

Inferring species interactions using Granger causality and convergent cross mapping

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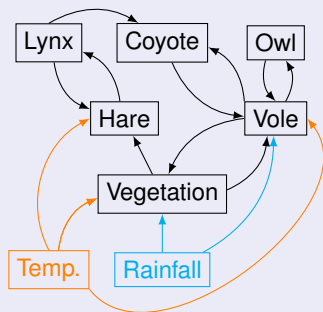
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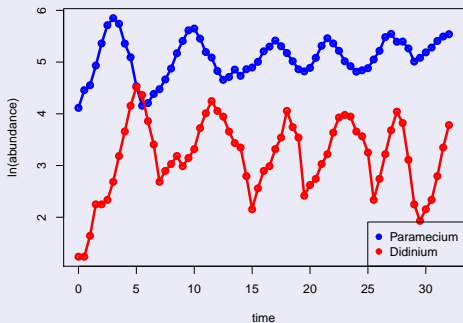
31 March 2021, Ecodep Seminar

Ecological interactions, causality, and time series

Interaction network in a dynamic sense \Leftrightarrow pop. growth rate_{*i*} = *f*(density_{*j*})



Time series data available



Veilleux (1979), predator = red, prey = blue

Granger Causality: back to basics

$\mathbf{x} = (x_t)_{t \in \llbracket 1, T \rrbracket}$ Granger-causes $\mathbf{y} = (y_t)_{t \in \llbracket 1, T \rrbracket} \iff$ including \mathbf{x} in a time series model for \mathbf{y} improves prediction of \mathbf{y} .

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$$y_t = \sum_{i=1}^p a_{1i} x_{t-i} + \sum_{i=1}^p a_{2i} y_{t-i} + \epsilon_t \quad (2)$$

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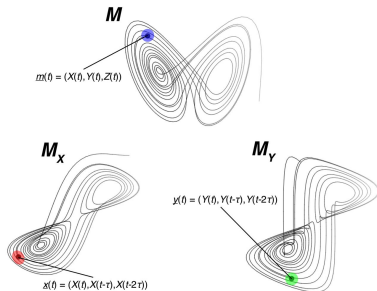
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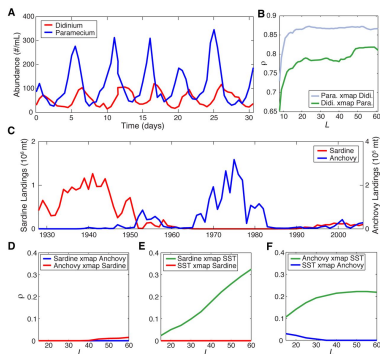
Sugihara et al. (2012). Detecting causality in complex ecosystems. *Science*, 338(6106), 496-500.

- Granger causality has problems with nonlinear processes (“separability” issues), works only for linear stochastic systems.
- New method = **Convergent Cross Mapping** (\exists other methods of state-space reconstruction, but less popular)

CCM: Sugihara et al. (2012)'s Convergent Cross-Mapping



Attractor reconstruction based on Takens theorem: build a 3-variable attractor with one variable 3 times delayed – from Sugihara et al. (2012)



Evaluation of causality with correlation coefficient $\rho(\mathbf{x}, \hat{\mathbf{x}}|M_Y)$ – from Sugihara et al. (2012)

CCM: X causes Y \Leftrightarrow predict X_t values from M_Y . “Causality reversion”.

Granger: X causes Y $\Leftrightarrow Y_{t+h} | (\mathbf{y}_{k \in \text{past}}, \mathbf{x}_{k \in \text{past}})$ better predicts Y_{t+h} than $Y_{t+h} | \mathbf{y}_{k \in \text{past}}$

What is a “linear stochastic system”, really? Multivariate AutoRegressive aka VAR(1) or MAR(1) models

In fact these are linear on the logarithmic abundance scale

$$\mathbf{x}_t = \ln(\mathbf{n}_t), \mathbf{x}_{t+1} = \mathbf{a} + \mathbf{B}\mathbf{x}_t + \mathbf{C}\mathbf{u}_t + \mathbf{e}_t, \mathbf{e}_t \sim \mathcal{N}_d(\mathbf{0}, \Sigma) \quad (3)$$

