## Individual-based modelling of Amazon forests suggests that climate controls productivity but traits control demography

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## 1. Supplementary Figures and Tables 1.1 Supplementary Figures



**Figure S1.** Detailed schematic of TFSv.2 structure. \* denotes processes added to the new model version, ^ denotes alterations to the original model. Woody biomass includes both stem and coarse roots.



**Figure S2.** Probability of mortality under different wood densities, growth rates and  $D/D_{max}$ . Example values - low growth rate: -6 mm yr<sup>-1</sup>, high growth rate: 25 mm yr<sup>-1</sup>, low  $D/D_{max}$ : 0.11, high  $D/D_{max}$ : 1, low wood density: 0.2 g cm<sup>-3</sup>, high wood density: 0.9 g cm<sup>-3</sup>.



**Figure S3.** Relationship between LMA (g m<sup>-2</sup> from Fyllas *et al.*, 2009) and maximum diameter ( $D_{max}$ , cm, calculated from ForestPlots.net data using the method of King *et al.*, 2006). a) Scatterplot of LMA and  $D_{max}$  (log scale) with linear regression line (p = 0.0002, R<sup>2</sup> = 0.03). b) Histograms of  $D_{max}$  data binned by LMA. c) Log-normal distributions for each LMA bin parameterized from the data and used to apply a  $D_{max}$  value to simulated trees based on LMA.



**Figure S4.** Distributions of wood density (WD, g cm<sup>-3</sup>, top left quadrant), leaf mass per area (LMA, g m<sup>-2</sup>, top right quadrant), leaf nitrogen (N, mg g<sup>-1</sup>, bottom left quadrant) and leaf phosphorus (P, mg g<sup>-1</sup>, bottom right quadrant) for the four study plots. Data from Fyllas *et al.* (2009) and the GEM-TRAIT project.



**Figure S5.** Trait distributions for model experiments. a-d) Distributions split by N to produce 'fast' and 'slow' leaf trait distributions. e-h) Distributions split by WD to produce high and low WD trait distributions.



**Figure S6.** Allocation of NPP between leaves (cyan), wood (blue) and fine roots (magenta) from observations (o) and simulations (s) for each plot.



and ALP clusters.



**Figure S8.** Distributions of stem (top row) and biomass (bottom row) mortality rates from observations (red, mortality rates taken from all census intervals of all plots within the local cluster) and simulations (blue dash, mortality rates from each year of the final 100 years of simulations). Median rate from observations (red line) and simulations (blue line) are shown. All units are % yr<sup>-1</sup>.



**Figure S9.** Distributions of annual number of recruits (green) and dead trees (blue) from the last 100 years of simulations from a single model run.



**Figure S10.** Distributions of above ground woody productivity from observations (red, rates taken from all census intervals of all plots within the local cluster) and simulations (blue dash, rates from each year of the final 100 years of simulations). Median rate from observations (red line) and simulations (blue line) are shown. All units are Mg C ha<sup>-1</sup> yr<sup>-1</sup>.



**Figure S11.** Growth trajectories of trees over time in a single 20 x 20 m subplot coloured by WD. Open circles – tree present in the top of the canopy, closed circles – tree present in subcanopy. The largest tree in the subplot dies in simulation year 2220. Then, the existing trees that were in the subcanopy move to the canopy and receive more light. Of those of a similar size, the lower WD trees grow fastest. Low wood density trees recruit less often in later simulation years due to a higher mortality rate and consequently lower presence in the adult population.



**Figure S12.** Change in community weighted mean trait values during the experimental simulations. Column 1 and 3 - ALP climate, column 2 and 4 - TAM climate, column 1 and 2 - 'fast' (blue) and 'slow' (green) traits distributions with split based on leaf N, column 3 and 4 - high (magenta) and low (cyan) WD distributions. Polygons show standard deviation ranges from 10 model runs.



Soil Moisture Index Figure S13. Histogram of simulated soil moisture indices from ALP-01 (blue) and TAM-05 (green), based on daily values from the years 1983-2012. Low values have more inhibition of photosynthesis.



