

1 Biodiversity as a multidimensional construct: Alternative SEM Models and Placement of Number of Taxa

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4 In Structural Equation Modeling (SEM), each model represents a hypothetical set of causative and
5 correlative relations (linkages) among measured and unmeasured variables. In the absence of any
6 specific model of interest, there are several possible models, each reflecting possible alternative
7 patterns of linkages among variables. Thus, one can examine a specific model that reflects a specific
8 structure or one can explore all identified, admissible models to find the model that best fits or predicts
9 the data. "Identified" means that the number of known parameters exceeds the number of unknown
10 parameters, thus the model may be resolvable. In many cases, however, even if the number of knowns
11 exceeds unknowns, the data may yield an inadmissible model. A model is deemed inadmissible if the
12 analytical algorithm yielded negative residual variances, an $R^2 > 1$, or an otherwise inadmissible solution
13 [1]. In some cases, a model is excluded because it could not be resolved because the iteration limit set
14 by the algorithm was reached and increasing the limit did not change the outcome. Thus, many models
15 can be constructed for a single set of variables, though generally only a fraction of them make sense
16 (e.g., biologically), can be identified, provide admissible results for a specific set of data, and can be
17 resolved within the iteration limit of the algorithm.

18 This exploratory approach in which many models are explored for a single set of variables, or
19 exploratory SEM, can identify the best predictive model for a specific data set. The most predictive
20 model, however, may not reflect the full set of linkages that are relevant; it only reflects linkages
21 supported by the data. A different set of data may yield a different model as the best predictor. The
22 full model and its rationale are therefore critical parts of the exercise (for a discussion of these and
23 related issues concerning SEM, see [2-7]).

24 In this study, the SEM-framework (Fig. 2) and its rationale are explained in the main text. Our single, full
25 model (Fig. 3, Fig. S1 A) is derived directly from the SEM framework and is based, in part, on the
26 biological argument that the number of taxa (i.e., species richness) covaries with most, if not all
27 biodiversity metrics (Fig S1 A and Fig. 2). However, there may be reasons to treat the number of taxa
28 differently. The number of taxa may be treated as a variable that directly influences the ecosystem
29 property (Fig. S1A). Alternatively, the number of taxa may be treated as a variable that directly
30 influences biodiversity metrics (Fig S1 C). Finally, another alternative would be to treat the number of
31 taxa as a variable that directly influences the taxonomic diversity dimension (TD), but not functional or
32 phylogenetic diversity dimensions (FD or PD, respectively, Fig. S1 D). There are many more alternatives,
33 but we examine these four (Fig. S1 A-D) to serve two purposes. First, we examine these alternatives to
34 address possible differences in the way researchers may wish to treat number of taxa in
35 multidimensional biodiversity analyses. Second, we simply wish to illustrate the exploratory approach
36 as a supplementary exercise.

37

38 Methods

39 We performed an exploratory SEM approach in which we examined the four alternative models shown
40 in Figure S1 and described above. We used the Specification Search function in the SEM statistical
41 software package, Amos [1], to search for alternative structures for each of the four models to
42 determine if there were alternatives that better fit our data (or were potentially more predictive) than
43 the full model. Alternative structures consisted of the full set of possible structures in which one or
44 more links were removed. Only models that are identified and admissible were considered. Unresolved
45 models that occurred because the iteration limit, initially set at 50 iterations, were rerun with the limit
46 set to 100. This procedure did not increase the number of models resolved, thus we considered these
47 models as effectively unresolvable for the data to hand.

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49 Results

50 In Table S1, we provide the total number of possible alternative models for each of the four models
51 shown in Figure S1. There are thousands of possible alternative models for each model shown in Figure
52 S1 (Table S1), the vast majority of which are either unidentified, inadmissible, or failed to be resolved
53 before the algorithm's iteration limit was reached. The model treating number of taxa as a covariate
54 (Fig. S1 A) was identified and admissible for plots with or without exposure to herbivory, but the
55 alternatives (Fig. S1 B-D) did not provide interpretable results (Table S1). By "interpretable," we mean
56 being able to compare model outcomes between plots exposed to or protected from herbivory. Only
57 one full model was identified; the model presented in Figure S1 D in which number of taxa was linked to
58 the taxonomic diversity dimension (TD) for plots protected from herbivory. Because the full model for
59 plots exposed to herbivory was inadmissible, we cannot compare whether different dimensions had
60 different influences on the ecosystem property (total cover) between the two treatments. Selecting
61 admissible alternatives would allow for predicting total cover based on diversity metrics or dimensions,
62 but our question concerned how the full models compared, not how best to predict total cover. All
63 models, full and alternatives, rejected the hypothesis that they fit the data, thus, as discussed in the
64 text, that although model fit methods in SEM remain under discussion [8-10], specific predictions could
65 be suspect.

