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APPENDIX 1 FINAL DATASET VERSUS ORIGINAL DATASET

To examine how well the semi-random selection of plots (n = 6,935) represents the original dataset (n = 37,513), we used a quantile-quantile representation (Q-Q plot) for all of the predictor variables (see the materials and methods section of the main text for more details on each of the 12 predictor variables) used in our modelling framework. These Q-Q plots are a graphical method to compare the distribution of two samples with different sizes by plotting their quantiles against each other. In that case, we plotted the original values for each variable from the original dataset against the values of the same variable from the final dataset.

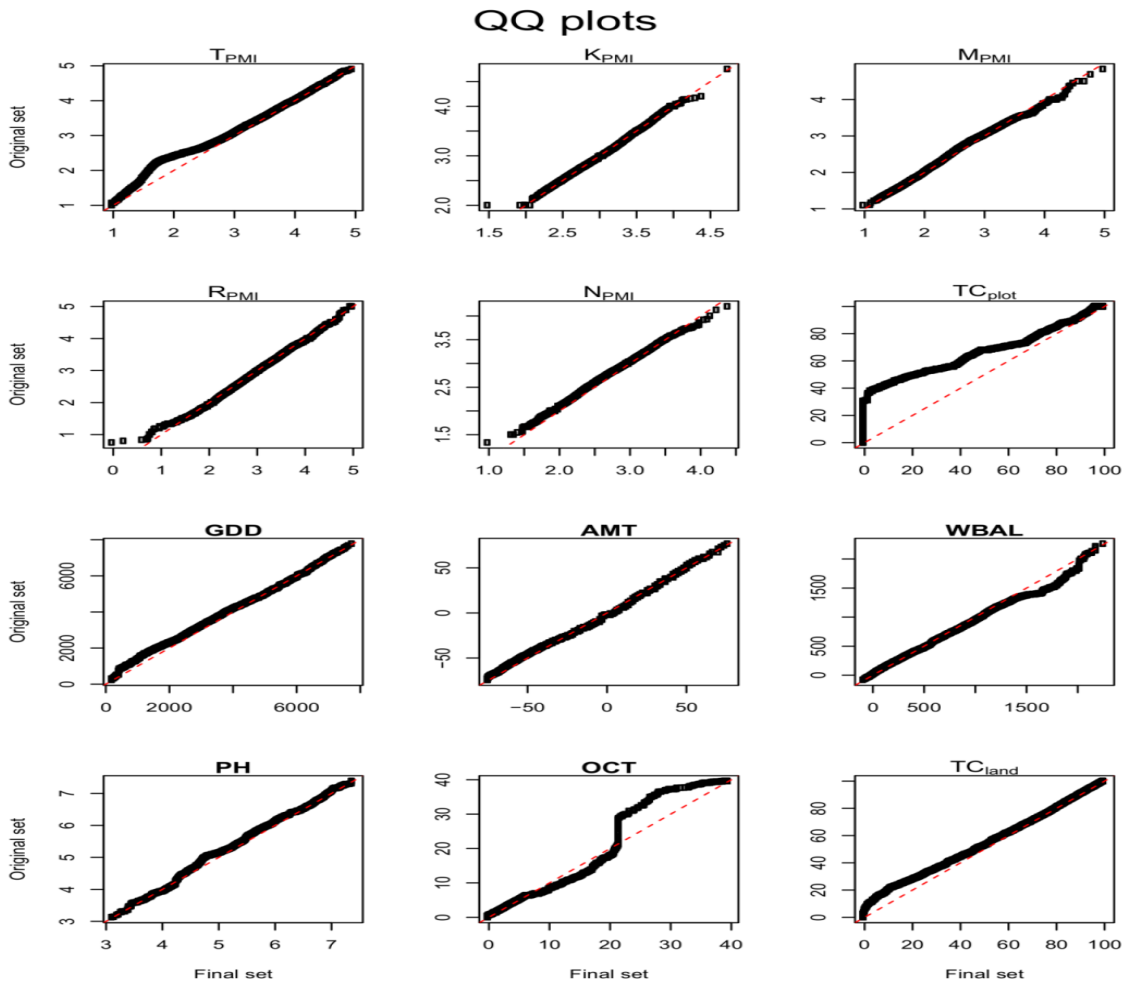

Figure A1: Q-Q plot for all of the variables with the samples from the original dataset (37,513 plots) versus the final dataset (6,935 plots), which was a semi-random subsample of the original dataset. The black circles represent the quantiles for each distribution, and the dashed red line the 1:1 relationship line. When the circles fall close to the 1:1 line, there is no significant difference between the two samples. See the materials and methods section of the main text for the full meaning of the acronyms used for each of the 12 predictor variables.

All of the predictor variables showed the same distributions between the initial and the final datasets, with the exceptions of tree cover (TC_{plot}) among the plot-grain variables and organic content in the top soil (OCT) among the landscape-grain variables (Fig. A1). Figure A2 shows the histograms for these two predictor variables. Note that the histograms remain similar between the final and original datasets for both variables. Therefore, we consider the final dataset obtained from a semi-randomised selection to be representative of the original dataset.