24 26 28 30 32 34 36 Mean Tree DBH (cm) Figure S14. Relationship between simulated stem density and mean tree diameter averaged over the last 100 years of experimental simulations (8 trait x climate combinations, 10 runs of each combination).



**Figure S15.** WD shifts from one simulation of each plot (blue - first year, green - last year of simulation) with mean (solid line) and standard deviation (dashed line).



**Figure S16.** Distribution of number of dead stems from 1000 randomisations based on  $P_m$  calculated from the outputs from final simulation year and original (blue) and reduced (green) WD.

# **1.2 Supplementary Tables**

Plot Code	Lat/Long	Number of	First census	Last census
		censuses	date	date
ALP-02	-3.9/-73.4	8	11/1990	03/2011
TAM-01	-12.8/-69.3	11	10/1983	09/2014
TAM-02	-12.8/-69.3	13	11/1979	09/2014
TAM-04	-12.8/-69.3	8	09/1983	09/2014
TAM-07	-12.8/-69.3	10	10/1983	09/2014
TAM-08	-12.8/-69.3	6	07/2001	09/2014
TAM-09	-12.8/-69.3	5	09/2010	09/2014

**Table S1.** Details of additional forest dynamics plots in Allpahuayo and Tambopata.

Parameter	Definition	Equation	Value	Reference
β0	Mortality regression parameter	1	-3.55	This
				study
$\beta_1$	Mortality regression parameter	1	-1.3	This
				study
$\beta_2$	Mortality regression parameter	1	-0.045	This
				study
β <sub>3</sub>	Mortality regression parameter	1	0.26	This
				study
β4	Mortality regression parameter	1	0.106	This
				study
μ	Location parameter of log-		3.587; 3.624; 3.732;	This
	normal distribution to select		3.818; 3.839 (for	study
	D <sub>max</sub> value from LMA		LMA < 80, 80-90,	
			90-100, 100-110,	
			>110 respectively)	
σ	Scale parameter of log-normal		0.463; 0.397; 0.430;	This
	distribution to select D <sub>max</sub> value		0.376; 0.368 (for	study
	from LMA		LMA < 80, 80-90,	
			90-100, 100-110,	
			>110 respectively)	
а	Parameter for estimation of	2	0.25	Fyllas et
	sapling number			al, 2010;
				Dupuy &
				Chazdon,,
				2006.
b	Parameter for estimation of	2	-0.5	Fyllas et
	sapling number			al, 2010;
				this study

 Table S2. Parameter values for equations presented in the main text.