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67 Discussion

68 Different researchers may have cause to deviate from our suggested generic model (Fig. 2), but for our
69 specific example, three alternative approaches (Fig. S1 B-D) in which the number of taxa (i.e., species
70 richness) was treated differently, did not provide interpretable results. The large number of
71 inadmissible and unresolved models most likely stems from insufficient data and it is possible the
72 alternative treatments of number of taxa we explored may work where more data are available.

73 It is important to note that we cannot, in our case study, shed light onto whether alternative models (Fig
74 S1 B-D) given the data we have. We have provided our rationale for the model presented in Fig. 2, but
75 further work, different systems, and different questions may lead to alternative models better suiting

76 different investigations. We also do not advocate nor discourage exploratory analyses of multi-
77 dimensional models of biodiversity's influence on ecosystem function as done here in this
78 supplementary material for our case study. We focused our analyses on testing the biologically
79 plausible model in which the number of taxa was considered a covariate of all biodiversity metrics (Fig.
80 2) and the data applied to the full models showed multidimensional biodiversity effects to differ
81 between herbivore-exposed and herbivore protected plots. However, when an alternative model is
82 more appropriate for the hypothesis under investigation, such as any of the three alternatives illustrated
83 in Figure S1 (B-D), such models should be examined. As in all SEM-based studies, the number of possible
84 models can be fairly large and many may not be identifiable (too many unknowns) or admissible
85 (unresolvable by analytical algorithms when sample sizes are small), as in our case.

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Table S1. Exploratory Structural Equation Model (SEM) for multiple dimensions of biodiversity applied to understory forest vegetation at Black Rock Forest, New York, exposed to or protected from deer herbivory. For each SEM model in which the treatment of number taxa is different (Fig. S1 A-D), a specification search was conducted using Amos and basic outcomes of the search are tabulated here. AIC is the Aikake Information Criterion which measures the likelihood of the model given the data and aids in model selection among a set of comparable models. The AIC for the best model is provided (maximum AIC is provided parenthetically); lower values reflect better fits. Herbivory was either present (i.e. "Yes") or not (i.e., exclosures were present, "No"). P reflects probability that model fits the data if P (<0.05 means that model was rejected as a good fit to the data). Results for the full model (i.e., all links illustrated in Fig. S1 A-D are present) are provided in the right most column. If the full model was admissible, the R² for the model's prediction of total cover is provided parenthetically.

	Number of models	Number of Admissible Models	Herbivory	Best Fit Model			Full model
				Parameters	AIC of best fit (poorest fit) model	P	Admissible (R ²) or Inadmissible
Covariate with Dimensions	32,768	14	Yes	21	174.0 (187.1)	<0.001	Admissible (0.76)
		7	No	16	179.0 (187.1)	<0.001	Admissible(0.19)
Directly influences Total Cover (Fig. S1 B)	8,192	8	Yes	17	167.6 (176.5)	<0.001	Inadmissible
		7	No	20	170.2 (187.1)	<0.001	Inadmissible
Influences Dimensions (Fig. S1 C)	262,144	163	Yes	18	117.9 (176.5)	<0.001	Inadmissible
		112	No	21	127.4 (179.0)	<0.001	Inadmissible
Directly influences TD (Fig. S1 D)	8,192	6	Yes	14	169.4 (177.4)	<0.001	Inadmissible
		3	No	16	179.0 (187.1)	<0.001	Admissible (0.65)

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Table S2 Correlation matrix for biodiversity metrics used in structural equation modeling example (see Fig. 3).
Pearson correlations. Bolded numbers mean $P < 0.05$, Bonferroni corrected.