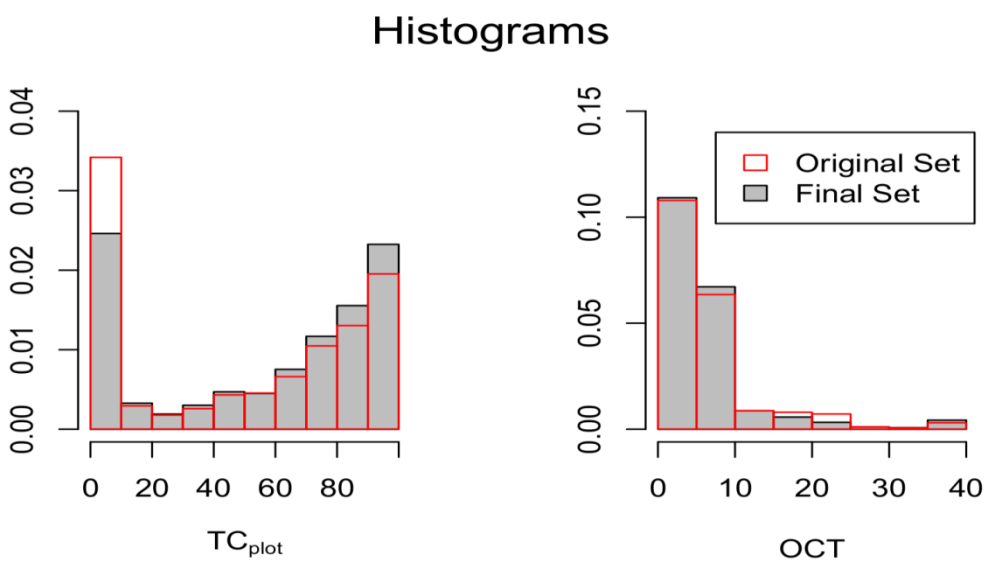

Figure A2: Histograms for the variables with significant differences between the original and the final dataset: tree cover at the plot grain (TC_{plot}) and organic content of the top soil (OCT) at the landscape grain.

APPENDIX 2 CALCULATION OF THE PREDICTOR VARIABLES AND THE CORRELATION MATRIX

Landscape variables calculation

Growing degree days (GDD) was calculated following Equation 1 (Synes and Osborne 2011), where the monthly (i) minimum mean temperature ($Tmin_i$) and the maximum mean temperature ($Tmax_i$) are replaced by the baseline temperature (Tbase=0 ºC) when they are less than Tbase (McMaster and Wilhelm 1997).

$$GDD = \Sigma_{i=1-12} \{[(Tmax_i + Tmin_i)/2] - Tbase\} \qquad \text{Eqn 1}$$

The absolute minimum temperature (AMT) was calculated following Equation 2 (Skov and Svenning 2004, Synes and Osborne 2011).

$$AMT = (0.006 * Tmin^2) + (1.316 * Tmin^2) - 2.19 \qquad \text{Eqn 2}$$

The water balance (WBAL) was calculated following Equation 3 (Skov and Svenning 2004), where $Prec_i$ represents monthly (i) precipitation, and PET_i represents monthly (i) potential evapotranspiration.

$$WBAL = \Sigma_{i=1-12} (Prec_i - PET_i) \qquad \text{Eqn 3}$$

PET_i was calculated following Equation 4 (Holdridge 1967, Lugo et al. 1999).

$$PET_i = 58.93 * Tbio_i /12 \qquad \text{Eqn 4}$$

where $Tbio_i = Tavg_i$ if $0 < Tavg_i < 30$ (otherwise $Tbio_i = 0$); and $Tavg_i$ represents the monthly (i) average temperature.

Two soil variables, organic content in the top soil (OCT) and soil reaction (pH), were re-projected from the original grid coordinate system in the ETRS89 Lambert Azimuthal Equal Area projection to our geographical coordinate system at 30” resolution. Because the original projected grids have different cell sizes than our working grid, we resampled the data using bilinear interpolation.

Correlations between predictive variables

Table A1 shows the correlation between the variables used as predictors in the models. In general, all variables show a low level of correlation, with few exceptions, at both the plot and landscape grain. At the plot grain, the continentality plot mean indicator values (K_{PMI}) were correlated with the soil moisture plot mean indicator values (M_{PMI}). At the landscape grain, GDD is correlated with

AMT and WBAL, and AMT is correlated with WBAL and pH. Tree cover at both grains (TC_{plot} and TC_{land}) shows no correlation with any of the other predictor variables, and more interestingly, they show an intermediate level of correlation with each other.

When comparing the plot variables with their equivalent at the landscape grain, we can see that some variables are strongly correlated—such as the temperature plot mean indicator (T_{PMI}) with GDD, AMT and WBAL—and that some other variables show an intermediate correlation—such as M_{PMI} with WBAL, soil reaction plot indicator values (R_{PMI}) with PH, and TC_{plot} with TC_{land}—whereas K_{PMI} and the nutrient plot indicator values (N_{PMI}) do not correlate at all with their homologous variables or any other variable.

Table A1: The correlation matrix of the predictor variables. Bolded values indicate strong correlations. The variables included in this study are the plot mean indicator values (PMI) for temperature (T), continentality (K), soil moisture (M), soil reaction (R), nutrients in the soil (N) and tree cover (TC_{plot}) at the plot grain, and growing degree days (GDD), absolute minimum temperature (AMT), water balance (WBAL), soil reaction (PH), organic content in the top soil (OCT) and tree cover (TC_{land}) at the landscape grain. Light plot mean indicator value (L_{PMI}) is also shown in this table.

		Plot variables					Landscape variables						L_{PMI}
		K_{PMI}	M_{PMI}	R_{PMI}	N_{PMI}	TC_{plot}	GDD	AMT	WBAL	PH	OCT	TC_{land}	
Plot variables	T_{PMI}	0.046	-0.463	0.354	0.211	0.252	**0.883**	**0.782**	**-0.817**	0.453	-0.182	0.21	-0.103
	K_{PMI}		**-0.767**	0.379	-0.672	-0.455	0.016	0.083	-0.129	0.247	-0.09	-0.235	0.708
	M_{PMI}			-0.457	0.599	0.309	-0.426	-0.505	0.466	-0.453	0.199	0.125	-0.614
	R_{PMI}				-0.064	-0.25	0.331	0.334	-0.362	0.447	-0.199	-0.238	0.492
	N_{PMI}					0.372	0.126	-0.038	-0.082	-0.06	0.045	0.178	-0.59
	TC_{plot}						0.24	0.099	-0.155	-0.231	0.027	0.387	**-0.736**
Landscape variables	GDD							**0.921**	**-0.898**	0.464	-0.243	0.189	-0.038
	AMT								**-0.779**	0.496	-0.24	0.096	0.146
	WBAL									-0.554	0.278	-0.164	-0.022
	PH										-0.168	-0.132	0.363
	OCT											0.096	-0.113
	TC_{land}												-0.475