			Fast vs slow traits				High wd vs low wd					
Variable	Duirson	df	Sum Ca	Maan Sa	Б	D	c.2	Sum Sa	Maan Sa	Б	D	c.2
variable	Driver		Sum Sq	Mean Sq	F	P 0.22	ω-	Sum Sq	Mean Sq	F	P	ω-
	Climata	1	566.52	566.52	1.015	0.52	0.04	5.05	692 72	9.0008	0.004	0.007
	Troits y	1	300.32	500.52	087.5	< 0.0001	0.94	085.75	085.75	1101.9	< 0.0001	0.95
	Climata	1	2 16	2 16	4.2	0.049	0.004	0.01	0 0 1	15.0	0.0004	0.01
CDD	Desidual	26	20.67	0.82	4.2	0.048	0.004	0.01	0.01	13.0	0.0004	0.01
Urr	Troite	30	29.07	11 279	214.4	< 0.0001	0.12	1 707	1 707	40.6071	< 0.0001	0.02
	Climate	1	69 548	69.548	1322.1	< 0.0001	0.13	85 221	85 221	2/77 2	< 0.0001	0.02
	Troita v	1	09.540	09.540	1322.1	< 0.0001	0.80	05.221	05.221	2477.2	< 0.0001	0.90
	Climate	1	0.207	0.207	3 9257	0.055		0.051	0.051	1 4722	0.2	
NPP	Residual	36	1 89/	0.207	5.7251	0.055		1 238	0.034	1.7/22	0.2	
	Traits	1	5 072	5 972	9 1731	< 0.0001	0.02	13 572	13 572	20 532	< 0.0001	0.04
	Climate	1	230.078	239.078	370.3	< 0.0001	0.02	286 173	286 173	622 703	< 0.0001	0.04
	Troite y	1	237.078	237.078	517.5	< 0.0001	0.07	200.175	200.175	022.703	< 0.0001	0.00
	Climate	1	1 976	1 976	3 135	0.09		7 52	7 52	16 364	< 0.0001	0.02
R	Residual	36	22 693	0.63	5.155	0.07		16 544	0.46	10.504	× 0.0001	0.02
K	Traits	1	12895	12895	35 9359	< 0.0001	0.05	28	28	0.0918	0.8	
	Climate	1	214845	214845	598 7	< 0.0001	0.05	216411	216411	718.9	< 0.0001	0.95
	Traits y	1	214045	214045	570.7	< 0.0001	0.07	210411	210411	/10.7	< 0.0001	0.75
	Climate	1	303	303	0 8458	0.4		1	1	0.0047	0.9	
Stems	Residual	36	12918	359	0.0150	0.1		10837	301	0.0017	0.9	
Stellis	Traits	1	16.13	16 1303	13 2942	0.0008	0.20	157 511	157 511	158 566	< 0.0001	0.68
	Climate	1	13.95	13 9495	11 4969	0.0000	0.17	33 3	33.3	33 5228	< 0.0001	0.00
	Traits x	1	15.75	15.7475	11.4707	0.002	0.17	55.5	55.5	55.5220	× 0.0001	0.14
	Climate	1	0.043	0.0427	0.0352	0.9		2 848	2 848	2 8667	0.1	
BA	Residual	36	43.68	1.2133	0.0002	015		35.76	0.993	2.0007	011	
	Traits	1	11089	11089	40.0252	< 0.0001	0.19	11060	11060	51.6489	< 0.0001	0.17
	Climate	1	33414	33414	120.6	< 0.0001	0.59	43665	43665	203.9	< 0.0001	0.69
	Traits x	-	00.111	00.11	12010	0.0001	0.07			20019	0.0001	0.05
	Climate	1	960	960	3.4637	0.07		93	93	0.4325	0.5	
AGB	Residual	36	9974	277		,		7709	214			
										142.363		
	Traits	1	0.5631	0.5631	8.8659	0.005	0.02	5.6217	5.6217	9	< 0.0001	0.16
	Climate	1	21.1891	21.1891	333.6	< 0.0001	0.88	27.3958	27.3958	693.8	< 0.0001	0.79
	Traits x											
Woody	Climate	1	0.0113	0.0113	0.1775	0.7		0.0578	0.0578	1.4639	0.2	
Productivity	Residual	36	2.2865	0.0635				1.4216	0.0395			
	Traits	1	0.079	0.079	3.2535	0.08		2.4201	2.4201	205.343	< 0.0001	0.21
	Climate	1	7.7324	7.7324	318.3	< 0.0001	0.88	8.6647	8.6647	735.178	< 0.0001	0.75
	Traits x											
	Climate	1	0.0132	0.0132	0.5452	0.5		0.0245	0.0245	2.077	0.2	
LAI	Residual	36	0.8744	0.0243				0.4243	0.0118			
	Traits	1	0.09443	0.094434	6.4335	0.02	0.12	1.14002	1.14002	157.7	< 0.0001	0.79
	Climate	1	0.05013	0.050129	3.4151	0.07		0.01255	0.01255	1.7358	0.2	
	Traits x											
	Climate	1	0.00006	0.000057	0.0039	0.9		0.01408	0.01408	1.9474	0.2	
pR	Residual	36	0.52843	0.014678				0.26022	0.00723			
-	Traits	1	0.12	0.120774	15.8214	0.0003	0.26	1.27314	1.27314	198.8	< 0.0001	0.84
	Climate	1	0.0266	0.026599	3.4845	0.07		0.00239	0.00239	0.3735	0.5	
	Traits x											
	Climate	1	0.0129	0.012915	1.6919	0.2		0.00025	0.00025	0.0392	0.8	
pМ	Residual	36	0.275	0.007634				0.23055	0.0064			

# **Table S3.** Full ANOVA results testing the importance of input traits distribution and climate on forest carbon cycling and structure variables.

