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69	Abstract
70	Survival rates of large trees determine forest biomass dynamics. Survival rates of small
71	trees have been linked to mechanisms that maintain biodiversity across tropical forests. How
72	species survival strategies change across size globally offers insight into the links between
73	biodiversity and ecosystem function across tropical forests. We tested patterns of size-dependent
74	tree survival across the tropics using data from 1781 species and over two million individuals to
75	assess whether complex and diverse tropical forests can be characterized by size-dependent life-
76	history survival strategies. We found species, across the tropics, were classifiable into four
77	"survival modes" that explain life-history strategies shaping the terrestrial forest ecosystem
78	carbon-cycle budget and also display the full range of life forms in the forest, from shrubs to

emergent canopy trees. Frequently collected traits, such as wood density, leaf mass per area, and 79 seed mass, were not generally predictive of these survival modes, suggesting poor alignment 80 81 between those traits and survival strategies across tropical forests. Mean annual temperature and cumulative water deficit predicted the proportion of biomass of survival modes, indicating 82 important links between evolutionary strategies, climate, and carbon cycling. We also applied 83 84 survival modes in demographic simulations to accurately predict biomass change over time in sites for which we had long-term data. Our results reveal globally identifiable size-dependent 85 survival strategies that differ across diverse systems in a consistent way. These modes and their 86 interaction with climate ultimately determine forest structure, carbon storage, and can link 87 climate change to future forest states. 88

Tropical forests store an estimated 500-1000 Pg of C in biomass and soils^{1,2}, making this 89 biome the most important component of the terrestrial carbon cycle. Whether intact tropical 90 forests will be sinks or sources of carbon in the future remains a critical question^{1,3} that will 91 fundamentally depend on how different forest species respond to climate change⁴. The great 92 diversity of tropical forests might buffer stands from shifts in standing biomass or might promote 93 94 changes due to the characteristics of the species that best tolerate novel climate conditions. 95 Forest carbon volume depends exponentially on the annual rate of tree survival, and tree survival rates in turn depend on climate⁵ and the strategies species use to tolerate climate variation. In 96 97 most forests, survival strategies range from short-lived species that die within decades to longlived species that retain carbon for centuries. Changes in forest composition due to differential 98 99 survival responses of species to novel climate variation or new regimes of extreme episodic events (i.e. droughts and storms), may cause large and rapid changes in the terrestrial carbon 100

balance that could potentially persist for centuries because different strategies may prove 101 differentially vulnerable to such changes. Climate-driven impacts on tree survival are potentially 102 more important than impacts on forest productivity (i.e., photosynthesis and allocation to 103 growth), which has a relatively constrained and slower influence on forest carbon dynamics⁶⁻⁹. 104 For species to coexist in diverse forests, they must have roughly equivalent fitness over 105 long time periods^{10,11}, yet differences in achieving that fitness can influence compositional shifts 106 when faced with novel long-term ecological changes. Tree species have evolved resource 107 108 allocation strategies that, over the course of life-history, emphasize investment in metabolic 109 maintenance, structural, defensive, and reproductive tissues. Variation in these allocation 110 strategies leads to variation in demographic rates (i.e. survival, growth and reproduction). The survival rates that emerge from allocation to maintenance, defense, and structure, can then 111 determine observed population distributions across space¹², size, and age structures¹³. Allocation 112 to tissues that increase survival are typically negatively correlated (or "trade-off") with allocation 113 to tissues involved in other demographic rates¹⁴. For example, using resources to build defensive 114 structures reduces resources available for growth. Allocation to tissues for increased survival can 115 lead to distinct vulnerabilities to stressors, such as pathogens¹⁵, pests, storms, drought, or 116 extreme temperatures¹⁶, or the reverse. Tolerance of climate change may vary with allocation 117 strategies resulting in important implications for forest biodiversity and carbon stocks. Greater 118 119 understanding of allocation strategies and how demographic rates vary with size should increase our ability to predict how diverse forests cycle carbon and provide insights into potential shifts in 120 those cycles. 121

Here we quantify tree survival strategies to provide a deeper understanding of basic ecological and evolutionary features of tropical forests. Using an exemplary dataset of more than two million trees across the tropics, we developed models of size-dependent survival. Using a cluster analysis, we aggregated the results of these models into groups of similar survival strategies that we call 'survival modes'. We then explore how these modes reflect important features of tropical forest carbon and diversity dynamics.