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APPENDIX 3 COMPLEMENTARY ANALYSIS WITH BOOSTED REGRESSION TREES AND MAXENT

To contrast the results with those of other statistical models, the same analyses were performed with the boosted regression trees (BRTs) (Ridgeway 1999, 2012, Elith et al. 2008) and Maxent (Phillips et al. 2006). We used Maxent 3.3.3.k with the default parameter settings, which have been proven to be reliable in a wide number of studies, and because of the impossibility of tuning the individual models for each species modelled in this study. For BRTs, we optimised the number of trees for each species using the "gbm.holdout" function in the "dismo" package. The parameters used in the BRTs were a Bernoulli family, an intermediate learning rate of 0.01, a train fraction of 0.7, and a tree complexity of 5, which allowed a fair degree of interactions between variables.

By definition, Maxent compares a background dataset with the presences. In our study, the background is the final dataset of the vegetation plots (*n*=6,935). Hence, the background is here defined as conceptually designed in Maxent: all of the vegetation plots where plant species were surveyed. BRT models were fitted similarly to GLM, using real presences and absences from the dataset.

The results are consistent with the outputs from the analyses of the generalised linear models (GLMs) and did not change our interpretations and conclusions. Overall, the effect of tree cover at the landscape grain was less evident for Maxent and BRTs than for GLMs.

Table A2: Median, minimum and maximum values for Area Under the Curve of the Receiver Operating Characteristics plot (AUC), correlation coefficient (COR), and true skill statistic (TSS) for 960 herb and shrub species modelled with boosted regression trees and different predictors sets (C: climate; S: soil; and T: tree cover). Evaluation was performed using a test dataset with 25% of the total plots.

	Variables	AUC [0.5 to 1]		COR [-1 to 1]		TSS [-1 to 1]	
		median	min–max	median	min–max	median	min–max
Plot Models	CST	0.927	0.630–0.999	0.383	-0.001–0.875	0.635	-0.001–0.989
	CS	0.923	0.531–0.999	0.367	-0.002–0.859	0.640	-0.019–0.988
	CT	0.913	0.572–0.999	0.312	-0.005–0.875	0.612	-0.007–0.987
	C	0.899	0.568–0.999	0.272	-0.008–0.841	0.559	-0.078–0.974
Landscape Models	CST	0.866	0.309–0.999	0.233	-0.010–0.772	0.476	-0.039–0.976
	CS	0.865	0.458–0.998	0.233	-0.017–0.766	0.498	-0.040–0.978
	CT	0.838	0.353–0.996	0.197	-0.019–0.776	0.474	-0.019–0.991
	C	0.839	0.448–0.995	0.201	-0.017–0.760	0.455	-0.096–0.980

Table A2 and Figure A3 show the accuracy and comparisons of the models when BRTs were evaluated in the test dataset (25 % of the sampling points not used in the model building). Figure A4 shows the response curves for the models grouping species by their shade tolerance (similarly to Fig. 4).

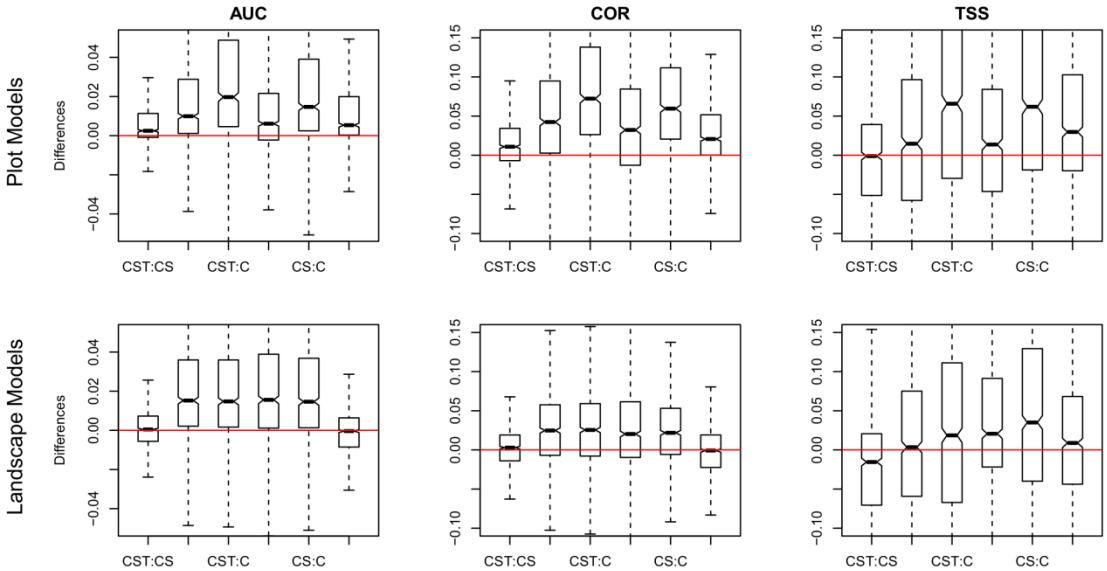

Figure A3: Pairwise accuracy comparisons between boosted regression tree models using Area Under the Curve of the Receiver Operating Characteristics plot (AUC), correlation coefficient (COR), and true skill statistic (TSS) for 960 low-stature plant species modelled with different predictor sets (C: climate; .S: soil; and T: tree cover). Boxplots show the differences in the accuracy measures. The horizontal line represents no differences between models, and two models differ in median accuracy when there is no overlap between the hashes of a given box plot (i.e., the confidence interval around the median) and this line.