**Table S4.** Results from two sample T-tests examining shifts in mean trait values during simulations based on community weighted mean (cwm) and basal area weighted mean (BAwm) of the first and last simulation year for two model experiments using opposing traits distributions and two climates.

Trait (units,							
mean	Climate	Trait	Year 1	Year 500			
weighting)	Applied	distribution	mean	mean	Т	df	р
		Fast	0.558	0.69	-7.0	9.1	<0.0001
	ALP	Slow	0.631	0.751	-7.4	9.5	<0.0001
WD ( $g$ cm <sup>-3</sup> .		Fast	0.565	0.711	-10.2	9.6	<0.0001
cwm)	ТАМ	Slow	0.630	0.729	-12.2	9.6	<0.0001
		Fast	0.556	0.658	-7.0	91	<0.0001
	ΔΙΡ	Slow	0.628	0.725	-7.7	97	
$WD (\alpha \text{ am}^{-3})$		Fast	0.020	0.723	10.7	10.2	<0.0001
DAwm)	TAM	Flaw	0.303	0.077	-10.7	0.7	<0.0001
DAwiii)	IAM	Jaw WD	0.027	0.708	-11.1	9.7	<0.0001
		LOW WD	0.4//	0.555	-8.9	10.0	<0.0001
2	ALP	High WD	0.720	0.765	-6.9	9.1	<0.0001
WD (g cm <sup>-3</sup> ,		Low WD	0.476	0.526	-6.4	9.3	<0.0001
cwm)	TAM	High WD	0.715	0.758	-9.2	11.4	<0.0001
		Low WD	0.475	0.524	-8.7	10.9	<0.0001
	ALP	High WD	0.718	0.754	-5.8	9.1	0.0003
WD (g cm <sup>-3</sup> ,		Low WD	0.474	0.512	-7.2	9.6	<0.0001
BAwm)	TAM	High WD	0.714	0.753	-8.0	11.1	<0.0001
		Fast	99.4	87.1	8.2	9.5	<0.0001
	ALP	Slow	120.1	117.3	1.8	12.0	0.1
$LMA (\sigma m^{-2})$		Fast	98.9	85.0	13.6	14.2	<0.0001
cwm)	ТАМ	Slow	121.6	115.9	2.6	9.8	0.03
ewilly	17101	Fast	00.0	9/1	3.5	9.6	0.05
	ALD	Slow	110.2	122.7	2.0	9.0	0.000
	ALF	Slow East	0.00 (	01.7	-2.0	11.2	
LMA (g m <sup>2</sup> ,	<b>T</b> 4 1 (	Fast	98.0	91.7	/.4	15.2	<0.0001
BAwm)	IAM	Slow	120.8	120.0	0.4	9.6	0./
		Low WD	108.7	101.9	4.1	10.8	0.002
	ALP	High WD	108.1	104.6	1.8	9.3	0.1
$LMA (g m^{-2},$		Low WD	109.3	101.9	4.7	9.5	0.0009
cwm)	TAM	High WD	105.5	102.8	1.9	11.8	0.09
		Low WD	108.0	109.2	-0.7	10.9	0.5
	ALP	High WD	107.3	111.3	-2.2	9.4	0.05
$LMA (g m^{-2})$		Low WD	107.6	106.9	0.6	9.5	0.6
BAwm)	TAM	High WD	104.7	107.3	-1.7	11.5	0.1
		Fast	25.2	25.8	-1.9	10.3	0.09
	ALP	Slow	16.6	16.0	3.5	9.3	0.006
Leaf N (mg g		Fast	25.4	26.1	-3.1	10.5	0.01
$\frac{1}{1}$ cwm)	там	Slow	16.5	16.2	2.6	97	0.01
, ewilly		Fast	25.2	25.5	0.0	10.8	0.05
	ALD	Slow	16.6	16.2	-0.9	0.2	0.4
L CNI (	ALF	Slow East	10.0	10.5	2.3	9.5	0.049
Lear N (mg g	TAM	rast	23.4	23.9	-2.0	11.3	0.03
<sup>-</sup> , BAwm)	IAM	Slow	16.5	16.3	1.5	9.4	0.2
		Low WD	22.0	21.5	0.9	9.1	0.4
	ALP	High WD	21.6	19.4	4.8	9.1	0.0009
Leaf N (mg g		Low WD	21.9	21.7	0.4	10.7	0.7
<sup>1</sup> , cwm)	TAM	High WD	22.5	21.0	3.3	12.0	0.007
		Low WD	22.1	21.4	1.4	9.2	0.2
	ALP	High WD	21.7	19.8	4.6	9.1	0.001
Leaf N (mg g		Low WD	22.0	21.7	0.7	11.1	0.5
<sup>1</sup> , BAwm)	TAM	High WD	22.6	21.1	3.5	12.6	0.004
, ,		Fast	1.34	1.29	1.0	9.4	0.3
	ALP	Slow	0.90	0.85	3.0	9.5	0.01
Leaf D (ma a-		Fast	1 33	1 41	_2 2	97	0.06
$\frac{1}{1}$ cwm)	там	Slow	0.88	0.70	53	11.0	0.00
, cwiii)		Fact	1.00	1.20	2.0	0.0	0.0002
	ALD	rast Slaar	1.33	1.29	2.0	9.9	0.07
Leat P (mg g	ALP	Slow	0.90	0.85	5.1	9.2	0.01
', BAwm)	TAM	Fast	1.34	1.39	-1.7	10.0	0.1

