



Vegetation Patterns and Competitive Dynamics along Elevation Gradients: Interactions between Environmental Factors and Vegetation in the Central Himalayas

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1. Abstract

Elevation gradients are generally characterized by a steady reduction in temperature with altitude, resulting in differences in growth conditions that often produce clear patterns of vegetation zonation. A south-north transect of the central Himalayas spans from a tropical climate in the south to alpine conditions in the north, offering an opportunity to investigate the relative roles of abiotic stress and competitive interactions in shaping plant community assembly. We hypothesise a shift from vegetation composition and productivity being characterised by realised niches, defined by competitive interactions at lower elevations, to physiological niches, shaped by stress (freezing temperature) at higher elevations. To investigate how these niche transitions influence community dynamics and ecosystem processes, we used a dynamic vegetation model with regional plant functional types (PFTs) parameterised with trait data, including allometric relationships. The model effectively captured spatial and temporal variability in vegetation structure and productivity along the gradient, with simulated patterns closely matching observed vegetation zonation across the transect. The establishment and performance of the PFTs were dependent on their climatic niche and the local abundance of competing PFTs, with persistence shaped by specific traits and adaptation strategies. At low elevations, where competitive interactions dominate, tropical shade-intolerant raingreen and tropical shade-tolerant evergreen PFTs dominated carbon mass production and vegetation cover. In contrast, shorter stature, evergreen phenology, and cold-tolerant types were favoured at high elevations, reflecting reduced interspecific



37 competition and physiological adaptation to low temperature stress. Along the elevation
38 gradient, PFT functional diversity declined with elevation, but evenness in composition
39 increased. Conversely, low-elevation communities supported higher functional diversity,
40 yet vegetation structure and function (e.g., LAI, FPC, and carbon mass) were dominated
41 by a few competitively superior PFTs. We conclude that vegetation dynamics along the
42 temperature gradient are governed by a trade-off between competitive ability and stress
43 tolerance, as reflected in shifts in structure, composition, and productivity, which are
44 shaped by environmental conditions, functional traits, and adaptive strategies of the
45 vegetation.

46

47 **Keywords:** Elevation gradient, temperature, competition, community composition,
48 Himalayas, traits, dynamic vegetation model.

49

50 **2. Introduction**

51 Elevation gradients are characterized by rapid changes in climatic conditions,
52 particularly a decline in temperature with altitude (Zhu et al., 2022). With rising
53 elevation, temperature changes predictably in accordance with the 'lapse rate', creating
54 differences in growth conditions, which may be further exaggerated by small-scale
55 variations in precipitation, topography, aspect, exposure, geology, soil types, and
56 biogeochemical processes governing nutrient cycling and resource availability. These
57 variations in growth conditions act as environmental filters (stress factors) (Asner et al.,
58 2014; De Frenne et al., 2013; Zhu et al., 2022) which influence ecological processes and
59 interactions that give rise to emergent eco-evolutionary patterns such as niche
60 differentiation, functional trait distribution, plant strategies, and competitive exclusion
61 (Asner et al., 2014; Muñoz Mazón et al., 2020). Distinct community composition and
62 structure may result, with clear vegetation zonation shaped by the interplay of
63 environmental filtering and competition interaction along the gradient.

64

65 Temperature gradients are among the most influential environmental axes shaping
66 vegetation patterns globally. The Himalayas provide a striking example of this, with
67 distinct zonation observed from the tropical lowlands in the south to the alpine
68 conditions in the north. Cooler and wetter conditions at higher elevations, and hot with
69 seasonally dry conditions at low elevations, play a significant role in shaping the



70 composition and survival of plant species (Måren et al., 2015). Additionally, competition
71 for light, space, and soil resources drives vegetation function, diversity, and species
72 composition along the elevation gradient (Maharjan et al., 2021; Thakur & Chawla, 2019),
73 creating a biotic filter that results in different vegetation zones, community composition,
74 and plant diversity (species richness and evenness). The combined effects of these abiotic
75 and biotic filters on vegetation across elevations are reflected in differences in functional
76 traits, growth strategies of vegetation, and community composition at different positions
77 along the gradient (Midolo et al., 2019; Silva et al., 2023). As a result, vegetation at higher
78 elevations often exhibits thicker leaves and frost tolerance adaptations such as reduced
79 leaf area, increased epidermal thickness, and increased antifreeze proteins (Satyakam et
80 al., 2022). In contrast, lower elevation species have larger leaves with higher specific leaf
81 area (SLA), larger and wider branching patterns, and fast growth rates to take advantage
82 of abundant resources and warm temperatures (Shah et al., 2019; Sigdel et al., 2022).
83 Despite these clear vegetation patterns, the relative contributions of trait-mediated
84 competitive interactions and adaptation to stress on vegetation structure, composition,
85 and productivity remain poorly understood along the Himalayas' elevation gradient.

86

87 The complex interaction between growth conditions and vegetation functional traits, and
88 their role in structural dynamics and competitive interactions along this gradient, can be
89 effectively captured by incorporating characteristic plant traits into dynamic vegetation
90 models (DVMs) (De Paula et al., 2021; Sitch et al., 2003; Smith et al., 2014). By encoding
91 the traits and response mechanisms of real-world vegetation for different plant functional
92 types (PFTs) in these models and demonstrating agreement between modelled and
93 observed vegetation structural and functional characteristics along the gradient, we may
94 disentangle the environmental and community dynamic drivers of ecosystem
95 productivity. DVMs represent vegetation as groups of functionally similar species,
96 represented as PFTs, which share similar traits (morphological, ecophysiological, and life
97 history characteristics) and climatic niches (bioclimatic limits for establishment or
98 survival). Distinct traits and life history strategies, encoded as PFT parameters, influence
99 their performance and interactions in model simulations, reflecting functional trade-offs
100 in the adaptations of species that affect their performance when growing under different
101 environmental conditions (Díaz et al., 2016; Pierce et al., 2013).

102



103 We tested how plant strategies reflected in their traits, competition, and interactions with
 104 environmental factors collectively shape vegetation structure, composition, and
 105 productivity along the Himalayas elevation gradient. We employed an individual-based
 106 dynamic vegetation model, LPJ-GUESS (Smith et al., 2001, 2014), to simulate structural,
 107 compositional, and functional variability along a south-north transect of the central
 108 Himalayas spanning from a tropical seasonal climate in the lowlands to alpine conditions.
 109 Our approach leverages empirical data on vegetation traits and life history strategies
 110 along the same gradient. The simulated PFTs were defined based on empirical data on
 111 vegetation traits and life history strategies for major species and taxa found along the
 112 Himalayan transect. By comparing simulated outcomes with field observations, we
 113 evaluate how well the mechanisms embedded in the model explain spatial patterns in
 114 structure, composition, and function variability. We also examine species richness and
 115 evenness as emergent properties of functional composition, reflecting how changing
 116 growth conditions influence diversity. Overall, this study illustrates the complex interplay
 117 between growth conditions, traits, and competitive dynamics, thereby enhancing our
 118 understanding of the ecological processes that shape plant communities along the
 119 elevation gradient of the central Himalayas.

