic extreme years using time-series satellite data

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Abstract

The study explored the dependence of the Spatio-temporal pattern of rainfall and its variability on the spatial distribution of forests in Central Indian Landscape, which covers ~1 Million Km², includes five states, and supports a population of 329 million people. The monsoon rainfall is, thus, a crucial source of freshwater for these population. We analyzed the relationship between rainfall and satellite-derived vegetation vigour, vegetation fraction, and elevation across 22 experimental zones across central India (i.e., forested, non-forested, and agricultural regions; buffer zones within and outside forests). Around 87% of annual rainfall is received during monsoon, with maximum rainfall (~1600 mm) in Odisha and minimum (~900 mm) in Maharashtra. The average rainfall was greater (~1500 mm) inside forests than in non-forested regions (~1000 mm). Moreover, 245 mm km⁻² yr⁻¹ of rainfall observed over forests during monsoon, but only 215 mm km⁻² yr⁻¹ in non-forested areas. Overall, rainfall increases from forest edge towards forest core logarithmically at a rate of ~10 mm km⁻¹ yr⁻¹, and it decreases exponentially when moving away from forest edge at an average rate of -20 mm km⁻¹ yr⁻¹ over 0-to-50 km range, and at a rate of -7.5 mm km⁻¹ yr⁻¹ over 50-to-100 km range. This rate of decrease was maximum in Madhya Pradesh and Jharkhand and minimum in Chhattisgarh. The results confirmed a crucial role of forests in the distribution of monsoon rainfall, but in the elevated and Western-Ghats regions orographic effect is dominant. These findings are of great concern to forest policymakers to conserve and protect the central Indian forests.

Keywords: Tropical forest, Central India, Rainfall variability, Western-Ghats, MODIS, CHIRPS.

38 1. Introduction

39 Global warming may increase the average annual temperature in India from 1.33 °C to 4.44 °C by the end of the
40 21st century (Sanjay and Revadekar, 2020). This is likely to be associated with decreasing water availability and
41 recurring droughts. During the nineteenth and twentieth centuries, India experienced seven major droughts (1876–
42 1882, 1895–1900, 1908–1924, 1937–1945, 1982–1990, 1997–2004, and 2011–2015), and several were linked
43 with famines that caused millions of deaths (Mishra et al. 2019). Although the Vegetation of the central Indian
44 landscape plays a significant role in regulating the climate of the Indian sub-continent, global warming-induced
45 changes in the local climate may affect the central Indian forests and, thereby, disrupt this regulation (Sukumar et
46 al. 2016; Roxy et al. 2017). Additionally, central India is under high anthropogenic pressure as millions of people
47 depend on forests for their livelihoods, fuel, biomass, medicines, forest products and other ecological services
48 (Saxena 2003; SFR 2017; Singh et al. 2020). Thus, an increasing human population is already threatening India's
49 tropical Vegetation through deforestation and livelihood impacts, putting this crucial climate regulatory
50 mechanism at further risk (Chaturvedi et al. 2010; Zhu et al. 2016; Mishra et al. 2016).

51 Rai and Dimri (2019) studied the long-term trends in, and the seasonality of, rainfall in India and revealed an
52 increasing trend in central India during 1971-2015. However, Sanikhani et al. (2018) observed a decreasing
53 monsoon rainfall trend over Madhya Pradesh and Chhattisgarh based on ground observations from 1901 to 2010,
54 with an increasing trend observed only in the post-monsoon months (i.e. November and December). In view of
55 global warming and the increasing likelihood of extreme rainfall events (Roxy et al. 2017) and forest fires, as well
56 as population growth, preserving the status and health of India's tropical Vegetation is vital for its own services
57 and, indirectly, for its regulatory services in sustaining rainfall at a regional scale in the central Indian sub-
58 continent. The projected changes in climate including high drought frequency, coupled with deforestation and
59 forest degradation, are expected to affect greatly the livelihoods of central India's large population (Chaturvedi et
60 al. 2010; Mohanty 2020). Hence, exploring the links between forests and rainfall at the regional level is essential.
61 Since the central Indian forest is fragmented, with large and small patches of intact forests, the precise role of this
62 forest in regulating rainfall patterns and water availability are poorly understood. Therefore, greater understanding
63 of the influence of the central Indian forests on rainfall distribution at this regional scale is needed.

64 The hydrological system is regulated by air, land temperature, and precipitation variation across different
65 areas, and these together affect the ecological processes of natural Vegetation (Andreae et al. 2004; Griffin and
66 Prager 2017) which, in turn, alter atmospheric feedback mechanisms and affect the occurrence of climatic events
67 (Sheil 2018). It is still unclear whether forests are net users or producers in the water cycle (Ellison et al. 2017;

68 [Bennett and Barton 2018](#)). [Marsh \(1864\)](#) believed forests to be great water producing "biotic pumps", but not a
69 factor influencing climatic patterns and atmospheric circulation at a larger scale. [Makarieva and Gorshkov \(2007\)](#)
70 reinforced the biotic pump theory and explained the physics behind the underlying processes in detail. In simple
71 terms, massive areas of forest, like the Amazon and Congo, attract rain by sucking moist air from the oceans to
72 interior parts of continents located hundreds of kilometres away. However, the biotic pump hypothesis remains
73 controversial ([Meestres et al. 2009](#)). Also, meteorologists believe that rainfall regimes, their distribution and shifts
74 across the globe can be better understood by meteorological parameters and rainfall variation than through changes
75 in the forest-induced atmospheric water cycle. Although research has provided various explanations, none can
76 satisfactorily model the relationship between Vegetation and climate at the global scale ([Sheil 2018](#)).

77 Rainfall is a natural phenomenon, and its occurrence and spatial distribution depends on multiple
78 atmospheric and biospheric factors ([Morales 1977](#)). Although climatologists tried to address this issue with
79 general circulation models (GCMs), no climatic models explain the influence of forests on cloud formations and
80 moisture convection ([Stevens and Bony 2013](#)). Most climatic models have a coarse spatial resolution leading to
81 large uncertainties ([Svoboda et al. 2014](#)) in predicting regional rainfall and microclimatic variation ([Stevens and](#)
82 [Bony 2013](#); [Sheil 2018](#); [Maclean 2020](#)). Hence, it is vital to understand rainfall regimes at watershed-to-basin
83 levels in the forested regions of the world ([Kurtzman et al. 2009](#)). Regional topography, land use and land cover
84 (LULC), and local climatic variability are potentially important for the characterization of spatial rainfall patterns
85 and hydrological processes at multiple spatial scales ([Meestres et al. 2009](#); [Sanchez-Moreno et al. 2013](#); [Putnam](#)
86 [and Broecker 2017](#); [Spracklen et al. 2018](#)).

87 Historically the world's tropical forests have reduced from 12% to 5% of the Earth's surface area due to
88 deforestation. Four hundred twenty million hectares of forest area was lost since 1990, with an average net loss
89 of 4.7 M ha yr⁻¹ during 2010 to 2020, to make way for agricultural land and in response to the demand for food
90 and wood ([FAO 2020](#); [Hansen et al. 2013](#); [Brandon 2014](#); [Spracklen et al. 2018](#)). However, [Tian et al. \(2014\)](#)
91 reported a significant loss of forests from 89 million ha to 63 million ha from 1880 to 2010, and these forest loss
92 must have affected India's climate feedback loop ([Devaraju et al., 2015](#); [Paul et al., 2016, 2018](#); [Masroor et al.,](#)
93 [2020](#); [Haughan et al. 2022](#)). Similarly, in Amazon, the impact of deforestation can be seen clearly through a
94 reduction in rainfall and recurring patterns of drought ([Li et al. 2008](#); [Anderson et al. 2010](#); [Atkinson et al. 2011](#);
95 [Spracklen and Garcia-Carreras 2015](#); [Staal et al. 2020b](#)).

96 Ground-based rainfall networks are important for evaluating the link between forests and rainfall, but such
97 networks are distributed unevenly across the globe. Advances in remote sensing such as the provision of satellite-

98 based continuous rainfall data have filled this gap and provided the opportunity to study the interdependence
99 between forests and rainfall distributions regionally and globally (Sykes 2009; Meng et al. 2014; Gebremicael et
100 al. 2019). For example, remote sensing satellite-based rainfall and vegetation indices have been used to
101 characterize and model vegetation vigour and its variability, forest degradation, and climatic changes (Paruelo et
102 al. 2001; Bonan 2008; Krishnaswamy et al. 2013; Zhang et al. 2015; Gao et al. 2018; Singh et al. 2021).

103 Here, we investigate the dependence of the spatio-temporal distribution of rainfall on the spatial distribution
104 of forests in the central Indian forested landscape. Specifically, in a natural experiment we explored and compared
105 quantitatively the spatio-temporal variability in rainfall within (i) forested, (ii) adjacent non-forested and (iii)
106 agricultural regions. Further, the aim was to measure the rate of change in rainfall in the presence and absence of
107 forests across different buffer zones, and the variability in rainfall in different elevation and density classes inside
108 and outside forests. We used CHIRPS monthly rainfall data, MODIS normalised difference vegetation index
109 (NDVI), vegetation continuous field (VCF) and ASTER elevation data to examine the inter-annual and monthly
110 variability in rainfall in the different strata. We selected the central Indian tropical forested landscape spreading
111 over five states of India as the study site.

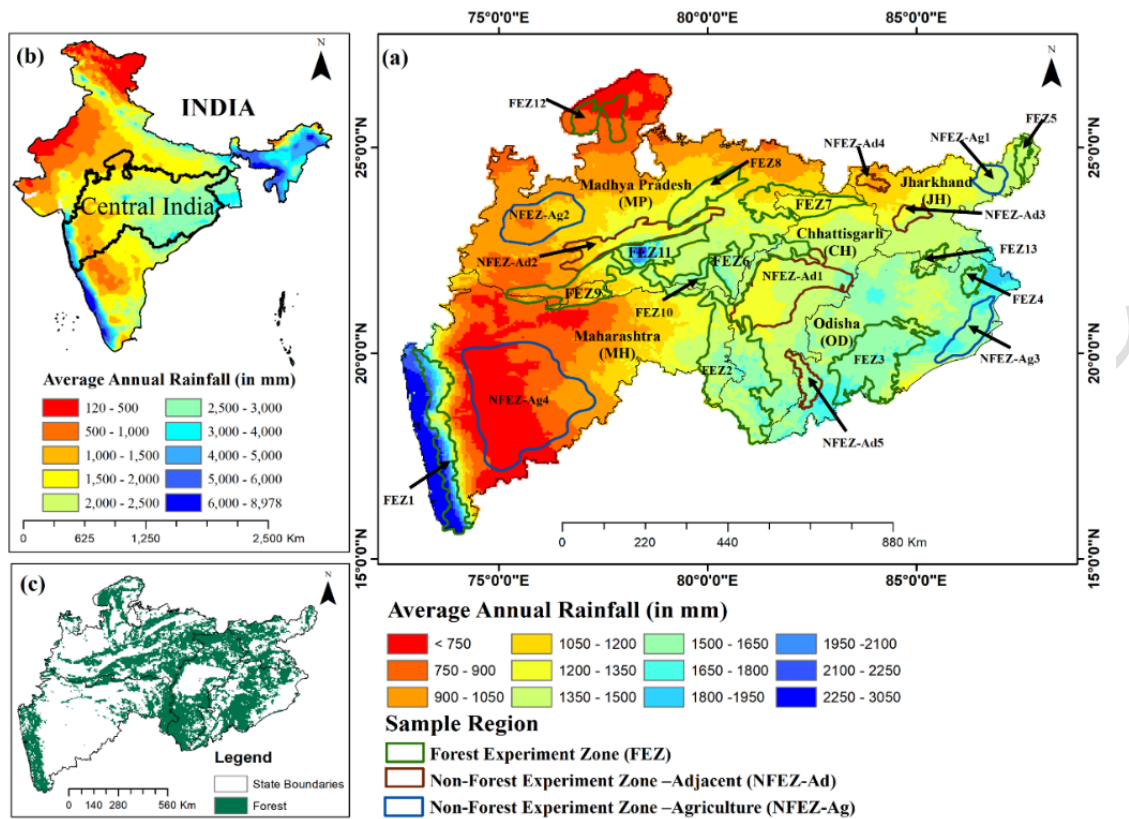
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113 **2. Materials and Methods**

114 **2.1 Study area**

115 Central India is a complex tropical forested landscape spread over five Indian states (Maharashtra (MH), Madhya
116 Pradesh (MP), Chhattisgarh (CH), Odisha (OD) and Jharkhand (JH)) covering a total area of 9,86,580 km²,
117 extending between 15°- 26° N and 72° - 88° E (**Fig. 1a**). It contributes 2,93,273 km² of the total Indian forested
118 area (i.e. 8,09,537 km²), including human-dominant agricultural systems (SFR 2021). It has a series of protected
119 forest patches conserved as wildlife sanctuaries (108 nos.), national parks (22 nos.), tiger reserves (17 nos.),
120 elephant reserves (8 nos.) and undisturbed core forest areas that regulate the ecological balance by preserving
121 biodiversity and the regional climate (Sharma et al. 2013; Singh et al. 2020). During the monsoon (June to
122 September), the region receives more than 80% of its annual rainfall (Roxy et al. 2017). The Western Ghats and
123 the Eastern Ghats are two mountain ranges located along the west and east coast of India. Central India refers to
124 the Deccan plateau region which lies between these two mountain ranges. (Please see **figure S15** for elevation
125 variation over the study area) The average maximum temperature rises to 42 °C during the summer, and the
126 minimum temperature reaches 10 °C in winter (Duhan et al. 2013). Vast stretches of this tropical deciduous forest
127 form the catchments of several central highland rivers, which provide irrigation and drinking water in the region

128 (Krishnaswamy et al. 2013) and shelter for numerous flora and fauna, including the protected, but endangered
 129 tigers (Sharma et al. 2013).