Ives et al. (2003). Estimating community stability and ecological interactions from time-series data. *Ecol. Monogr.*, 73(2), 301-330.

$$B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix}$$

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Why log? Power-law models with lognormal noise $N_{t+1,1} = e^a N_{t,1}^{b_{11}} N_{t,2}^{b_{12}} N_{t,3}^{b_{13}} e^{\epsilon_{1t}}$

Reasons why linear Granger causality might in fact apply to highly nonlinear ecological systems

- Even the simplest MAR/VAR(1) on the log-linear scale are quite robust to nonlinearities (Certain et al. 2018 *Methods in Ecology and Evolution*)
≈ 80 – 95% of signs recovered for 7 two-species models (T=100) + one food web (models with mostly fixed point equilibria).
- In general we use more time lags. MAR(p) models.

$$\mathbf{x}_t = \sum_{q=1}^p \mathbf{B}_q \mathbf{x}_{t-q} + \mathbf{e}_t \quad (4)$$

Nonlinearity can be expressed as higher-order lags. A well-known example with a single time series

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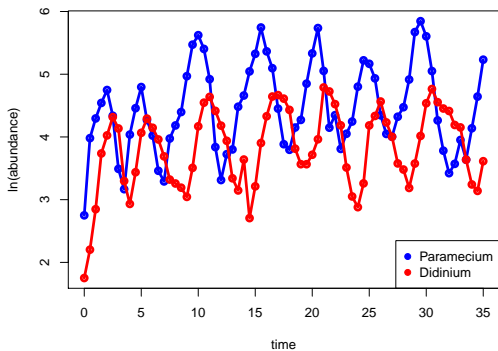
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We (re)evaluate the relative performances of Granger causality and convergent cross-mapping using a number of time series going from highly nonlinear — sensu *deterministic chaos* — to linear — sensu MAR(1).

Sugihara et al. (2012)'s data and models

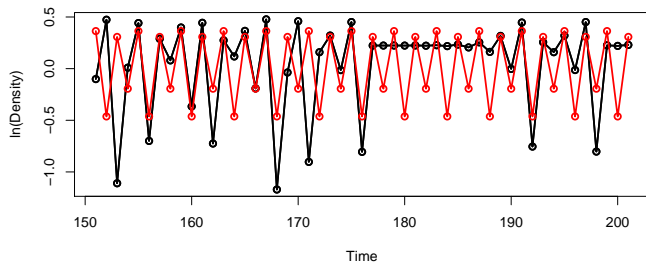


- Veilleux predator-prey data

- Chaotic and deterministic 2-species logistic competition model

$$N_{1,t+1} = N_{1,t}(3.8 - 3.8N_{t,1} - 0.02N_{t,2}) \quad (5)$$

$$N_{2,t+1} = N_{2,t}(3.5 - 3.5N_{t,2} - 0.1N_{t,1}) \quad (6)$$



Additional two-species models - competition with stochasticity

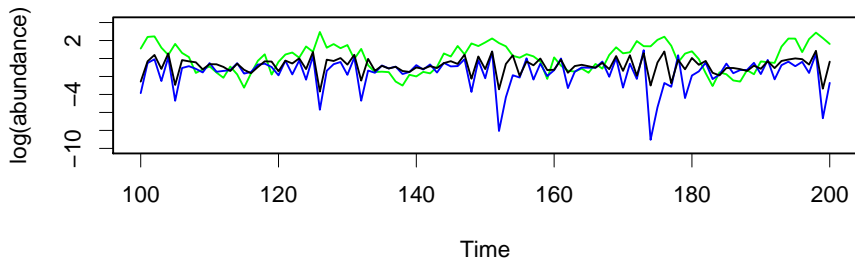
Ricker-based competition models

$$N_{1,t+1} = N_{1,t} \exp(3 - 4N_{1,t} - 2N_{2,t} + \epsilon_{1,t}) \quad (7)$$

$$N_{2,t+1} = N_{2,t} \exp(2.1 - 0.31N_{1,t} - 3.1N_{2,t} + \epsilon_{2,t}). \quad (8)$$

$$N_{1,t+1} = N_{1,t} \exp(3 + 0.5u_t - 4N_{1,t} - 2N_{2,t} + \epsilon_{1,t}) \quad (9)$$

$$N_{2,t+1} = N_{2,t} \exp(2.1 + 0.5u_t - 0.31N_{1,t} - 3.1N_{2,t} + \epsilon_{2,t}). \quad (10)$$