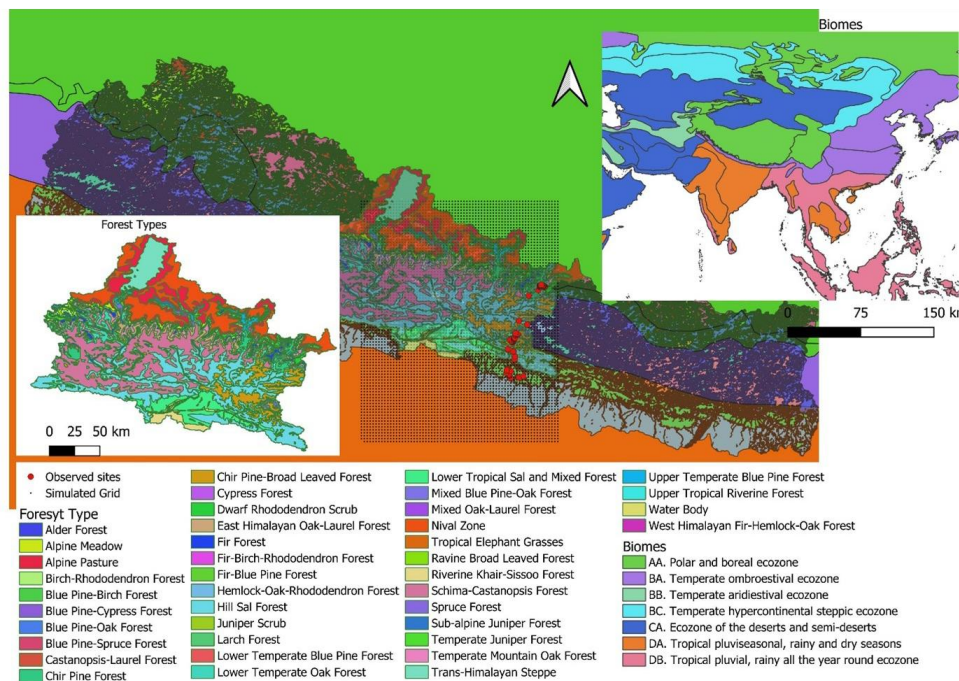
120 **3. Methods**

121 **3.1 Study site**

122 The study focuses on a species-rich elevation gradient of the central Himalayas (Figure
 123 1). Along the gradient, temperature decreases by approximately 6.5 °C per vertical
 124 kilometer, reflecting the standard lapse rate, where the average annual temperature in the
 125 tropical zone is 28 °C and around 10 °C in the alpine region (MoFSC, 2016; Poudel et al.,
 126 2020). Nearly 80% of the total annual rainfall occurs during the monsoon (June to
 127 September) (Maharjan et al., 2021), where average annual rainfall ranges from 165 mm
 128 (northern end of the gradient, i.e., Trans-Himalayan region) to 5244 mm (1550-2000 m
 129 altitude) in the lower and middle part of the gradient (Luitel et al., 2020; Poudel et al.,
 130 2020). Precipitation peaks at around 1000 m altitude asl and then rapidly decreases with
 131 an increase in elevation (Luitel et al., 2020; Poudel et al., 2020). Vegetation follows the
 132 temperature patterns ranging from tropical (24 °C) to temperate forests and to colder
 133 sub-alpine vegetation (6.9 °C) (Shrestha et al., 2015), where growth condition varies
 134 significantly due to variations in temperature and precipitation patterns. Within a
 135 horizontal span of 100 km along the gradient, 160 different tree species were recorded in



136 a plot-level survey conducted in forest areas, where vegetation composition and
137 dominance changes with elevation (DFRS, 2015; Pokhrel and Sherpa, 2020).
138



139
140 Figure 1: Map of the study area with major global Biomes (data source: Olson et al., 2001),
141 Forest types (data source: <https://rds.icimod.org/>), trait data observed sites (Maharjan
142 et al., 2021), and simulated grids along the elevation gradient of the central Himalayas.
143

144 3.2 Vegetation model description and customization

145 The Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) is a process-based
146 dynamic vegetation model used for simulating and predicting ecosystem responses to
147 environmental changes at the regional or global level based on local, neighbourhood-
148 scale interactions among simulated plants (Smith et al., 2001, 2014). It represents
149 generalized ecophysiological processes such as photosynthesis, autotrophic (plant) and
150 heterotrophic (soil) respiration, carbon, water, and nitrogen cycling. The model adopts
151 gap dynamics theory (Bugmann et al., 1996; Scherstjanoi et al., 2014) to simulate tree
152 population dynamics emerging from the balance of plant establishment, growth, and
153 mortality (De Paula et al., 2021; Sitch et al., 2003; Smith et al., 2001). The model is applied
154 across a continuous geographic grid. Vegetation in each grid cell is represented as a



155 mixture of PFTs whose potential distribution in climate space is governed by bioclimatic
 156 envelopes for the establishment and survival. Within its bioclimatic envelope, the
 157 presence and abundance of a PFT are additionally subject to vegetation dynamics
 158 determined by the interactions between co-occurring individuals of other PFTs and the
 159 cascading effects on carbon assimilation and allocation, reproduction, and survival of
 160 individuals co-occurring within replicate local patches, nominally 0.1 ha in size. The
 161 overall vegetation of a grid cell is aggregated across multiple patches (here 15),
 162 representing random samples of the wider landscape of the grid cell. PFT-specific
 163 parameters and growth strategies determine performance under different climates, CO₂
 164 concentrations, and stages of vegetation development. The model accounts for structural
 165 responses to competitive and environmental conditions through adaptive allometric
 166 relations (DBH-Height, DBH-Crown Area, DBH-Crown Volume) and a dynamic bole height
 167 scheme for each cohort. This allows allometric scaling and carbon allocation to respond
 168 dynamically to the competition (crowding) conditions defined by the availability of
 169 photosynthetically active radiation (Paudel et al., Unpublished).

170

171 To represent the diversity of vegetation composition along the Himalayan elevation
 172 gradient, we modified the following features to customize the model for application to
 173 our study area.

- 174 • The default model has 12 PFTs, defined to represent the dominant biomes of the
 175 world. For this study, we defined a new set of regional tree PFTs tailored to local
 176 conditions using a multivariate clustering approach. These PFTs represented
 177 major hypothesised strategies and adaptation mechanisms employed by
 178 vegetation to cope with competition (biotic stress) and harsh climatic conditions
 179 (abiotic stress) along the elevation gradient. Tree PFT parameters and their
 180 derivation are further discussed in Section 3.3 below. Both C₃ and C₄ grass PFTs
 181 with default parameter values (defined for the global level) were retained for
 182 simulations (Peng et al., 2024).
- 183 • Bioclimatic limits (mean minimum and maximum temperature for the 20 years of
 184 coldest month for establishment and survival; mean minimum warmest month
 185 temperature for establishment) control each PFT's establishment and survival in
 186 a given grid cell. The model defines these limits for global biomes ranging from
 187 tropical to boreal ecosystems. For this study, four climatic limits are defined:



188 tropical, subtropical, temperate, and alpine. Climatic ranges for our study were
 189 adopted from Jackson (1994) and modified based on the ranges recorded by
 190 Maharjan et al. (2021).

191

192 **3.3 Data Sources for model input and parameterisation**

193 The CRU-JRA (v2.4.5d) global gridded climate dataset was downscaled to 3 km spatial
 194 resolution using bicubic interpolation (Latombe et al., 2018) and used as climate-forcing
 195 data for our model simulations. The CRU-JRA is a gridded daily dataset with $0.5^{\circ} \times 0.5^{\circ}$
 196 spatial resolution from 2001 to 2022 (Araghi and Martinez, 2024). We used monthly
 197 mean air temperature, precipitation, wind speed, incoming solar radiation, specific
 198 humidity, number of wet days, and minimum and maximum temperature as inputs. All
 199 variables except for precipitation were interpolated to daily values; for precipitation, the
 200 monthly sum was divided equally across the number of wet days per month. Soil
 201 properties and the atmospheric nitrogen deposition rates (Lamarque et al., 2013) were
 202 configured using $0.5^{\circ} \times 0.5^{\circ}$ spatial resolution. Annual atmospheric CO_2 concentration data
 203 from NOAA (1901- 022) are used as input data (Friedlingstein et al., 2023).

204

205 Trait values of the 31 most abundant tree species - based on the frequency of observation
 206 and total carbon contribution identified by Maharjan et al. (2021) were compiled from
 207 Maharjan et al. (2021), Jackson (1994), and Thakur & Phulara (2014). Tree allometry data
 208 (DBH, total tree height, crown radius, crown height) were compiled from the Tallo
 209 database (a global tree allometry and crown architecture database) (Jucker et al., 2022)
 210 and BADD (a biomass and allometry database for woody plants) (Falster et al., 2015).
 211 Elevation data across the simulated grid was extracted from Earth Resources Observation
 212 and Science (EROS) Center (2000) and was used for plotting simulated outputs.

