

The structure of pairwise interactions impacts species abundance distributions

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0.1 Methods

We projected species abundance distributions from an annual plant community using population dynamics models. First, we parameterized these models given the observed data, obtaining maximum-likelihood estimates of intrinsic fecundity rates (λ_i) and interaction coefficients among species (both intraspecific, α_{ii} , and interspecific, α_{ij}). We projected the dynamics of the community for 20 timesteps, and at each timestep we retrieved the three components of species abundance distributions in the community: total abundance, richness, and evenness (REF).

Taking as a baseline the inferred interaction matrix A_0 , we quantified the variation in SAD components under three perturbations of A_0 : decreasing diagonal dominance, decreasing interaction assymetry, and decreasing heterogeneity in the distribution of interaction strengths.

0.1.1 Dataset

Caracoles (note: update with 2020 and 2021 data)

0.1.2 Parameterizing population dynamics models

We estimated model parameters from the annual plant dataset using the `cxr` R package (REF). Specifically, we obtained a set of parameters (λ, A_0) (intrinsic growth rates for all species and interaction matrix) for three different population dynamics models, in order to evaluate the robustness of our results to different model formulations. The models we considered are the Ricker model, the Beverton-Hold model, and the Law-Watkison model (EQ).

[Add details about the estimation method: maximum-likelihood with bobyqa optimizer, constraints, etc].

0.1.3 Perturbing the interaction matrix

We defined three structural perturbations of A_0 that imply different homogeneizations of interaction coefficients. As the three perturbations are quantitative, i.e. imply variations in the interaction strength of specific elements α_{ij} of the matrix, we considered a 10-step gradient ranging from the estimated A_0 values to the most homogeneous matrices.

The first treatment is the decreasing of diagonal dominance, by which diagonal elements representing intraspecific interactions converge towards the overall mean of the coefficients $\bar{\alpha}_*$.

The second treatment is the decreasing of interaction asymmetry, by which the two coefficients of an interaction pair α_{ij}, α_{ji} converge towards their mean.

The third treatment is the decreasing of heterogeneity in the overall distribution of interaction strengths, by which all interactions α_* converge towards the overall mean $\bar{\alpha}_*$.

Overall, we obtained 31 interactions matrices for each model (an initial field-parameterized A_0 + 10 increasingly homogeneous matrices for each of the three perturbations).

0.1.4 Projecting abundances

We projected the dynamics of each of the 93 modelled communities with the `abundance_projection` function of the `cxr` package, and obtained the associated components of the species abundance distribution at each of the 20 timesteps projected. In particular, we used as baseline data the observed information for 2015 and 2016, in order to compare the projections at $t+1$ with the data gathered in 2016 and 2017, respectively.

0.2 Results

First, we compared the projections from the three population dynamics models fed with the field-parameterized matrices A_0 at $t+1$ with the observed abundances, i.e. we compared the projections from 2015 to 2016 with the observed 2016 values, and likewise for 2016-2017 (we did not consider 2018 either as an initial or final observed timestep because of a large flooding in the study area that year, that effectively wiped out most plant individuals from the study area) (Fig. 1).