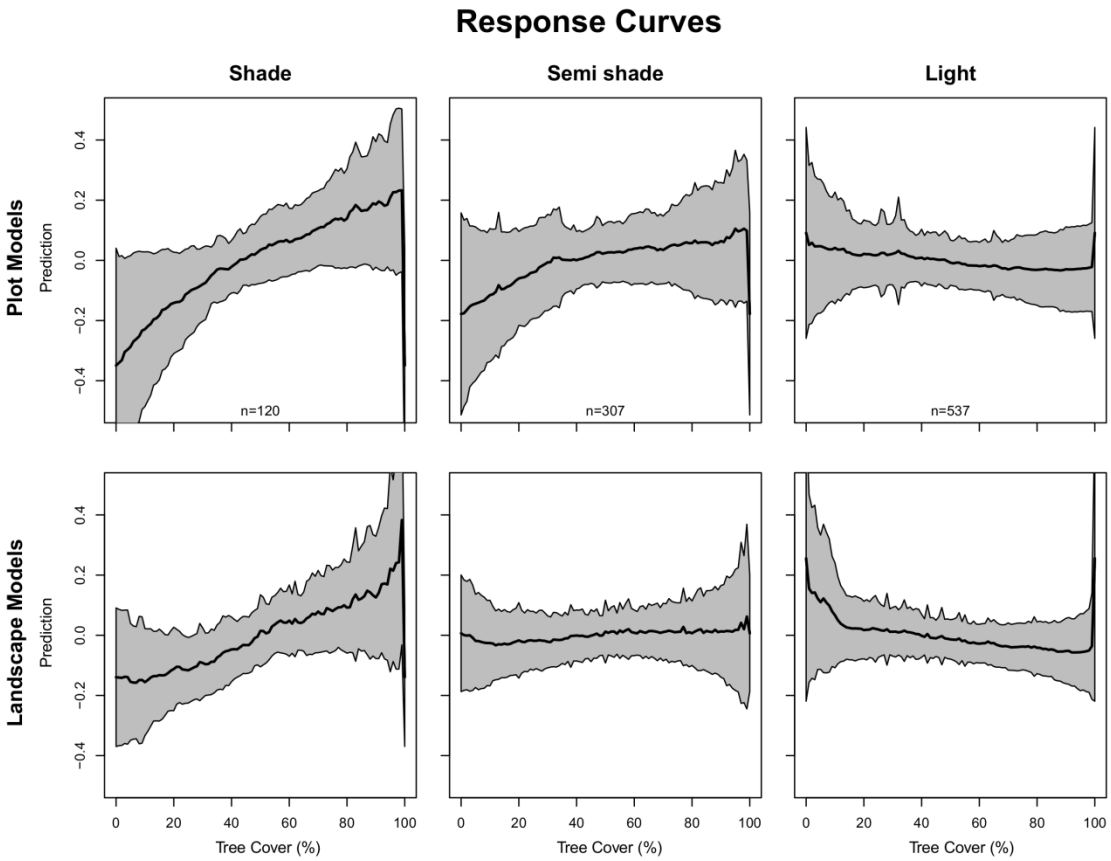

Figure A4: Mean response curves of all 960 species to the tree cover gradient using the most complex (CST) boosted regression tree models at both plot and landscape grain. The black line represents the mean response curve, and the light grey area the 99% confidence intervals. To compute these response curves, all other predictor variables were set at their mean values. The total number of herb and shrub species in each group is written above the x-axis.

Table A3 and Figure A5 show the accuracy and comparisons of the models when Maxent models were evaluated using the test dataset (25 % of the sampling points not used in the model building). Figure A6 shows the response curves for the models, grouping species by their shade tolerance (similarly to Fig. 4).

Table A3: Median, minimum and maximum values for Area Under the Curve of the Receiver Operating Characteristics plot (AUC), correlation coefficient (COR), and true skill statistic (TSS) for 960 herb and shrub species modelled with Maxent and different predictor sets (C: climate; S: soil; and T: tree cover). Evaluation was performed on a test dataset with 25% of the total plots.

	Variables	AUC [0.5 to 1]		COR [-1 to 1]		TSS [-1 to 1]	
		median	min–max	median	min–max	median	min–max
Plot Models	CST	0.947	0.667–0.999	0.372	-0.007–0.858	0.721	-0.004–0.976
	CS	0.942	0.650–0.999	0.357	0.017–0.842	0.719	0.088–0.994
	CT	0.929	0.629–0.999	0.309	0.012–0.853	0.683	0.045–0.979

	C	0.920	0.605–0.999	0.278	0.016–0.825	0.669	0.025–0.992
Landscape Models	CST	0.875	0.523–0.998	0.234	-0.022–0.775	0.583	-0.011–0.985
	CS	0.876	0.522–0.998	0.228	-0.022–0.767	0.580	-0.018–0.983
	CT	0.850	0.475–0.996	0.201	-0.024–0.769	0.545	-0.100–0.970
	C	0.850	0.466–0.997	0.196	-0.024–0.757	0.535	-0.103–0.969