213

214 A divisive hierarchical clustering approach was used to group tree species into distinct
 215 PFTs based on similarities in traits and life-history strategies. We clustered tree species
 216 into 13 functional groups based on their dominant temperature range (tropical, sub-
 217 tropical, temperate or alpine), leaf phenology (evergreen, raingreen, summergreen,
 218 broadleaved, and conifers), life history strategies (growing fast and slow, late and early
 219 successional species), shade requirement (shade tolerant, intermediate tolerant and
 220 intolerant); drought resistance class (drought tolerance, drought sensitive), as well as



221 traits such as wood density and total tree height (Supplementary Table 1). The resultant
222 PFTs are designed to represent the functional diversity required to simulate structure,
223 composition, and productivity along the elevation gradient.

224

225 The following parameters were updated for each tree PFT: leaf phenology, drought
226 tolerance, wood density, SLA, shade tolerance, leaf longevity, and leaf turnover rate (Table
227 1). The values of these parameters, compiled from the sources mentioned above, were
228 averaged across species included in the PFTs emerging from the clustering procedure
229 described above. In the model, shade tolerance is linked to life history strategies, which
230 influence growth, reproduction, and survival of PFTs across different light environments.
231 Here, parameters and their values (Supplementary Table 2), as defined by Hickler et al.
232 (2004), were adapted in model simulation to represent these dynamics. Similarly,
233 quantile regression was used to estimate allometric scaling parameters (DBH relative to
234 height, DBH relative to crown area, and DBH relative to crown volume) under three
235 different stand crowding conditions (5%, 50% and 95%), allowing us to evaluate
236 structural response to competition and their influence on ecosystem dynamics.

237

238 Table 1: Tree PFTs and parameter values used for simulation, including bioclimatic limits,
239 Shade tolerance parameters and their values, and allometric relations (see
240 Supplementary Table 1 & 2 for details).

PFTs	Parameters					
	Leaf phenology	Leaf longevity (years)	Shade tolerance	Wood density (kgC m^{-3})	SLA ($\text{m}^2 \text{kgC}^{-1}$)	Leaf Turnover (fraction/year)
Alpine broadleaved evergreen (ABE)	evergreen	2	intolerant	273	13	0.5
Alpine needleleaved (ANE)	evergreen	3	tolerant	280	9	0.33
Temperate summergreen (TeBSG)	summergreen	0.5	intolerant	265	18	1
Temperate broadleaved shade tolerant evergreen (TeBEt)	evergreen	2	Tolerant	281	15	0.5
Temperate broadleaved shade intolerant evergreen (TeIBE)	evergreen	2	intolerant	282	15	0.5
Temperate needleleaved (TeNE)	evergreen	3	intolerant	235	18	0.33



PFTs	Parameters					
	Leaf phenology	Leaf longevity (years)	Shade tolerance	Wood density (kgC m ⁻³)	SLA (m ² kgC ⁻¹)	Leaf Turnover (fraction/year)
Sub-tropical needleleaved (STrNE)	evergreen	3	intolerant	210	10	0.33
Sub-tropical rain green (STrRG)	raingreen	0.5	intolerant	200	25	1
Sub-tropical shade-tolerant evergreen (STrIBE)	evergreen	1	intermediate	265	20.85	1
Sub-tropical broadleaved evergreen (STrBE)	evergreen	2	tolerant	145	17	0.5
Tropical broadleaved shade-tolerant (TrBE)	evergreen	2	tolerant	290	22	0.5
Tropical Summergreen (TrBSG)	summergreen	0.5	intolerant	247	21	1
Tropical broadleaved raingreen (TrBRG)	raingreen	1	intolerant	245	18	1

241

242 3.4 Simulation protocol and model validation

243 Using the aforementioned forcing data and PFTs parameterized with traits, the model was
 244 run with 15 patches in each grid cell of 1000 m², simulating the period from 1901 to 2022.
 245 A spin-up of 500 years, recycling the first 30 years of the observed climate data set, was
 246 performed to achieve an initial steady state for vegetation structure. We ran LPJ-GUESS in
 247 cohort mode (Smith et al., 2001, 2014), using the BLAZE fire model to account for the
 248 impacts of weather-related fire disturbances on vegetation structure (Rabin et al., 2017)
 249 and applied a generic return interval of 100 years for patch-destroying disturbances,
 250 following Pugh et al.(2019).

251

252 We implemented a neighbour removal experiment in the model to assess the effects of
 253 competitive neighbour individuals and PFTs on the performance of the selected PFTs
 254 (Monteux et al., 2024). Individuals of all other woody PFTs except the PFT of interest were
 255 removed from the simulation after model year 1950. C₃ grass or C₄ grass forming the
 256 understory of the woody stand was retained. However, to allow the ecosystem to re-
 257 equilibrate and account for the effects caused by removing neighbours, we allowed target
 258 PFTs to grow for another 50 years (i.e., model year 2000) until the ecosystem recovered
 259 and productivity stabilized according to the prevailing environmental conditions.



260

261 We used Bi & Zhou (2022)'s gross primary productivity (GPP), produced using the leaf
 262 light use efficiency model from 2010 to 2020 (DRYAD), to compare with simulated GPP
 263 from 2010 to 2020 along the elevation gradient. Plot level above-ground carbon biomass
 264 data by Khanal & Boer (2023) estimated from the national forest inventory was compared
 265 with simulated patch-level carbon biomass from the model. Similarly, the bole height
 266 (height up to the first branch) measured and elevation range recorded by Maharjan et al.
 267 (2021) along the studied gradient were compared with simulated values to evaluate the
 268 model's ability to capture structure and compositional variability.

269

270 **3.5 Competition index and rank abundance curve (RAC) of FPC for evenness**

271 An index of competition was calculated for each PFT to quantify the effects of neighbour
 272 removal on the performance of the target PFT. The target PFT's performance was
 273 evaluated using simulated carbon mass production from 2000 to 2020 with and without
 274 competition. The competition index (CI) was calculated using the index matrices
 275 approach of Avolio et al. (2019) and Brooker & Kikvidze (2008) with modifications. We
 276 modified the equation by Avolio et al. (2019) and Brooker & Kikvidze (2008) to more
 277 intuitively represent each PFT's optimum competitive capacity relative to potentially co-
 278 occurring woody PFTs. A CI value of 1 indicates no effect from competitors, while a value
 279 close to 0 indicates a significant impact from the competitor's presence.

280

$$281 \quad CI_i = \left[1 - \frac{C_{mass-Ni} - C_{mass+Ni}}{\max(C_{mass-Ni}, C_{mass+Ni})} \right] \dots\dots\dots (Equ\ i)$$

282 where CI is the competition index in year i, C_{mass-N} and C_{mass+N} are the carbon masses
 283 of the target PFTs in the presence (+N) and absence (-N) of a competitor in year i.

284

285 The rank abundance curve (RAC) of relative foliar projective cover (FPC) of each tree PFT
 286 present in a grid cell was used to quantify species evenness, defined as similarity in local
 287 abundances among PFTs along the elevation gradient. Following Avolio et al. (2019),
 288 Smith & Wilson (1996) and Whittaker (1965), the natural logarithm of relative FPC was
 289 plotted against the inverse of PFT rank, and a regression between rank and log FPC was
 290 used to calculate the slope of the curve in each grid point using simulated FPC from 2000
 291 to 2022. The slope of the RAC was used as a robust (independent of species richness)
 292 measure of evenness by Smith & Wilson (1996). A steeper slope would indicate greater



293 dominance by one or a few PFTs relative to other co-occurring PFTs, while a flatter slope
294 indicates greater evenness. Evenness was plotted against elevation to examine the
295 patterns of change in evenness in relation to changes in growth conditions. Similarly, the
296 number of PFTs in each latitude band was used as an indicator of functional richness,
297 representing the diversity of ecological strategies. We hypothesise that with an increase
298 in elevation, evenness increases due to reduced competition, and the abundance of PFTs
299 decreases as environmental stress limits species adaptations in higher elevations.

