Appendix S1. Supporting results

Table S1. Number of trees, relative abundance, proportion of liana infested trees and average number of lianas per tree for all trees and those in the third to tenth most abundant families, in each census in main plots (a) MP1 and (b) MP2. These data extend those in Table 1 of the main text.

(a) MP1	Number of trees in plot		Trees with lianas (%)		Average number of lianas per tree	
Tree family	1988	2018	1988	2018	1988	2018
Meliaceae	144	134	59.0	70.9	2.40	1.94
Phyllanthaceae	130	113	74.6	81.4	2.72	2.16
Lauraceae	126	143	54.8	71.3	1.67	1.66
Annonaceae	116	102	50.9	65.7	1.50	1.58
Myrtaceae	100	95	62.0	67.4	2.00	1.86
Malvaceae	98	104	59.2	68.3	2.16	1.80
Sapotaceae	89	92	74.2	83.7	2.70	2.32
Fagaceae	83	66	56.6	56.1	2.46	1.44

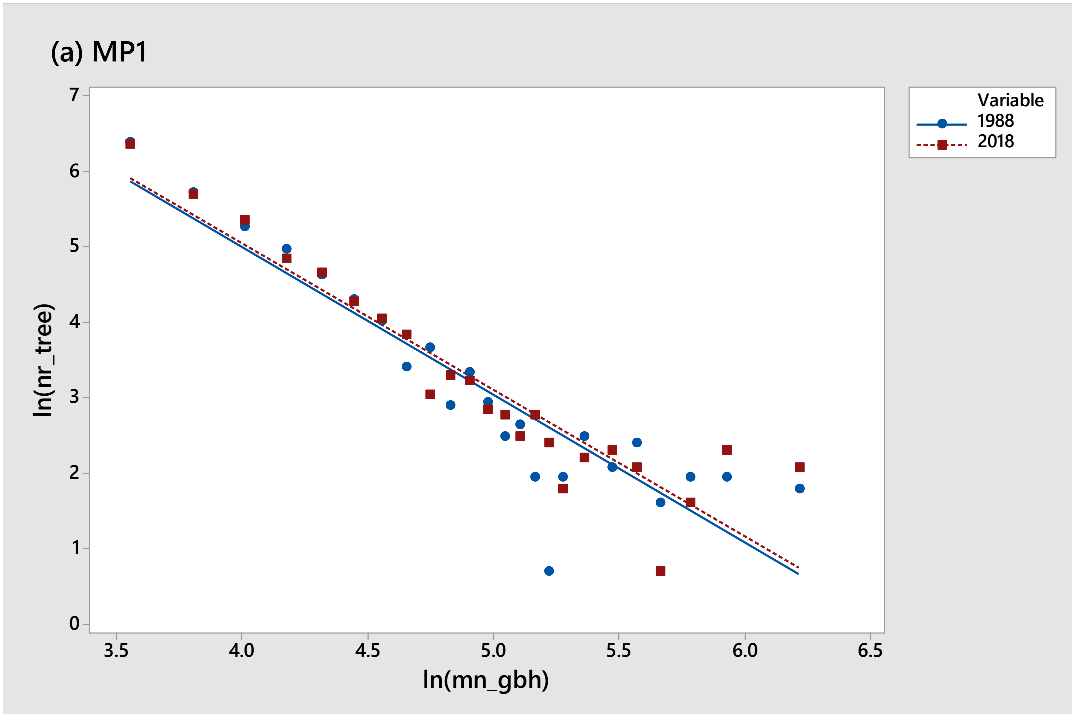
(b) MP2	Number trees in plot		Trees with lianas (%)		Average number of lianas per tree	
Tree family	1988	2018	1988	2018	1988	2018
Meliaceae	105	142	61.9	67.6	2.39	1.73
Phyllanthaceae	104	104	74.0	69.2	2.84	1.63
Lauraceae	94	101	63.8	61.4	1.93	1.50
Annonaceae	98	113	69.4	56.6	2.39	1.37
Myrtaceae	86	71	73.3	66.2	3.40	1.67
Malvaceae	79	80	50.6	66.3	1.86	1.65
Sapotaceae	41	51	63.4	74.5	2.78	2.18
Fagaceae	66	64	39.4	57.8	1.85	1.41

Table S2. Average annualized mortality rates (m_a) over the four periods between censuses at Danum in the two plots, MP1 and MP2 (1986-96, 1996-2001, 2001-07, 2007-15), for trees ≥ 30 cm gbh at the starts of intervals, in three size classes (scl: 1, 30-< 60; 2, 60 -< 120; and ≥ 120 cm gbh), found for all trees in all families (All), those in the Dipterocarpaceae (Dipt) and those in the Euphorbiaceae (Euph), with proportional differences (Diff.) in rates for MP1 over MP2.

		m_a (%/yr)		Diff.[a]
fam	scl	MP1	MP2	(%)
All	1	2.50	1.88	33.0
	2	2.41	1.81	33.2
	3	2.07	1.53	35.3
Dipt	1	2.70	1.99	35.7
	2	1.86	1.72	8.1
	3	1.61	1.62	−0.6
Euph[b]	1	3.67	2.27	61.7
	2	3.41	2.83	20.5
	3	--	--	--

[a] as $(m_{a\text{-}MP1} - m_{a\text{-}MP2}) / m_{a\text{-}MP2}$; [b] for scl = 3, too few trees to estimate m_a.

Fig. S1. Ln-ln plots of numbers of trees ≥ 30 cm gbh (nr_tree) versus mean size class gbh in the two main plots (a) MP1, and (b) MP2, at Danum, for the two liana census dates 1988 and 2018. Slopes of the lines (± SE) from linear regression [and the adjusted R^2-values of the fits] were: MP1, 1988, −1.959 ± 0.188 [82.5%]; 2018, −1.940 ± 0.160 [86.4%]; MP2, 1988, −1.967 ± 0.151 [88.0%]; 2018, −1.869 ± 0.117 [91.7%].