To understand the ecological significance of these survival modes, we : 1) investigated how survival modes contribute to carbon fluxes through differences in growth rates and biomass turnover; 2) examined if the modes of survival that emerge from the demographic data are related to the commonly collected plant traits of wood density, leaf mass per area and seed mass; 3) tested whether the relative abundance of these survival modes relate to climate variables and 4) tested the predictions of our model results against the observed biomass at each site through time.

135 **Results**

Survival models were fit for 1781 species occurring across 14 pan-tropical large area forest 136 dynamics plots (ranging from 2 to 52 ha each with 371 ha in total in which all stems ≥ 1 cm 137 diameter at breast height are recorded (Supplementary Table 1). The parameters from these 138 models were included in a principal component analysis (PCA) (Fig. 1 details the workflow). 139 140 The PCA revealed clear axes of evolved life-history strategies (Supplementary Fig. 1). For example, PCA axis one defines a continuum characterized by relatively stable survival 141 probability across the life-cycle at one extreme (either high or low survival) and at the other by 142 143 notable increases and decreases in survival probability with size at small and large sizes 7

respectively, i.e. species with more extreme thinning due to competition for resources when
relatively small, and senescence or mortality causes related to old age and exposure in the other
direction. Axis two differentiates species based on long-term survival rate (i.e. the upper
asymptote of the survival curve).

Species were hierarchically clustered by loadings of the PCA analysis which creates a dendrogram from a similarity matrix. An optimizing analysis of the inertia of cluster numbers across the dendrogram resolved four survival modes (Fig. 2, Methods). To test the robustness of our survival modes, we bootstrapped the Jaccard similarity index for all clusters which were well above the 0.75 threshold¹⁷ indicating stable clustering for our size-dependent survival modes (Supplementary Table 2).

Although annual survival probability across much of the life-cycle was high for most species (greater than 0.95), there were species with much lower long-term survival rates (less than 0.78, Supplementary Table 2). Further, the degree of juvenile mortality varied between modes indicating differences in the strength of mortality mechanisms in small sizes across the four modes. Finally, there were also clear differences between the maximum sizes at which species showed increased mortality (senescence) indicating important mode-dependent lifeexpectancies (Fig. 2).

161 The four survival modes clustered along multiple axes, but there was a clear delineation 162 among species of size at senescence which allows us to group them by life form. *Understory* 163 species are characterized by their small maximum diameters, with an across-site mean 99th 164 percentile diameter of 9.8 ±2.4 cm (mean ±1 sd). *Transient* species are distinguished by their 165 very low overall survival with an across-site mean maximum-survival rate of 78% yr⁻¹ and an 167 8

166	across-site mean 99 th percentile diameter of 14.3 \pm 9.4 cm. There are two groups of large stature
167	tree species or species capable of reaching canopy sizes. Canopy species are the group with
168	intermediate maximum size, across-site mean 99 th percentile diameter of 27.8 \pm 7.0 cm and lower
169	small-diameter survival rates compared to Large Canopy species which have larger maximum
170	diameter, across-site mean 99 th percentile diameter of 68.4 \pm 18.5 cm and relatively higher
171	survival at smaller diameters. Our analysis has an abundance threshold of 200 individuals;
172	species with lower abundance are Unclassified, and it is possible that some of them display other
173	survival modes that were too rare to describe statistically.
174	Survival modes varied in abundance (Supplementary Table 3) and dynamics across
175	forested plots (Fig. 3). The Canopy mode was typically the most species rich, followed by the
176	Understory and Large Canopy modes (Supplementary Table 4). The species included in the
177	cluster analysis represented 76.7% (range: 46.9-97.0%) of the biomass on average across the

178 plots (Supplementary Table 3 & Supplementary Fig. 2).