130
 131 **Figure 1.** (a) Study area showing different experimental zones overlaid on a map of average annual rainfall (based
 132 on 2001-2018 data), (b) study area extent within India, overlaid on a map of average annual rainfall (based on
 133 2001-2018 data) and (c) forest mask.

134 The region is also marked by the presence of Tendu (*Diospyros melanoxylon*) leaf collected for Bidi
 135 (cigarette) making and non-timber forest products (*Madhuca indica*), which provide income to millions of local
 136 people (Hunter 1981; Saxena 2003; Mahadule and Vimmy 2011; Singh et al. 2020). The climate change-induced
 137 erratic and recurring rainfall deficit is likely to affect the agricultural and forest productivity of the region, and
 138 people's livelihoods. Bundelkhand in Madhya Pradesh, Palamu in Jharkhand, Marathwada, and Vidarbha in
 139 Maharashtra are drought-prone regions in the central Indian landscape (Singh and Jeganathan 2016; Singh et al.
 140 2019). Five major types of forest exist in India, with the largest land surface area (~68.5% of total forest cover)
 141 occupied by tropical forests (Champion and Seth 1968). Within the tropical forest, tropical dry deciduous (~38%)
 142 and tropical moist deciduous (~30%) forests cover the largest part, especially spreading across central India
 143 (Jeganathan and Nishant 2014), and they play a significant role in regulating the climate of the Indian
 144 subcontinent. India's contribution to carbon sequestration is enormous: natural forests sequester about 145.6

145 million tonnes-equivalent of CO₂ annually (SFR 2021), acting as a carbon sink and, hence, providing a potential
146 carbon credit under the Kyoto Protocol in the international market (SFR 1995).

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148 **2.2 Data**

149 **2.2.1. Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data**

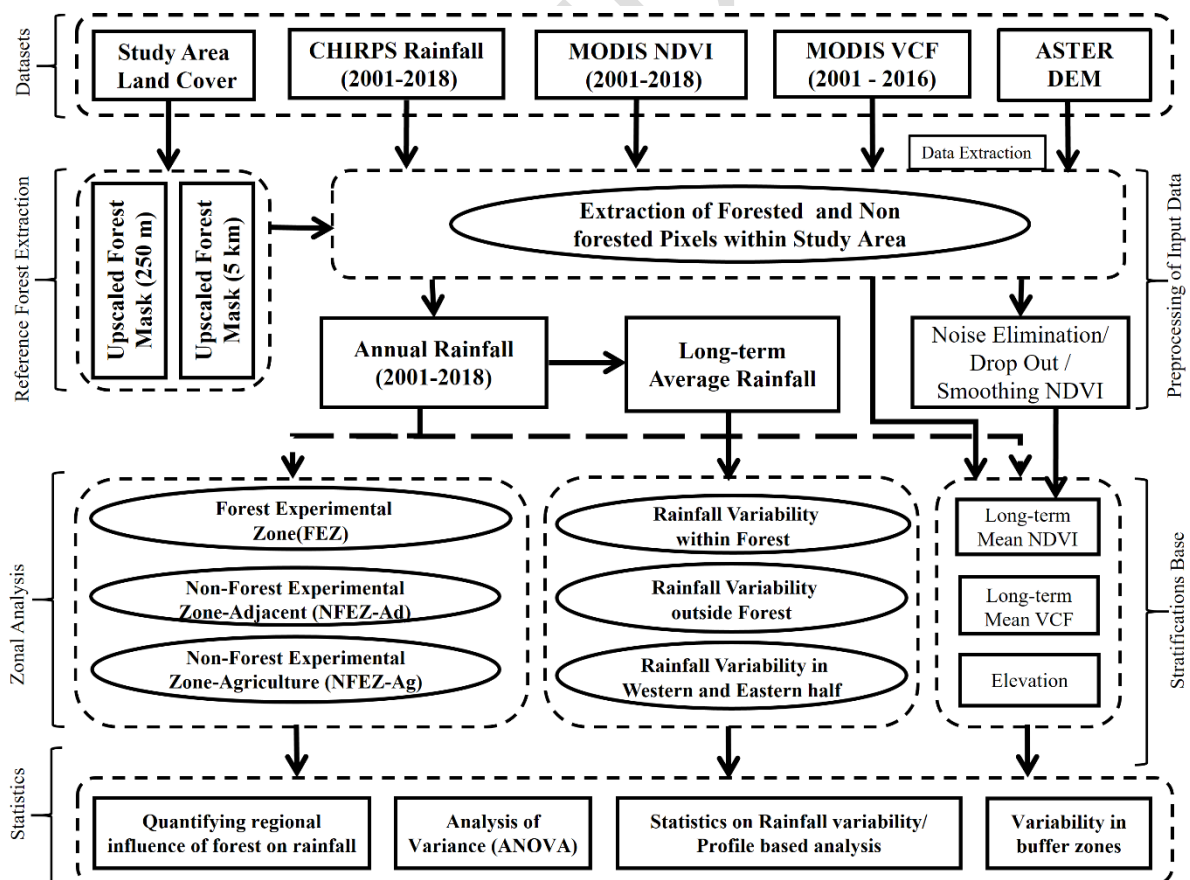
150 The most comprehensive archive of gridded rainfall data at a spatial resolution of 0.05° (~5 km) and at a quasi-
151 global level since 1981 is provided by the Climate Hazards Group Infra-Red Precipitation with Station (CHIRPS)
152 data (Funk et al. 2015). The monthly precipitation dataset (CHIRPS version 2.0) from 2001 to 2018 was used in
153 this research (downloaded from <ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRP/month-ly/>). The CHIRPS
154 data utilizes satellite-derived precipitation estimates and *in situ* gauge station data to create gridded rainfall time-
155 series (Funk et al. 2015). CHIRPS data were used by many researchers across the globe (Duan et al. 2016; Aadhar
156 and Mishra 2017; Dinku et al. 2018; Gao et al. 2018; Saeidizand et al. 2018; Singh et al. 2020). Aadhar and
157 Mishra (2017) observed varying levels of bias in the CHIRPS rainfall data including under-estimation in the
158 Western Ghats and over-estimation in North East India relative to low bias over semi-arid regions in the western
159 part of India. In the present research, since we were interested mainly in the relative variability in rainfall within
160 forested and non-forested landscapes, this bias is effectively cancelled out. Also, the study region falls under semi-
161 arid and dry sub-humid climates (Tewari et al., 2013) and, hence, the bias is minimal in these regions. Moreover,
162 various previous studies have cross-validated CHIRPS datasets with other datasets and found that CHIRPS
163 performed better with station data (Jonah et al., 2021; Saicharan et al., 2023).

164

165 **2.2.2. MODIS data and its pre-processing**

166 The NDVI is one of the most widely used vegetation indices and correlates well with vegetation cover, density,
167 health, photosynthetically active radiation and primary productivity (Herrmann et al. 2005). Hence, in this
168 research, we used Moderate Resolution Imaging Spectro-radiometer (MODIS) - MOD13Q1 V6 Terra time-series
169 NDVI data (16-day interval; 250 m spatial resolution) over 18 years (2001 to 2018) from the LPDAAC (Land
170 Processing Distributed Active Archive Center (<https://lpdaac.usgs.gov>)). Central India is covered by six MODIS
171 tiles (i.e. h24v06, h24v07, h25v06, h25v07, h26v06, h26v07). NDVI composites were extracted individually, and
172 noisy pixels were eliminated based on quality flags. Each annual NDVI time-series was corrected for dropouts
173 and outliers using valid temporal neighbours, and finally smoothed using the discrete Fourier transform (Dash et
174 al. 2010; Jeganathan et al. 2010; Singh et al. 2021).

175 A forest mask was prepared, using the most recent comprehensive vegetation type map (CVT) produced at
 176 1:50,000 scale using the LISS III sensor (23.5 m) for the Indian subcontinent (Roy et al. 2015), based on a two-
 177 tier approach (i.e. 23.5 m to 250 m, and 250 m to 5 km) (Singh et al. 2020). At first we created a new binary map
 178 having two classes i.e., forest (1) and no-forest (0) from CVT. Then we estimated percentage of forest pixels
 179 within each of the 250m pixel grids of MODIS data. Next, the grids having >75% of forest were considered as
 180 forest mask at 250m (Tier-1). Similarly, from the 250m forest mask we estimated the forest percentage within
 181 each of the 5km pixel grids of CHIRPS data. Then the grids having >20% of forest were considered as forest mask
 182 at 5km (Tier-2). The smoothed NDVI data were upscaled from 250 m to 5 km using mean aggregation (Singh et
 183 al., 2021). Then, aggregated NDVI values falling within the 5 km forested mask were extracted for further area
 184 analysis with rainfall to investigate inter-annual rainfall variability inside and outside forests. In addition, MODIS
 185 VCF data (MOD44B v006; 250 m spatial resolution) were used to stratify forest density, and ASTER global
 186 digital elevation model (ASTGTM v003; 30 m spatial resolution) data were used to stratify elevation. The VCF
 187 and elevation data were upscaled to 5km based on mean aggregation, and used to derive area statistics with
 188 rainfall. A schematic illustration of the methodology followed in this research is shown in Fig. 2.



189
190 **Figure 2.** Overall methodology.

191 2.3 Methods

192 2.3.1. Level-1: regional level stratified analysis

193 First, the annual rainfall time-series for 18 years was analysed and compared to understand the general pattern
194 and spatio-temporal variability in normal, dry and wet years. Next, long-term average rainfall (LTA_RF) for the
195 whole region was estimated and scrutinised to understand its variability inside and outside forested regions based
196 on different stratification levels: (a) within different NDVI classes, (b) within different forest density classes, and
197 (c) within different elevation ranges. For this purpose, a long-term average NDVI map (LTA_NDVI) was prepared
198 and classified into nine classes based on vegetation vigour, ranging from sparse vegetation to highly dense
199 vegetation (Gu and Wylie, 2015; Singh et al., 2020, 2021). The LTA_VCF data were classified into eight classes
200 revealing different percentages of tree cover (Adzhar et a., 2021). These classes were used to understand the
201 relation of rainfall with vegetation vigour and density. The elevation data (ranging from 1 to 1643 m) were
202 classified into 10 classes to study the effect on altitude on rainfall. Rajeevan et al. (2008) observed an increase in
203 the number of extreme events over central India during the last five decades. Many studies have shown that central
204 India observed a decreasing trend in annual rainfall (Paul et al. 2016; Sahany et al. 2018; Kumar et al. 2019; Singh
205 et al. 2021). With warming expected to continue over central India due to global climate change, it is necessary
206 to examine the monthly rainfall pattern. Thus, long-term monthly average rainfall was calculated from the 18
207 years (2001-2018) time-series of rainfall data. Also, the state-level variability in the rainfall pattern was analysed.

209 2.3.2 Level-2: analysis based on experimental zones

210 To evaluate the spatio-temporal association between rainfall and forests, we quantified the rainfall variability in
211 different places, inside and outside of forests and in forest and non-forest classes, and compared them. For this
212 experiment, we demarcated 22 zones (Fig. 1a). We categorized these zones as (i) Forest experimental zone (FEZ)
213 (i.e. inside the forested areas), (ii) Non-forest experimental zone-adjacent (FEZ-Ad) (i.e. adjacent to forested
214 regions, but outside forest edges) and (iii) Non-forest experimental zone-agriculture (FEZ-Ag). A total of 13 FEZ,
215 5 FEZ-Ad and 4 FEZ-Ag zones were demarcated manually across the study region (Fig.1a). At first, LTA-RF
216 was analysed in each of these zones to characterize the rainfall variability. Also, buffer zones were created inside
217 and outside FEZ to characterize the rate of increase or decrease in the LTA_RF in these two contrasting
218 environments. Core zones represent intact forested areas, and outside buffer zones represent heterogeneous areas
219 where all human interaction occurs, which usually have greater disturbances and temperatures than core areas. In

220 addition, rainfall variability in the western and eastern coastal zones was analysed over the four buffer zones, each
221 of 50 km (up to 200 km), to understand the role of forests in coastal areas.