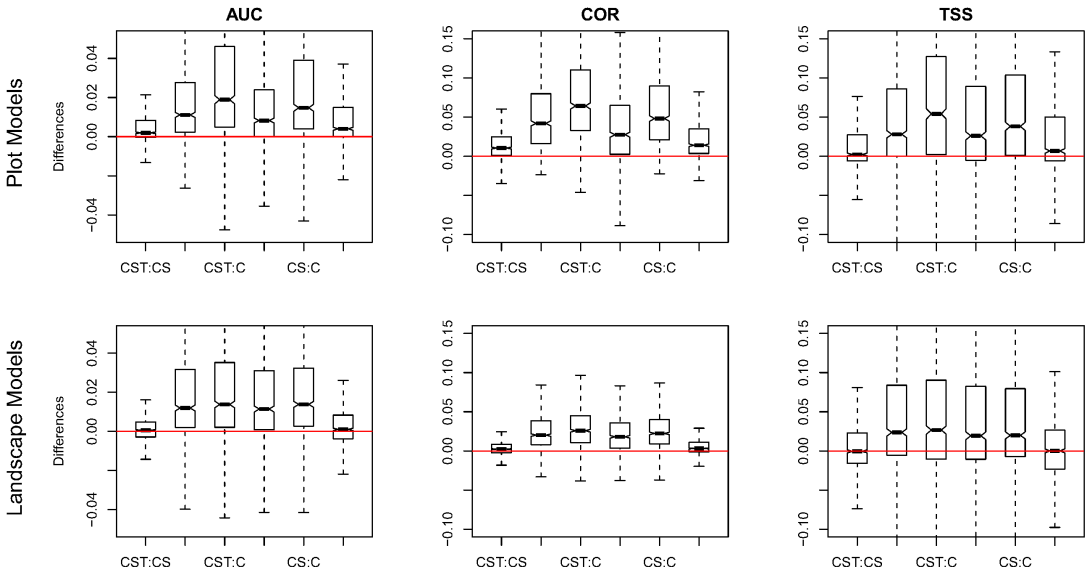

Figure A5: Pairwise accuracy comparisons between Maxent models using Area Under the Curve of the Receiver Operating Characteristics plot (AUC), correlation coefficient (COR), and true skill statistic (TSS) for 960 low-stature plant species modelled with different predictor sets (C: climate; .S: soil; and T: tree cover). The boxplots show the differences in the accuracy measures. The horizontal line represents no differences between models, and two models differ in median accuracy when there is no overlap between the hashes of a given boxplot (i.e., the confidence interval around the median) and this line.

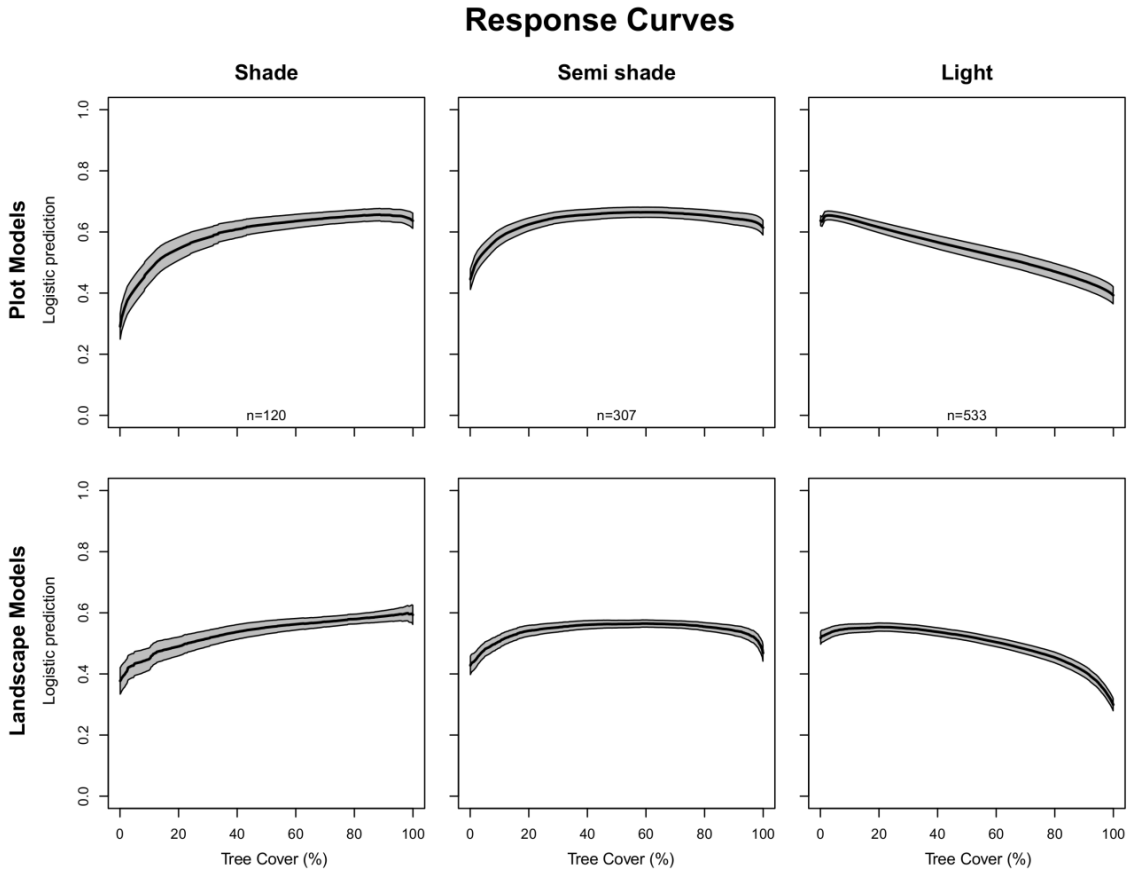

Figure A6: Mean response curves of all 960 species to the tree cover gradient using the most complex (CST) Maxent models at both plot and landscape grain. The black line represents the mean response curve, and light green area the 99% confidence intervals. To compute these response curves, all other predictor variables were set at their mean values. The total number of herb and shrub species in each group is written above the x-axis.

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APPENDIX 4 CONTROLLING FOR TEMPORAL VARIATION

To account for the possible bias introduced in our results by inter-annual variations in climate or tree cover conditions, we repeated all our analyses using Logistic Mixed Models (LMMs) with survey year as the random effect. Table A4 shows the predictive power of this new set of models. In summary, the results are very similar to the outputs of our GLMs, indicating that inter-annual variation does not affect our results and conclusions.

Table A4: Median, minimum and maximum values for Area Under the Curve of the Receiver Operating Characteristics plot (AUC), correlation coefficient (COR), and true skill statistic (TSS) for 960 low-stature plant species modelled with different predictor sets (C: climate; S: soil; and T: tree cover). Evaluation was performed on a test dataset with 25% of the total plots.