		Slow	0.89	0.79	5.9	11.6	<0.0001
		Low WD	1.18	1.13	1.2	9.0	0.3
	ALP	High WD	1.12	0.99	4.1	9.0	0.003
Leaf P (mg g		Low WD	1.17	1.11	2.0	10.1	0.07
<sup>1</sup> , cwm)	TAM	High WD	1.17	1.07	3.0	13.2	0.01
		Low WD	1.20	1.12	2.0	9.0	0.08
	ALP	High WD	1.14	1.03	2.8	9.0	0.02
Leaf P (mg g		Low WD	1.18	1.12	2.2	10.5	0.048
<sup>1</sup> , BAwm)	TAM	High WD	1.19	1.09	2.9	12.8	0.01

### 2. Supplementary Methods

#### Methods S1 – Data uncertainty and traits data collection

Error statistics of the field measurements are presented as standard error. Respiration terms of the carbon cycling measurements are associated with large uncertainties due to scaling (e.g. up-scaling leaf respiration measurements to the total leaf area of the plot, stem respiration measurements to the total stem surface area accounting for stem growth rates), and are therefore conservative estimates of errors for the Ra terms were made (see Appendix S1 of Malhi *et al.* (2015) for further details). The close match between GPP estimated from GEM measurements and flux-towers gives confidence in the method (Malhi *et al.* 2015). The standard errors from the inventory plot data are based on variation between censuses.

Functional trait data (LMA, N, P, WD) were taken from Fyllas *et al.*, (2009) and the GEM-TRAIT project (Supplementary Figure S1). The traits data from Fyllas *et al.*, (2009) were collected from 21, 13, 24, and 28 trees for ALP-01, ALP-30, TAM-05, and TAM-06, respectively, between 2001 and 2005 (Patiño *et al.*, 2009). Data from the GEM-TRAIT project were collected from 29, 26, 62, and 51 trees for ALP-01, ALP-30, TAM-05, and TAM-06, respectively. Sampling strategy for data from Fyllas et al., (2009) was based on selecting up to six 'climbable' trees spread throughout the plot, and sampling this tree and crowns accessed from this tree. The GEM-TRAIT project sampled all species that make up 80% of the plot basal area. As stem WD data were not available for GEM-TRAIT samples, we used values taken from the Global Wood Density Database (Chave *et al.*, 2009, Zanne *et al.*, 2009). All leaf traits were measured from branches exposed to full sun.