222

223 **2.3.3. Analysis of Variance (ANOVA)**

224 In this research, ANOVA was used to test the rainfall magnitude and variability in different years and different
225 rainfall conditions: (i) Level-1: in different experimental zones (FEZ, NFEZ-Ad & NFEZ-Ag); (ii) Level-2: in
226 forested and non-forested areas; and (iii) Level-3: in different spatial profiles across the study area.

227

228 **2.3.4. Profile-based analysis**

229 To explore the rainfall distribution across the study area we created four different linear profiles: AB – Easter
230 Coast to Western edge; CD – Easter Coast to North-western edge; EF – Western Coast to North-eastern edge; GH
231 – Western coast to Northern edge of the study region (see **Fig. 12** for details). We created a forest density map
232 based on the percentage of forested pixels occurring within 5 km grid cells. Each profile line was used to extract
233 long-term average rainfall, forest density and annual rainfall from dry (2002), normal (2011) and wet (2013) years.
234 Finally, all the extracted values for each profile were plotted against the cumulative distance of each pixel from
235 the starting point along each profile.

236

237 **3. Results**

238 **3.1. Spatio-temporal variability of rainfall**

239 The long-term average rainfall derived from the 18 year time-series dataset is shown in **Fig. 1a**. The average
240 rainfall was higher in the states of Odisha (OD) and Chhattisgarh (CH), and while the lowest rainfall was seen
241 mostly in MH, MP and the Northwestern part of Jharkhand (JH), where vegetation density is the lowest. Table 1
242 shows the area statistics describing the long-term average annual rainfall during 2001 to 2018 over the study area.
243 The highest rainfall was observed along the Western Ghats located near the coastal region of MH. The forests
244 near the coastal region of the study area received a high magnitude of average rainfall (around 1650 – 1800 mm).
245 The accumulated rainfall over 18 years is shown in **Fig. S1**. Around 20.29 % of the total study area received above
246 > 1500 mm of long-term average rainfall. It is highly likely that the spatial distribution of rainfall over the Western
247 Ghats is due mainly to the orographic effect of topography ([Tawde and Singh, 2014](#); [Thakur et al. 2019](#); [Phadtare
248 et al., 2022](#)).

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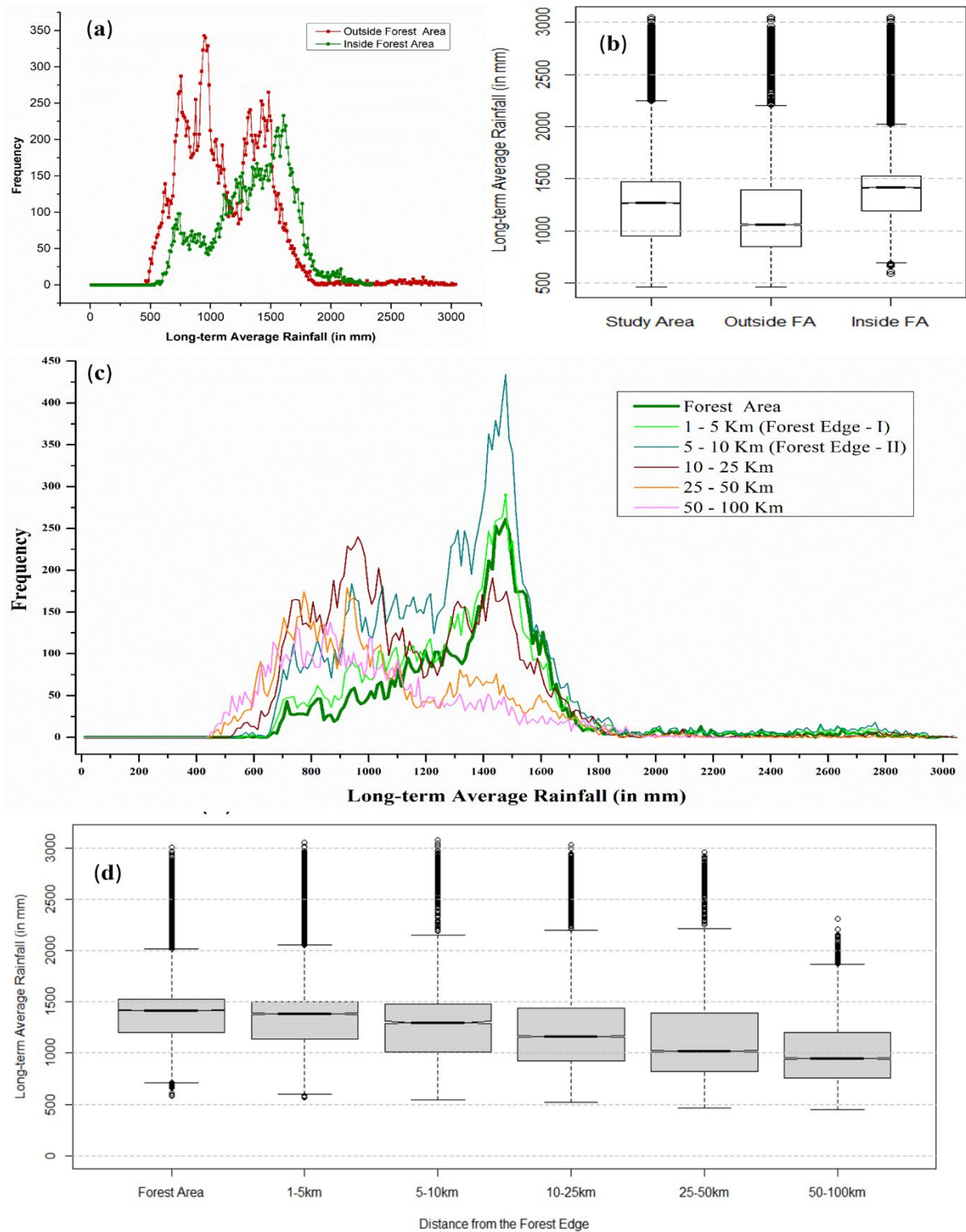
251 **Table 1.** Area statistics of long-term annual average rainfall (2001 to 2018) over Central India
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Rainfall (mm)	Area in Km²	Area in %
< 750	79800	9.22
750 - 900	99450	11.49
900 - 1050	129450	14.96
1050 - 1200	95100	10.99
1200 - 1350	113550	13.12
1350 - 1500	194200	22.44
1500 - 1650	115475	13.34
1650 - 1800	27625	3.19
1800 - 1950	6225	0.72
1950 - 2100	4500	0.52
2100 -2250	4375	0.51
2250 - 3050	17350	2.00

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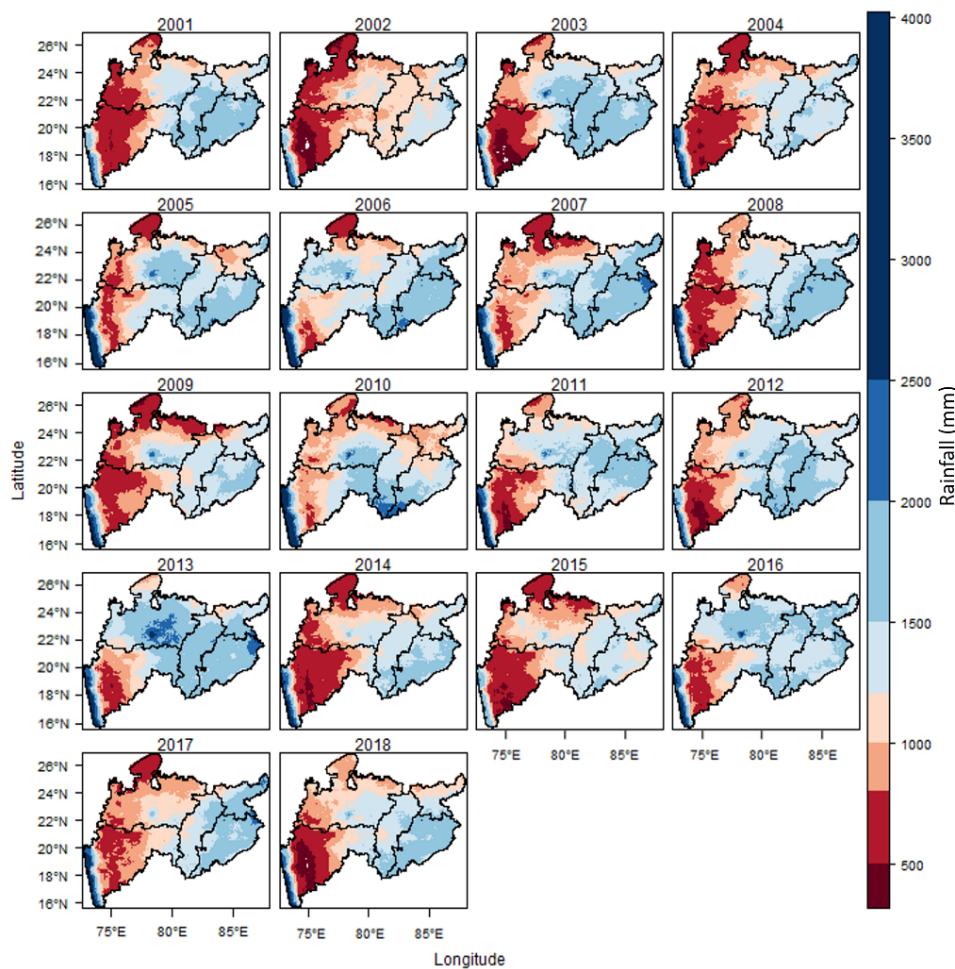
271 **Figure 3.** Rainfall variability in the study region. (a) Difference in the frequency of rainfall inside and outside

272 forest areas, (b) Box-plot of rainfall range, (c) Frequency of rainfall in different buffer zones away from forest

273 areas, (d) Box-plot of rainfall range at different distances from forest areas.

274 **3.2. Spatial-temporal variability of rainfall inside and outside forested regions**

275 To characterize the distribution of rainfall on an inter-annual basis over the study area the rainfall variability was
276 quantified annually for inside and outside forested areas (**Fig. S2**). The frequency distribution of rainfall (**Fig. 3a**)
277 in the non-forested area appears to be bimodal (peaks at 900 mm and 1400 mm) representing two contrasting
278 environments in the western (high) and easternmost states (low), respectively. In Odisha, the forested regions are
279 well distributed (where rainfall is high), but in Maharashtra there is a large patch of non-forest area (where rainfall
280 is low) (**Fig. 4**). Interestingly, the rainfall is high in the smaller patches of non-forest area which are surrounded
281 by dense forested zones, as in Odisha and in the south of Chhattisgarh. Rainfall variability outside the forested
282 region can be linked mainly to three factors: (a) distance from the coast, (b) surrounding dense forest patches and
283 (c) topographic juxtaposition ([Kattel et al., 2012](#); [Muluneh et al., 2017](#); [Liu et al., 2020](#)). The higher frequencies
284 of lower rainfall magnitude (500 to 1000 mm) were observed mainly over the non-forested region, while inside
285 the forested region higher rainfall magnitudes are observed (1000 to 1800 mm). Similarly, mean rainfall is greater
286 than 1400 mm inside the forested region (**Fig. 3b**).



287

288

Figure 4. Inter-annual rainfall variability during 2001 to 2018.

289 The annual variability in rainfall over 18 years was assessed for inside and outside forested regions (**Fig. S2a**
 290 **and Fig. S2b**), and the average rainfall was found to be low for outside forested areas compared to inside forested
 291 regions ($p < 0.05$), irrespective of whether it was a wet or dry year. The spatial-temporal pattern of the annual
 292 average rainfall over 18 years and the long-term accumulated rainfall in the study area are shown in **figures 1a &**
 293 **S1**. It is seen that the eastern region received more rain (see blue shades) than the western region, except in the
 294 Western Ghats. **Table 2** shows the area percentage in different rainfall classes observed over 18 years in central
 295 India. Comparatively, the Western Ghats received the highest magnitude of orographic rainfall. In **Fig. 4**, one can
 296 see a consistent rainfall pattern of above 1000 mm in forested regions such as for Chhattisgarh, Odisha, south-
 297 eastern Madhya Pradesh and Jharkhand. This result suggests an association of rainfall with forested areas.