	Models	AUC [0.5 to 1]		COR [-1 to 1]		TSS [-1 to 1]	
		median	min–max	median	min–max	median	min–max
Plot Models	CST	0.950	0.706–1.000	0.444	-0.007–0.884	0.685	-0.022–0.970
	CS	0.946	0.732–1.000	0.428	-0.004–0.884	0.681	-0.030–0.978
	CT	0.935	0.608–0.999	0.394	-0.006–0.878	0.693	0.000–0.985
	C	0.931	0.557–0.999	0.380	0.000–0.876	0.698	0.060–0.995
Landscape Models	CST	0.879	0.528–0.999	0.278	-0.015–0.861	0.519	-0.066–0.959
	CS	0.877	0.537–0.999	0.276	-0.015–0.860	0.516	-0.068–0.956
	CT	0.873	0.506–0.999	0.271	-0.020–0.847	0.569	-0.073–0.972
	C	0.874	0.544 –0.999	0.266	-0.019–0.847	0.584	-0.054–0.970

Because the random effects also affect the results of these models, the conditional probabilities approach is not valid. A common alternative is to compute the average marginal probability by graphing the average changes in probability of the outcome across the range of the predictor of interest while keeping the other predictor variables at their original values. In our study, we used 100 different values in the range of tree cover (0-100). These plots (Fig. A7) show a pattern similar to those from the GLMs (see Fig. 4 in the main manuscript), but that pattern is less evident for shade-intolerant species, most likely because many of these species are alpine or subalpine. Using average marginal probability provides response curves to climatic conditions that could be far from the ideal conditions for each species, which is the opposite of conditional probabilities, where the response curves for each variable are calculated under the optimal values for the rest of the variables in the model for each species.

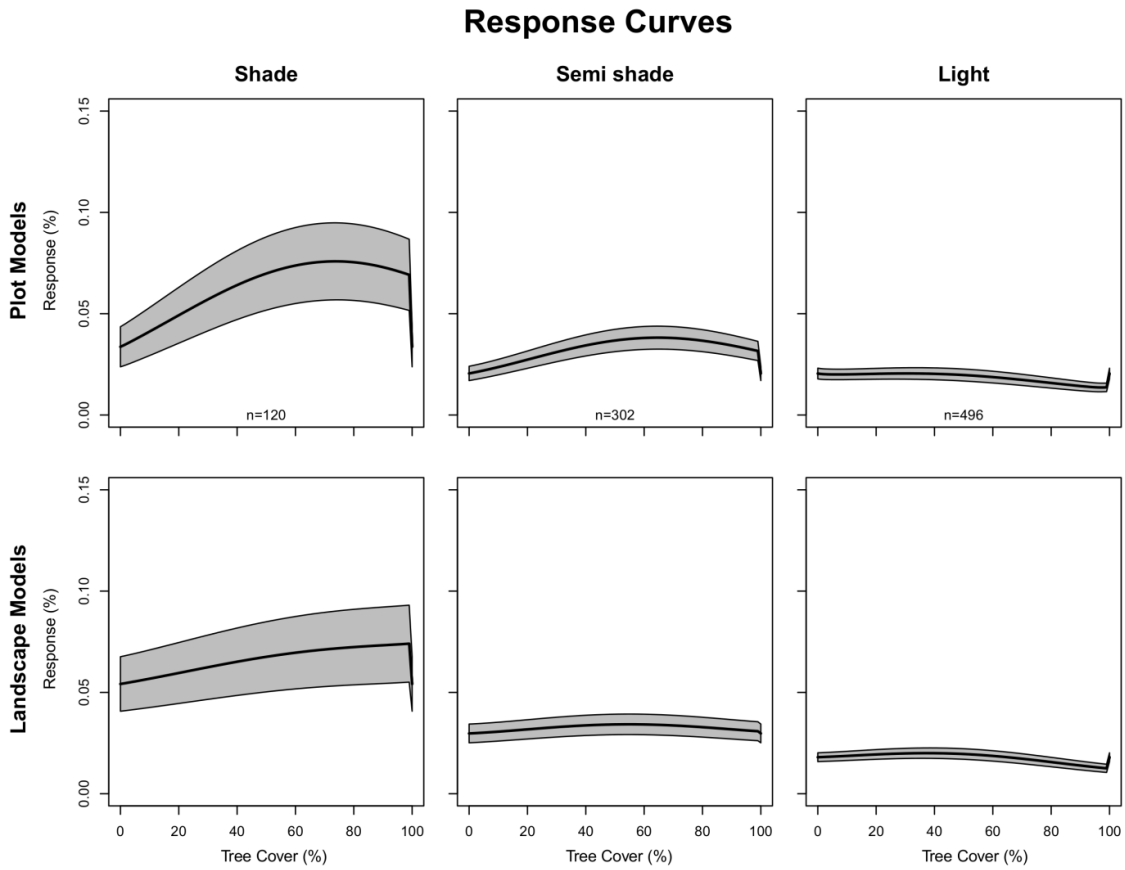

Figure A7: Mean response curves (as "average marginal probabilities" instead of the "conditional probabilities" shown by the GLMs) of all 960 species to the tree cover gradient using CST Logistic Mixed Models with the survey year as a random effect at both the plot and landscape grain. To compute these response curves, the tree cover variables were set to a specific value in their range (0-100), and other predictors were kept at their original values. The average prediction for each value of tree cover is calculated for each species. The black line represents the mean response curve across species, and the light grey area the 99% confidence intervals. The total number of herb and shrub species in each shade tolerance group (L1–L2 for shade; L3 for semi-shade; and L4–L5 for light) is given at the bottom of the top graphs.