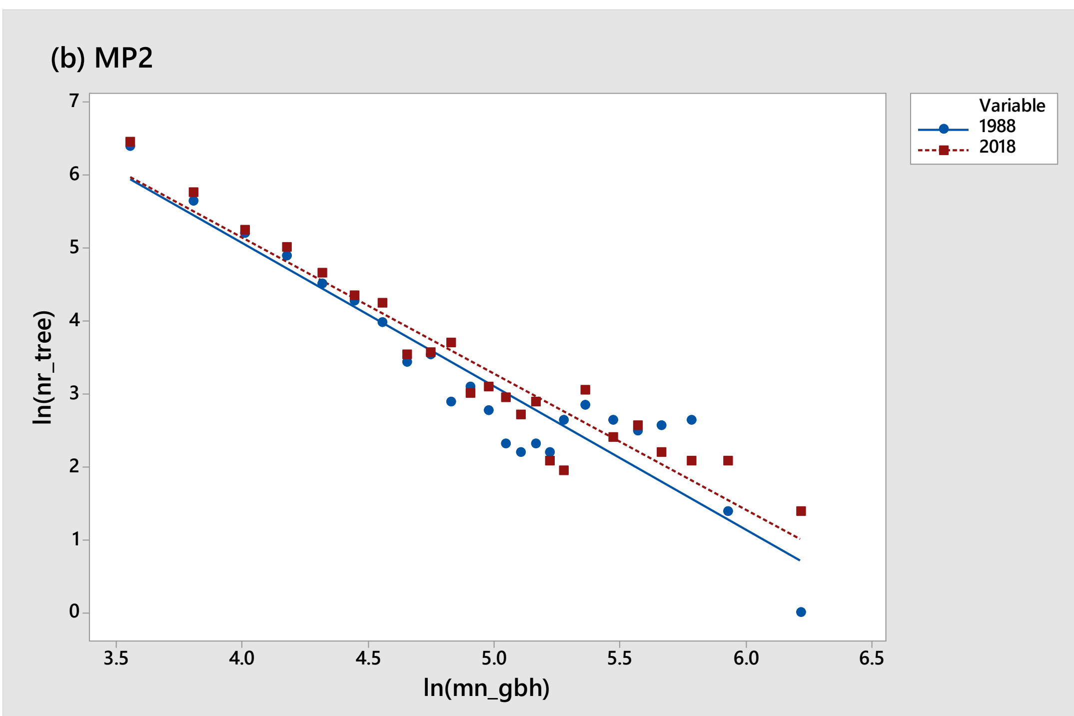
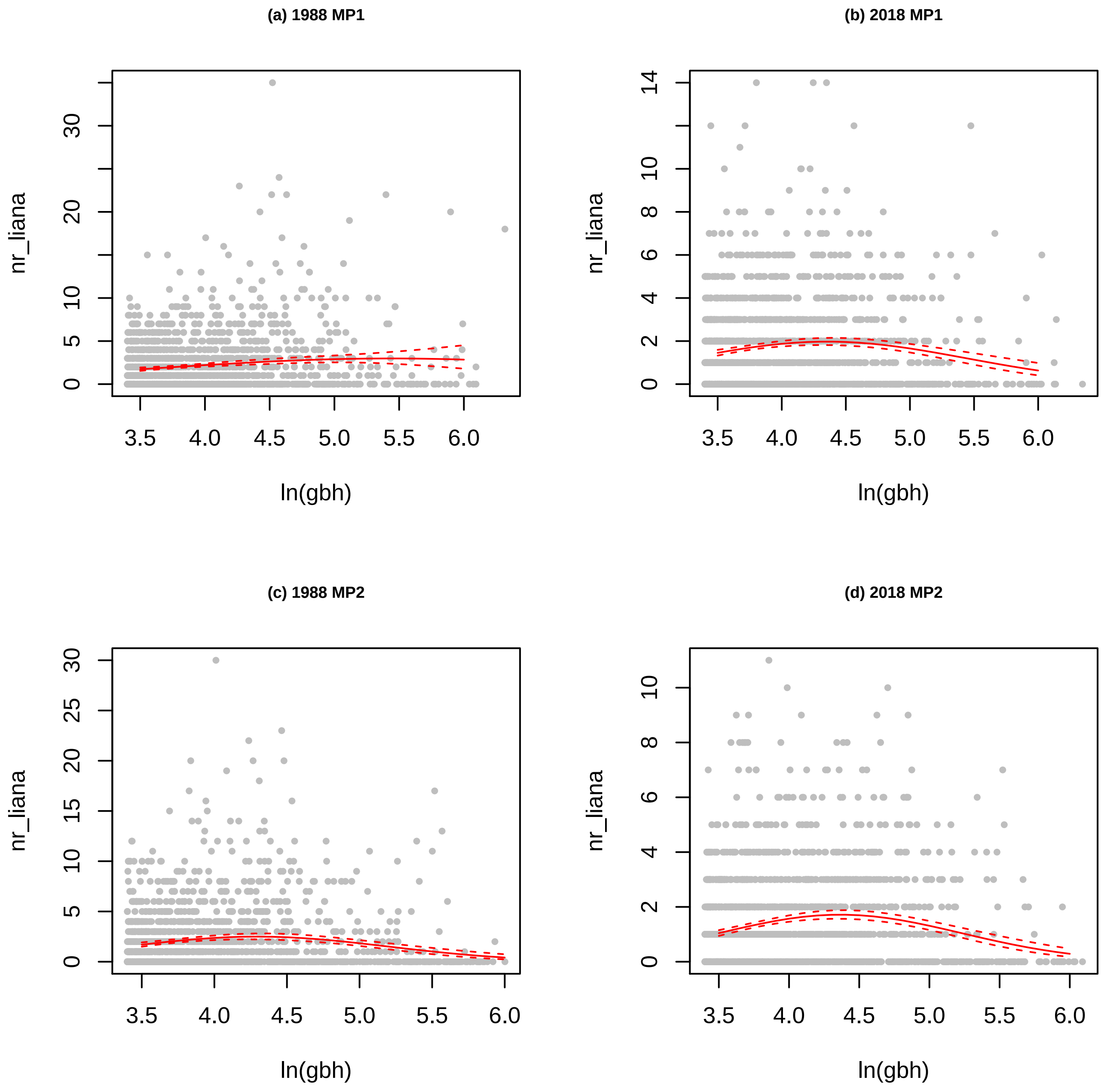


Fig. S2. Relationships from negative binomial GLM regressions for the number of lianas per tree (nr_liana) versus tree size (gbh – ln-transformed) in main plots 1 and 2, at each census date: solid line, 1988; dashed line, 2018, as simplified in Fig. 3 main text, but here showing the scatter of values for the individual trees.



(a) 1988 MP1
(b) 2018 MP1
(c) 1988 MP2
(d) 2018 MP2
nr_liana
ln(gbh)

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Appendix S2. Regression model statistics

Probability levels: ***, $P \le 0.001$; **, $P \le 0.01$; *, $P \le 0.05$; ^{o}, $P \le 0.10$, ^{ns}, $P > 0.10$.

Table S1a. Regressions of numbers of lianas per tree on tree girth at breast height (gbh) and elevation (GLM, negative binomial error) in the censuses of 1988 and 2018.

		MP1		MP2	
census	term	est ± se	*t*	est ± se	*t*
1988	intercept	−2.891 ± 1.634	-1.769^{ns}	−9.989 ± 1.981	−5.041**
	ln(gbh)	1.533 ± 0.757	2.026*	5.157 ± 0.925	5.572***
	$[\ln(\text{gbh})]^2$	−0.1385 ± 0.0864	-1.602^{ns}	−0.6006 ± 0.1064	−5.643***
	elevation	−0.01467 ± 0.00428	−3.430***	−0.00939 ± 0.00334	−2.810**
2018	intercept	−6.740 ± 1.434	−4.701***	−11.873 ± 1.613	−7.361***
	ln(gbh)	3.494 ± 0.670	5.214***	5.812 ± 0.758	7.671***
	$[\ln(\text{gbh})]^2$	−0.4014 ± 0.0774	−5.183***	−0.6650 ± 0.0878	−7.576***
	elevation	−0.01162 ± 0.00356	−3.269**	−0.01605 ± 0.00255	−6.296***

Table S1b. Regressions of numbers of lianas per tree on tree girth at breast height (gbh) and elevation (HGLM, quasi-Poisson error) in the censuses of 1988 and 2018.