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Table 2. Area statistics in different rainfall categories during 2001 to 2018.

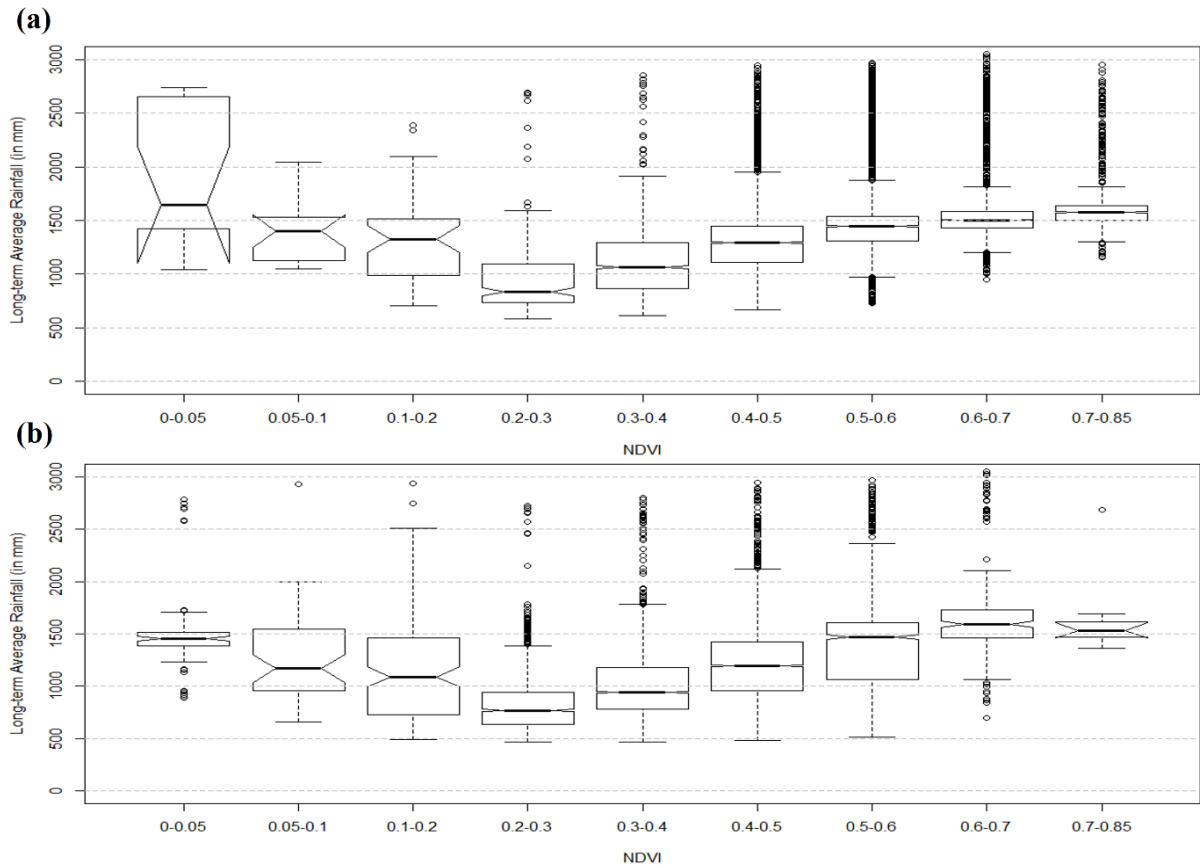
Year	Rainfall Classes (in mm)									
	1 - 300	300- 500	500 - 800	800 - 1000	1000 - 1500	1500 - 2000	2000 - 2500	2500 - 3000	3000 - 3500	3500 - 4100
2001	0.00	0.24	23.22	13.88	34.76	26.85	1.05	0.00	0.00	0.00
2002	0.17	6.66	21.77	17.34	49.70	3.22	1.05	0.01	0.00	0.00
2003	0.05	4.79	13.48	12.38	34.55	32.87	1.73	0.05	0.00	0.00
2004	0.00	0.71	25.43	17.53	47.94	5.70	1.91	0.78	0.00	0.00
2005	0.00	0.01	10.69	16.55	42.48	26.14	1.35	1.14	1.52	0.11
2006	0.00	0.01	6.22	8.08	51.02	30.06	1.54	1.16	1.87	0.04
2007	0.00	0.00	12.33	18.84	32.97	30.65	2.58	1.37	1.06	0.21
2008	0.00	0.72	17.74	16.17	37.35	25.14	1.39	1.23	0.24	0.02
2009	0.00	0.62	24.92	17.37	45.41	9.04	1.58	0.88	0.18	0.00
2010	0.00	0.00	3.76	24.18	46.47	18.72	3.75	1.25	1.71	0.15
2011	0.00	1.32	10.02	12.23	51.32	21.82	1.37	0.88	0.82	0.21
2012	0.00	2.42	9.33	16.62	44.06	25.68	1.78	0.11	0.00	0.00
2013	0.00	0.06	5.56	7.02	31.11	48.17	6.11	1.58	0.40	0.00
2014	0.00	1.46	24.85	16.00	42.24	13.01	1.33	1.08	0.04	0.00
2015	0.00	1.61	23.81	15.44	53.93	4.85	0.35	0.00	0.00	0.00
2016	0.00	0.01	7.53	10.20	49.57	29.82	1.49	0.91	0.43	0.04
2017	0.00	0.00	15.78	23.48	37.11	20.01	2.02	1.20	0.40	0.00
2018	0.01	4.60	10.71	15.57	47.29	19.81	1.03	0.92	0.04	0.00

301

302 3.3. Rainfall variability with NDVI, forest density and elevation

303 Various studies revealed that NDVI and rainfall are correlated in areas limited in water. We analysed the
 304 variability in the long-term average rainfall in different classes of long-term average NDVI (**Fig. 5a**). In Fig. 5a,
 305 one can observe a high rainfall in low NDVI classes, contrary to the association revealed above. However, one
 306 has to consider the observed regional variability from the point of view of different factors. Interestingly, the

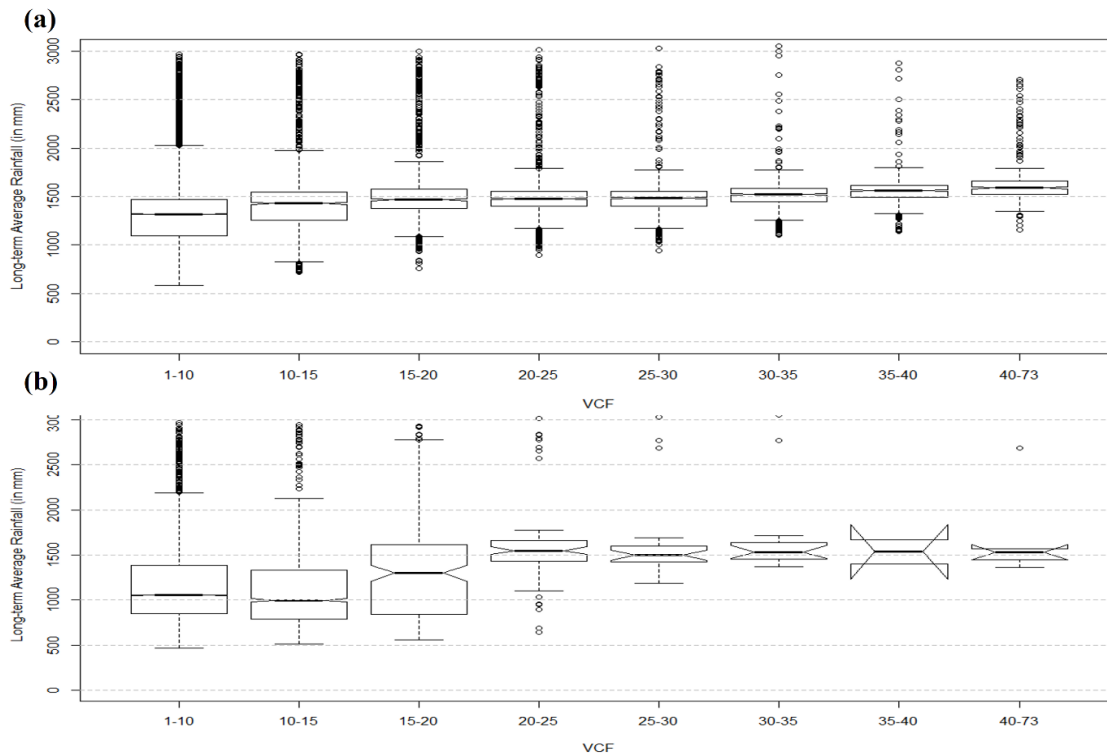
307 highest rainfall amounts found in the lower NDVI classes 0.0-0.05 are mainly from the Western Ghats region. An
 308 increasing rainfall pattern was observed when the NDVI values increased from 0.2 to 0.85 (For details see S3). In
 309 **Figure 5b** one can also see increases in rainfall with NDVI similar to **Figure 5a** and, hence, this again is
 310 contradictory.



311
 312 **Figure 5.** Rainfall variability within different NDVI classes: (a) inside forested region and (b) outside forested
 313 region.

314 Here again, the juxtaposition of pixels surrounded by forest patches needs to be considered. As there were so
 315 many smaller patches of non-forest pixels surrounded by dense forest patches in the eastern part of the study area,
 316 these patches alter the rainfall statistics when grouped together with other larger patches of non-forest area of the
 317 western region. To avoid confusion, we divided the study region into two halves: east and west, and also ignored
 318 non-forest patches from the Western Ghats region which has a strong influence from orographic phenomena (**Fig**
 319 **S4 & S5**). While Comparing the variability in the long-term average rainfall in different forest density classes
 320 inside and outside forested regions, a clear increasing trend in rainfall pattern in the higher density classes is
 321 observed (**Fig. 6a**). The role of altitude (along with forest/non-forest zones) was examined for its association with
 322 rainfall. The average rainfall was higher in the lower elevation classes than in the higher elevation classes, with

323 lower elevation mainly in the western and eastern coastal regions. It is observed that the variance in rainfall was
 324 low inside forested regions even at different elevations (See Fig. S5 for spatial distribution). However, the variance
 325 was large in the non-forested areas. An increasing rainfall pattern is observed as the elevation increases beyond
 326 400 m (Fig. 7a & b). Table 3 provides area statistics about rainfall variability in different classes of NDVI,
 327 elevation and vegetation density (i.e. VCF).

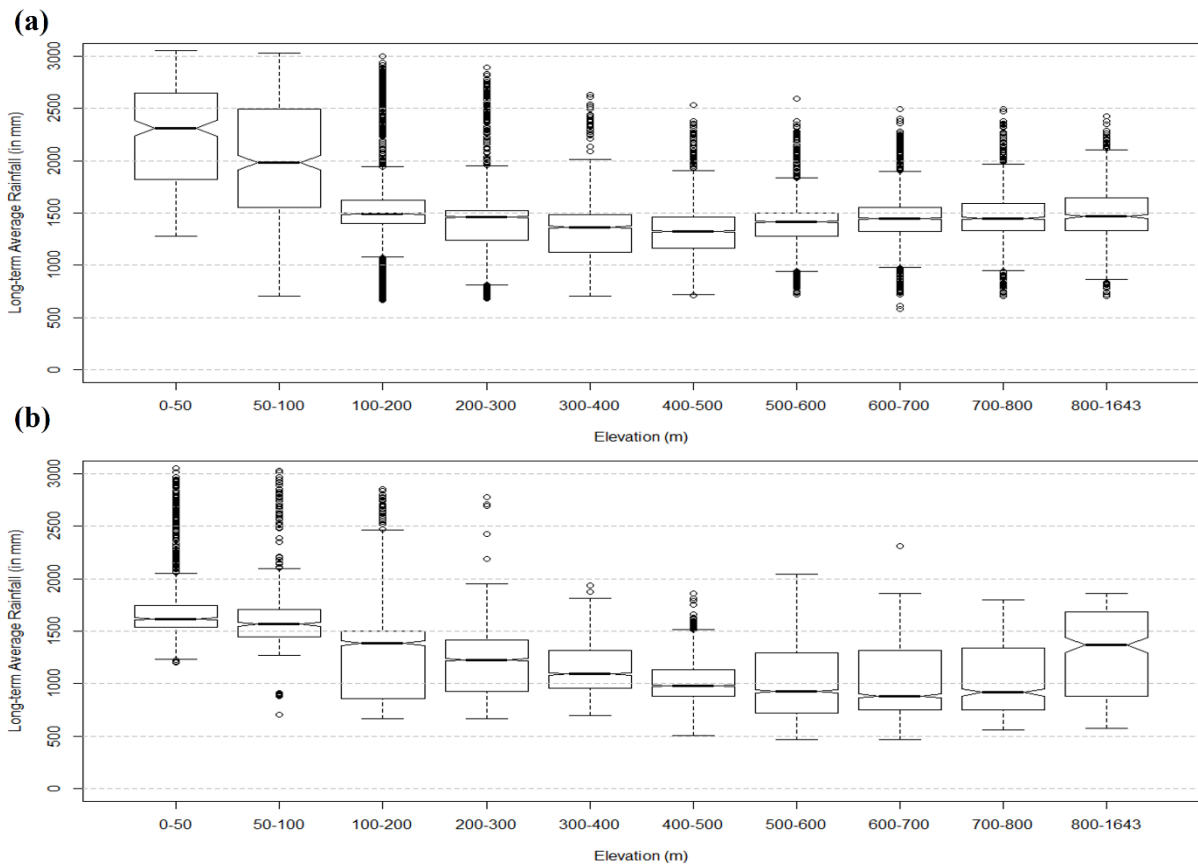


328
 329 **Figure 6.** Rainfall variability within different VCF classes: (a) inside forested region and (b) outside forested
 330 region.