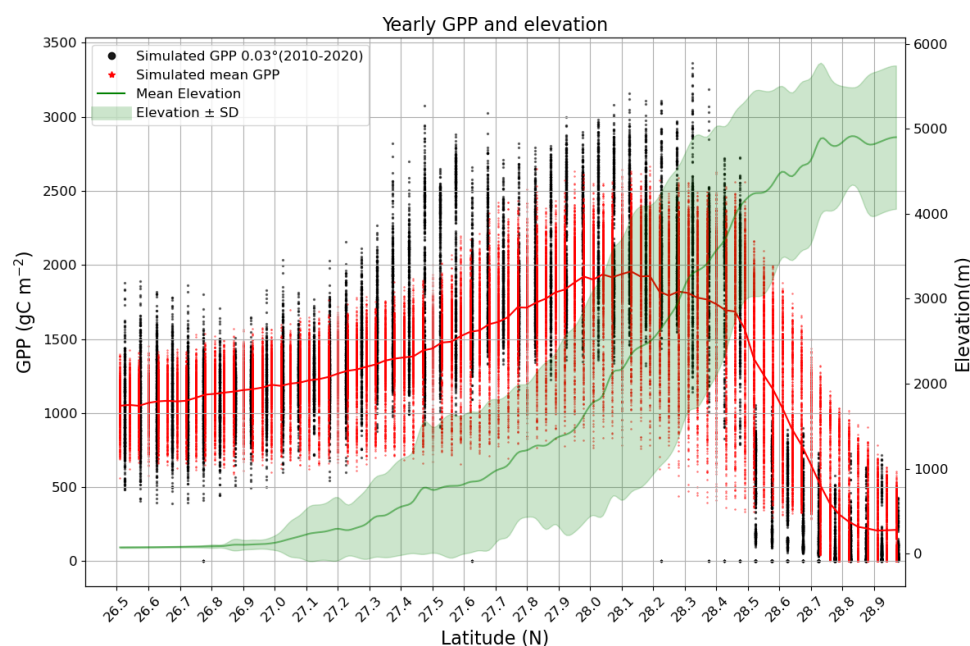
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301 **4. Results**

302 **4.1 Spatial variability in productivity and structure along the gradient**

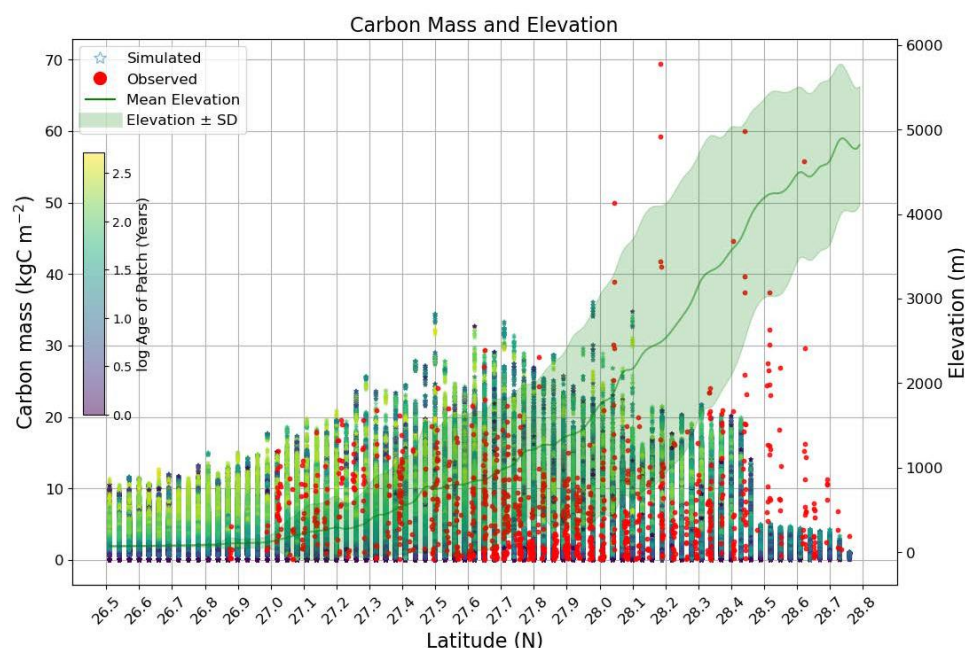
303 Simulated annual GPP showed strong agreement with GPP estimated by Bi and Zhou et
304 al. (2022) using the leaf light use efficiency model, both displaying a gradual increase in
305 productivity up to approximately 2500 meters. In both datasets, at the northern end of
306 the gradient, annual GPP decreased sharply as temperature declined, with some grids
307 having very low productivity (GPP value close to zero) (Figure 2). These patterns align
308 with shortening of productive seasons and decreasing temperature in alpine zones,
309 reflecting a shift from productive lower elevations to physiological constraints
310 (Supplementary Figures 2 & 3 for monthly GPP) at higher elevations.

311



312
 313 Figure 2: Simulated annual GPP (0.03°) and annual GPP from the DRYAD database (0.05°)
 314 from 2010 to 2020 across grids along the elevation gradient of the Himalayas.

315
 316 Simulated above-ground biomass at the patch level closely matched observed plot-level
 317 above-ground biomass in the forest area across the gradient, indicating that the model
 318 effectively captures spatial variability in carbon mass distribution (Figure 3). However, in
 319 the northern regions of the gradient, where *Rhododendron* PFTs dominate, the model
 320 underestimated the observed biomass (Figure 3). In contrast, the model slightly
 321 overestimated above-ground carbon biomass in the mid-latitude range (27.4 – 28.0 °N),
 322 corresponding to areas with higher PFT abundance. This mid-elevation peak in biomass
 323 accumulation, followed by a decline at higher elevation, suggests increasing physiological
 324 constraints under alpine conditions. Notably, the patch-level above-ground biomass did
 325 not show any patterns with the simulated age of the patch. In some simulated grids, young
 326 patches exhibited higher above-ground carbon productivity compared to older ones,
 327 suggesting that trait-based responses and environmental conditions have a stronger
 328 influence on productivity than patch age.

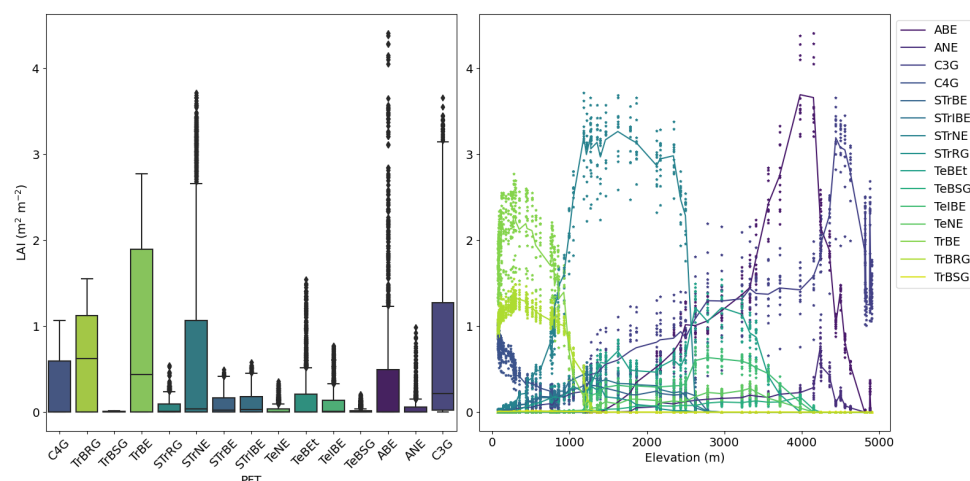


329

330 Figure 3: Simulated above-ground carbon mass per patch (2010-2015) with the age of the
 331 patch (in years) and observed above-ground carbon mass per plot in forest areas along
 332 the elevation gradient of the Himalayas.

