Conjugate Interaction - Dispersal Matricies that Optimizes the Community Stability

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- Motivation: Complexity versus Stability question: Weak interactions stabilize food webs.
- Aim #1: Comparing the stability of uniform interaction / dispersal matrices with exponentially distributed interaction / dispersal matrices, as a function of $\alpha_a = \alpha_m$.

Community (A) Dispersal (M)

$$\sim U(-1,1)$$
 $\sim U(-1,1)$
 $\sim U(-1,1)$ $\sim \exp(\alpha_m)$
 $\sim \exp(\alpha_a)$ $\sim U(-1,1)$
 $\sim \exp(\alpha_a)$ $\sim \exp(\alpha_m)$

- Aim #2: Stability as a linear or a non-linear function of parameters: When both matricies are exponentially distributed with α_a and α_m , how does stability change as a multiplicative / additive function of the $\{\alpha_a, \alpha_m\}$ pair?
- **Aim** #3: Generalization: Find conjugate interaction-dispersal matrix pairs that optimizes the stability of a food web.
- Aim #4: Validation: Can we use real data sets do validate the stability of the conjugate pairs?
- **Aim** #5: Future work : Abundance vector, source and sink added to the system, perturbation in abundance.

Parameter Definitions

- \bullet N: Number of species.
- P_N : Number of patches (habitats).
- X_i^l : Abundance of species i in patch l.
- a_{ij}^l : Interaction coefficient between species i and species j in patch l.

• $m_i^{l\to k}$: Migration coefficient of species i from patch l to patch k.

Simulation Rules

- \bullet Dispersal is symmetric, i.e., $m_i^{l \to k} = m_i^{k \to l}$
- Same species have the same dispersal rate, i.e., $m_i^{l\to k}=m_i \ \forall k,l.$
- Initial Conditions: Each patch is identical, and abundance of species are randomly drawn.
- Governing ODE

$$\frac{dX_i^l}{dt} = r_i^l X_i^l + \sum_{j=1}^N a_{ij}^l X_i^l X_j^l - \sum_{k=1(l \neq k)}^{P_N} m_i^{l \to k} X_i^l + \sum_{k=1(k \neq l)}^{P_N} m_i^{k \to l} X_i^k$$
 (1)

• Jacobian Matrix: Can be automatized via MATLAB. (Or can be symbolically hardcoded as well)

$$\mathbf{J} = \begin{bmatrix} \frac{\partial f(X_1^1)}{\partial X_1^1} & \frac{\partial f(X_1^1)}{\partial X_2^1} & \cdots & \frac{\partial f(X_1^1)}{\partial X_N^1} & \frac{\partial f(X_1^1)}{\partial X_1^2} & \frac{\partial f(X_1^1)}{\partial X_2^2} & \cdots & \frac{\partial f(X_1^1)}{\partial X_N^N} \\ \frac{\partial f(X_2^1)}{\partial X_1^1} & \frac{\partial f(X_2^1)}{\partial X_2^1} & \cdots & \cdots & \cdots & \cdots & \cdots & \frac{\partial f(X_2^1)}{\partial X_N^N} \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \frac{\partial f(X_N^1)}{\partial X_1^1} & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \frac{\partial f(X_N^1)}{\partial X_1^1} & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \frac{\partial f(X_N^2)}{\partial X_1^1} & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \frac{\partial f(X_N^2)}{\partial X_1^1} & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f(X_N^2)}{\partial X_1^1} & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \frac{\partial f(X_N^2)}{\partial X_1^1} & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f(X_N^P)}{\partial X_1^1} & \frac{\partial f(X_N^P)}{\partial X_1^2} & \dots & \dots & \dots & \frac{\partial f(X_N^P)}{\partial X_N^P} \end{bmatrix}$$

For the case N=2, P=2:

$$\begin{split} \frac{dX_1^1}{dt} &= r_1^1 X_1^1 + a_{1,1} (X_1^1)^2 + a_{1,2} X_2^1 + m^{2 \to 1} X_1^2 - m_1^{1 \to 2} X_1^1 \\ \frac{dX_2^1}{dt} &= r_2^1 X_2^1 + a_{2,2} (X_1^2)^2 + a_{2,1} X_1^2 + m_2^{2 \to 1} \\ \frac{dX_1^2}{dt} &= r \\ \frac{dX_2^2}{dt} &= r \end{split}$$