Many-species models

Ricker-based Lotka-Volterra

$$\mathbf{n}_{t+1} = \mathbf{n}_t \circ \exp(\mathbf{r} + \mathbf{A}\mathbf{n}_t + \mathbf{e}_t), \mathbf{e}_t \sim \mathcal{N}(0, \sigma^2 \mathbf{I}) \quad (11)$$

$$\mathbf{A} = \begin{pmatrix} -4 & -2 & -0.4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.31 & -3.1 & -0.93 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.636 & 0.636 & -2.12 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.111 & -0.111 & 0.131 & -3.8 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5 & -2 & -2 & -0.4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.31 & -3.1 & -0.93 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.636 & -0.636 & -2.12 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -4 & -2 & -0.4 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.31 & -3.1 & -0.93 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.636 & 0.636 & -2.12 \end{pmatrix} \quad (12)$$

Many-species models

Linear MAR(1) approximation of this Ricker-based Lotka-Volterra model

$$\mathbf{x}_t = \ln(\mathbf{n}_t) \quad (13)$$

$$\mathbf{x}_{t+1} = \mathbf{J}\mathbf{x}_t \quad (14)$$

$$\text{with } J_{ij} = \delta_{ij} + a_{ij}N_j^* \quad (15)$$

Many-species models

Nonlinear (Lotka-Volterra) model with interaction matrix $\mathbf{A} = (a_{ij})$ with 20 species + associated MAR(1) model linearized on the log-density scale

$$a_{ij} = \chi_{ij} [a_{min} + (a_{max} - a_{min})\text{Beta}(2, 2)] \quad (16)$$

$$\chi = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix} \quad (17)$$

Causality evaluation

2 species data and models (300 timesteps)

- **Pairwise Granger causality tests** with $\alpha = 0.1$ & effect size threshold. Number of time lags p selected by BIC. Wald tests with `grangertest` in the R package `lmtest` (Zeileis and Hothorn, 2002, v0.9-36). For conditional Granger causality testing: `causality` in package `vars` (Pfaff, 2008, v1.5-3), F-tests.
- **Convergent cross-mapping** with $\rho > 0.1$ and $p\text{-value} < \alpha$. P-values are surrogate-based (i.e., permutation-based). `rEDM` (Ye et al., 2018, v0.7.1). Comparison to p-values of Cobey and Baskerville (2016).

For many species models (700 timesteps for 20 species), we did the above pairwise causality analyses with a Benjamini and Hochberg (1995) correction to control the false discovery rate . We also tried **conditional Granger causality**:

- LASSO-penalized MAR(1) models with structured penalties, using the R package `SIMoNe` (Chiquet et al., 2008; Charbonnier et al., 2010, v1.0-3). `SIMoNe` = Statistical Inference for MODular NETworks. *Weighted LASSO approach, combining elements of group and adaptive LASSO.*

Weighted (structured) LASSO

For details see Charbonnier et al. (2010). Latent structure of network \mathcal{P} is structured into \mathcal{Q} classes. We note Z_{iq} the indicator function (a random variable) whose value is 1 if species i belongs in class q (e.g. network module). Follows Ambroise et al. (2009), who use the mixture framework of Daudin et al. (2008).

$$\hat{\mathbf{A}} = \operatorname{argmax} \log \mathcal{L}(\mathbf{Y}, \mathbf{A}; \mathbf{Z}) = \operatorname{argmax} \left\{ \operatorname{Tr}(\mathbf{V}'\mathbf{A}) - \frac{1}{2} \operatorname{Tr}(\mathbf{A}'\mathbf{S}\mathbf{A}) - \|\mathbf{P}^{\mathbf{Z}} \star \mathbf{A}\|_1 \right\} \quad (18)$$