		MP1		MP2	
census	term	est ± se	*t*	est ± se	*t*
1988	intercept	−2.760 ± 1.452	-1.902^{o}	−9.352 ± 1.866	−5.013***
	ln(gbh)	1.493 ± 0.671	2.226*	4.841 ± 0.878	5.512***
	$[\ln(\text{gbh})]^2$	−0.1428 ± 0.0765	-1.866^{o}	−0.5711 ± 0.1021	−5.596***
	elevation	−0.01478 ± 0.00391	−3.783***	−0.01000 ± 0.00294	−3.402**
2018	intercept	−6.769 ± 1.480	−4.575***	−11.504 ± 1.620	−7.102***
	ln(gbh)	3.511 ± 0.695	5.052***	5.626 ± 0.763	7.370***
	$[\ln(\text{gbh})]^2$	−0.4057 ± 0.0808	−5.018***	−0.6428 ± 0.0889	−7.231***
	elevation	−0.01093 ± 0.00347	−3.148**	−0.01635 ± 0.00242	−6.750***

Table S1c. Regressions of numbers of lianas per tree on tree girth at breast height (gbh) and elevation (GLM, negative binomial error) in the censuses of 1988 and 2018 for trees in the Euphorbiaceae(Euph) and Dipterocarpaceae (Dipt) respectively. The significance levels in parenthesis are the result of HGLM accounting spatial autocorrelation.

	MP1-1988, Euph		MP2-2018, Dipt	
term	est ± se	*t*	est ± se	*t*
intercept	−24.983 ± 9.394	−2.659** [*]	−12.803 ± 5.268	−2.431* [*]
ln(gbh)	12.926 ± 4.754	2.719** [*]	6.237 ± 2.343	2.663** [**]
$[\ln(\text{gbh})]^2$	−1.5820 ± 0.5958	−2.655** [*]	−0.7004 ± 0.2554	−2.742** [**]
elevation	−0.02383 ± 0.00987	−2.415* [*]	−0.02271 ± 0.01046	−2.172* [^{ns}]

Table S2a. Logistic regressions of tree survival 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988, and elevation (GLM, binomial error).

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	−0.776 ± 0.379	−2.047*	−0.370 ± 0.383	-0.966^{ns}
nlianas$^{1/2}$	−0.1449 ± 0.0482	−3.007**	−0.2008 ± 0.0482	−4.169***
ln(gbh)	0.1948 ± 0.0913	2.133*	0.1530 ± 0.0901	1.697^{o}
elevation	−0.00174 ± 0.00607	-0.287^{ns}	0.01210 ± 0.00436	2.772**

Table S2b. Regressions of tree survival 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988, and elevation (GLM, binomial error), under repeated random sampling per subplot. Statistics are means of values from *N*' = 500 runs: each regression had *n* = 100 trees. All $P(t) > 0.05$.

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	−0.8445 ± 1.6567	−0.504	−0.6336 ± 1.6405	−0.357
nlianas$^{1/2}$	−0.1125 ± 0.2056	−0.533	−0.1826 ± 0.2025	−0.902
ln(gbh)	0.1949 ± 0.3995	0.486	0.2186 ± 0.3851	0.527
elevation	−0.00060 ± 0.02604	−0.021	0.01217 ± 0.01825	0.657

Table S2c. GLMM regressions of tree survival 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988, and elevation (binomial error), accounting for spatial autocorrelation (cluster = subplot), for trees in the Dipterocarpaceae.

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	0.652 ± 0.832	0.784^{ns}	0.926 ± 0.897	1.033^{ns}
nlianas$^{1/2}$	−0.2020 ± 0.1295	-1.640^{ns}	−0.4064 ± 0.1327	−3.064**
ln(gbh)	0.0999 ± 0.1839	0.543^{ns}	−0.0781 ± 0.1746	-0.447^{ns}
elevation	−0.03859 ± 0.01983	-1.946^{o}	0.00482 ± 0.01264	0.381^{ns}

Table S2d. GLMM regressions of tree survival 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988, and elevation (binomial error), accounting for spatial autocorrelation (cluster = subplot), for trees in the Euphorbiaceae.

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	−2.147 ± 1.925	-1.115^{ns}	0.596 ± 1.823	0.327^{ns}
nlianas$^{1/2}$	−0.4311 ± 0.1898	−2.272*	−0.3445 ± 0.1380	−2.497*
ln(gbh)	0.3864 ± 0.4946	0.781^{ns}	−0.1827 ± 0.4801	-0.381^{ns}
elevation	−0.00411 ± 0.01986	0.207^{ns}	0.01513 ± 0.01298	1.165^{ns}

Table S3a. Linear regressions of tree relative growth rate (rgr) 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988 (LM, gaussian error).

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	0.781 ± 0.071	11.067***	0.610 ± 0.059	10.262***
$nlianas^{1/2}$	−0.0364 ± 0.0095	−3.838***	−0.0328 ± 0.0082	−3.979***
ln(gbh)	−0.1080 ± 0.0171	−6.309***	−0.0791 ± 0.0143	−5.523***

Table S3b. Spatial autoregressions of tree relative growth rate (rgr) 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988 (GLS, gaussian error), based on a correlogram, and using an inferred distance matrix with neighbour range 0-20 m).

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	0.759 ± 0.071	10.727***	0.597 ± 0.060	10.011***
$nlianas^{1/2}$	−0.0371 ± 0.0095	−3.921***	−0.0347 ± 0.0082	−4.203***
ln(gbh)	−0.1030 ± 0.0171	−6.0358***	−0.0747 ± 0.0143	−5.238***

Table S3c. Linear regressions of tree relative growth rate (rgr) 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988 (LM, gaussian error), under repeated random sampling per subplot. Statistics are means of values from *N*' = 500 runs: each regression had *n* = 100 trees.

	MP1[a]		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	0.790 ± 0.205	3.855***	0.620 ± 0.187	3.311***
$nlianas^{1/2}$	−0.0377 ± 0.0257	$−1.469^{ns}$	−0.0299 ± 0.0256	$−1.168^{ns}$
ln(gbh)	−0.1088 ± 0.0498	−2.185*	−0.0800 ± 0.0449	$−1.780^{o}$

Table S3d. General least squares regressions of tree relative growth rate (rgr) 1988-2018 on number of lianas per tree and tree girth at breast height (gbh) in 1988 (GLS, mixed-model, gaussian error), accounting for spatial autocorrelation (corExp variogram), for trees in the Dipterocarpaceae.