331 **Table 3.** Area statistics in % for different categories of NDVI, Elevation and VCF.
 332

NDVI Classes	ELEVATION		VCF	
	IN	OUT	Classes (in m)	Classes (in %)
0 - 0.05	0.56	1.60	0 - 50	0
0.05 - 0.1	0.09	0.21	50 - 100	1-10
0.1 - 0.2	0.28	0.93	100 - 200	10- 15
0.2 - 0.3	1.59	6.66	200 - 300	15 - 20
0.3 - 0.4	12.91	36.10	300 -400	20 - 25
0.4 - 0.5	31.37	46.51	400 - 500	25 - 30
0.5 - 0.6	26.53	7.07	500 - 600	30 - 35
0.6 - 0.7	20.78	0.86	600 - 700	35 - 40
0.7 - 0.85	5.89	0.06	700 - 800	40 - 73
-	-	-	800 - 1643	-

333 *Note:* IN = Inside forest, OUT = Outside Forest



334
 335 **Figure 7.** Rainfall variability in different elevation zones over forested region (a) and non-forested region (b).

336 **3.4. Month-wise and state-wise rainfall variability**

337 **Figure 8** shows the spatial-temporal pattern of long-term average monthly rainfall over the central Indian
 338 landscape. During the winter months of January, February and March, the average rainfall is reduced to 63.13 mm
 339 and the western side of the continent remains drier than the eastern side. A similar pattern is observed during the
 340 summer months of May and June, but the average rainfall increased to 197.99 mm. During the monsoon season
 341 (June to September) the central Indian region received the maximum rainfall. During the monsoon, MH received
 342 much lower rainfall than the rest of the regions. The lowest rainfall was observed in the study region during
 343 December. Overall, the rainfall received over central India varied across the landscape, but a clear pattern of high
 344 rainfall was observed in the forested regions during the monsoon, which provides a clear indication of the role of
 345 forests in attracting rainfall (**Figure 8**). Among the states, MH exhibited the highest variance in rainfall, with the
 346 majority of the land area converted to agriculture, while CH and JH exhibited the least variance, where forest is
 347 well distributed and dense. **Table 4** shows area statistics of different ranges of rainfall in different months over
 348 central India. The long-term monthly average rainfall of the five states over 18 years is shown in **Table 5** and **Fig.**
 349 **S7.** OD's long-term average rainfall (1559.94 mm) was the highest over the 18 years, followed by CH (1421.14

350 mm), JH (1334.17 mm), MP (1100.98 mm) and MH (1102.73 mm). MP received around 91.76% of its rainfall
 351 during the monsoon, while MH and CH received approximately 87.96% and 86.79%, respectively, which shows
 352 a high dependency of these states on the monsoon. **Table 6** shows the long-term average annual rainfall, and
 353 rainfall received during monsoon. It was found that MP received more of its rainfall during the monsoon season
 354 than OD (91.76% and 81.50%, respectively), although OD received the maximum rainfall in a year. Therefore,
 355 examining the factors responsible for controlling the central Indian rainfall becomes necessary as the distribution
 356 of monsoon rainfall is not uniform across the study region. MH experienced the highest variability in rainfall and
 357 is prone to frequent drought, followed by MP, JH, and CH. The least variability was observed in OD (see Figs.
 358 **S8 & S9**).

359 **Table 4.** Area statistics of long-term average monthly rainfall.
 360

Rainfall (mm) classes	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1 -5	59.72	63.40	59.08	65.66	50.81	48.47	48.47	48.47	48.47	48.47	56.25	86.52
5 -20	34.28	25.44	24.96	20.16	30.53	0.24	0.00	0.00	0.00	4.44	33.00	13.48
20 -50	6.00	11.09	15.95	13.52	10.18	4.16	0.00	0.04	0.00	16.89	10.56	0.00
50 -100	0.00	0.08	0.00	0.66	6.77	13.43	1.07	1.05	0.00	23.24	0.19	0.00
100 -150	0.00	0.00	0.00	0.00	1.41	16.46	2.04	1.89	0.21	4.99	0.00	0.00
150 - 200	0.00	0.00	0.00	0.00	0.29	15.21	1.75	3.58	6.56	1.81	0.00	0.00
200 - 300	0.00	0.00	0.00	0.00	0.00	0.47	8.37	13.27	18.98	0.17	0.00	0.00
300 - 400	0.00	0.00	0.00	0.00	0.00	0.73	21.56	20.32	23.47	0.00	0.00	0.00
400 - 600	0.00	0.00	0.00	0.00	0.00	0.83	15.14	10.89	2.17	0.00	0.00	0.00
600 - 1000	0.00	0.00	0.00	0.00	0.00	0.00	1.61	0.49	0.14	0.00	0.00	0.00

361
 362
 363
 364

Table 5. State-wise long-term monthly average rainfall (in mm).

State	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEPT	OCT	NOV	DEC
CH	15.11	17.50	21.65	20.55	25.40	192.81	397.18	407.38	236.01	72.81	10.66	4.08
JH	14.90	19.25	17.79	25.11	56.62	195.23	348.06	320.11	238.42	90.27	5.87	2.54
MP	14.80	12.47	11.24	4.10	8.17	137.84	372.94	328.14	171.31	28.56	7.04	4.38
MH	5.69	5.06	9.10	9.37	18.33	208.75	305.58	261.41	194.20	61.83	18.78	4.61
OD	11.34	21.25	21.40	32.99	61.60	221.37	394.08	382.14	273.82	115.02	21.28	3.64

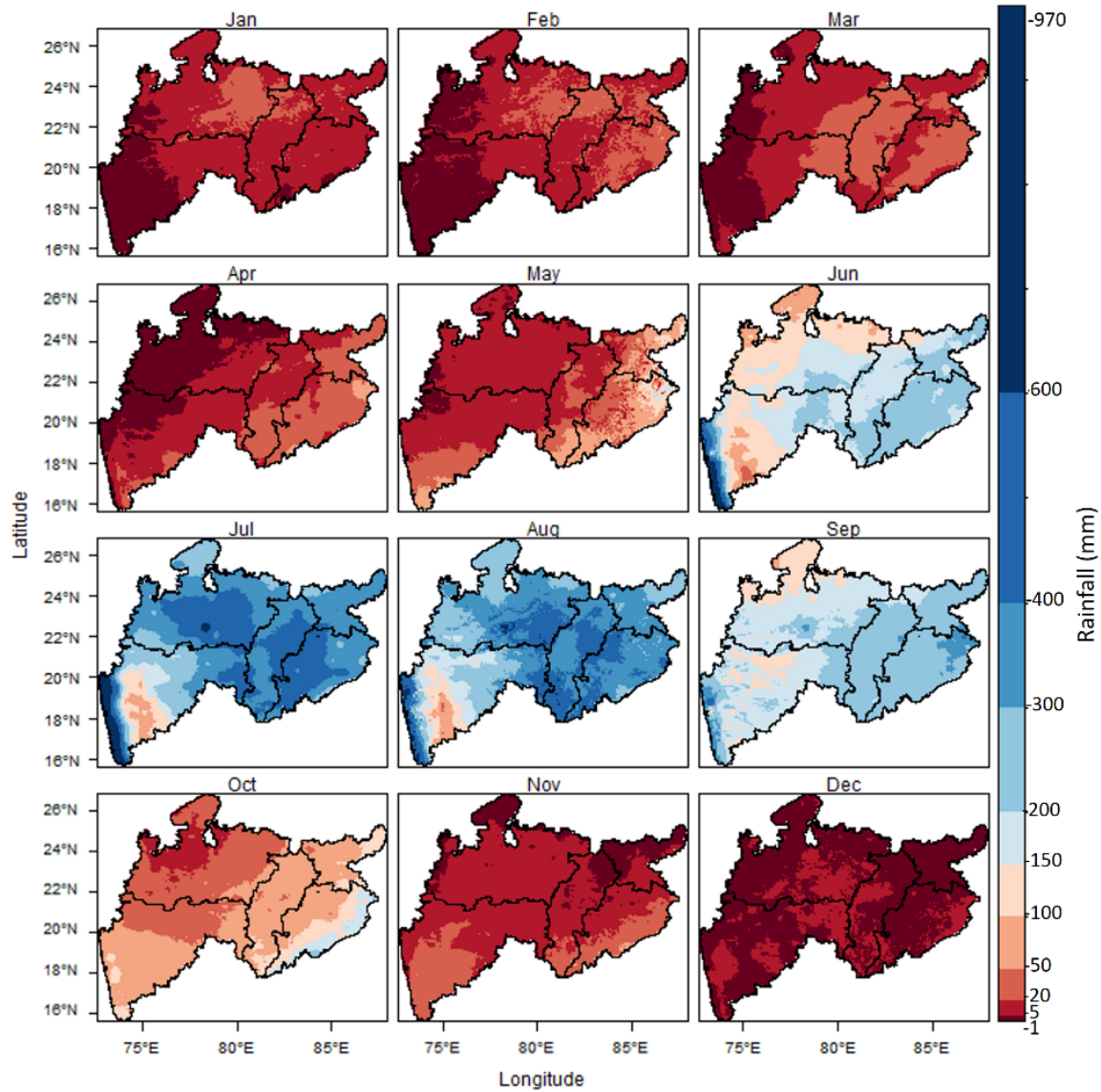
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Table 6. State-wise long-term average rainfall during and monsoon months.

State	Annual Rainfall	Monsoon Rainfall	Relative Monsoon Contribution (in %)
Chhattisgarh (CH)	1421.14	1233.37	86.79
Jharkhand (JH)	1334.17	1101.82	82.58
Madhya Pradesh (MP)	1100.98	1010.23	91.76
Maharashtra (MH)	1102.73	969.94	87.96
Odisha (OD)	1559.94	1271.42	81.50

370



371

372

Figure 8. Temporal variability of long-term monthly average rainfall of 18 years.

373

The accumulated rainfall inside and outside forested area was analysed in (a) different months, (b) different states

374

and (c) over the full study region. It was observed that the amount of accumulated monsoon rainfall observed

375

during 2001 to 2018 in the states MH, MP, CH, JH and OD within forest (non-forest) are: 1051 (577), 769 (692),

376 890 (885), 786 (800) and 918 (910) mm km⁻², respectively. The accumulated monsoon rainfall observed within
377 forest (non-forest) area in the buffer zones 0-50 km, 50-100 km, 100-150 km and 150-200 km from the western
378 coast are: 1661 (1651), 1119 (830), 709 (501) and 612 (397) mm km⁻², respectively. Similarly, the accumulated
379 monsoon rainfall observed within forest (non-forest) areas in the buffer zones 0-50 km, 50-100 km, 100-150 km
380 and 150-200 km from the eastern coast are: 816 (838), 890 (902), 907 (876) and 911 (905) mm km⁻², respectively.
381 Overall, the amount of rainfall observed during the monsoon within the forest (non-forest) area in the full study
382 region was 245 (215) mm km⁻² yr⁻¹. Interestingly, the total area of forest in the 0-100 km buffer in the western
383 coast is 75% more than the eastern coast, and this can be attributed to the difference in rainfall in the eastern coast.