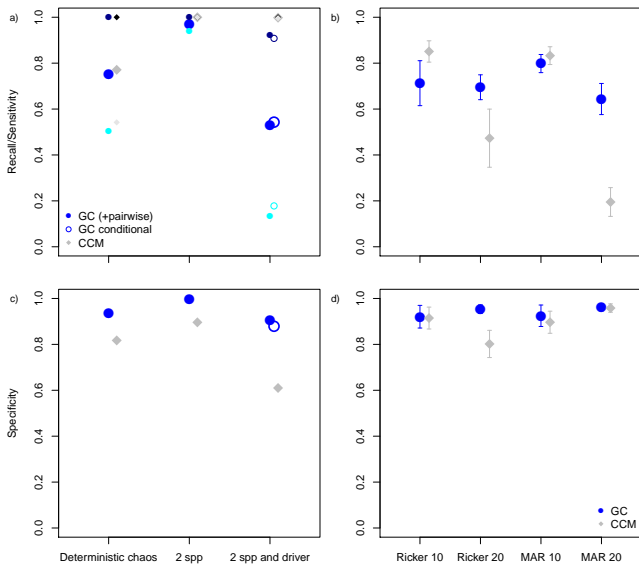
where $\mathbf{P}^{\mathbf{Z}} = (P_{ij}^{\mathbf{Z}})_{i,j \in \mathcal{P}} = \sum_{q,l \in \mathcal{Q}} \frac{Z_{iq}Z_{jl}}{\lambda_{ql}}$ are the penalties encapsulating the network structure. **There is a latent network model which says if two species are connected.**

The particular structure of the model allows to reduce this global LASSO optimization to d LASSO-style problems, which makes it much faster. Tuning of the penalty parameter is then done using BIC (Charbonnier et al., 2010).

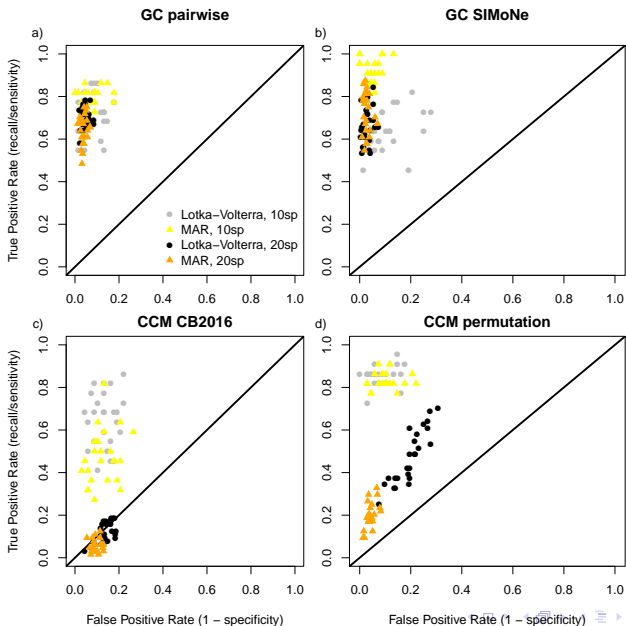
Notational details: $\mathbf{A} = \mathbf{B}'$ with \mathbf{B} from Ives et al. (2003), $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_1, \dots, \mathbf{x}_T]'$ the matrix of observed (log)densities and \mathbf{Y} the one a time step after $\mathbf{Y} = [\mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_{T+1}]'$.

- $\mathbf{S} = \frac{1}{T} \mathbf{X}'\mathbf{X}$ is the empirical variance-covariance matrix
- $\mathbf{V} = \frac{1}{T} \mathbf{X}'\mathbf{Y}$ is the temporal autocovariance matrix