333

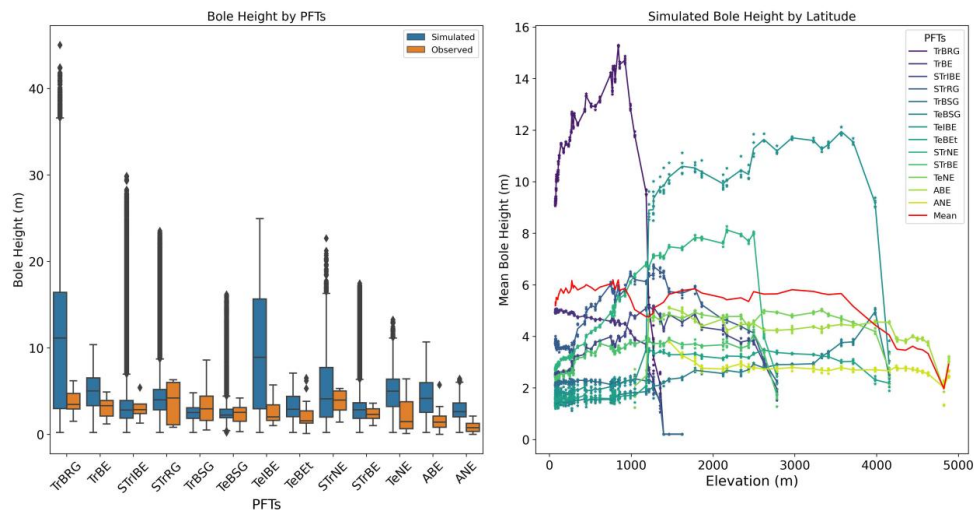
334 Similar to productivity and biomass, vegetation structural attributes also varied along the
 335 elevation gradient. Simulated leaf area index (LAI) for tree PFTs increases gradually along
 336 the gradient from around $5 \text{ m}^2 \text{ m}^{-2}$ to around $8 \text{ m}^2 \text{ m}^{-2}$, primarily due to the presence of
 337 evergreen PFTs at higher elevations, whose LAI remains constant throughout the year. Six
 338 PFTs contribute the most to LAI, each with varying zones (elevational range) of
 339 dominance. In the southern part of the gradient, two PFTs - tropical broadleaved
 340 raingreen and tropical broadleaved evergreen - exhibit higher PFT-specific LAI. Sub-
 341 tropical needle-leaved PFTs form maximum LAI in mid-latitude ($\sim 3.2 \text{ m}^2 \text{ m}^{-2}$), followed
 342 by alpine evergreen broadleaved ($\sim 4 \text{ m}^2 \text{ m}^{-2}$) in higher elevation. C_4 and C_3 grasses
 343 contribute significantly to LAI along the gradient, with C_3 grasses being dominant in cold
 344 regions, with an LAI of $3.2 \text{ m}^2 \text{ m}^{-2}$ (Figure 4).



345
 346 Figure 4: Boxplot of Simulated LAI by PFTs and line plot of LAI (line represents mean LAI
 347 for each PFT and dots representing LAI at simulated grid across latitude) across the
 348 elevation gradient by PFTs.

349
 350 The comparison of simulated (2010-2015) and measured bole heights shows that both
 351 follow the same patterns, although the model exhibits more pronounced variability
 352 across most PFTs (Figure 5). It shows that bole height varies with PFTs, with tropical
 353 broad-leaved raingreen (TrBRG) having a large bole height, followed by temperate shade-
 354 intolerant evergreen (TeIBE) (Figure 5). The overall mean bole height remains similar up
 355 to the temperate zone (approximately up to 3500 m), after which it decreases sharply,
 356 particularly in the upslope alpine zone, where bole heights remain smaller (Figure 5).
 357 This overall pattern of taller bole height at lower elevation likely reflects intensive
 358 competition for light, where individuals grow taller to avoid shading. In contrast, the
 359 decline in bole height in higher elevations is consistent with both physiological
 360 constraints and adaptive strategies that favour short bole height under alpine conditions.

361



362
363 Figure 5: Boxplot of simulated and observed bole height (median with ranges and
364 outliers) and bole height for PFTs (dot denoting the bole height of each cohort of PFTs
365 simulated in the grid), along with the mean bole height (red line) across PFTs along the
366 elevation gradient.

367
368 **4.3 PFT performance and competition index along the elevation gradient**

369 The result indicates that the total carbon mass production depends on both the
370 abundance of PFTs' and their location within the elevation range. It shows that total
371 carbon mass production at the ecosystem level is highest in lower elevations (around
372 1000 m), where climatic conditions supported a balanced contribution to productivity
373 from broadleaved evergreen, deciduous trees, and conifers (Supplementary Figure 4 for
374 total carbon mass production along the elevation). In lower elevations, tropical
375 broadleaved raingreen PFTs had the maximum carbon mass, whereas temperate shade-
376 intolerant evergreen PFTs had the maximum carbon mass production in temperate
377 regions. In colder areas, where only two tree PFTs were adaptive within their prescribed
378 bioclimatic limits, alpine broadleaved evergreens (*Rhododendron* species) have the
379 maximum contribution to carbon mass production. These findings highlight that PFTs'
380 composition and their contribution to carbon mass production are driven by their
381 climatic niche (elevational range) and adaptive capacity to existing climatic and
382 competition conditions (Figure 6).



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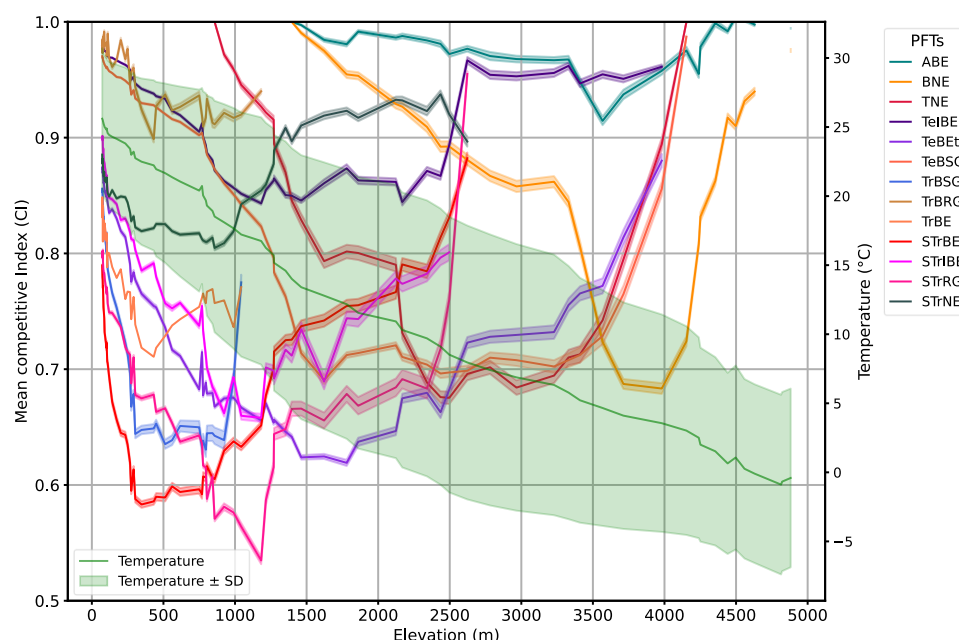
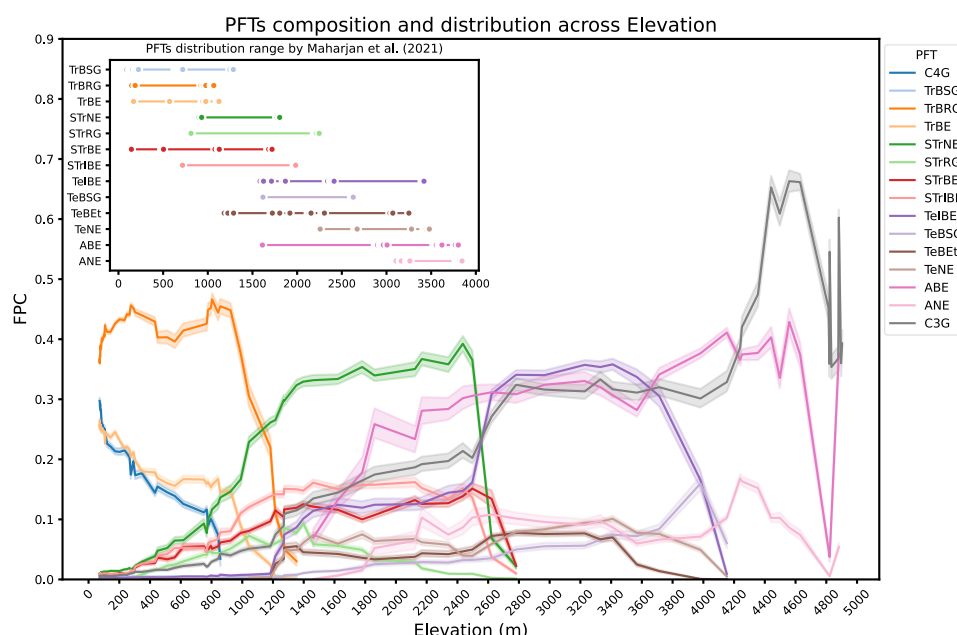