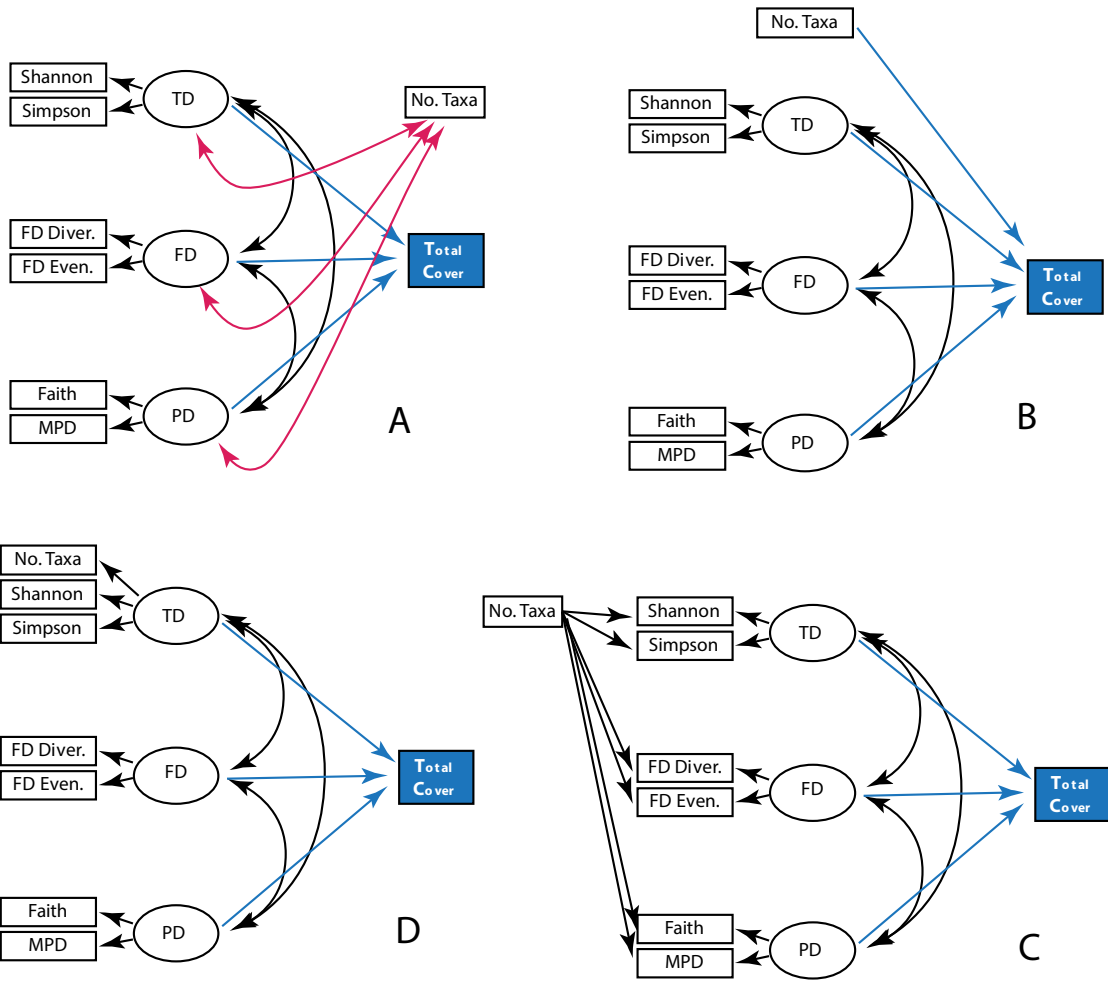
	Shannon	Simpson	FD Divergence	FD Evenness	FD Richness	Phylogenetic Faith	Phylogenetic MPD
Simpson	0.96						
FD Divergence	-0.01	-0.14					
FD Evenness	0.07	0.02	-0.10				
FD Richness	0.48	0.33	0.58	-0.14			
Phylogenetic Faith	0.49	0.33	0.58	-0.14	0.97		
Phylogenetic MPD	0.93	0.88	0.07	0.01	0.60	0.62	
Number of Taxa	0.52	0.37	0.53	-0.18	0.95	0.97	0.59

94 Figure Captions

95 Figure S1. Four possible SEM models for the relationship between multiple dimensions of biodiversity
96 and an ecosystem property; TD, FD, and PD related to total vegetation cover in understory vegetation
97 plots at Black Rock Forest. See caption to Figure 3 for further detail. A. Number of species is a covariate
98 of TD, FD, and PD. B. Number of taxa as a variable that directly influences the ecosystem property. C.
99 Number of taxa directly influences biodiversity metrics. D. Number of taxa directly influences the
100 taxonomic diversity dimension.

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103

104

105 Figure S1

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107 Literature cited

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