#### **Methods S2 - Model Improvements**

Light competition Tree canopy layer was previously defined using the perfect plasticity approximation (PPA, Purves et al., 2007) whereby all trees in the plot are ordered by height, and crown areas are summed, beginning with the tallest individuals. Once the cumulative crown area equals the ground area of the plot, the individuals so far included are assigned to the top canopy layer (layer 1), and all shorter trees are assigned to the subcanopy (layer 2). PPA is designed for use in temperate forest where typically there is a single canopy layer, with smaller trees in shade. In contrast, tropical forest canopy layers are heterogeneous and comprise multiple canopy layers (e.g., between one and six canopy layers were found in 45 canopy samples in Costa Rica, Clark et al., 2008). Hence, we utilized an alternative formulation of the PPA devised by Bolhman & Pacala (2012). Unlike the original PPA formulation, Bohlman & Pacala (2012) continued to cumulatively sum crown area with trees in the second layer until the ground area was again equaled, with such trees assigned to layer 2, and subsequently continues again to fill a third canopy layer. This is continued until all trees have been assigned a canopy layer. A further development to the canopy structure was made by performing the PPA algorithm in 20 x 20 m subplots rather than the entire plot. This subplot size was selected for two reasons. First, the 400 m area is approximately the area of the largest tree crowns in tropical forests, and second, forest inventory data is often recorded with this size subplot so validation of the method is possible. Working at the subplot rather than whole plot level allows for within plot canopy height heterogeneity and prevents the large trees in the plot from influencing the light received by all other trees in the plot. The tree height boundaries (Z\* in Purves et al., 2007) between canopy layers can then be different in each subplot. Further, using the original PPA at the whole plot level commonly produced only one canopy layer (i.e., all trees in the top layer and receiving full light) which is not realistic for a tropical forest. Light interception is based on canopy layer; trees in the top layer receive full incoming radiation, light received by trees in the second layer has travelled through one canopy layer before reaching the tree crown, light received by trees in the third layer has travelled through two canopy layers before reaching the tree crown etc. For the purposes of light interception, the LAI of canopies above a lower layer tree crown are set to 2, following observations from Clark et al., (2008).

**Tissue turnover** When running TFS v.1 with annual feedbacks, leaf biomass pool size based on leaf litter fall and allocation to leaf biomass, individual leaf area index (LAI) was found to shift outside of typical bounds (maximum LAI of 8 recorded from five species of tree in Panama, Kitajima *et al.*, 2005 and mean LAI of 2 in canopy strata from 45 vertical canopy samples in Costa Rica, Clark *et al.*, 2008), with values reaching 30 for some individuals within 3 years of simulation. This behavior is due to the use of the assigned plant trait LMA in determining the total leaf surface area (LA) of an individual. LMA is used to calculate LA from leaf biomass. For an equal leaf biomass, an individual with low LMA will have a larger LA than one with high LMA. Assuming static leaf lifetime (LL, days) and NPP allocation across all individuals, as leaf biomass increases the LA, and hence LAI of low LMA individuals reaches unrealistically high values. To counter this we introduce into the model a known tradeoff between LMA and LL using data from Wright *et al.*, (2004), whereby LL is shorter for trees with low LMA and longer for trees with high LMA.

 $LL = 30.4 \times 10^{(1.11 \times \log(LMA) - 1.3)}$ 

Equation S1

This reduces the large build up of leaf area for low LMA individuals and enhances the return on investment for high LMA individuals, an important ecological trade-off.

A minor change to branch retention time ( $\tau_{br}$ , days) was made by applying a 0.33 % loss per year of stem biomass, following field estimates of approx. 1 Mg C ha<sup>-1</sup> yr<sup>-1</sup> branch fall (Chambers *et al.*, 2001).

$$\tau_{br} = \left(\frac{100}{0.33}\right) \times 365$$
 Equation S2

Biomass pools were updated annually, by addition of the years NPP of the organ and subtraction of losses (e.g. leaf fall, fine root turnover or branch loss) to the previous years' value. All allometries were reversed to determine the plant dimensions from the updated biomass values. In the case of diameter and height from stem biomass, a Newton-Raphson iterative solver was used to determine the two unknowns.