Figure 7: Mean competitive index of PFTs and mean annual temperature (green line) with standard deviation of temperature in the last 30 years (green shaded area) along the elevation gradient.

4.4 Community composition and evenness along the elevation gradient

The simulated results show that PFT composition and dominance change with elevation and associated temperature, where the number of PFTs decreases with an increase in elevation. In lower elevations, three PFTs - tropical broadleaved raingreen, tropical broadleaved evergreen, and C₄ grass - dominate despite over ten PFTs in that area. At the higher end of the gradient, alpine needle-leaved and alpine evergreen broadleaved form tree crown cover, where C₃ grass dominance increases with elevation, reaching up to 70% in FPC. Sub-tropical needleleaved and temperate shade-intolerant evergreen PFTs dominate the mid-elevation range, showing variability in PFT composition and distribution along the gradient. In the mid-elevation gradient, an area dominated by sub-tropical and temperate PFTs, PFT composition changes more frequently than the gradient's other ends (Figure 8).



417

418 Figure 8: PFTs distribution and composition by fractional projective cover along the
 419 elevation gradient (inset figure shows the PFTs distribution ranges recorded by Maharjan
 420 et al., 2021 in the elevation gradient).

421

422 The RAC coefficient value, calculated for each simulated grid using the FPC value of trees,
 423 shows that PFT's evenness increases rapidly along the elevation gradient starting from
 424 mid-elevation (after 2000 m) (Figure 9). As latitude increases, PFT abundance decreases
 425 significantly, from a maximum of 10 PFTs in lower elevations to just 2 in higher elevations
 426 (Figure 9). In the high PFT abundance area, the competition was higher, reflected by the
 427 competitive dominance of a few PFTs (Supplementary figure 5). For example, tropical
 428 broadleaved raingreen, tropical broadleaved evergreen in lower elevation, sub-tropical
 429 conifers, and subtropical intermediate shade tolerant broadleaves in the mid-elevation
 430 range (Supplementary figure 5). These patterns suggest a symmetrical competition for
 431 light and nutrients at lower elevation despite richness in species composition. In contrast,
 432 regions with low PFT abundance exhibited higher evenness (coefficient value close to 0),
 433 indicating reduced competition and a stronger role of environmental filtering. Here, plant
 434 adaptation to temperature and soil nutrient limitation becomes the primary driver of
 435 vegetation structure and composition. A more detailed breakdown of PFT-specific FPC



distributions and dominance patterns along the elevation gradient is provided in
 Supplementary Figure 5.

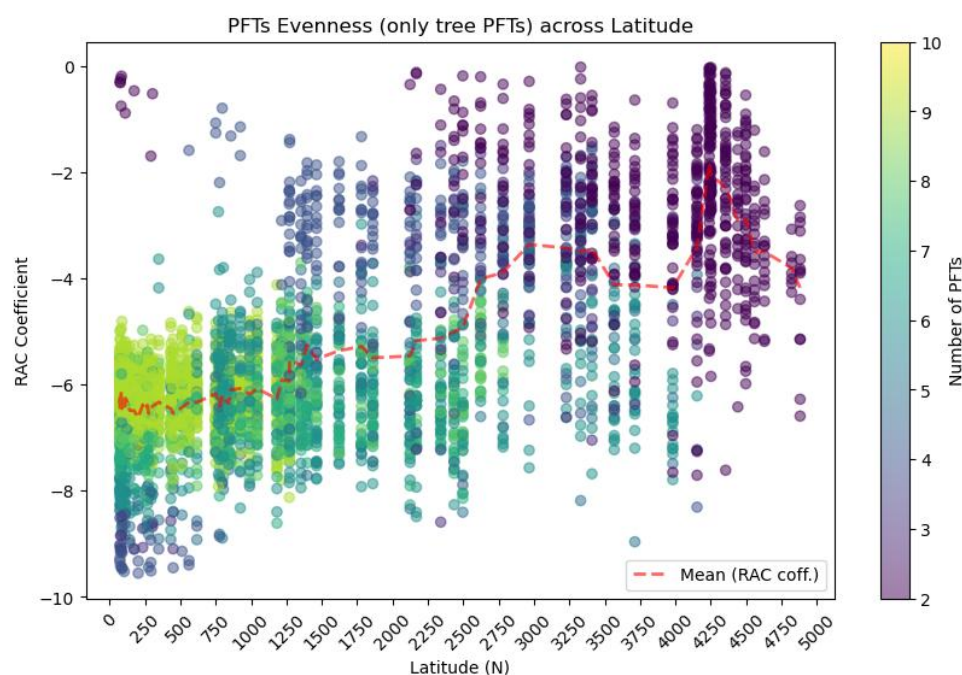
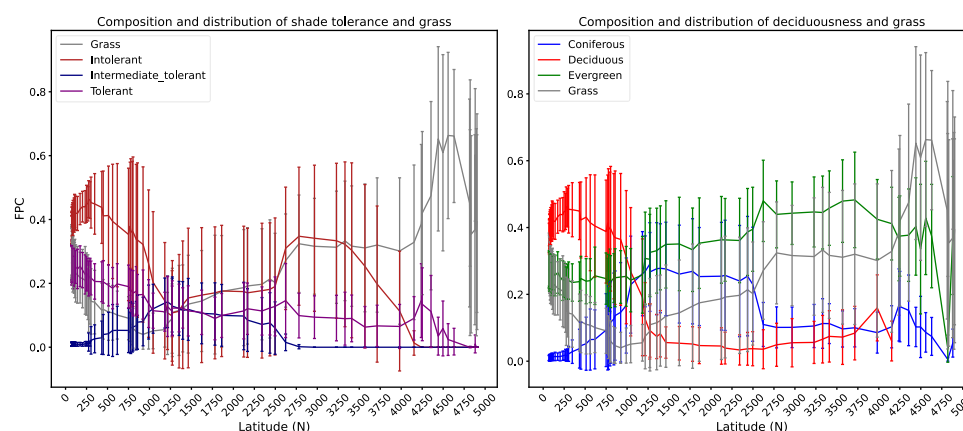


Figure 9: PFTs evenness (RAC coefficient) across latitude with the number of PFTs (present) in each simulated grid.