179 We calculated carbon lost to mortality at each site in order to understand the influence of these survival modes on carbon residence times. Total carbon loss from tree mortality ranged 180 from 0.14 - 5.6 Mg C·ha⁻¹·yr⁻¹ with a mean of 2.28 Mg C·ha⁻¹·yr⁻¹ for all survival modes 181 including Unclassified (Fig. 3). The Lambir plot in Malaysia had the highest absolute rate of 182 annual carbon loss. The dry tropical forest Palamanui plot in Hawaii had the lowest rate of 183 184 annual carbon loss due to tree mortality. Somewhat surprisingly, the plots that are commonly struck by typhoons and hurricanes (Luquillo, Palanan and Fushan) had intermediate rates of 185 186 carbon loss due to mortality even though the plots experienced storms during sampled intervals, 187 demonstrating that species at these sites are potentially selected to tolerate disturbances instead

of recover from them. The overall portion of carbon loss due to mortality varied greatly among
these forests, though on average Indo-Malaysian forests had the highest rates of absolute carbon
loss (Fig. 3); alternately, relative to total biomass neo-tropical forests lost slightly more biomass
(Supplementary Table 3).

Common plant traits had limited ability to predict survival modes, indicating that species 192 193 within given survival modes were diverse in these traits. Only the Transient mode was significantly less dense wood that the other survival (ANOVA F= 9.65, p-value<0.001, Fig 4a), 194 when we limited the analysis to sites (7 of 14) that had locally collected wood density values the 195 Large Canopy and the Transient groups had significantly lower wood density than the 196 Understory and Canopy survival modes (Supplementary Fig. 3). Leaf mass per area (LMA) 197 varied significantly among survival modes, with the *Transient* and *Large Canopy* species having 198 significantly lower LMA than the Understory and Canopy species (ANOVA, F=7.28, p-199 value<0.001) (Fig 4b). The relation between the natural log of seed mass and survival mode 200 201 revealed no significant difference among clusters (ANOVA F=2.26, p-value= 0.086) (Fig. 4c). These analyses were constrained by the low current availability of functional trait data: LMA 202 was only available for 40.4% and seed mass for only 8.1% of species. This result does, however, 203 204 support an emerging consensus in the trait literature that using traits as proxies for life-history strategies may be constrained to specific contexts and questions, and does not offer an easy link 205 between measurements and performance¹⁸⁻²⁰. 206

We related mean annual temperature (MAT), mean annual precipitation (MAP) and cumulative water deficit (CWD) at each forest to the relative percent biomass of *Large Canopy* survival mode species (Supplementary Fig. 4) to understand if there were climate dependencies

in survival mode composition. Multiple linear tobit regression (p-value = 0.000083, McFadden's 210 pseudo $R^2 = 0.24$, note this is not the same as OLS R^2 and a model with a statistically good fit to 211 the data will have McFadden's pseudo- R^2 between 0.2 and 0.4) indicated that Large Canopy 212 biomass relative abundance had a negative relation to MAT, but had a positive relation to CWD 213 and no relation to MAP. The relative percent biomass of *Canopy* and *Large Canopy* survival 214 215 modes were inversely related (Supplementary Fig. 2). Transient survival mode biomass was miniscule and was not modeled. The Understory mode relative biomass was positively related to 216 MAT (p-value = 0.031, McFadden's pseudo $R^2 = 0.12$), but lacked any significant relation to 217 CWD or MAP. 218

To further explore the characteristics of the survival modes, especially to understand how 219 survival and growth interact to affect the progression of individuals through their life-cycle, we 220 calculated mean growth rates by survival mode. We found that growth rates significantly differed 221 222 among survival types where the *Large Canopy* survival mode had the largest mean annual growth rate 2.18 mm·yr⁻¹, while the *Understory* survival mode was the slowest growing 0.52223 $\text{mm} \cdot \text{yr}^{-1}$ (Fig. 5). A similar pattern was found when we expressed growth in terms of biomass 224 accumulation (Supplementary Fig. 5). The Canopy mode has nearly half the growth rate of the 225 226 Large Canopy mode suggesting carbon residence times of these two groups may be similar, but the *Large Canopy* mode would sequester more carbon in a similar time frame. 227