**Subcanopy alterations** Individuals below the first canopy layer (subcanopy trees) showed very low growth. To improve this, two changes were made to processes for subcanopy trees. First, the LL of trees in shade is known to be longer than that of trees in full light. Hence, we extended the LL of subcanopy trees following a relationship based on data from Lowman, 1992; Miyaji *et al.*, 1997; Sterck, 1999; Reich *et al.*, 2004; Lusk & Corcuera, 2011; and Kitajima *et al.*, 2013, Supporting Information Methods Figure 1, Equation S3.



**Supporting Methods 2 Figure 1.** Leaf lifetime of plants of the same species growing under high light conditions and under low light conditions. Grey dashed line: y = x. Red solid line: linear regression model y = 190 + 1.54x. Data from 60 observations from Lowman, 1992; Miyaji *et al.*, 1997; Sterck, 1999; Reich *et al.*, 2004; Lusk & Corcuera, 2011; and Kitajima *et al.*, 2013. Each data point is a species.

$$LL_s = 190 + 1.54LL$$

Equation S3

Where  $LL_s$  is the leaf lifespan of a tree in the shade, and LL is the originally assigned LL (based on the relationship with LMA (Equation S1).

Second, leaf respiration was altered. Leaf respiration rate ( $R_L$ , µmol m<sup>-2</sup> s<sup>-1</sup>) is typically modeled as a fraction of Vc<sub>max</sub>. In TFS v.1, Equation S4 was used to estimate leaf respiration rate.

$$R_L = f \times V c_{max}$$

Equation S4

where the parameter f = 0.015. However, subcanopy trees with limited light rarely meet the maximum rate of photosynthesis, and have been shown to have lower rates of respiration (Weerasinghe *et al.*, 2014). While the exact nature of the relationship between Vc<sub>max</sub> and leaf respiration at different light levels is not well quantified, we reduced the parameter f to 0.01 for trees in layer 2 and 0.005 for trees in layer 3 and below (top of canopy trees use the original f).

Other minor changes were made. At initialization, leaf biomass was determined by the aboveground woody biomass based allometry of Yamakura *et al.*, 1986, which gave a similar pattern to other published allometric equations for leaf biomass (Equation S5).

 $B_L = 9.146 \times 10^{-2} \times B_S^{0.7266}$ 

Equation S5

Crown area was determined by an allometric equation based on data from Tambopata, Peru, one of the study forests used in this analysis (Goodman, unpublished). Root respiration in TFS v.1 was equal to leaf respiration. This somewhat overestimated root respiration and here we set root respiration equal to leaf respiration x 0.6.

#### Methods S3 – Parameterization and model selection for probability of mortality

The equation for probability of mortality ( $P_m$ ) was parameterized from data from 69 forest plots located in the western Amazon from the RAINFOR ForestPlots.net database (Lopez-Gonzalez et al., 2011). We used data for all individual trees present (alive or dead) in at least three censuses and for which a D<sub>max</sub> value was available. The model considered the effect of wood density (WD, g cm<sup>-3</sup>), diameter growth rate (Gr, cm yr<sup>-1</sup>) and D relative to maximum diameter (D/D<sub>max</sub>). The diameter growth rate for a tree was calculated from the census interval preceding the census interval after which the tree was defined as alive or dead, following Chao et al. (2008).

The logistic model of the following form was used:

$$P_m = \frac{1}{(1 + e^{-(k)})}$$
Equation S6

where k represents the predictors of the logistic model. Models using all possible combinations of the three predictors were compared to determine the model form with the most support from the data (Table S3.1).