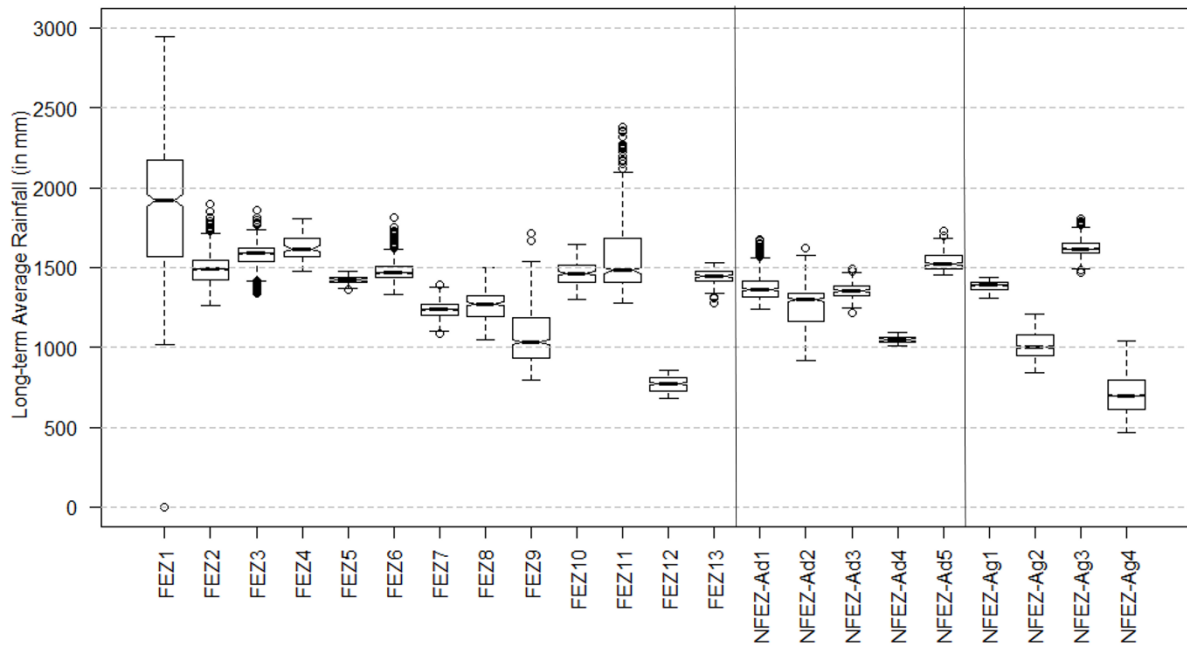
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385 **3.5. Spatio-temporal variability in rainfall in different experimental zones**

386 To examine the spatial distribution and variability of rainfall in different areas, we demarcated the study area into
387 different experimental zones (**Fig. 1a**) (i.e. FEZ, FEZ-Ad and FEZ-Ag) and different buffer zones within and
388 outside forested regions based on the MODIS and CHIRPS time-series vegetation and rainfall data, as described
389 in section 2.3.2.

390 **3.5.1. Forest Experimental Zone (FEZ)**

391 The variation in rainfall in different forest zones is depicted in **figure 9**. Of the 13 FEZs, zone FEZ1 received the
392 maximum average rainfall (~1900 mm), which might be due to two factors such as its closeness to the western
393 coast and the orographic effect of the Western Ghats topography. The zone FEZ12 received the lowest rainfall
394 (~800 mm), which might be due to the low density of forests in that zone and its location far from coasts. The
395 other zones FEZ2 to FEZ6, FEZ10, FEZ11 and FEZ13 also received high average rainfall (~1500 mm). On the
396 other hand, FEZ7 and FEZ8 received relatively less rainfall (~1300 mm) and FEZ9 received around 1000 mm.
397 The highest variance in rainfall was observed in FEZ1, FEZ9 and FEZ11, which might be due to the fragmentation
398 of forest patches in these regions. The zones FEZ9 and FEZ12 seem to be sensitive to drought as they received
399 less rainfall than all other zones. **Figure S10** reveals the inter-annual variability in the rainfall in all these 13 FEZs.
400 During 2002, 2004, 2009, 2014 and 2015 there was an overall reduction in the rainfall in most of the zones, except
401 FEZ1 and FEZ11 as these zones fall into high elevation regions and receive consistently the maximum rainfall in
402 all years. It was observed that the size, density, fragmentation, elevation and distance from the coast of the forested
403 zones affected the rainfall amount and variability.



404
405 **Figure 9.** Long-term average annual rainfall variability within the experimental zones.

406 **3.5.2. Non-Forest Experimental Zone-Adjacent (NFEZ-Ad)**

407 The non-forest regions located adjacent to forests and surrounded by forested area have the benefit of receiving
 408 high rainfall because of their closeness to forests. All the 5 NFEZ-Ad zones received consistently high rainfall
 409 (>1000 mm) (**Fig. 9** and **S7**). NFEZ-Ad5 received the maximum rainfall (>1500 mm) because this patch is narrow,
 410 and it is the smallest in size, located close to the large forest patches of FEZ2 and FEZ3 (**see Fig. 1a & 9**). On the
 411 other hand, NFEZ-Ad4 received less rainfall (~1100 mm) than the other zones. NFEZ-Ad2 had the highest rainfall
 412 variability among all the zones. The reason could be its shape and extent over a large area where the surrounding
 413 forest patches are fragmented and varied in density (**Fig. 1a**). All these NFEZs experienced a reduction in rainfall
 414 during the drought years similar to FEZ, but NFEZ-Ad4 seems to be more sensitive (**Fig. S11**).

415 **3.5.3. Non-Forest Experimental Zone-Agriculture (NFEZ-Ag)**

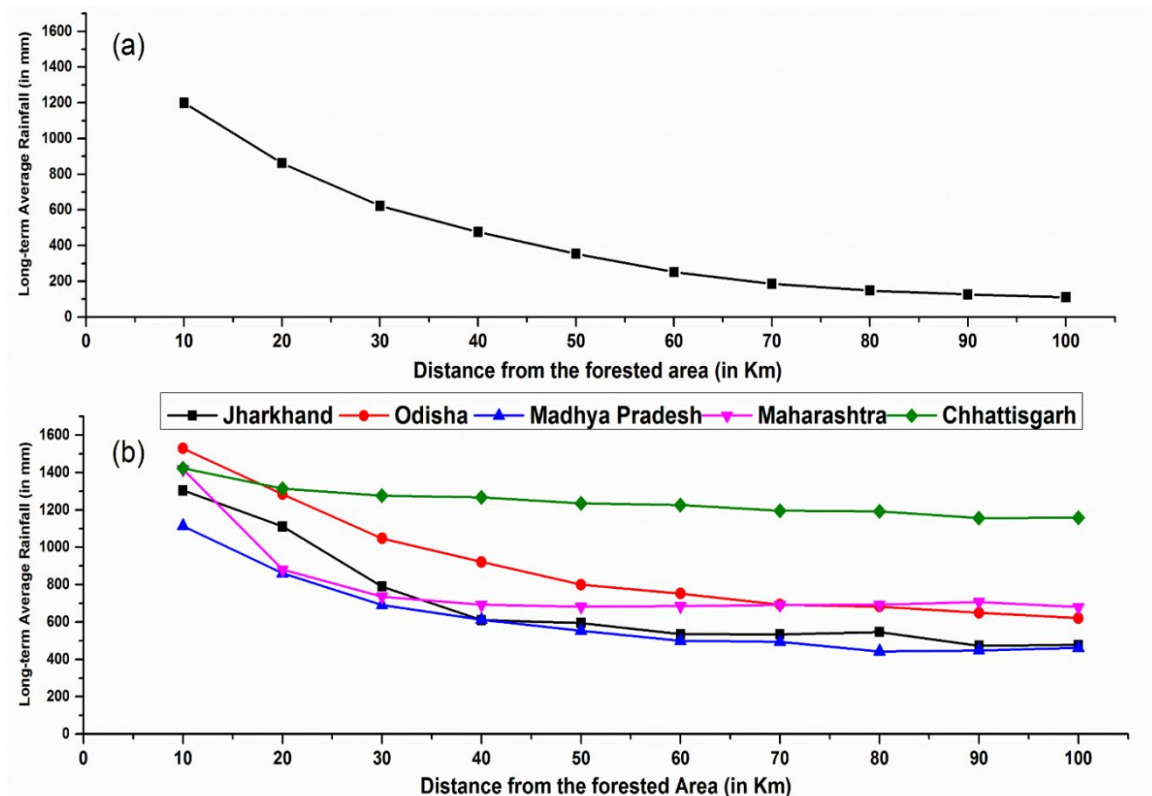
416 Of the four agricultural zones, NFEZ-Ag4 received the lowest rainfall (~700 mm) (**Fig. 9 & S12**). This zone in
 417 MH is a vast stretch of intensive agriculture where rainfall is highly erratic. In contrast, the NFEZ-Ag2 zone in
 418 MP received higher rainfall than NFEZ-Ag4 which might be due to the effect of adjacent forest patches. NFEZ-
 419 Ag3 received the highest average rainfall (~1600 mm) and the apparent reason could be its closeness to the eastern
 420 coast. High rainfall in NFEZ-Ag1 is likely due to the orographic effect supported by surrounding forest patches.
 421 Figure S8 reveals the inter-annual rainfall variability in these zones over 18 years. NFEZ-Ag4 & Ag2 are at the
 422 lowest receiving end and are sensitive to drought, and NFEZ-Ag1 & Ag3 profit greatly from the monsoon. Though

423 NFEZ-Ag4 falls in the rain-shadow region, the lack of forest patches in NFEZ-Ag4 compounds the situation of
424 low rainfall occurrence here.

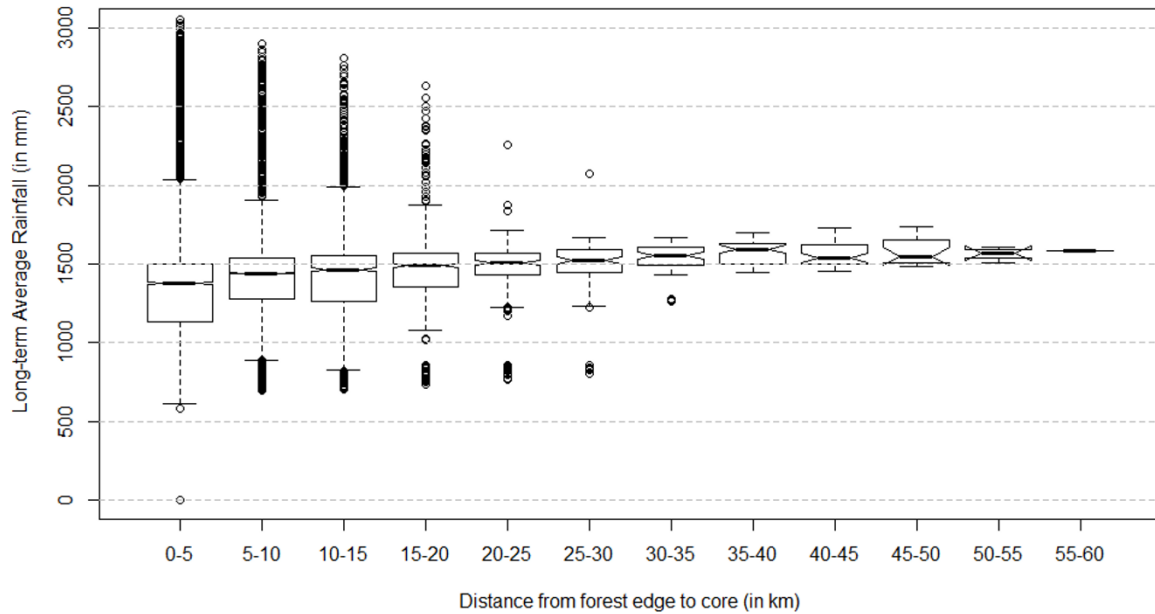
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426 3.6. Spatio-temporal variability of rainfall in the buffer and core zones.

427 To gain more insight into the spatial distribution of rainfall, buffer analysis was carried out where buffer zones
428 at 10 km intervals were created outside the edge of the forested areas. Also, buffer zones of 5 km interval were
429 created inside the forested areas from the edges. **Figures 10** and **11** show the variability in rainfall in these two
430 groups of buffer zones. The hypothesis is that rainfall should increase inside the forests and should decrease at
431 increasing distance from forests. First, we estimated the average rainfall in different buffer zones located in
432 different forested regions across the study area. Interestingly, a clear pattern of exponential reduction in rainfall
433 was observed with increasing distance from forests at an average rate of $-20 \text{ mm yr}^{-1} \text{ km}^{-1}$ over a 0-to-50 km range,
434 and at the rate of $-1.5 \text{ mm yr}^{-1} \text{ km}^{-1}$ over a 50-to-100 km range.



435 **Figure10.** Variability in the long-term average rainfall with respect to distance from forested area in the central
436 Indian landscape (a) and in different states (b).



437

438 **Figure 11.** Variability in the long-term average rainfall at different distances within the forests (from edge to
 439 core).