We found strong correlation (marginal R² 0.97) between observed biomass in each survival mode and biomass predicted from an Individual Based Model (IBM) run at each site, in which individuals were classified by survival mode (Fig. 6). Biomass was small and changed little across census intervals, particularly for the *Understory* and *Transient* survival modes. The

accuracy of predictions of biomass varied for the *Large* Canopy and *Canopy* modes. Predicted
biomass was underestimated in the *Large Canopy* mode at Lambir and Laupahoehoe by 47.68
and 42.15 Mg·hectare⁻¹, respectively. In contrast, expected biomass was overestimated in the *Canopy* and *Large Canopy* modes at BCI, by 14.45 and 26.62 Mg·hectare⁻¹ respectively.

236 Discussion

Our results provide objective and quantitative descriptions of global size-dependent tropical tree 237 survival that reflect some of the classic descriptors of tree species demographic strategies²¹. We 238 239 discovered groups of species that differ in how they survive as they grow. We found mortality at small sizes varies among the survival modes, likely reflecting the tradeoffs inherent in competing 240 for limited resources (e.g. light) in the understory²², or susceptibility to pests²³ and 241 pathogens^{24,25}. We also found that survival modes varied in their senescence phase, where causes 242 of mortality are likely driven by reallocation of resources from resistance or tolerance of 243 structural damage²⁶, water limitation¹⁶ and accumulation of pathogens²⁷ to increased investment 244 in reproduction. Our contention that this difference in survival at large sizes is a life-history 245 strategy and not simply a product of a lower average survival rate for earlier senescing modes is 246 supported by the fact that three of the four modes had very similar maximum survival rates, but 247 differed remarkably in their size at senescence. 248

Past studies have indicated that tree survival under environmental stress can depend on tree size^{16,28}. We discovered that climatic factors correlated well with the relative biomass of survival modes. The climate correlates with different proportions of survival modes suggests differences in carbon residence times and forest structure with climate. Higher relative biomass in the *Large Canopy* survival mode was observed in forests with lower MAT and longer dry

seasons and less *Canopy* species biomass. Considering that larger individuals can be more 254 susceptible to drought¹⁶, the cumulative water deficit result seems counter-intuitive at first, but it 255 may be that these species are deciduous or have particular adaptations for water limitation 256 tolerance in forests with intense dry seasons. Alternately, the prevalence of the Large Canopy 257 mode may be driven by other environmental factors not considered here, such as soils or 258 259 biogeographic history. The increase in the prevalence of the *Understory* mode with increasing temperature suggests an advantage to being shaded in warmer forests. Indeed, photosynthetic 260 efficiency and stomatal conductance decline above a temperature threshold²⁷, which may provide 261 262 an advantage to being shaded in warmer forests though the best fit to the data was linear. Differences in the dominance of these survival modes among tropical forests are likely driven by 263 many mechanisms and understanding those drivers is an important next step towards accurately 264 forecasting the fate of forests. 265

Widely collected plant traits explained some of the differences in size-dependent survival 266 267 modes in our analysis. Wood density has been previously recognized as a significant predictor of tree survival^{29,30} and growth-survival trade-off in saplings³¹, but variation in size-dependent 268 survival was not explicitly considered in those analyses. We found that clear associations 269 270 between trait means and survival modes were demonstrated only for the Transient mode, which likely describes many aggressive light-dependent pioneering species. Lower LMA in the 271 272 Transient and Large Canopy modes combined with mean growth rates of those modes suggests that those species likely have higher metabolic costs, potentially lower leaf nitrogen 273 concentrations, and shorter life leaf-span³². Variation in seed mass may reflect a suite of 274 strategies independent from allocation to size-dependent survival at the sizes we examined. Seed 275

mass among reproductive adults might correlate better with individual growth rates or different
species' reproduction life-history strategies³³ and seed mass may correlate with survival in
individuals < 1cm diameter at breast height (DBH).