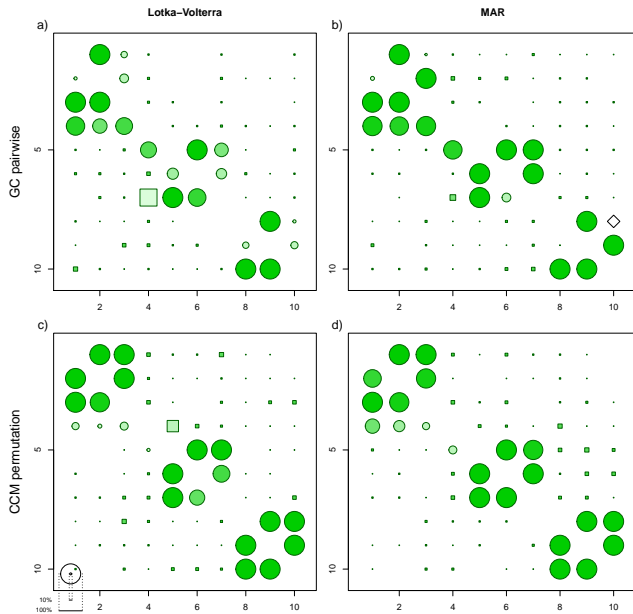
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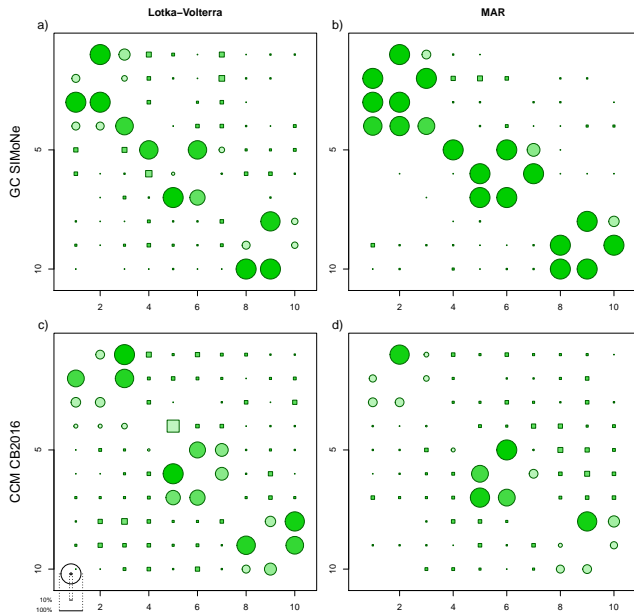
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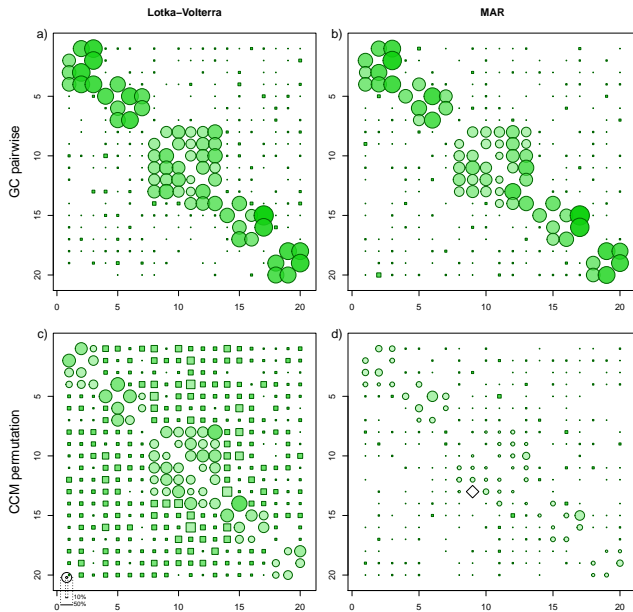
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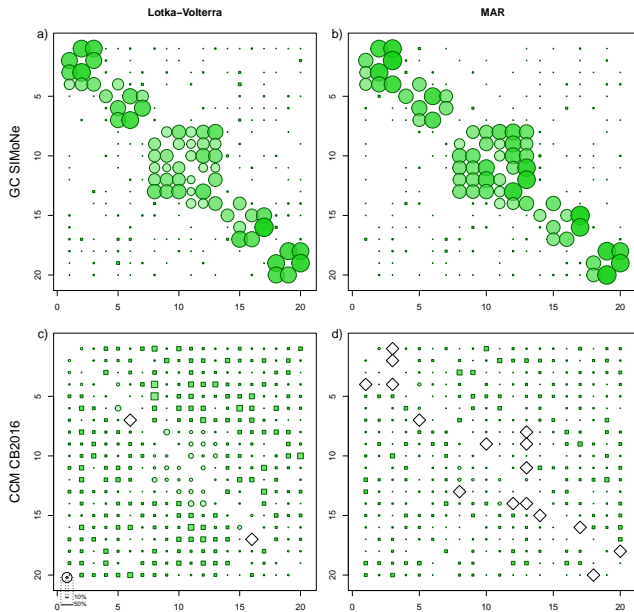
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- **In most 2-species cases of fluctuating community dynamics that we studied linear both Granger causality and convergent cross-mapping work fine.**
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- Bottomline: nothing wrong with using Granger causality for limit cycles and chaotic attractors. Nothing wrong with convergent cross-mapping for stochastic systems. **Both methods define (causal) interactions in the same way.**