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APPENDIX 5 ILLUSTRATION OF THE ELEVATIONAL STRATIFIED SAMPLING

To illustrate the elevational stratified sampling for the elevational study, we plot the histograms of the number of plots within bins of 50 m elevation for two different subsets: high tree cover (> 50% TC_{plot}) and low tree cover (< 50% TC_{plot}). These two subsets are exactly equal and are represented by the overlap between the two initial histograms and a maximum of 50 plots per elevational bin (Fig. A8).

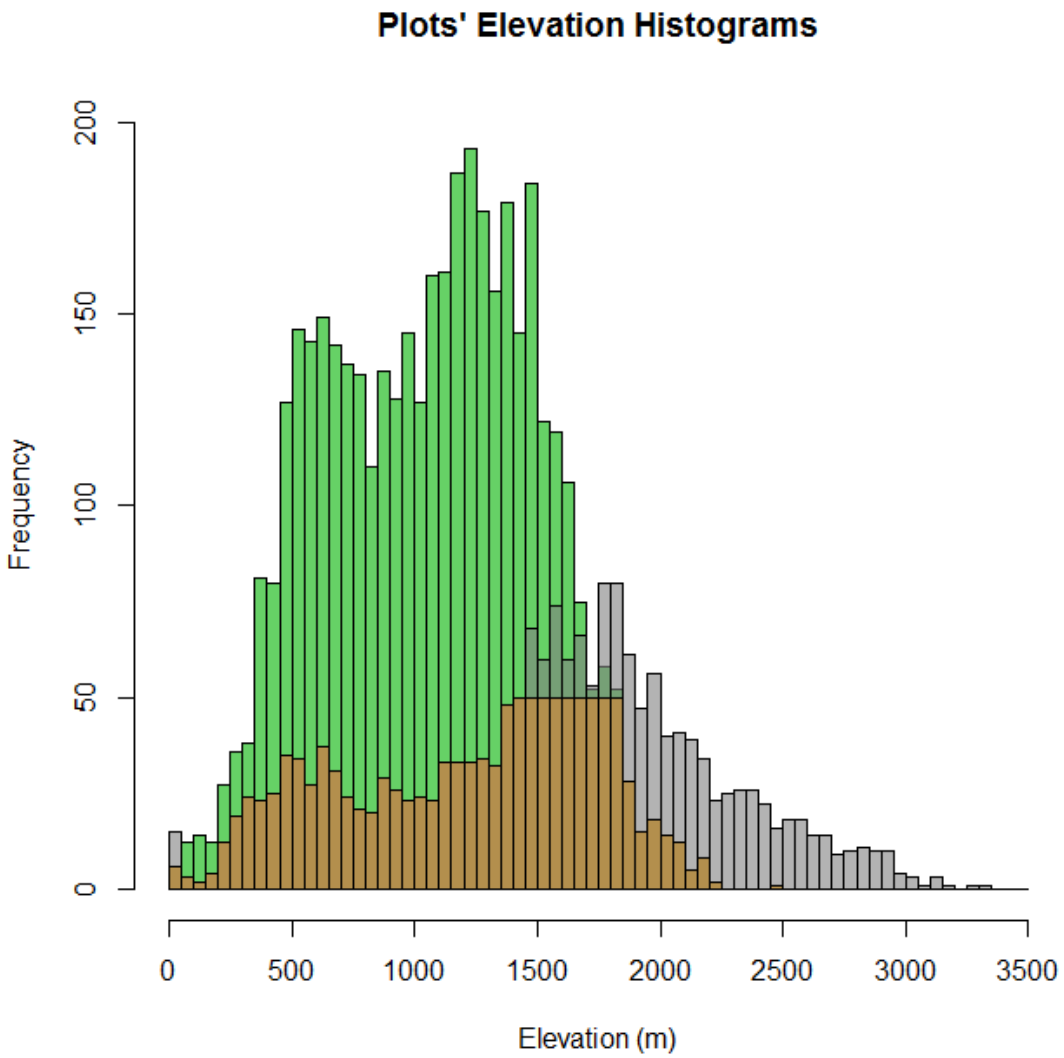

Figure A8: Plot's elevation histograms. Green bars represent the plots with high tree cover (> 50%), whereas the grey bars represent plots with low tree cover (< 50%). Brown bars represent the subsample selected to perform the elevational analysis of both subsets (high and low tree cover).

APPENDIX 6 SPATIAL AUTOCORRELATION OF THE TREE COVER EFFECT

We quantified the geographical extent to which tree cover could affect herb and shrub distributions. To do so, we analysed the spatial autocorrelation of this effect in the most complex set of models (CST; see Appendix S5) by randomly selecting, without replacement, 2,000 plots from the final dataset and computing the differences between the predictions of the CST and CS models for these plots and then calculating the Moran's I correlograms for each species. To reduce computation time, and because we were not interested in the significance of the correlograms, we ran the analyses without permutations. We summarised all 960 correlograms by plotting them together, showing the average trend with its confidence interval.

The effect of tree cover on the predictions for the CST model was itself spatially clustered, showing a similar pattern as both tree cover variables (TC_{plot} and TC_{land}; Fig. A9). In the case of the plot-grain models, the spatial structure of the prediction differences was only higher than that of the variable itself for the first distance class, mostly affecting predictions at ≤1 km. However, at the landscape grain, the prediction differences showed a slightly higher spatial structure than the tree cover variables, up to 5 km (Fig. A9).