The model was parameterized using simulated annealing. Simulated annealing is an iterative parameter estimation technique mimicking the process of cooling of a crystal. The minimal internal energy state of the solid crystal is the one where its atoms are arranged in a perfectly regular grid. Sufficiently slow cooling with the possibility to escape non-regular confirmations is expected to lead to such a near perfect final grid – and the configuration found will be the minimum energy configuration. The algorithm is as follows. We want to maximise the log-likelihood of the mortality model with respect to the model parameters, or i.e. minimize (-1)\*loglikelihood. (-1)\*log-likelihood is thus the analogue of the internal energy state of the solid. An initial temperature T<sub>0</sub> is chosen and temperature decreased each iteration according to  $T_n = T_0 \cdot \gamma^n$ . Each step model parameter values are altered randomly with the size of the adjustment decreasing as the process continues. A new value of (-1)\*log-likelihood is then calculated given the forest inventory dataset. If the value of (-1)\*log likelihood has decreased, the new parameter values are kept for the next iteration. If it has not decreased the new values are possibly nonetheless retained with the small probability  $p = \exp(-\frac{Enew-Eol}{j \cdot T})$  where j is a constant. This aims to permit to escape local minima. The constants of the simulated annealing algorithm were: T<sub>0</sub> = 10;  $\gamma$  = 0.999995; number of iterations = 400000; j = 1; s = 1.2. The start value of all parameters was 1.

The log-likelihood function for a mortality process with mortality data  $X=(x_1,...,x_N)$  for N trees, a sequence of zeros (when the tree is dead) and ones (when the tree is alive), is similar to that used by Lines et al. (2010) and Aubry-Kientz et al. (2013):

$$l(X|M) = \sum \ln \begin{cases} 1 - P(m,i) \text{ if tree i survived} \\ P(m,i) \text{ if tree i died} \end{cases}$$
 Equation S7

Here P(m,i) is the probability of death of tree *i* during the period considered given model parameters *m*. The likelihood function is  $(X|m) = \binom{N}{k} \prod_{i=1}^{N} (1 - P(m,i))^{x_i} P(m,i)^{1-x_i}$ .

Models with all possible combinations of predictors were compared using AIC. The best model was composed of all three predictor variables, with WD the best single predictor, and WD and Gr the best of the models with two predictors. Interestingly, Gr performed very poorly as a single predictor, likely because both high and low growth rates can be indicative of high mortality, where fast growing trees have short lifespans, and slow growing trees may be suppressed and/or undergoing disease or senescence.

To assess error in the parameter variables of the full model, the parameter estimation procedure was bootstrapped 10 times, and the standard deviation of the parameter estimates was calculated from these 10 replicates. Parameter values and standard deviations are shown in Table S3.2.

Table S3.1 Model selection for estimation of probability of mortality. K – number of parameters, AIC – Akaike Information Criterion,  $\Delta$ AIC, difference in AIC from the minimum AIC model.

Model (k)	K	Log	AIC	ΔAIC
		Likelihood		
$\beta_0 + \beta_1 WD + \beta_2 Gr + \beta_3 (D/D_{max}) + \beta_4 (D/D_{max})^2$	5	-16825.73	33661.46	0
$\beta_0 + \beta_1 WD + \beta_2 Gr$	3	-16847.48	33700.96	39.5
$\beta_0 + \beta_1 WD + \beta_3 (D/D_{max}) + \beta_4 (D/D_{max})^2$	4	-16865.93	33739.86	78.4
$\beta_0 + \beta_2 Gr + \beta_3 (D/D_{max}) + \beta_4 (D/D_{max})^2$	4	-16875.36	33758.72	97.26
$\beta_0 + \beta_1 WD$	2	-16883.76	33771.52	110.06
$\beta_0 + \beta_3 (D/D_{max}) + \beta_4 (D/D_{max})^2$	3	-16904.16	33814.32	152.86
$\beta_0 + \beta_2 Gr$	2	-23704.65	47413.3	13751.84
β <sub>0</sub>	1	-16922.8	33847.58	186.12

Table S3.2 Parameter estimates and standard deviation from 10 bootstraps.

Parameter	Value	Standard Deviation
β <sub>0</sub>	-3.55	0.014
β1	-1.3	0.017
β <sub>2</sub>	-0.045	0.00065
β <sub>3</sub>	0.26	0.025
β <sub>4</sub>	0.106	0.016

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