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	1.744 ± 0.149	11.682***	1.435 ± 0.145	9.901***
$nlianas^{1/2}$	−0.0320 ± 0.0233	$−1.373^{ns}$	−0.0330 ± 0.0245	$−1.350^{ns}$
ln(gbh)	−0.2736 ± 0.0320	−8.588***	−0.2153 ± 0.0297	−7.262***

Table S3e. General least squares regressions of tree relative growth rate (rgr) 1988-2018 as for Table S3d, accounting for spatial autocorrelation (corExp variogram), for trees in the Euphorbiaceae.

	MP1		MP2	
term	est ± se	*t*	est ± se	*t*
intercept	0.262 ± 0.198	1.324^{ns}	0.288 ± 0.122	2.352*
$nlianas^{1/2}$	−0.0034 ± 0.0203	$−0.166^{ns}$	−0.0230 ± 0.0104	−2.217*
ln(gbh)	−0.0228 ± 0.0511	$−0.445^{ns}$	−0.0368 ± 0.0325	$−1.133^{ns}$

Table S4. Regressions of numbers of lianas per tree in 1988 and 2018, on tree relative growth rate 1988-2018 (rgr) and girth at breast height (gbh) for the census, and elevation (GLM, negative binomial error).

		MP1		MP2	
census	term	est ± se	*t*	est ± se	*t*
1988	intercept	−1.320 ± 2.447	−0.539^{ns}	−10.890 ± 2.772	−3.928***
	$rgr_{88\text{-}18}$	−0.4856 ± 0.2041	−2.380*	−0.8052 ± 0.2213	−3.638***
	$\ln(gbh_{88})$	1.029 ± 1.126	0.914^{ns}	5.597 ± 1.297	4.315***
	$[\ln(gbh_{88})]^2$	−0.1035 ± 0.1275	−0.812^{ns}	−0.6556 ± 0.1492	−4.392***
	elevation	−0.01875 ± 0.00673	−2.787**	−0.00536 ± 0.00483	−1.109^{ns}
2018	intercept	−7.880 ± 2.287	−3.446***	−19.058 ± 2.450	−7.780***
	$rgr_{88\text{-}18}$	−0.6961 ± 0.1699	−4.098***	−0.8944 ± 0.1799	−4.972***
	$\ln(gbh_{18})$	4.167 ± 1.022	4.078***	9.011 ± 1.108	8.136***
	$[\ln(gbh_{18})]^2$	−0.4765 ± 0.1121	−4.429***	−1.0024 ± 0.1233	−8.129***
	elevation	−0.01514 ± 0.00513	−2.948**	−0.01696 ± 0.00361	−4.702***

Table S5. On the interaction term in negative binomial GLM models

Model 4: $\text{nlianas} = \beta_0 + \beta_1\cdot\text{date} + \beta_2\cdot\ln(\text{gbh}) + \beta_3\cdot\text{date:}\ln(\text{gbh}) + \beta_4\cdot[\ln(\text{gbh})]^2 + \beta_5\cdot\text{date:}[\ln(\text{gbh})]^2$

From the results in Table 9 (main text), applying: $\beta_{int} = \beta_1 + \beta_3\cdot\ln(\text{gbh}_i) + \beta_5\cdot[\ln(\text{gbh}_i)]^2$:

(a) MP1:

ln(gbh)	β_{int}	$\exp(\beta_{int})$
3.5	−0.164	0.849
3.75	*−0.149*	*0.862*
4.0	*−0.164*	*0.849*
4.5	−0.288	0.750
5.5	−0.908	0.403

(b) MP2:

ln(gbh)	β_{int}	$\exp(\beta_{int})$
3.5	−0.486	0.615
3.75	*−0.444*	*0.641*
4.0	*−0.417*	*0.659*
4.5	−0.356	0.701
5.5	−0.320	0.726

Table S6. Inferred relationships for nlianas vs ln(gbh) in MP1 and MP2, (a) inferred from a GLM model with year as factor included, and (b) in comparison to earlier GLMs for the years separately.

(a) Inferred coefficients from model 4 in Table 9 (main text):

	Ref "88"	For -> "18"
MP1	intercept −3.24263	+ (−3.9479) = −7.19053
	ln(gbh) 1.59732	+ 2.0145 = 3.61182
	$[\ln(gbh)]^2$ −0.14719	+ (−0.26723) = −0.4142
MP2	intercept −10.40812	+ (−1.83716) = −12.2453
	ln(gbh) 5.27499	+ 0.58736 = 5.86236
	$[\ln(gbh)]^2$ −0.61432	+ (−0.05763) = −0.6720

(b) Separate GLM regressions for each year:

	MP1		MP2	
	1988	2018	1988	2018
intercept	−3.2129	−7.2876	−10.436	−12.1619
ln(gbh)	1.5835	3.6602	5.2886	5.8200
$[\ln(gbh)]^2$	−0.14563	−0.42035	−0.6160	−0.6667

Table S7. Mean number of lianas per tree as predicted by models 1 to 4, for MP1 and MP2 separately, for all trees and those in the Dipterocarpaceae and Euphorbiaceae. The values are averages of *N*' = 500 randomizations. Predictions were made with the means of ln(gbh) and $[\ln(gbh)]^2$ taken for plots (a), combined, and (b), separate.

(a)		MP1, est ± se		MP2, est ± se	
Family	M	1988	2018	1988	2018
All	1	2.163 ± 0.096	1.686 ± 0.078	2.017 ± 0.099	1.335 ± 0.066
	2	2.141 ± 0.095	1.687 ± 0.077	2.017 ± 0.099	1.335 ± 0.066
	3	2.132 ± 0.094	1.685 ± 0.077	2.015 ± 0.099	1.333 ± 0.066
	4	2.124 ± 0.093	1.661 ± 0.076	1.960 ± 0.095	1.295 ± 0.064
Dipt	1	1.834 ± 0.294	0.998 ± 0.170	1.364 ± 0.211	0.841 ± 0.132
Euph	1	1.918 ± 0.223	1.882 ± 0.228	1.998 ± 0.273	1.045 ± 0.155

(b)		MP1, est ± se		MP2, est ± se	
Family	M	1988	2018	1988	2018
All	1	same as in (a)	--	--	--
	2	2.143 ± 0.095	1.685 ± 0.077	2.017 ± 0.099	1.334 ± 0.066
	3	2.136 ± 0.094	1.685 ± 0.077	2.015 ± 0.099	1.333 ± 0.066
	4	2.127 ± 0.093	1.663 ± 0.076	1.965 ± 0.096	1.291 ± 0.064
Dipt	1	same as in (a)	--	--	--
Euph	1	same as in (a)	--	--	--

Appendix S3. Comparison of four models of change in lianas

Table S1. Means and standard errors of the fitting statistics for the models 1 – 4 (see main text and Table 9).