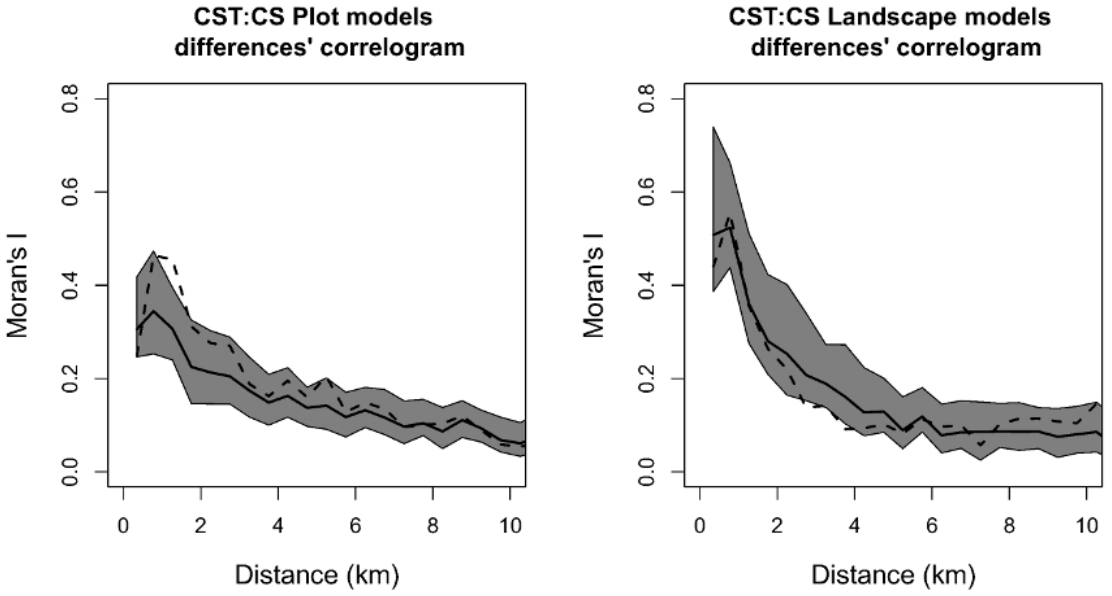

Figure A9: Moran's I correlograms of the tree cover effect (as the difference between the predictions of the CST and CS models over a random set of 2,000 plots) for models with plot- and landscape-grain predictor variables. The black lines represent the median among 960 species correlograms, with the grey zones indicating the first and third quartiles (25 and 75%). The dashed lines represent correlograms for plot- and landscape-grain tree cover.

APPENDIX 7 HUMAN INFLUENCE ALONG THE ELEVATIONAL GRADIENT

Here, we explored human influence in the plots using our original database. We used Landolt indicator values (Landolt et al. 2010) for human influence (as EM in Flora Indicativa) to compute plot mean indicator values (Human Influence). We show here how the lowest elevation plots are highly influenced by human activities (Fig. A10). Furthermore, we compared the differences between areas of high and low tree cover (boxplots in Fig. A10), showing that the differences among higher elevations are smaller, whereas at lower elevations low tree-cover areas are more influenced by human beings.

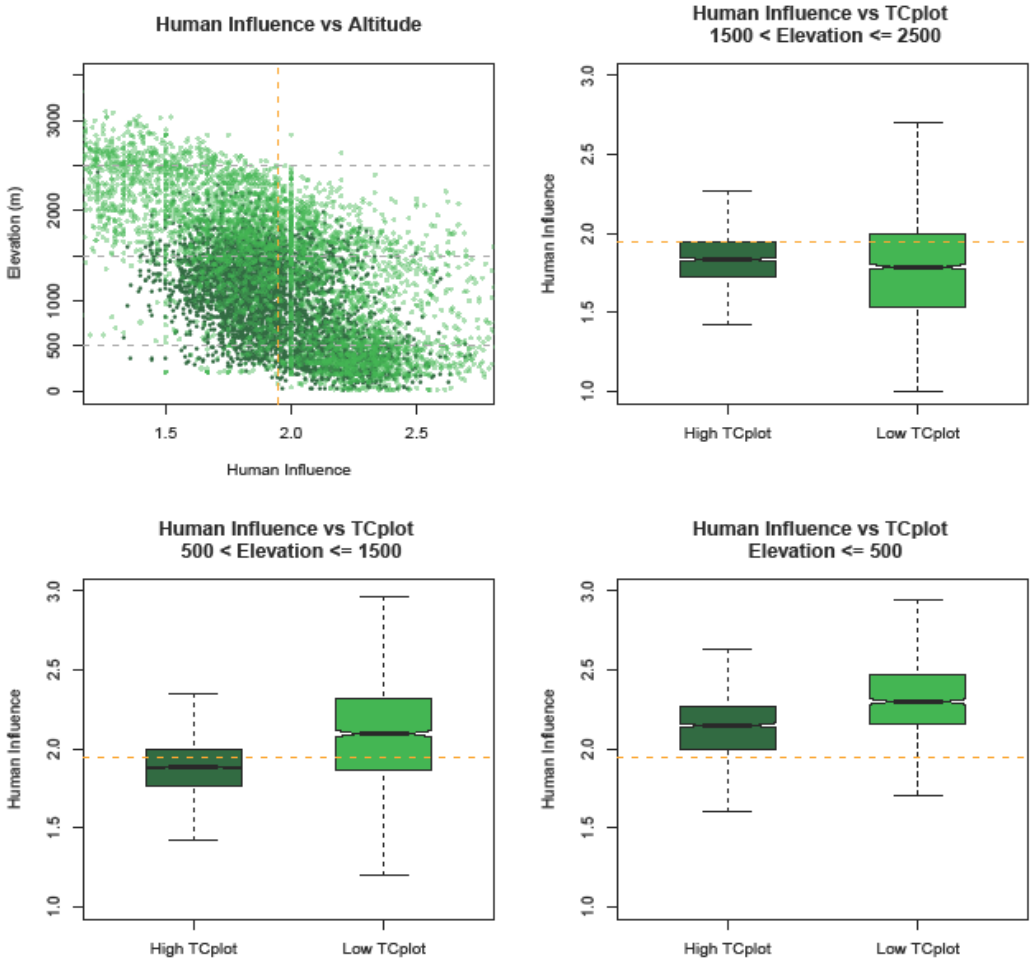

Figure A10: Human influence in the studied plots as a function of the elevation and comparisons between low and high tree-cover plots in different elevation belts. Light green dots and boxplots represent plots with low tree-cover, whereas dark green dots and boxplots represent plots with high tree-cover.

References

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