440 **3.7. ANOVA statistical analysis**

441 The statistical null hypothesis was that there is no difference in the mean rainfall and its variability between the
 442 forested and non-forested areas, and across the different experimental zones (and, thus, forests do not contribute
 443 in bringing rainfall to the region). Therefore, ANOVA was performed to test the rainfall variability in different
 444 zones, and also in different years. We found that the mean rainfall variation was significantly different ($p < 0.05$)
 445 between the experimental groups at inter and intra-year stratifications, and during extreme years like 2002 (dry
 446 year), 2011 (normal year) and 2013 (wet year). We found that FEZ4 and NFEZ-Ag3 experienced almost the same
 447 average rainfall of 1621.18 mm and 1620 mm, respectively, due to closeness to the coastal zone which supersedes
 448 the effect of forests on rainfall. Another two nearby experimental zones, FEZ8 and NFEZ-Ad2, experienced a
 449 similar average rainfall of 1256.06 mm and 1251.43 mm, revealing the benefit of being close to forested regions.

450 **Tables S1, S2, and S3** provide the results from the ANOVA test for the different years. **Table 7** provides the
 451 ANOVA results for the rainfall variability between forested and non-forested pixels, intersected with four
 452 different spatial profiles across the landscape. All the ANOVA results confirm that the mean rainfall and
 453 variability are clearly different in the forested and non-forested zones and the null hypothesis is rejected and the
 454 alternative hypothesis is supported.

455

456

457 **Table 7.** Testing the influence of forest on rainfall within the forest area and outside forest area along different
 458 profiles using one-way ANOVA.

Summary		Rainfall outside Forest	Rainfall within Forest
Spatial Profile Line	Rainfall Occurrence		
AB Spatial Profile Line	Average	1236.69	1391.03
	SD	308.25	190.40
	Variance	95021.20	36255.56
	standard error	30.82	19.04
	F	27.04	
	F Critical	3.87	
	P-value	3.84E-07	(significant)
	N	120	164
CD Spatial Profile Line	Average	1245.02	1295.86
	SD	222.32	286.46
	Variance	49426.03	82057.74
	standard error	22.23	28.65
	F	2.08	
	F Critical	3.88	
	P-value	0.15	(not significant)
	N	83	197
EF Spatial Profile Line	Average	1046.79	1365.32
	SD	306.03	348.19
	Variance	93653.29	121233.30
	standard error	30.60	34.82
	F	99.76	
	F Critical	3.86	
	P-value	2.56E-21	(significant)
	N	185	259
GH Spatial Profile Line	Average	815.05	1151.72
	SD	183.06	592.99
	Variance	33512.03	351633.81
	standard error	18.31	59.30
	F	52.16	
	F Critical	3.87	
	P-value	3.81E-12	(significant)
	N	182	138

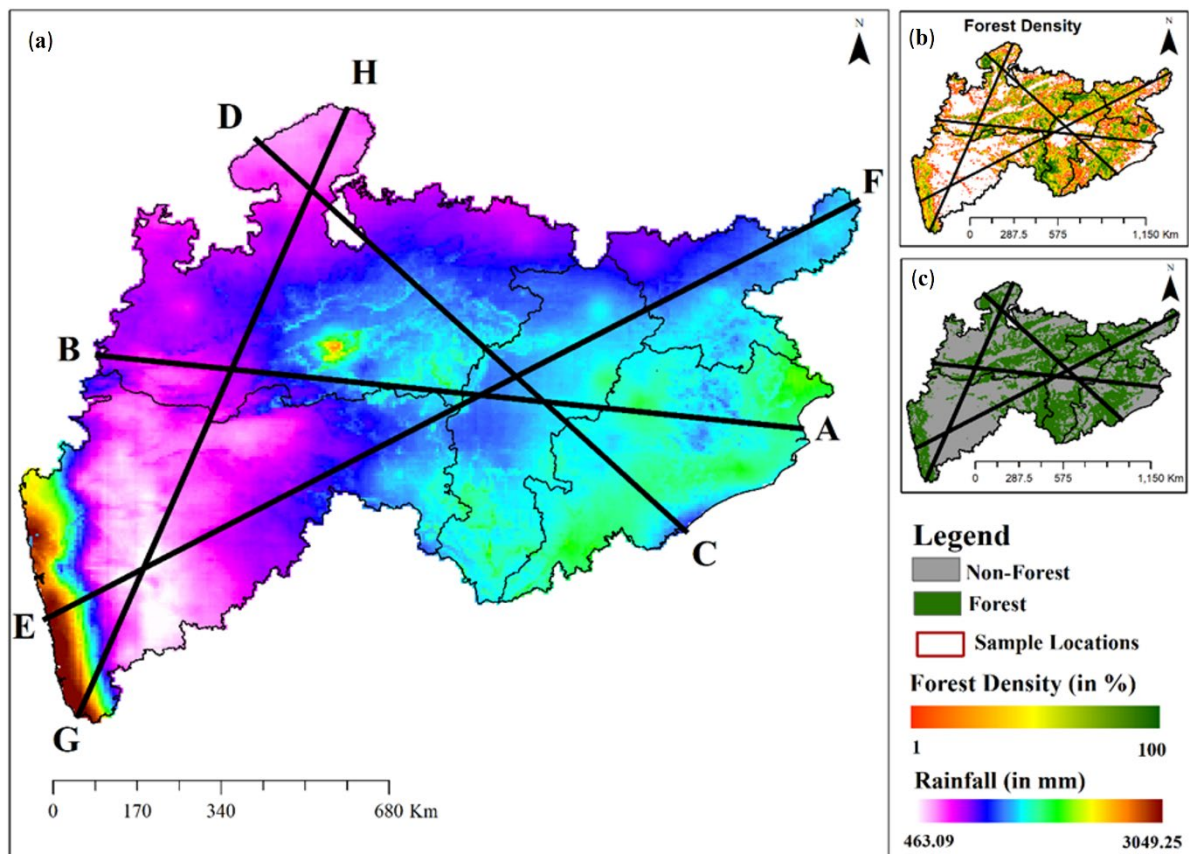
459 ***Note: SD = Standard Deviation, N= Total number of samples

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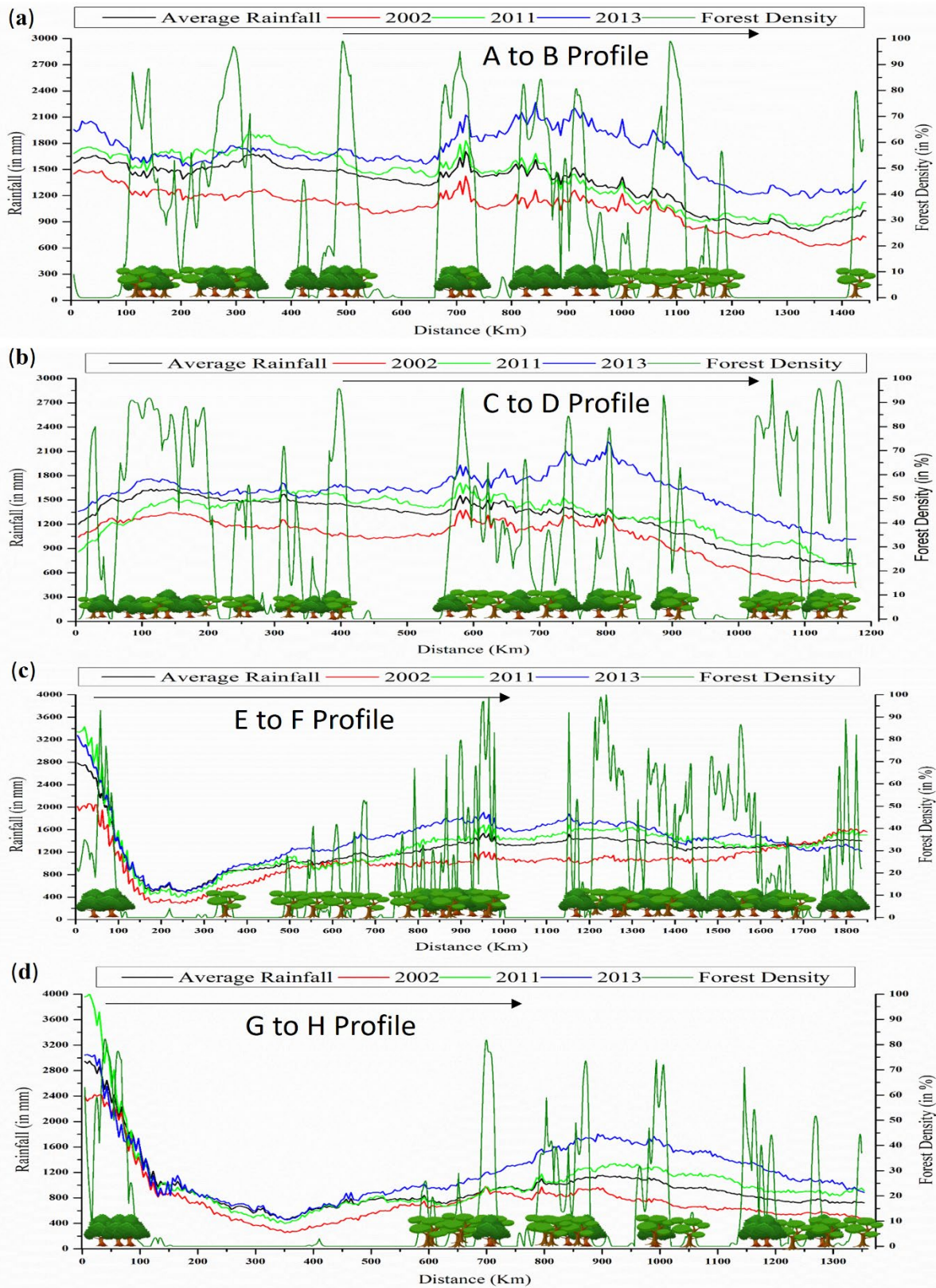
461 **3.8 Profile analysis**

462 To characterize the rainfall variability across the study area, we took four different profiles traversing different
 463 lengths and breadths of the study area. **Figures 12a and 13** show the spatial extents of these profiles along with
 464 rainfall. **Figure 12b** depicts the spatial distribution of forest density while **Figure 12c** depicts the forest and non-
 465 forest areas. These four profiles were intersected with the rainfall during normal (2011), dry (2002) and wet (2013)
 466 years, and plotted to understand the effect of presence of forest on rainfall (**Fig. 13**). It is clearly evident that an

467 increasing pattern of rainfall (**Figures 13 a, b, c & d**) was observed while moving towards forested areas, and an
 468 exponential reduction was observed while moving away from forested regions (**Fig. S13**). These effects are
 469 dominant (**Figure 13 c, d**) in MH when the profile line crosses the locations where agriculture practices are
 470 followed over the vast region. **Table 7** shows the influence of forest on the different profiles tested using ANOVA.
 471 It is found that the rainfall pattern and its variability in profiles AB, EF and GH was significantly ($p < 0.05$)
 472 different over forest and non-forested areas. Interestingly, in the CD profile one can see a reduction in rainfall in
 473 the north-western region where the forest is fragmented and less dense, but in the agriculture region, covered by
 474 forest on all sides (in Chhattisgarh) and falling within the zone of influence of forest, the reduction was minimum.
 475 These rainfall-forest linked profile pictures (**Fig. 13a-d**) further confirm the influence of natural Vegetation on
 476 rainfall.



477
 478 **Figure 12.** Rainfall and Vegetation variation along different directional profiles (AB, CD, EF and GH): (a) long-
 479 term average annual rainfall, (b) forest density and (c) forest and non-forest area.



480

481 **Figure 13.** Rainfall variability during extreme rainfall years and the presence of natural Vegetation across the

482 study area (as forest density in the secondary axis). (Note: The spatial extent of the profile lines is provided in

483 Figure 12)

484 4. Discussion

485 The influence of forests in regulating the regional distribution of rainfall was realized very early by humans,
486 indeed since the Indus civilization (Bhattacharya 2014; Sheil 2014). Creed et al. (2019) stressed that forests and
487 water are an integrated system and, thus, there a global consensus on transboundary management policies is
488 required for achieving the UN sustainable development goals. Meteorologically, various factors affect the
489 distribution of rainfall intensity over India. For example, warming in the Arabian Sea, the Indian Ocean and the
490 Bay of Bengal affect moisture transport mechanisms over central India (Jin and Wang 2017; Roxy et al. 2017).
491 However, a full deterministic understanding of the spatial (and spatio-temporal) variation in rainfall has not yet
492 been achieved. Roxy et al. (2017) questioned the mechanism behind the observed increases in extreme events
493 over central India, noting that meteorological models are still not able to predict the frequent droughts observed.
494 Various models, ground and satellite-based studies reported that forest-rainfall feedbacks are likely to influence
495 water availability under climate change scenarios (Bergkampt et al. 2003; Spracklen et al. 2012; Staal et al. 2020a).
496 Our findings revealed that rainfall decreased exponentially outwards from forest edges to non-forested areas,
497 inline with reported increases with distance from the ocean (Makariaeva et al. 2009).