279 Our model predictions fit observed forest biomass well in an IBM. Despite large amounts of demographic data being available globally, few studies have moved beyond descriptions of 280 281 mortality averaged over species or coarse size classes. Models in which survival probability changes as a continuous function of size are necessary to accurately represent the variation in the 282 283 way that individuals of different species move through the life-cycle, thus allowing more biologically nuanced forward projection of populations and communities. Even when combined 284 with a relatively simple growth model, the survival modes presented here were able to capture 285 the change in biomass at each site attributed to each survival mode. 286

The IBM projections demonstrate that our survival modes might offer benchmarks for 287 biome models that simulate forest dynamics at a global scale (e.g. terrestrial biome models 288 (TBMs)) or dynamic global vegetation models (DGVMs), where vegetation is coupled with 289 climate. Attempts at modelling carbon fluxes in DGVMs have led to very divergent results due 290 to the potential response of forests, both in estimates of future atmospheric carbon³⁴ and in 291 terrestrial vegetation carbon stocks⁶. The evolutionary strategies of tree survival, integrated 292 within the ecological models of environmental conditions might provide a better pathway 293 towards forecasting these diverse systems^{6,35}. To do so, however, requires integration of field 294 data, statistical models, and size-structured TBMs that can accept demographic data as inputs. 295 296 We compared the observed mortality rates from our plot data with mortality rates from one size-297 structured DGVM, Functionally Assembled Terrestrial Ecosystem Simulator (FATES), with one

298	tropical broadleaf evergreen plant functional type ³⁶ . We found that FATES underestimated small
299	tree survival, but over-estimated large tree survival compared to our data. Specifically, the
300	annual mortality rate of trees larger than 70cm DBH in FATES was 1.47%, while the observed
301	mean annual mortality rate from ForestGEO plots for the same size class was 2.85%
302	(Supplementary Fig. 6), which could result in overestimation of carbon storage in the FATES
303	model. This deviation of the FATES model is not on the surface a large error; however mortality
304	rates compound annually, and this almost two-fold underestimate of annual mortality reflects a
305	significant mismatch to the pace of forest dynamics over decades. Incorporation of size-
306	dependent survival constraints could improve how we assess, and perhaps how we model
307	mortality for the suite of DVGMs that can incorporate size-based survival ³⁷ .
308	Despite the large range of species diversity and biomass turnover represented in our
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318 Methods

We used a global dataset of tree demography to build models of survival probability as a 319 function of size. We used data from 14 plots that follow the same methodology: all woody stems 320 \geq 1cm in diameter at breast height have been identified to species, mapped, and measured every 321 five years (following³⁸ and summarized in Supplementary Table 1). All species with > 200322 observations across the censuses were included in the following analyses, comprising a total 323 sample of over two million individuals in 1781 species. All analyses were conducted in R³⁹. 324 We estimated size-dependent survival by fitting a functional form to the data for every 325 species in each census interval (see Fig.1 for workflow diagram). We used a Bayesian 326 framework (see Supplementary Table 5 for details of model fitting), and fit the model in R using 327 Stan⁴⁰. The basic form of the survival function allows for variations in the classic 'U-shaped' 328 mortality curve^{13,41-43} (ours is inverted to survival). Because the data are heavily weighted to 329 small individuals and the mechanisms that cause mortality across size can vary significantly, we 330 combined two logistic functions to describe mortality across size (see Supplementary Fig. 7 for 331 332 examples of the species specific fits and Supplementary Fig. 8 for sites). The probability of 333 survival is therefore given by

334
$$S = \left(\frac{\kappa}{1 + \exp\left(-r1\left((x - p1)\right)\right)}\right)^{k} \text{ for all } x < thresh$$
 (Equation 1)