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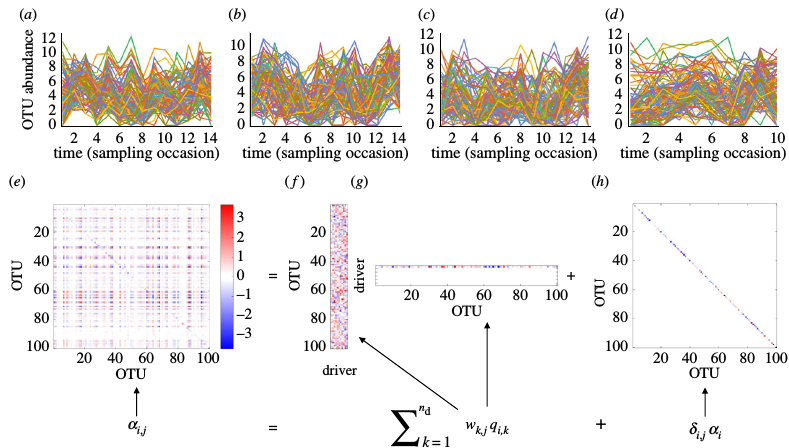
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- One could probably select p and the interaction matrices with BIC. Another approach: select both p and matrices using group LASSO (Nicholson et al., 2017a,b; Mainali et al., 2019). R package BigVAR, a little tricky.

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- Weighted LASSO (modular version of the LASSO) for high-dimensional $MAR(p)$ modelling has comparable performance to pairwise Granger causality tests: why?
- We have used a max time lag $p = 1$ with the weighted LASSO because (1) Charbonnier et al. (2010); Chiquet et al. (2008)'s very efficient R package was restricted to $MAR(1)$ modelling and (2) BIC suggested $p = 1$ for 20 species.
- One could probably select p and the interaction matrices with BIC. Another approach: select both p and matrices using group LASSO (Nicholson et al., 2017a,b; Mainali et al., 2019). R package BigVAR, a little tricky.
- Note that we have so far avoided modelling strongly autocorrelated environmental forcing + many-species dynamics but this is a common situation!
- Another idea: abandon the sparsity assumption altogether.

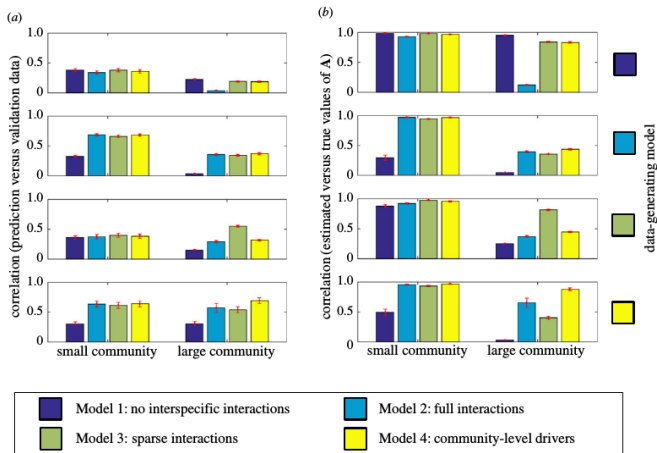
The community-level drivers method – dimension reduction

Ovaskainen et al. (2017) How are species interactions structured in species-rich communities? A new method for analysing time-series data. *Proceedings B*, 284: 20170768.



The community-level drivers method – dimension reduction

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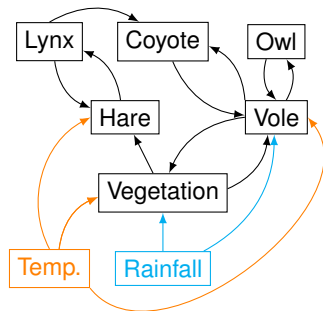


Want to know more? Questions?

Now published in *Theoretical Ecology*. Reprint at <https://arxiv.org/abs/1909.00731>

Code at <https://github.com/fbarraquand/GCausality>

Contact frederic.barraquand@u-bordeaux.fr



Follow-up questions:

- how do links that we infer depend on links that we assume?
- Identifiability issues in such models (postdoc position open).

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