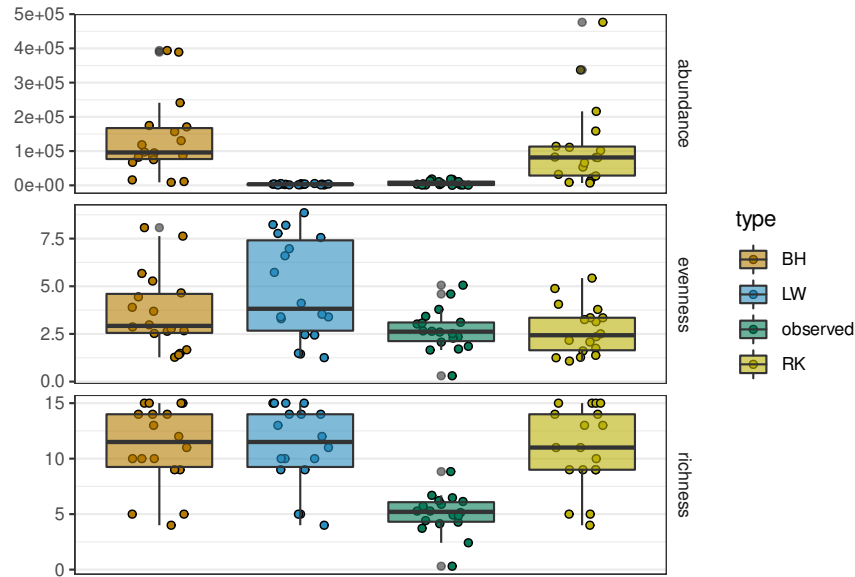


Figure 1: observed-predicted (each point corresponds to one caracoles plot at one year)

Second, for the three models and four matrix types (observed and the three perturbations), we checked the variation of SAD components in time, up to the 20 timesteps projected (Fig. 2).

