# When does network matters?

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#### Why we see these results?

In our trophic model, the Jacobian at equilibrium splits neatly into a diagonal matrix  $\mathbf{D}$  (encoding each species' self-regulation) and an off-diagonal interaction part  $\mathbf{M}$ :

$$J = DM$$
,  $D = diag(d_1, ..., d_S)$ ,  $M = -I + A^*$ ,

where for each species

$$d_i = \begin{cases} \frac{r_i}{K_i} B_i^* & \text{(resource)} \\ \frac{m_i}{f_*} B_i^* & \text{(consumer)}. \end{cases}$$

When interaction strengths are moderate—so that the typical off-diagonal magnitude  $\sigma = \operatorname{std}(M_{ij})$  is much smaller than the smallest  $d_i$ —first-order perturbation theory shows the leading eigenvalue of  $J = -D + \sigma G$  shifts by

$$\Delta \lambda \approx \sigma G_{ii} \approx 0$$

in expectation. Thus the most unstable eigenvalue (governing resilience, return-times, reactivity, etc.) is set almost entirely by the **diagonals**  $d_i$ . Randomizing or erasing A (our ladder steps 9–11) leaves D unchanged, so **community-level metrics forget the network**.

#### When network structure does matter?

If interaction scale grows so that

$$\sigma \sim \min_i d_i,$$

the  $O(\sigma)$  corrections no longer vanish and off-diagonals begin to shift the leading eigenvalue. Ecologically, very strong competition or predation restores a network imprint on resilience and return-times. Similarly, metrics probing non-local dynamics (multistability, cycles, stochastic variance) will re-inject network effects.

### The special role of Self-Regulation Loss (SL)

For each species,

$$SL_i = \frac{B_i^*}{K_i}$$

measures its realized equilibrium relative to its monoculture carrying capacity. Since

$$\mathbf{B}^* = (I - A)^{-1} \mathbf{K} = (I + A + A^2 + \cdots) \mathbf{K},$$

 $SL_i$  depends on all orders of A. Even after randomizing A, recalculating  $B^*$  via the Neumann series ensures  $SL_i$  remains first-order sensitive to the exact interaction pattern. In contrast, bulk metrics hinge only on D

## How to prove it formally

- 1. Eigenvalue perturbation
- Write  $J = -D + \sigma G$ , with G zero-mean. Use standard matrix perturbation to show

$$\lambda_{\max}(J) = -\min_{i} d_i + O(\sigma^2/\Delta d).$$

- 2. Neumann-series expansion
- Expand  $(I A)^{-1} = \sum_{n>0} A^n$  to express

$$\frac{B_i^*}{K_i} = 1 + \sum_{i} A_{ij} \frac{K_j}{K_i} + O(\sigma^2).$$

• Show that randomizing A alters the first-order term in  $SL_i$  but only second-order in resilience.

#### **Implications**

- **Predicting return-times**: measure each species' demography  $(r_i, K_i, m_i, \xi_i, B_i^*)$  and you can forecast bulk stability without mapping the full network.
- Mapping coexistence: to know which species are suppressed or facilitated, you must recover  $SL_i$  via the full interaction matrix.
- Threshold of network relevance: by tuning interaction strength or connectance until  $\sigma \approx \min d_i$ , you can pinpoint when network architecture reclaims control over community dynamics.