(a) MP1

Variable	Mean	SE Mean	Minimum	Median	Maximum
AIC.1	6365.4	4.35	6099.0	6366.2	6650.4
AIC.2	6357.9	4.31	6092.4	6357.9	6640.2
AIC.3	6353.7	4.29	6087.7	6352.5	6637.2
AIC.4	6341.1	4.30	6076.3	6340.7	6633.0
pseudoR2.1	0.8670	0.0137	0.2031	0.8585	1.9315
pseudoR2.2	1.3936	0.0193	0.4440	1.3659	2.7016
pseudoR2.3	1.7345	0.0240	0.5610	1.6994	3.3372
pseudoR2.4	2.6418	0.0284	1.2031	2.5737	5.0361
dev.1	1796.9	1.11	1726.9	1796.6	1864.0
dev.2	1798.1	1.11	1729.9	1797.8	1865.1
dev.3	1798.8	1.11	1731.3	1798.6	1865.6
dev.4	1800.2	1.11	1732.0	1800.0	1868.4
df.1	1698.3	0.956	1636.0	1697.0	1758.0
df.2	1697.3	0.956	1635.0	1696.0	1757.0
df.3	1696.3	0.956	1634.0	1695.0	1756.0
df.4	1694.3	0.956	1632.0	1693.0	1754.0
ano.12.p	0.02262	0.00277	0.00000	0.00261	0.63825
ano.13.p	0.01191	0.00164	0.00000	0.00055	0.42979
ano.14.p	0.000277	0.000085	0.000000	0.000003	0.031996
ano.23.p	0.05927	0.00489	0.00001	0.01764	0.97359
ano.24.p	0.001937	0.000347	0.000000	0.000071	0.104181
ano.34.p	0.005916	0.000968	0.000000	0.000477	0.329315
ano.12.LR	9.532	0.218	0.221	9.061	27.566
ano.13.LR	15.725	0.308	1.689	15.007	40.145
ano.14.LR	32.285	0.395	10.559	31.308	65.398
ano.23.LR	6.193	0.163	0.001	5.631	20.342

ano.24.LR	22.753	0.353	6.158	21.831	58.006
ano.34.LR	16.560	0.313	2.221	15.298	43.995

(b) MP2

Variable	Mean	SE Mean	Minimum	Median	Maximum
AIC.1	6060.2	4.30	5764.5	6062.0	6349.0
AIC.2	6061.6	4.29	5766.5	6063.9	6350.8
AIC.3	6062.2	4.30	5768.5	6064.2	6351.1
AIC.4	6021.8	4.29	5720.5	6023.2	6310.3
pseudoR2.1	1.9824	0.0218	0.7837	1.9496	3.9091
pseudoR2.2	2.0151	0.0221	0.7863	1.9792	3.9207
pseudoR2.3	2.0934	0.0216	0.9085	2.0522	4.0485
pseudoR2.4	4.5676	0.0334	2.7187	4.5068	7.9302
dev.1	1752.8	1.08	1663.5	1753.9	1826.4
dev.2	1752.8	1.08	1663.5	1753.8	1826.3
dev.3	1752.9	1.08	1663.5	1753.8	1826.2
dev.4	1754.6	1.08	1665.9	1755.3	1827.7
df.1	1744.3	0.904	1683.0	1745.0	1806.0
df.2	1743.3	0.904	1682.0	1744.0	1805.0
df.3	1742.3	0.904	1681.0	1743.0	1804.0
df.4	1740.3	0.904	1679.0	1741.0	1802.0
ano.12.p	0.5737	0.0113	0.0158	0.5849	0.9988
ano.13.p	0.4895	0.0122	0.0009	0.4979	0.9995
ano.14.p	0.000001	0.000000	0.000000	0.000000	0.000065
ano.23.p	0.4282	0.0132	0.0003	0.3906	0.9979
ano.24.p	0.000000	0.000000	0.000000	0.000000	0.000021
ano.34.p	0.000000	0.000000	0.000000	0.000000	0.000011
ano.12.LR	0.5821	0.0347	0.0000	0.2984	5.8279
ano.13.LR	1.9707	0.0829	0.0010	1.3945	14.0560
ano.14.LR	46.387	0.477	24.443	45.558	94.141
ano.23.LR	1.3886	0.0789	0.0000	0.7372	13.0457
ano.24.LR	45.805	0.480	24.337	45.301	94.123
ano.34.LR	44.416	0.471	22.774	43.638	89.277

Table S2. Frequencies with which the probability of the chi-squared estimate of deviance change was the lowest, and the delta-AIC value was the highest, between compared models.

	MP1			MP2		
	ano.p	dAIC	LR	Ano.p	dAIC	LR
12	1	0	0	0	0	0
13	6	3	0	0	0	0
14	455	475	500	5	13	500
23	0	0	0	0	0	0
24	20	14	0	57	114	0
34	18	8	0	438	373	0