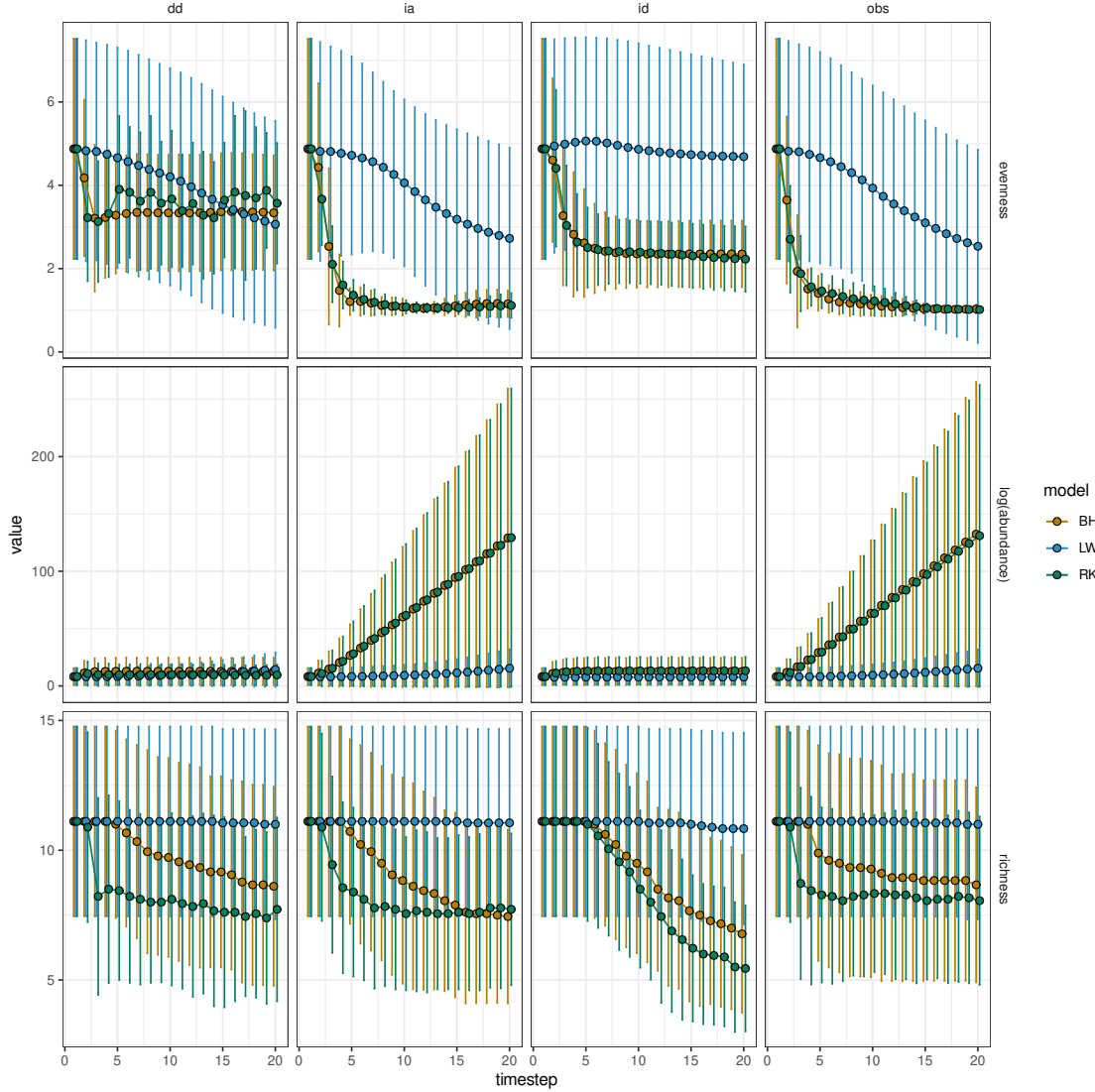


Figure 2: temporal trends on SAD components with the three population dynamics models and the four matrix types considered. obs: field-parameterized interaction matrix; dd: decreased diagonal dominance; id: decreased heterogeneity of the interaction strength distribution; ia: decreased interaction asymmetry. Points are the average over all plots and the two years projected, and error bars represent one standard deviation of these averages.

Third, we obtained the relative differences that each perturbation triggered in each SAD component. Here I show the difference between the projections with the field-parameterized matrix and each of the perturbed matrices at the timestep 10 of the projections. As the perturbations are quantitative, I show the effect at 10 different points of a gradient, from less perturbed to more perturbed.

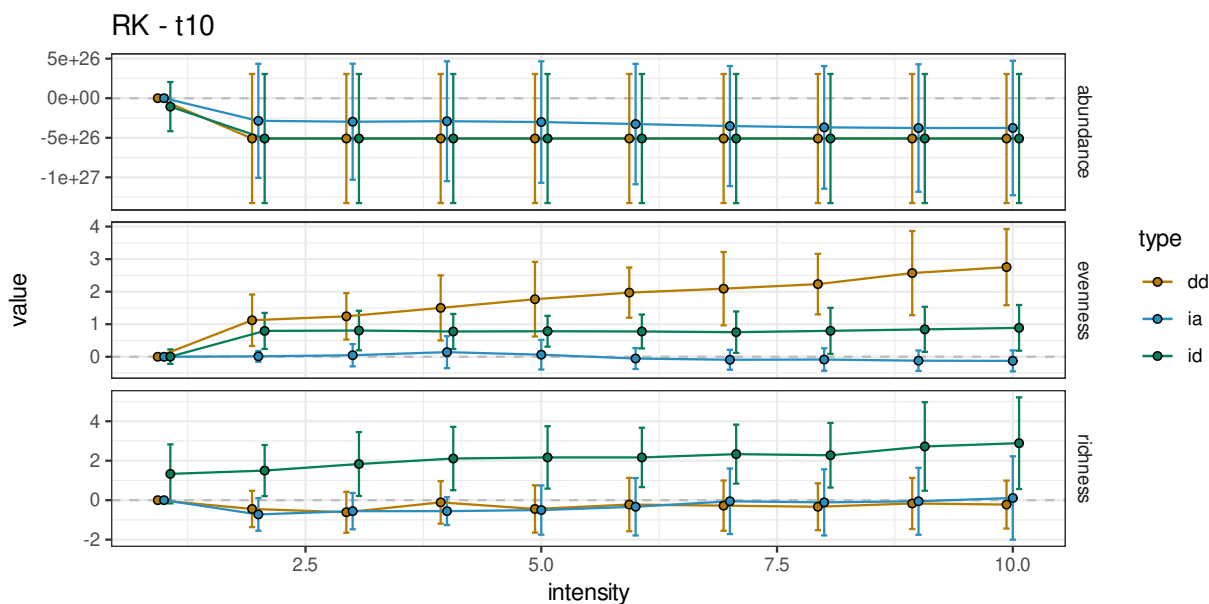


Figure 3: Effect of each perturbation intensity on each SAD component, relative to the projection with the field-parameterized matrix. Higher intensity (increasing x axis) represents a more homogenous matrix. dd: diagonal dominance, ia: interaction asymmetry, id: interaction distribution. Ricker model, results in timestep 10