498 Pradhan et al. (2019) showed that, in north-eastern (NE) India, high evapotranspiration (ET) from forested
499 regions supplies water vapour to the atmosphere during summer which may contribute to the high rainfall
500 observed over forests in the NE during summer. However, in central India, moisture supply to the atmosphere
501 through ET from the forested region is very low during the summer for two reasons: (a) plants are deciduous in
502 nature and lack leaves in summer (already shed to avoid water loss), and (b) the region is water scarce in summer.
503 For example, Meghalaya receives around 400 to 800 mm of rainfall in summer, but Madhya Pradesh receives
504 only 100 to 200 mm. In central India, ET arises mainly from forests, primarily from two types; dry and moist
505 deciduous. They are drought resistant and extract water from their deep and wide spreading rooting systems
506 (Neptad et al. 1994). When the tropical deciduous forest starts greening in May-June ET increases and, hence,
507 accelerates moisture supply inducing cooling on the clouds and causing subsequent rainfall in the region. Of four
508 ways to cool the southwestern moisture-laden winds (i.e. adiabatic, conductive, radiative and evapo-transparative
509 cooling), two types are often observed in central India. One is through adiabatic cooling due to the Western Ghats
510 and central hilly areas, and the other is evapotranspiration-induced cooling by natural Vegetation. To induce ET
511 cooling, greening of the central Indian forests has to materialise before the actual arrival of the moist monsoon
512 winds. Such an effect would be possible if the root system of natural Vegetation inherits temporally correlated
513 genetic traits (Makarieva and Gorshkov 2007), hence, stressing the importance of native species in the local

514 ecosystem. However, the exact triggering mechanism in the root system of trees requires ground-level and species-
515 level detailed study which is out of scope of this research.

516 Further evidence of increased ET during the monsoon and post-monsoon, acting as a moisture feedback to
517 maintain the balance of ground water, was also observed over central India (Goroshi et al. 2017). Kannemadugu
518 (2019) observed that long-range convective transport of dry dust due to north-western winds contributes in
519 increasing aerosol optical depth in central India during the pre-monsoon. However, southwestern winds, caused
520 by a low pressure system over the Tibetan plateau, bring moist ocean winds to central India, and ET from natural
521 Vegetation helps in condensing these moist winds. O'Connor et al. (2021) conducted a study on 14 biomes
522 distributed across the globe and showed that a forest buffering effect on precipitation was found in 10 biomes.
523 They observed that the tropical region receives ~50% of the precipitation due to the presence of forests. In another
524 study based on a dynamic recycling model, Roxy et al. (2017) observed that forests contributed in capturing 29%
525 of rainfall. Due to the continuous stretch of forest patches in MP, CH and OD a larger extent of precipitation-shed
526 over India can be seen on the eastern side (Fig. 4).

527 Interestingly, we found that a higher magnitude of rainfall was observed consistently over the forested region,
528 on an inter-annual basis (Fig. 3 and 4), and higher frequency of low rainfall was observed outside the forested
529 region. It was found that inter-annual rainfall variability was uniform inside the forest area, while the rain was
530 unevenly distributed outside the forested area. During the drought years (2002 and 2015), the RF variability was
531 low in forested areas, but high in non-drought years (2011 and 2016). Interestingly, the rainfall variability was
532 high outside the forest area irrespective of wet or drought conditions and year (Fig. S2). On the other hand, it was
533 observed that the Positive Indian Ocean Dipole (IOD), which brings more monsoon rainfall over India during the
534 months of July and August (Anil et al. 2016), was associated with rainfall over the forested region (Fig. 8).

535 Remote sensing-based NDVI data revealed greening trends across the globe (Zhu et al. 2016; Chen et al.
536 2019) and over central India Singh et al. (2021) which is expected to increase ET over the study area and, hence,
537 increase rainfall intensity. Knox et al. (2011) conducted a similar study to the present one to characterize the
538 variability in precipitation over forest areas, non-forest areas and forest edges in the Amazon. They found that
539 rainfall tends to be influenced by the presence of natural Vegetation, supporting the results presented here. In this
540 research, the mean rainfall in the different elevation classes with forests was found to be consistently around 1500
541 mm with less variability than in the non-forested area where the mean rainfall was around 1000 mm. Makarieva
542 et al. (2013) showed that tropical forests experienced less rainfall variation at the centre of continents or
543 landscapes, located far away from the oceans. However, rainfall magnitude is greater in elevated regions of the

544 world (IPCC 2014). Zeng et al. (2015) linked changes in rainfall to elevation in the Sichuan province of China, in
545 monthly, seasonal and annual rainfall events. Similarly, in this study, the effect of relief on the rainfall distribution
546 was observed, and the 800-1643 mm elevation class received maximum rainfall irrespective of the presence of
547 forests. However, the presence of forests induced more rainfall in the 300 to 800 m elevation range.

548 The average rainfall was found to decrease exponentially with an increase in distance from forest edges. Such
549 a decrease might vary due to transpiration differences at the edges due to variation in land cover composition
550 (Giambelluca et al. 2003). Makarieva and Gorshkov (2007) explored rainfall variability with distance from forests.
551 They obtained samples from various parts of the world, but did not include the Indian Subcontinent. Srivastava et
552 al. (2017) reported intra-seasonality rainfall variability, and observed a relationship between evaporation, soil
553 moisture and rainfall. Although the central Indian forest is a fragmented landscape, its role in capturing the
554 monsoon rainfall is relatively similar to that of any other forest, be it in the Amazon or Congo, as well as
555 maintaining a balance in the hydrological cycle and multiple ecosystem services.

556 In this research, it was found that the long-term average rainfall was higher in the eastern half of the study
557 area than the western half, under different NDVI classes. On the other hand, the rainfall variability was greater in
558 the western side as shown in figures S4 & S5. Interestingly, all forested sample zones experienced different
559 amounts rainfall despite falling into the same or different climate zones, which could be due to differences in
560 forest density, species type or understory composition. Also, the zones adjacent to forested regions experienced a
561 similar magnitude of average rainfall (e.g. NFEZ- Ad1 & Ad3, Fig. 9). Also, meteorologically, differences in
562 differential heating across heterogeneous land surfaces, evaporation rates, atmospheric circulation and water
563 availability, could lead to variability in rainfall and cloud formation (Bonan 2008; Knox et al. 2011; Spracklen et
564 al. 2012). As per Makarieva and Gorshkov's (2007) hypothesis, a transitional increase in rainfall towards inland
565 over the forested landscape from the eastern and western coast was observed in this research. The spatial profiles
566 AB and CD in Figure 12 revealed a clear increase in rainfall associated with forests, likely due to the ET effect
567 described above, and a decrease towards the coast and the MP borders. On the other hand, the spatial profiles
568 EF and GH showed the orographic effect on rainfall due to the presence of the Western Ghats (Tawde and Singh,
569 2014; Phadtare et al., 2022). The rainfall on the rain shadow side was lower, but started increasing towards the
570 forest areas (Fig. 13).

571 Reduced rainfall intensity and high rainfall variability have been linked to deforestation in various parts of
572 the world like the Amazon and African Sahel, and a weakening of the monsoon (Bonan 2008; Staal et al. 2020b).
573 In this research, we observed that rainfall is consistently high in regions with high forest density. Results from

574 various studies imply that increasing rates of global deforestation and degradation would reduce the forest density
575 which, in turn, is likely to affect rainfall intensity. Recent droughts in the Amazon region and reduced water depth
576 downstream could be linked to increased deforestation and fragmentation reducing the cumulative tree projection
577 area and volume of moisture transport leading to a reduction in net condensation volume in the Amazon basin
578 (Chen et al. 2009; Atkinson et al. 2011; Lewis et al. 2011). Spracklen et al. (2012) examined the rainfall over
579 tropical regions and reported that moist air passing over extensive vegetative areas produced at least twice the
580 rainfall compared to less forested areas. This is also true in the present study because of the high leaf area index,
581 which maintains high evapotranspiration fluxes in the continuous intact natural undisturbed forested area (Fig.
582 13) (Bonan 2008; Sheil and Murdiyarso 2009; Knox et al. 2011; Ellison et al. 2017). Relief and altitude differences
583 cause adiabatic expansion of moist air, which condenses after reaching a certain height (Makarieva and Gorshkov
584 2007; Ellison et al. 2017).

585 Rainfall variability in central India is not uniform, either spatially or temporally, even though the south
586 western moist winds blow over the entire central Indian landscape. The results of this study suggest, in particular,
587 that the presence of deciduous forests in central India plays an important role in generating precipitation through
588 condensation services. Considering its major role in condensation, it is vital to conserve, manage and protect the
589 large deciduous forests of the central Indian landscape to minimise the impact of future climate change on the
590 region and sustain society. Without awareness of this fragility, and actions to protect the forests, it is possible that
591 the monsoon system over central India may experience a regime shift under large-scale fragmentation and/or
592 deforestation of this forested landscape. We recommend further detailed investigation, and declaration of the
593 central Indian forested landscape as a Monsoon Hotspot to protect it from further degradation due to pressure
594 from climate change, increasing population and human disturbances. We also recommend further studies on large-
595 scale regional eco-hydrology and estimation of the precipitating effect of major ecological reserves.

596

597 **5. Conclusion**

598 Tropical forests balance the regional climate and help in reducing warming during the summer months. In
599 the drought-prone central Indian region the valuable ecosystem services of forests, such as biodiversity
600 conservation and ecotourism, as well as the aforementioned adjustments to the micro-climate and water storage,
601 make them a crucial element of the biosphere. This research investigated the inter-annual rainfall variability over
602 the forested and non-forested landscapes of central India on a monthly and inter-annual basis using 18 years of
603 time-series rainfall data. We investigated the association of rainfall with forests under various conditions, with the

604 ultimate aim of understanding the possible influence of forests on the spatial pattern of rainfall. We found that the
605 long-term average rainfall was higher in the forest rich eastern region than the agriculture-dominated western
606 region. However, focusing on forests only, rainfall in the eastern coastal region (<100 km from coastline) was
607 found to be less than in the western coast. The highest rainfall variability was observed in the agriculture-
608 dominated MH whereas the least rainfall variability was observed in the forest-dominated CH and OD.

609 In summary, we suggest that rainfall over central India is controlled majorly by two factors: (a) the orographic
610 effect and (b) evapotranspiration from natural Vegetation. The high rainfall in the western aspect of the Western
611 Ghats region is due to a dominant orographic effect, and the reduced rainfall in the agriculture region of MH is
612 due mainly to its disadvantaged position in the leeward rain-shadow. A buffer analysis confirmed that core areas
613 inside forests receive higher rainfall than the edges and, crucially, rainfall decreases outwardly with distance from
614 the forested areas. Moreover, as illustrated by the spatial profiles of rainfall, the presence of vegetation exhibited
615 a large correlation with rainfall occurrence. It is possible that the distribution of forests induces the condensation
616 of the moisture-laden monsoon wind over tropical central India, in addition to other meteorological variables.
617 However, vegetation-climate feedback mechanism is complex as there are many terrestrial and atmospheric
618 factors control monsoon rainfall distribution in India, and forest could be one of the important factor. This research
619 highlights the potential role of forests in regulating the spatial distribution of rainfall in the central Indian
620 landscape. Further research on this critical regulatory ecosystem service is required.

621

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629

630 **Author contribution**

631 BS and CJ designed the study, carried out data analysis and wrote the manuscript. VSR, PMA, MDB, CPS, JD
632 and PSR participated in logical discussion for improving the concepts, data analysis and contributed in editing

633 and enhancing the write-up. All authors discussed results, discussion and conclusion. All the authors have given
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635

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638

639 **Data availability** The data analysed to carry out the current study are freely available from the LPDAAC (Land
640 Processing Distributed Active Archive Center (<https://lpdaac.usgs.gov>) The monthly precipitation dataset of
641 Climate Hazards Group Infra-Red Precipitation with Station data (CHIRPS version 2.0) is also freely available
642 for downloading from 1981 onwards(<ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRP/month-ly>). Data used in
643 this research cab be available from the corresponding author on reasonable request.

644

645 **Code availability** The open source R computing and analysis software was used in this research. Figures
646 generated using R codes are available from the corresponding author on reasonable request.

647

648 **Declarations**

649 **Competing interests** The authors declare no competing interests.

650

651 **Ethics approval** Not applicable.

652

653 **Consent to participate** The authors declare that they all participated in the preparation of final draft of the
654 manuscript and contributed accordingly.

655

656 **Consent for publication** The authors declare that they all agree to the publication of this manuscript.

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