Deciduousness and shade tolerance are two dominant plant adaptation mechanisms of vegetation along the elevation gradient. The proportion of shade-tolerant species distribution decreases with elevation. Intermediate shade tolerance (*Schima wallichii*) has maximum FPC in the mid-elevation ranges (1200 - 2500 m), suggesting that these elevation ranges offer a balance in light and temperature conditions, favouring flexible growth strategies. The deciduous broadleaved species form dominant crown coverage in lower elevation, their contribution to FPC decreases with increased elevation, where cold temperature limit their performance. Evergreen conifer's contribution to FPC increases with an increase in elevation up to 4500 m, i.e., up to where *Pinus* species mostly grow (Figure 10). At the cold end of the gradient, the alpine broadleaved evergreen, especially *Rhododendron*, contributes the maximum in FPC. The dominance of evergreen trees at higher elevations reflects an adaptation strategy to cold climates, where year-round leaf



455 retention allows for rapid photosynthetic response to short favourable growing periods.
 456 Notably, around 1000 m elevation (Figure 10), both shade tolerance and deciduousness
 457 exhibit high evenness in PFT distribution, indicating a transitional zone where multiple
 458 plant adaptation strategies coexist due to overlapping ecological niches shaped by
 459 complex interaction between plant traits and environmental conditions.
 460



461
 462 Figure 10: Distribution and composition of PFTs adaptation strategies (shade tolerance
 463 and deciduousness) and grasses (line represents mean and bar represents standard
 464 deviation) along the elevation gradient.

466 5. Discussion

467 We evaluated the complex interaction between growth conditions, PFT abundance,
 468 productivity, and competitive interactions by simulating these assumed factors and their
 469 interdependent dynamics along the Himalayan elevation gradient. As expected, our model
 470 predicted shifts in ecosystem structure, composition, and productivity along the
 471 Himalayan elevational gradient, driven by shifting interactions between climatic
 472 conditions, especially temperature and nutrient availability, and plant adaptation
 473 strategies. Competition between co-occurring PFTs in crowded stands influenced the
 474 emergent composition and productivity, particularly at lower elevations, where warmer
 475 temperature and higher resource availability allowed species to occupy their realised
 476 niches. In contrast, colder and nutrient-limited conditions at higher elevations
 477 constrained community composition and structure to a few cold-tolerant species with
 478 short bole heights, operating within their physiological niches, resulting in more even but



less diverse stands. These patterns support our hypothesis that vegetation structures, composition, and productivity along the elevation gradient are structured by a shift from realised niches, defined by competitive interactions at lower elevations, to physiological niches, shaped by stress (freezing temperature) at higher elevations.

The model reliably reproduced key ecological patterns along the elevation gradient, with strong agreement between simulated outcomes and observations or independent reconstructed variables, supporting the plausibility of the results and the underlying mechanisms. Simulated GPP decreased with elevation, in agreement with the estimate from the leaf light use efficiency model by Bi & Zhou (2022), reflecting the dependency of GPP on temperature and growing-season length. This decline aligned with the distribution of cold-tolerant PFTs such as *Rhododendron* (ABE) and Coniferous species (ANE) found in higher elevations, consistent with the National Forest Inventory, which identifies that *Rhododendron* and *Abies* are the two most dominant species in higher elevations of the Himalayas (DFRS, 2015). Although the model does not represent detailed soil chemistry, the presence of these PFTs in the simulation aligns with their known adaptation mechanisms to high pH and low nutrients, characterized by a wide distribution range. Conifers and *Rhododendron* species are native to the Himalayan range and exhibit a wide physiological niche space that allows adaptation in high pH and low nutrient soil from temperate to alpine (sub-alpine) habitats (Thakur et al., 2024). The simulated results showed that the above-ground carbon biomass gradually increases before a significant decline with elevation (temperature) due to climatic stress, which is consistent with the patterns reported by Thakur et al. (2024). The higher estimation of observed values at the higher elevation could arise from variability in topographic factors that create favourable microclimatic conditions for the growth of *Rhododendron* and *Abies* forests, particularly in deep gorges and on southern aspects. The Himalayas region is characterized by a unique environmental condition where temperature and soil water availability vary on a short spatial scale (Thakur & Chawla, 2019; Tito et al., 2020) resulting in structural diversity and competitive dynamics, allowing certain PFTs to extend their realised niche beyond broader patterns along the gradient.

Vegetation structure along the elevation gradient was significantly impacted by the environmental conditions. In lower elevations, where climatic conditions are more



512 favourable and soil nutrients are abundant, PFTs tend to exhibit higher bole heights as a
 513 strategy to maximize light interception, avoid asymmetric competition for light, and
 514 reduce shading for competitors. Additionally, taller bole height of trees in these
 515 conditions may result from a trade-off, where some resources are allocated away from
 516 other parts, such as stem and branch development. Pokhrel and Sherpa (2020) also found
 517 that tree height, DBH, and above-ground biomass are significantly associated with
 518 elevation along the elevation gradient of the central Himalayas. With the increase in
 519 altitude, tree growth declines, and light competition also declines, where trees tend to
 520 have similar basal area and total tree height (Coomes and Allen, 2007). In contrast, LAI
 521 increased with an increase in elevation. In higher elevations, an increase in LAI was
 522 associated with the abundance of evergreen vegetation (Figure 5 & 10), especially
 523 *Rhododendron* and *Abies* species. *Rhododendron* presence in higher elevations is linked
 524 with survival strategies, including heat dissipation to avoid damage by excessive radiation
 525 in warm seasons and physiological mechanisms such as increasing intercellular fluid
 526 concentration and using reactive oxygen to withstand chilling temperatures (Li et al.,
 527 2022). However, these strategies are explicitly not represented in our model. Additionally,
 528 traits such as reduced height, smaller individual leaf area, lower SLA, and trade-offs in
 529 vessel diameter and density could also facilitate the wide distribution of *Rhododendron*
 530 species (Pandey et al., 2021).

531

532 The simulated vegetation community exhibited a distinct shift in compositional patterns
 533 across the elevation gradient. In lower elevations, the coexistence of a large number of
 534 PFTs resulted in higher functional diversity, likely due to favourable growth conditions, as
 535 the presence of large PFTs within their physiological niches led to higher competitive
 536 dominance by a few PFTs. Among 10 different PFTs, *Shorea robusta* (PFT-TrBRG) emerged
 537 as the dominant climax species at the lower elevations, showing consistency with national
 538 forest inventory data, which shows that *Shorea robusta* and its associated species, such as
 539 *Terminalia alata*, *Mollunthous philippines*, and *Lagerstroemina parviflora*, are the most
 540 common and productive in terms of biomass in the southern part of the central Himalayas
 541 (DFRS, 2015). Its competitive dominance and higher productivity were associated with
 542 drought and fire resistance (Gautam and Devoe, 2006). In contrast, higher elevations
 543 supported only a few PFTs (Supplementary Figure 5), with community composition
 544 shaped by abiotic stress such as low temperature and short growing seasons (Figure 7).



545 Ahmad et al. (2025) also stated that functional diversity is higher in lower elevation, even
 546 though species richness and phylogenetic diversity are higher in mid-elevation across the
 547 Himalayas. This pattern is broadly consistent with the stress-gradient hypothesis, which
 548 posits that abiotic stress dominates in harsher conditions, and competition is more
 549 influential in a benign environment (Bertness and Callaway, 1994). Additionally, the
 550 simulated PFTs composition is consistent with Mid-domain effects (Colwell and Lees,
 551 2000; Smith and Wilson, 1996) with a large number of PFT peaks at the intermediate
 552 elevation range (1000- 2000 m), likely due to geometric constraints on range overlap
 553 (Figures 6, 8, and 10). The overall species composition pattern showed a monotonic
 554 decrease in species richness and diversity with increasing elevation gradient, with higher
 555 heterogeneity and the presence of unique species adapted to extreme climatic conditions
 556 (Sekar et al., 2024). At the lower end of the gradient, with more seasonal rainfall and dry
 557 conditions, the vegetation was characterized by lower evenness and higher competitive
 558 dominance, as PFTs relied on realised niche occupation (Figure 8).