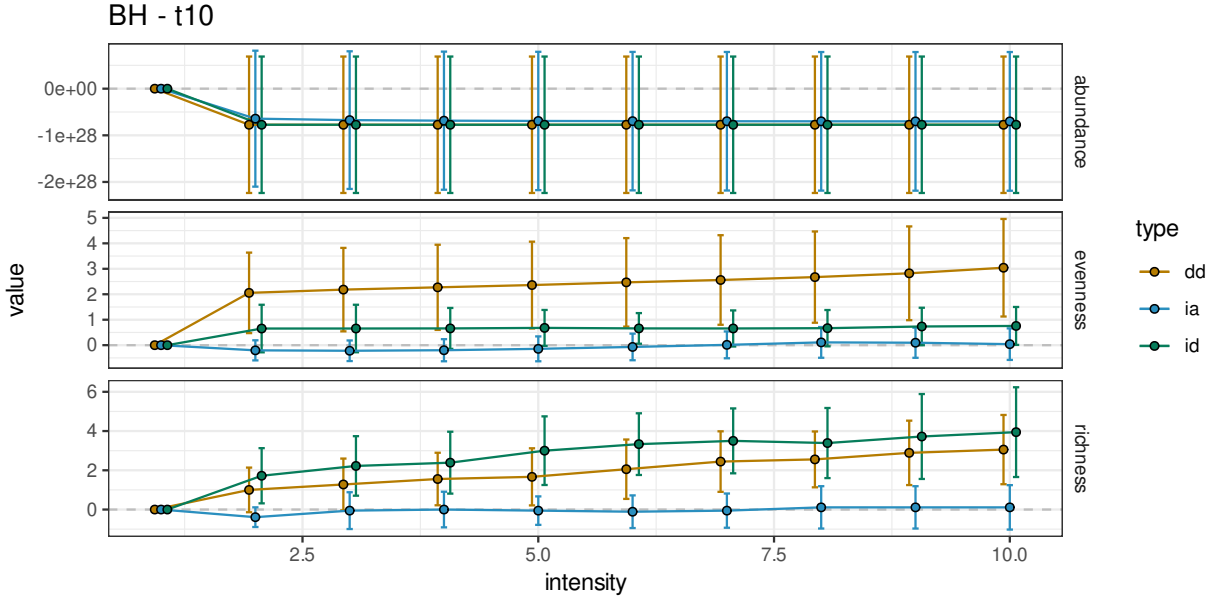


Figure 4: Effect of each perturbation intensity on each SAD component, relative to the projection with the field-parameterized matrix. Higher intensity (increasing x axis) represents a more homogenous matrix. dd: diagonal dominance, ia: interaction asymmetry, id: interaction distribution. Beverton-Holt model, results in timestep 10