335

336
$$S = \left(\frac{K}{1 + \exp\left(-r2\left((x - p2)\right)\right)}\right)^{t} \text{ for all } x \ge thresh$$

where S is annual survival probability, *K*, *r* and *p* are the upper asymptote, the rate of change and the inflection point of the survival curve, *x* is size (DBH in mm), *t* is the time in years between

censuses, and *thresh* is the size threshold at which the two functions meet. The threshold was set 339 at the median DBH size (see Supplementary Fig. 7). This ensured that species had an equal 340 341 number of observations informing each of the two curves. Subscripts 1 and 2 denote parameters for the curves describing survival in individuals below and above the size threshold respectively. 342 The parameters in these functions hold distinct meanings across tree life-history. K 343 344 determines the maximum annual survival probability, and usually remains constant over most of the tree's life-history, especially in large statured species. Mortality of small individuals, often 345 due to thinning in the understory is determined by r1 and p1, and r2 and p2 define survival at the 346 largest sizes. 347

The five parameters from the joint survival functions (K, r1, p1, r2, p2) for each species 348 in each census interval were standardized to unit scale and included in a Principal Components 349 Analysis (PCA). To ensure that species had equal weight in the PCA, species were weighted 350 equal to the inverse of the number of census intervals over which they were modelled. We 351 352 derived modes of survival across species by performing a hierarchical cluster analysis on the first five dimensions of the PCA using the "HCPC" function for hierarchical cluster analysis from the 353 R package *FactoMineR*⁴⁴. The HCPC function builds a dendrogram of species relatedness from a 354 355 similarity matrix. It then calculates the within- and between-group sum of squares (also termed "inertia") for a range of potential cluster numbers and selects the number of clusters where the 356 change in between group variance is minimized⁴⁵. Four clusters were selected using this 357 algorithm, and we tested the robustness of the recommended clusters with Jaccard similarity 358 index produced via bootstrapping function, clusterboot in the *fpc* package¹⁷. To visualize these 359 modes (i.e., the four clusters, Fig. 2 and Supplementary Fig. 7), we used the mean values of 360

parameter sets within each cluster and their covariances to randomly draw 1000 simulated
survival curves. At each millimeter increment, from 1 to the maximum size, we then selected the
median, 50% and 90% quantile values. We also plotted the survival function corresponding to
the most representative species of each mode (Supplementary Fig. 8), i.e. the species from each
cluster closest to the centroid.

366 In calculations of biomass loss due to mortality for each survival mode, biomass was calculated for the main stem of each tree using general tropical allometries for trees without 367 height measurements⁴⁶, as tree height measurements are not part of the ForestGEO monitoring 368 protocol. These allometries estimate height based on diameter of the stem and an environmental 369 370 index to ultimately calculate biomass. For each survival mode, annual carbon loss due to mortality was based on tree diameter at the beginning of the census interval and made annual by 371 dividing by the mean census interval time (typically ~5 years) and we also report mean mortality 372 rate by survival mode at each site for comparability (Supplementary Fig. 9). Absolute annual 373 374 diameter growth rates were calculated for each survival mode by subtracting diameters at the beginning of the census interval from the ending diameter and dividing by the time between 375 censuses for each tree. 376

We tested the correlation between survival modes and three common functional traits: wood density, leaf mass per area (LMA), and seed mass. Trait values for wood density (n=1781, some species were assigned genus or family level values when species specific values were not available) were obtained from compiled databases⁴⁷⁻⁴⁹, half of the plots had locally collected wood density values. Leaf mass per area (n=719) and seed mass (n=144) data were collected locally^{31,50-52}. Differences between trait means among survival modes were compared with a

383	Tukey HSD test. To test associations between survival modes and climate variables, we
384	calculated mean annual temperature ⁵³ (MAT), mean annual precipitation ⁵³ (MAP) and mean
385	Climatic Water Deficit (CWD) for each plot (1901-2013) ⁵³ . As a metric of aridity, annual CWD
386	(mm yr ⁻¹) was calculated as the sum of monthly deficit values which is the difference between
387	potential and actual evapotranspiration ^{46,54} . Because the response variable was a percentage
388	bounded at 0 and 100, multiple tobit regression models were run with backwards selection using
389	the vglm function in the VGAM package ⁵⁵ on MAT, MAP and CWD. Residual diagnostics
390	indicated that the Palamanui plot data was an outlier and was subsequently removed from the
391	analysis of climate relations; none of the remaining plots data had undue leverage on the
392	regression. The best fit model by AICc contained MAT and CWD as significant predictors.