Appendix S4. Liana densities at the species level

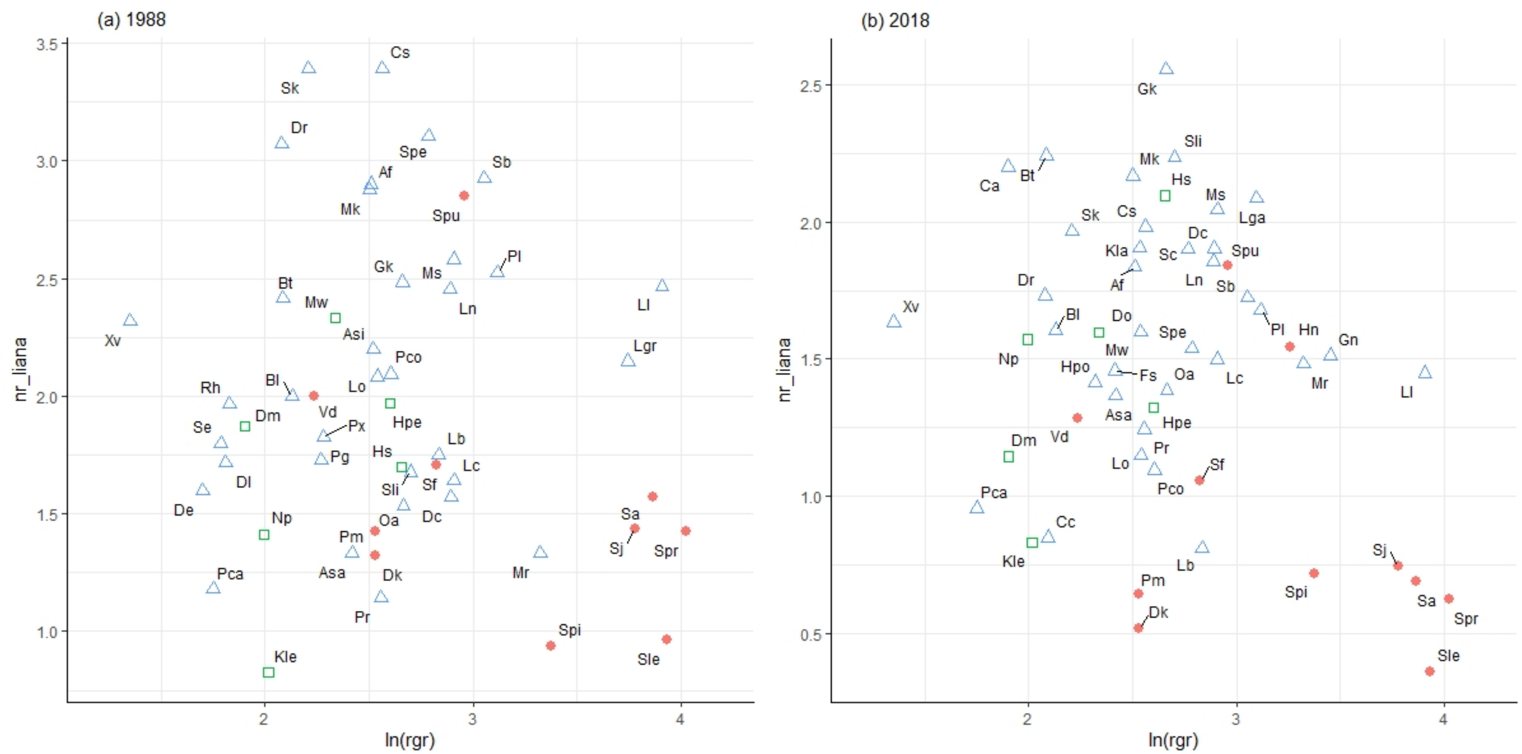
Table S1. Mean and SE of number of lianas per tree (≥ 30 cm gbh) at Danum in 1988 and 2018, for those species with $n \geq 20$ trees per species in the two plots (MP1 and MP2) combined. Nomenclature follows the revisions of 2015. Abbreviations (Abbr.) are used in Figs 4-6 in the main paper, and Fig. S1 in this appendix.

Species name	Authority	Family	Abbr.	1988			2018		
				n	mean	se	*n*	mean	se
Aglaia silvestris	(M.Roem.) Merr.	Meliaceae	Asi	20	2.20	0.91			
Aporosa falcifera	Hook.f.	Phyllanthaceae	Af	122	2.90	0.31	85	1.84	0.17
Ardisia sanguinolenta	Blume	Primulaceae	Asa	30	1.33	0.35	38	1.37	0.23
Baccaurea tetrandra	(Baill.) Müll.Arg.	Phyllanthaceae	Bt	77	2.42	0.32	79	2.24	0.23
Barringtonia lanceolata	(Ridl.) Payens	Lecythidaceae	Bl	76	2.00	0.32	66	1.61	0.22
Canarium denticulatum	Blume	Burseraceae	Ca				20	2.20	0.57
Chisocheton sarawakanus	(C.DC.) Harms	Meliaceae	Cs	51	3.39	0.59	53	1.98	0.31
Cleistanthus contractus	Airy Shaw	Phyllanthaceae	Cc				20	0.85	0.27
Dacryodes rostrata	(Blume) H.J.Lam	Burseraceae	Dr	27	3.07	0.56	26	1.73	0.41
Dimorphocalyx muricatus	(Hook.f.) Airy Shaw	Euphorbiaceae	Dm	62	1.87	0.34	76	1.14	0.15
Diospyros elliptifolia	Merr.	Ebenaceae	De	20	1.60	0.42			
Dipterocarpus kerrii	King	Dipterocarpaceae	Dk	25	1.32	0.64	25	0.52	0.16
Drypetes longifolia	(Blume) Pax & K.Hoffm.	Putranjivaceae	Dl	32	1.72	0.50			
Dysoxylum cyrtobotryum	Miq.	Meliaceae	Dc	49	1.57	0.40	82	1.90	0.26
Dysoxylum rigidum	(Ridl.) Mabb.	Meliaceae	Do				20	1.60	0.39
Fordia splendidissima	(Miq.) Buijsen	Leguminosae	Fs				24	1.46	0.36
Gironniera nervosa	Planch.	Cannabaceae	Gn				39	1.51	0.42
Gonystylus keithii	Airy Shaw	Thymelaeaceae	Gk	31	2.48	0.59	36	2.56	0.38
Hancea penangensis	(Müll.Arg.) Sierra et al.	Euphorbiaceae	Hpe	36	1.97	0.43	34	1.32	0.25
Hancea stipularis	(Airy Shaw) Sierra et al.	Euphorbiaceae	Hs	30	1.70	0.49	21	2.10	0.54

Hopea nervosa	King	Dipterocarpaceae	Hn				33	1.55	0.43
Hydnocarpus polypetalus	(Slooten) Sleumer	Flacourtiaceae	Hpo				24	1.42	0.30
Knema latericia	Elmer	Myristicaceae	Kla				21	1.90	0.36
Koilodepas laevigatum	Airy Shaw	Euphorbiaceae	Kle	29	0.83	0.30	24	0.83	0.22
Lithocarpus gracilis	(Korth.) Soepadmo	Fagaceae	Lgr	27	2.15	0.71			
Lithocarpus leptogyne	(Korth.) Soepadmo	Fagaceae	Ll	28	2.46	1.07	29	1.45	0.31
Lithocarpus nieuwenhuisii	(Seemen) A.Camus	Fagaceae	Ln	57	2.46	0.56	49	1.86	0.38
Litsea caulocarpa	Merr.	Lauraceae	Lc	39	1.64	0.33	54	1.50	0.23
Litsea garciae	Vidal	Lauraceae	Lga				23	2.09	0.47
Litsea ochracea	(Blume) Boerl.	Lauraceae	Lo	36	2.08	0.48	20	1.15	0.35
Lophopetalum beccarianum	Pierre	Celastraceae	Lb	20	1.75	0.61	58	0.81	0.14
Maasia sumatrana	(Miq.) Mols et al.	Annonaceae	Ms	79	2.58	0.34	70	2.04	0.27
Madhuca korthalsii	(Pierre ex Burck) H.J.Lam	Sapotaceae	Mk	115	2.88	0.32	126	2.17	0.18
Mallotus wrayi	King ex Hook.f.	Euphorbiaceae	Mw	202	2.33	0.20	207	1.60	0.13
Microcos reticulata	Ridl.	Malvaceae	Mr	30	1.33	0.40	31	1.48	0.31
Neoscortechinia philippinensis	(Merr.) Welzen	Euphorbiaceae	Np	58	1.41	0.38	35	1.57	0.48
Nothaphoebe species a	---	Lauraceae	Nsp	20	1.20	0.44			
Ochanostachys amentacea	Mast.	Olacaceae	Oa	30	1.53	0.48	26	1.38	0.35
Parashorea malaanonan	Merr.	Dipterocarpaceae	Pm	66	1.42	0.33	59	0.64	0.16
Pentace laxiflora	Merr.	Malvaceae	Pl	95	2.53	0.40	96	1.68	0.18
Polyalthia cauliflora	Hook.f. & Thomson	Annonaceae	Pca	39	1.18	0.31	23	0.96	0.27
Polyalthia congesta	(Ridl.) J.Sinclair	Annonaceae	Pco	21	2.10	0.66	21	1.10	0.24
Polyalthia rumphii	(Blume ex Hensch.) Merr.	Annonaceae	Pr	21	1.14	0.31	45	1.24	0.31
Polyalthia xanthopetala	Merr.	Annonaceae	Px	29	1.83	0.60			
Pternandra galeata	Ridl.	Melastomataceae	Pg	22	1.73	0.50			
Reinwardtiodendron humile	(Hassk.) Mabb.	Meliaceae	Rh	31	1.97	0.34			
Scorodocarpus borneensis	(Baill.) Becc.	Olacaceae	Sb	55	2.93	0.53	58	1.72	0.21
Shorea argentifolia	Symington	Dipterocarpaceae	Sa	28	1.57	0.68	29	0.69	0.38
Shorea fallax	Meijer	Dipterocarpaceae	Sf	75	1.71	0.42	86	1.06	0.15
Shorea johorensis	Foxw.	Dipterocarpaceae	Sj	76	1.43	0.38	75	0.75	0.18
Shorea leprosula	Miq.	Dipterocarpaceae	Sl	29	0.97	0.37	25	0.36	0.18
Shorea parvifolia	Dyer	Dipterocarpaceae	Spr	106	1.42	0.34	115	0.63	0.15