559

560 The PFTs' performance and dominance along the gradient depended on the climatic
 561 condition and their allometric relations. Overall, tropical broadleaved raingreen (TrBRG)
 562 was the most productive, followed by temperate evergreen (TeIBE) and alpine evergreen
 563 (ABE) across the elevation gradient. This result is consistent with the national forest
 564 inventory report, which states that *Shorea robusta* (37.83 ton ha⁻¹), *Quercus* species
 565 (46.09 ton ha⁻¹), and *Rhododendron* species (11.22 ton ha⁻¹) are the most productive
 566 species in Nepal, with significant contributions from Pinus species (DFRS, 2015). Khanal
 567 et al. (2024) also concluded that species growth and carbon mass production depends on
 568 the wood density and size-density relation. *Rhododendron* (ABE) demonstrated wide
 569 niche space, and *Shorea robusta* (TrBRG), with its strong climatic niche and role climax
 570 vegetation, illustrates how PFT performance is shaped by the climatic niche at the
 571 elevations in which the species occurs. The results show that competitive dominance was
 572 not visible in higher elevations, with no individual PFTs becoming dominant. Similar to
 573 our finding, Naud et al. (2019) also highlighted that no individual species becomes
 574 dominant with increased altitude when species richness decreases, which is similar in the
 575 Himalayas.

576



577 A range of mechanisms, including deciduousness, shade tolerance, and drought
 578 resistance, contributed to the presence and abundance of PFTS under different
 579 environmental conditions along the gradient in our simulations. In lower elevations,
 580 deciduousness as an adaptation to escape seasonal drought was dominant, whereas, in
 581 higher elevations, cold and shade tolerant PFTs were abundant, reflecting their functional
 582 strategy to adapt to stresses such as cooler temperatures, shorter growing seasons, and
 583 harsher growing conditions. Similarly, allometric traits such as crown dimension-DBH,
 584 height-DBH, and wood density affected competitive interaction and competitive
 585 dynamics. In lower elevations, PFT coverage in the crown showed a clear hierarchy with
 586 the differences in competitive dominance in productivity and FPC. Previous studies have
 587 shown that traits shape the distribution of vegetation (Maharajan et al., 2021), and
 588 competition determines productivity under favourable conditions (Sauter et al., 2021).
 589 Our study further emphasized that growth conditions, coupled with biotic and abiotic
 590 interactions, and trade-offs between growth and adaptation to multiple stresses drive the
 591 overall ecosystem functioning along the elevation gradient. This is reflected in differences
 592 in productivity and vegetation structure along the elevation gradient, with variation in
 593 species abundance and evenness according to environmental conditions.

594

595 **5.1 Limitations**

596 We used high-resolution climate data (3 km) as forcing data to capture heterogeneity in
 597 climatic conditions along the elevation gradient. This approach successfully captured
 598 broad elevational patterns in the dynamics and composition of the ecosystem. However,
 599 the model does not fully capture the variability in microclimatic conditions created by
 600 small-scale topography. This may partially account for the underestimation of above-
 601 ground carbon stock, especially in high elevations. With the elevation increase, climatic
 602 heterogeneity amplifies with more diverse climatic conditions (Guan et al., 2024).
 603 Integrating slope and aspect in the model could enhance its ability to characterize
 604 vegetation dynamics and composition dynamics, particularly in mountain regions where
 605 variation in radiation, soil moisture, and temperature across slope orientations plays a
 606 crucial role.

607

608 Even though dynamic vegetation models like LPJ-GUESS integrate competition for space,
 609 light, and soil resources among neighbouring plants, this competitive framework may not



610 fully account for how trait-based plasticity alters competitive interactions under different
 611 growth conditions. This can limit the model's ability to capture the full range of ecosystem
 612 dynamics. Integrating the allometric relation defined based on growth (competition)
 613 conditions helped to better characterise above-ground competition for light and space,
 614 whereas competition for below-ground resources, i.e. water and nitrogen in the model,
 615 largely follows proportionately with plant size. In reality, differential root profiles,
 616 including deep water access via tap roots characteristic of certain tree taxa, and other
 617 factors such as mycorrhizal associations or release of root exudates to promote nutrient
 618 mineralisation and uptake are known to predict plant success in environments
 619 characterised by below-ground resource limitations (Freschet et al., 2021). Dynamic root
 620 allocation based on resource availability in different layers is not currently simulated in
 621 LPJ-GUESS. Integrating root trait data, especially the distribution of fine roots in different
 622 soil profiles, root and mycorrhizal association (De Paula et al., 2021), and interlinking
 623 them with soil depth, may better capture below-ground competition processes. The
 624 current version of LPJ-GUESS incorporates a climate-driven prognostic wildfire scheme
 625 (SIMFIRE-BLAZE; Rabin et al., 2017) which impacts the composition, structure, and
 626 dynamics of the vegetation. However, other forms of disturbance, such as wood cutting
 627 and managed fires, herbivory, insect pest impacts, and wind-throw shape vegetation
 628 composition and demography, compounding with the biophysical and ecological
 629 mechanisms included in the model (Brewer, 2011; Grime, 1973; Hall et al., 2012; Laurent
 630 et al., 2017).

631

632 **6. Conclusions**

633 After incorporating trait data and allometric relations reflecting regional PFTs from our
 634 Himalayan study region, we successfully reproduced spatial and temporal patterns in
 635 vegetation composition, structure, and productivity along the elevation gradient. Our
 636 model shows that environmental conditions, biotic and abiotic interactions, allometric
 637 relations, and associated functional trade-offs jointly shape ecosystem processes and
 638 drive the competition patterns and adaptation mechanisms of vegetation along the
 639 elevation gradient. At the productive end of the gradient, competitive interactions among
 640 woody PFTs in crowded stands had a strong influence on PFT performance and
 641 abundance. These interactions, together with the realised niches of PFTs, led to reduced
 642 evenness in PFT distribution, as certain PFTs become dominant in different climatic



643 conditions. This did not translate into higher PFT richness in the way predicted by
 644 classical niche theory, suggesting favourable environmental conditions may buffer
 645 competitive exclusion and promote species coexistence despite competitive dominance
 646 hierarchies. In contrast, under more stressful conditions, only a few PFTs survive and
 647 grow, exhibiting higher evenness in composition and shorter stature. The increase in
 648 evenness with elevation reflects reduced crowding and weak asymmetric competition,
 649 with the surviving PFTs adapting and persisting by occupying their physiological niches
 650 in response to prevailing abiotic stress, particularly cold and freezing temperatures. Our
 651 findings highlight how variations in climatic conditions, resource availability, the climatic
 652 niche of PFTs, and unique adaptation mechanisms interact with PFT traits and adaptation
 653 strategies to shape vegetation composition patterns and productivity, thereby acting as
 654 overall controls on ecosystem function along the gradient. Further study, integrating
 655 heterogeneity in topographic conditions with different disturbances, along with a
 656 representation of underground competition (especially root profiles and groundwater
 657 dynamics), could enhance our understanding of ecosystem responses to global changes
 658 and extreme events, as well as their adaptation mechanisms in the central Himalayas.

659

660

661 **Code and Data Availability**

662 The customized LPJ-GUESS version used in this study has been archived in the **LPJ-GUESS**
 663 **Zenodo community** [<https://doi.org/10.5281/zenodo.17214801>]. The forcing data,
 664 simulated output, that reproduce the analyses presented in the manuscript have been
 665 deposited in **Zenodo** [<https://doi.org/10.5281/zenodo.17214851>].

666

667 **Author Contribution**

668 **PP:** conceptualization and design (lead); data curation (lead); simulation (lead); formal
 669 analysis (lead); writing – original draft (lead); writing – review and editing (lead). **SO:**
 670 Supervision (supporting); writing – review and editing (supporting). **MT:** Supervision
 671 (supporting); writing – review and editing (supporting); Supervision (supporting);
 672 writing – review and editing (supporting). **MP:** Supervision (supporting); writing –
 673 review and editing (supporting). **DM:** Supervision (supporting); writing – review and



674 editing (supporting). **BS:** Supervision (lead); conceptualization and design (supporting);
 675 writing – original draft (supporting); writing – review and editing (equal).

676

677 **Competing Interest**

678 The contact author has declared that none of the authors has any competing interests.

679

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684

685 **7. Reference**

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