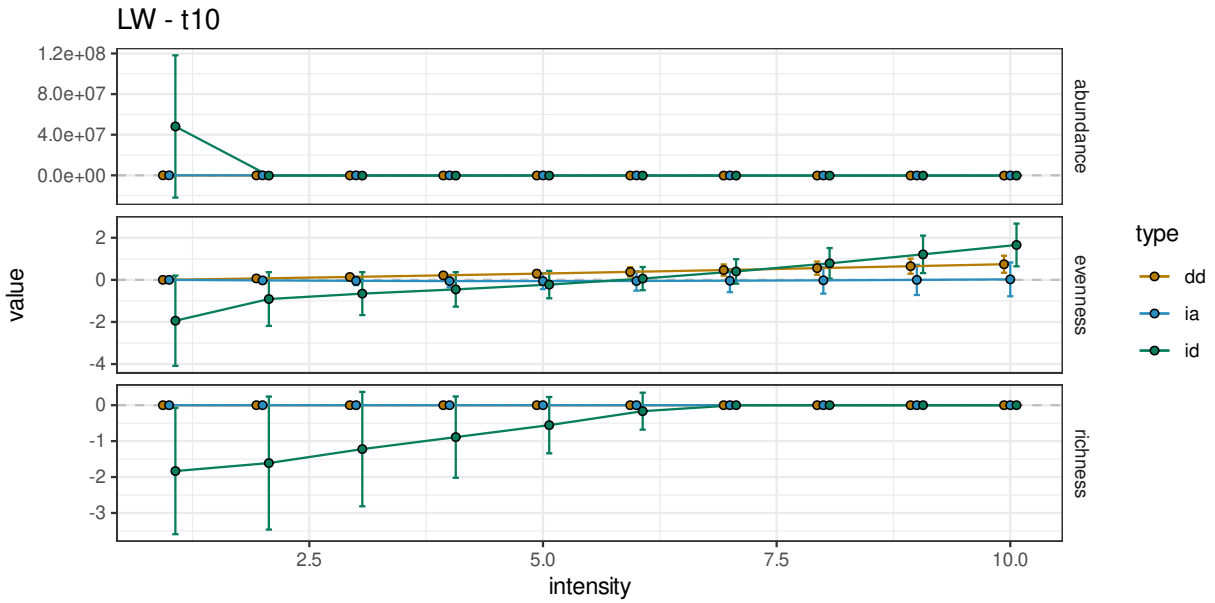


Figure 5: Effect of each perturbation intensity on each SAD component, relative to the projection with the field-parameterized matrix. Higher intensity (increasing x axis) represents a more homogenous matrix. dd: diagonal dominance, ia: interaction asymmetry, id: interaction distribution. Law-Watkinson model, results in timestep 10

0.3 Preliminary interpretation

- Projections are very sensitive to the underlying model - mostly in terms of total abundance, that for the Ricker and Beverton-Holt model explodes to unrealistic values
- Aside from that, which can render the results unreliable, a few trends seem to be consistent:
 - evenness and richness tend to decrease with time in all projections and matrix types, including the observed parameterization, but total abundance does not.
 - I'm not sure how to interpret the last figures, in the sense that all perturbations seem to have qualitatively similar effects compared to the observed matrices:
 - * decreasing diagonal dominance: decreases abundance, increases evenness, richness is constant or increases
 - * decreasing interaction asymmetry: decreases abundance, evenness and richness not affected
 - * decreasing interaction heterogeneity: decreases abundance, evenness increases or constant, richness generally increases
 - Furthermore, it seems that initial perturbations, albeit small, have stronger effects than subsequent increases on the perturbation (i.e. the variation from no changes in the matrix to small changes are stronger than any other increase in the perturbation, as seen in the bumps from the first to the second points in Figures 3, 4, 5).

0.4 Issues

We are dealing with perturbations in interaction matrices and their effect on abundance projections. First, the abundance projections themselves are unrealistic (abundance explodes in 2 of 3 models), so the rest of the results are difficult to believe. Second, I was expecting more differences between the effects of the different perturbations, but it is true that these structural metrics (diagonal dominance, interaction asymmetry, interaction heterogeneity) have only been studied in relationship to their effects on coexistence or stability, not in their effects over abundances or evenness.

In order to minimize concerns over unrealistic projections, we can:

- drop the caracoles data and stick to simulations, as well as choose one model that does not explode and stick with it.
- try to improve the field-parameterization of the interaction matrices, for example by using the approach from Maynard et al. 2019 (aquí el link)