Shorea pauciflora	King	Dipterocarpaceae	Spu	33	2.85	0.58	31	1.84	0.35
Shorea pilosa	P.S.Ashton	Dipterocarpaceae	Spi	47	0.94	0.32	57	0.72	0.18
Syzygium castaneum	(Merr.) Merr. & L.M.Perry	Myrtaceae	Sc				20	1.90	0.51
Syzygium elopurae	(Ridl.) Merr. & L.M.Perry	Myrtaceae	Se	30	1.80	0.46			
Syzygium kunstleri	(King) Bahadur & R.C.Gaur	Myrtaceae	Sk	33	3.39	0.76	29	1.97	0.34
Syzygium lineatum	(DC.) Merr. & L.M.Perry	Myrtaceae	Sl	31	1.68	0.43	30	2.23	0.39
Syzygium peregrinum	(Blume) Merr. & L.M.Perry	Myrtaceae	Sp	48	3.10	0.57	39	1.54	0.35
Vatica dulitensis	Symington	Dipterocarpaceae	Vd	26	2.00	0.76	21	1.29	0.34
Xanthophyllum vitellinum	(Blume) D.Dietr.	Polygalaceae	Xv	25	2.32	0.55	30	1.63	0.33

Fig. S1. Relationships between mean species' number of lianas per tree (nr_lianas) and the stem relative growth rate (rgr, mm/m/yr), for species with ≥ 20 trees in plots MP1 and MP2 combined in (a) 1988 and (b) 2018. Closed red circles, Dipterocarpaceae; open blue squares, Euphorbiaceae; open green triangles, other families. This figure complements Fig. 4 of the main text.



Ecosphere/Changes in liana density over 30 years in a Bornean rain forest supports the escape hypothesis/D. M. Newbery and C. Zahnd

Appendix S5. Code for statistical analyses

1. R-code for the randomization functions (written by CZ)

```
# Change in liana abundance with time. A and B are auxiliary functions used later in C-E.
# In C-E extraction of parameter estimates and statistics was omitted, in E the model
# comparisons with ANOVA were also omitted. C-E were run for each plot, and for
# dipterocarps and euphorbs in each plot separately.

# A. Randomly sample close to half of the rows (tag is the tree numbers).
randomRows <- function(dat, n = round(((1/2) * nrow(dat)) -1, 0)){
	sample(dat$tag, n, replace = F)
} # end of randomRows function.

# B. Create a flagging column in the dataset based on randomRows (A).
flagging <- function(dat, f){
for(i in 1:nrow(dat)){
if(dat$tag[i] %in% f){
dat$flag[i] <- 1
}else{
dat$flag[i] <- 0
}
}
return(dat)
} # end of flagging function.

# C. Change in proportion of liana infested trees (df is the input data frame)
randomProp <- function(df, iter = 500){
set.seed(8751)
# initialize output vectors, e.g.:
p_val <- rep(NA, iter)
# Run the 500 random subsamplings:
for(i in 1:iter){
# randomly select close to half of all rows and create a flagging column:
temp <- randomRows(dat = df)
flagged <- flagging(dat = df, f = temp)
# subset data based on flagging column for 1988 and 2018:
flagged88 <- subset(flagged, flagged$flag == 1)
flagged88 <- subset(flagged88, !is.na(flagged88$liana_pres88))
flagged18 <- subset(flagged, flagged$flag == 0)
flagged18 <- subset(flagged18, !is.na(flagged18$liana_pres18))
# Calculate total number of trees and proportions with lianas (liana_pres indicate liana
# presence (1) or absence (0) on each tree):
proportions <- integer(2)
```

```
proportions[2] <- sum(flagged88$liana_pres88)
proportions[1] <- sum(flagged18$liana_pres18)
lengths <- integer(2)
lengths[2] <- nrow(flagged88)
lengths[1] <- nrow(flagged18)
# The chi-squared test:
test <- prop.test(proportions, lengths, correct = TRUE)
# save results into output vectors, e.g.:
p_val[i] <- round(test$p.value, 6)
}
# here all output vectors can be put together into a data.frame and returned from the
# function.
} # end of randomProp function.
```