393 We projected the biomass at each site across census intervals using an Individual Based Model (IBM) parameterized with mean parameters for each survival mode, i.e. stems were 394 395 assigned a survival mode and each year grew and survived with probabilities corresponding to 396 the 95th% growth rate and the size-dependent survival curve of that mode. The site level IBM was initialized by the diameter distribution for each survival mode in the first census and then 397 projected forward in time the length of the census interval at each site. At the end of the 398 399 projection, we calculated biomass in each survival mode based on the mean wood density of each mode. We used the 95th percentile of growth rates by survival mode in the model to best 400 401 capture canopy tree growth rates which are the greatest contributors to biomass, we also present the results using mean growth rate for comparison (Supplementary Fig. 10). Biomass was 402 403 calculated as above using the mean wood density of each survival mode rather than species specific values. 404

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419	revise the manuscript. All authors contributed to the final version of the manuscript.
420	The authors declare no competing interests.
421	Data availability: The data that support the findings of this study are available from the
422	corresponding author upon reasonable request. Individual plot data can be requested from:
423	http://www.forestgeo.si.edu/group/Data/Access+the+data
424	

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559 Figure Captions

560 Figure 1. Schematic diagram of the workflow for this analysis.

Figure 2. Survival probability as a function of DBH for each of the four identified survival 561 562 modes. Survival modes were derived from a hierarchical cluster analysis on the parameters from 563 the survival function fit to 1781 species at 14 large area forest plots. In each species, the survival function consists of two curves fit to individuals above and below a species specific size 564 565 threshold. The means of the size thresholds for species within each mode are shown with the vertical dashed lines. In each mode, the solid line represents the mean of the survival functions 566 from species within the mode and the lighter and darker shaded regions show the 50% and 90% 567 uncertainty range around the mean. Parameters for each mean curve are listed in Supplementary 568 569 Table 2.

Figure 3. Site-level mean annual aboveground carbon loss to mortality for each survival mode
across all census intervals including error bars for standard error. Species that did not have
enough individuals to model survival are presented as Unclassified. Corollary figure for
mortality rates presented in Supplementary Fig. 10.

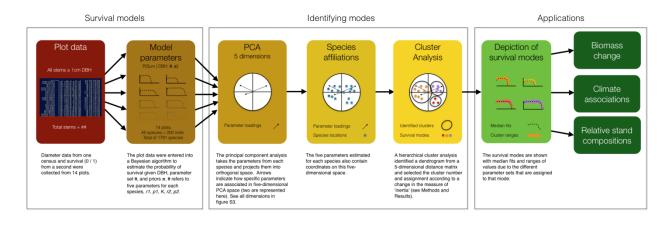
Figure 4. In general, traits do not map strongly onto the four survival modes. A) Natural log
transformed wood specific gravity at all sites. B) Leaf mass per area at 6 sites (Lambir, BCI,
Luquillo, Laupahoehoe, Palamanui and Fushan), C) Natural log transformed seed mass and
survival modes at Luquillo, Laupahoehoe, Palamanui and BCI where there were no significant
differences between survival modes. Letters represent significant differences among survival
modes in traits at alpha=0.05 by Tukey HSD test.

580

Figure 5. Plot level average annual individual growth rate by survival mode boxplots with the
width scaled to the square-root of the number of species that make up the survival mode for all
forest plots. Significant differences (n=14, alpha=0.5, Tukey HSD test) denoted by letters above
category.

585

- 586 Figure 6. Observed biomass by survival mode versus predicted biomass from an individual based
- model at each site (marginal $R^2 = 0.9735$). The line between points traces census interval
- typically diverging from the dashed line, which represents the 1:1 line, with time.



591 Figure 1