D. Frequency of trees in liana density classes.

```
randomCount <- function(df, iter = 500){
set.seed(8751)
# initialize output vectors, e.g.:
p_val <- rep(NA, iter)
# randomly select close to half of all rows and create a flagging column:
for(i in 1:iter){
temp <- randomRows(dat = df)
flagged <- flagging(dat = df, f = temp)
# subset data based on flagging column for 1988 and 2018:
flagged88 <- subset(flagged, flagged$flag == 1)
flagged88 <- subset(flagged88, !is.na(flagged88$nr_liana88))
flagged18 <- subset(flagged, flagged$flag == 0)
flagged18 <- subset(flagged18, !is.na(flagged18$nr_liana18))
# Find the most liana count classes possible with no class having < 5 counts in either year.
maxi88 <- max(flagged88$nr_liana88)
maxi18 <- max(flagged18$nr_liana18)
maxi <- integer(1)
maxi <- max(c(maxi88, maxi18))
classes <- c(0:maxi)
counts88 <- integer(length(classes))
for(j in 1:(length(classes))){
counts88[j] <- nrow(flagged88[flagged88$nr_liana88 == (j-1),])
}
counts18 <- integer(length(classes))
for(k in 1:(length(classes))){
counts18[k] <- nrow(flagged18[flagged18$nr_liana18 == (k-1),])
}
cs <- factor(0:maxi)
s <- 1
while(counts88[s] >= 5){
s <- s + 1
}
```

```
t <- 1
while(counts18[t] >= 5){
t <- t + 1
}
shorten <- min(c(s, t))
}
cs[shorten:length(classes)] <- as.character(cs[shorten])
# Sum the trees in the liana density classes defined above:
of88 <- as.vector(tapply(counts88, cs, sum))
of18 <- as.vector(tapply(counts18, cs, sum))
of <- c(of88, of18)
mtrx <- matrix(of, nrow = length(of88))
mtrx <- mtrx[1:shorten,]
# run the chi-squared test:
test <- chisq.test(mtrx)
# save results into output vectors, e.g.:
p_val[i] <- test$p.value
}
# here all output vectors can be put together into a data.frame and returned from the
# function.
} # end of randomCount function.

# E. Mean number of lianas per tree:
randomMean <- function(df, iter = 500){
set.seed(8751)
# initialize output vectors for all 4 models and model comparisons with ANOVA, e.g.:
inter.zval.1 <- vector(mode="numeric",iter)
year.se.2 <- vector(mode="numeric",iter)
# randomly select close to half of all rows and create a flagging column:
for(i in 1:iter){
temp <- randomRows(dat = df)
flagged <- flagging(dat = df, f = temp)
# subset data based on flagging column for 1988 and 2018 and recombine subset data:
flagged88 <- subset(flagged, flagged$flag == 1)
flagged88 <- subset(flagged88, !is.na(flagged88$nr_liana88))
flagged88a <- subset(flagged88, select = - c(size_class18, liana_pres18, bamboo18,
                                   nr_liana18, stat18, GBH18, bamboo88))
   names(flagged88a) <- c("plot", "subplot", "tag", "f_code15" ,"g_code15",
                  "sp_code15", "GBH", "stat", "nr_liana", "uni_code",
                  "liana_pres", "size_class", "flag")
flagged88a$year <- as.factor("88")
flagged18 <- subset(flagged, flagged$flag == 0)
flagged18 <- subset(flagged18, !is.na(flagged18$nr_liana18))
flagged18a <- subset(flagged18, select = - c(size_class88, liana_pres88, bamboo18,
                                   nr_liana88, stat88, GBH88, bamboo88))
   names(flagged18a) <- c("plot", "subplot", "tag", "f_code15", "g_code15",
                  "sp_code15", "uni_code", "GBH", "stat", "nr_liana",
```

```
                    "liana_pres", "size_class", "flag")
flagged18a$year <- as.factor("18")
comb <- rbind(flagged88a, flagged18a)
# create lnGBH:
comb$lnGBH <- log(comb$GBH)
comb$lnGBHq <- (comb$lnGBH)^2
# run the 4 glm.nb models:
mod1 <- with(comb, glm.nb(nr_liana ~ year, link = log))
mod2 <- with(comb, glm.nb(nr_liana ~ year + lnGBH, link = log))
mod3 <- with(comb, glm.nb(nr_liana ~ year * lnGBH, link = log))
mod4 <- with(comb, glm.nb(nr_liana ~ year * lnGBH + lnGBHq + year:lnGBHq, link = log))
# calculate pseudo R-squared for each model, e.g.:
LLM <- -(summary(mod1)$deviance)/2
LL0 <- -( summary(mod1)$null.deviance)/2
pseudoR2.1 <- ((LL0-LLM)/LL0)*100
rm("LLM", "LL0") # (do the same for the other models)
# here pairwise model comparisons with anova would be made as described in the main
# text.
# here all parameter estimates and statistics from the models and model comparisons
# would be saved in the output vectors.
}
# here all output vectors can be put together into a data.frame and returned from the
# function.
} # end of randomMean function.
```

2. Regression modelling with spatial autocorrelation

Essential R-commands (applied by DMN).

```
# basic input/variable calcs and summary/anova/plotting/etc commands not shown.

# 'liana2er.88' or 'liana2er.18' are base data.frames,'liana2er.88s' or 'liana2er.18s'

# those for survivors. 'elevplus' has within-plot elevations of 1988 added to 2018 trees.


# 1. nr_lianas (variable names for 1988 -- similar for 2018). [GBH is girth at breast height]

# calculate distance matrix (plot/census specific)

distMat <- as.matrix(dist(cds,method="euclidean",diag=TRUE,upper=TRUE,p=2))

distMat.inv <- ifelse(distMat == 0, 0, 1/distMat)

# negative binomial glm (run for census x plot separately)[lnGBH88q is lnGBH88 squared]

nb_mod.88 <-
glm.nb(formula=nr_liana88~lnGBH88+lnGBH88q+elevplus,data=liana2er.88,link=log)

# hglm with spatial correlation matrix (run for census x plot separately)

hglm_mod.88 <- hglm(fixed = nr_liana18~lnGBH88+lnGBH88q+elevplus,

 rand.family = SAR(D = distMat.inv),

 data = liana2er.88,random = ~1|tag,family = quasipoisson(link="log"))

# glmmML (for family level analyses): spatial neighbours as subplot coords (20-m x 20-m grids).

mod1s <- glmmML(surv18~nr_liana.sqrt+lnGBH88+elevplus,cluster = subpl, family=binomial)


# 2. tree survival (nr_liana.sqrt is square-root of number of lianas)

# binomial glm (run for plots separately)[surv18 is survival 1988-2018]

bin_mod <- glm(surv18~nr_liana.sqrt+lnGBH88+elevplus,binomial)

# autologistic regression with distance-based correlation term

autol.mod <- logistic.regression(ldata=liana2er.88,y='surv18',x=c('nr_liana.sqrt',

 'lnGBH88','elevplus'), penalty=TRUE,autologistic=TRUE,type="inverse.squared",

 coords=cds,bw=20,style="B")
```

```
# 3. tree growth (run for plots separately)[rgr18 is relative growth rate 1988-2018]

# gaussian gls, or equvalently lm, regression

gls.mod <- gls(rgr18~nr_liana.sqrt+lnGBH88,liana2er.88s)

# A. gls regression with variogram-based spatial correlation function

gls_mod.exp <- update (gls.mod, corr = corExp(c(60,0.9), form = ~ x + y, nugget=T))

# B. spatial lm regression (using distance to nearest neighbours, defined by Moran's I

# and Geary's C statistics.

cds.nb <- dnearneigh(as.matrix(cds),d1=0,d2=20)

cds.lw <- nb2listw(cds.nb,style="B",zero.policy=TRUE)

spatlm.mod <- spautolm(rgr18 ~ nr_liana.sqrt + lnGBH88, data = liana2er.88s,

 family = "SAR", listw = cds.lw, zero.policy = TRUE)
```