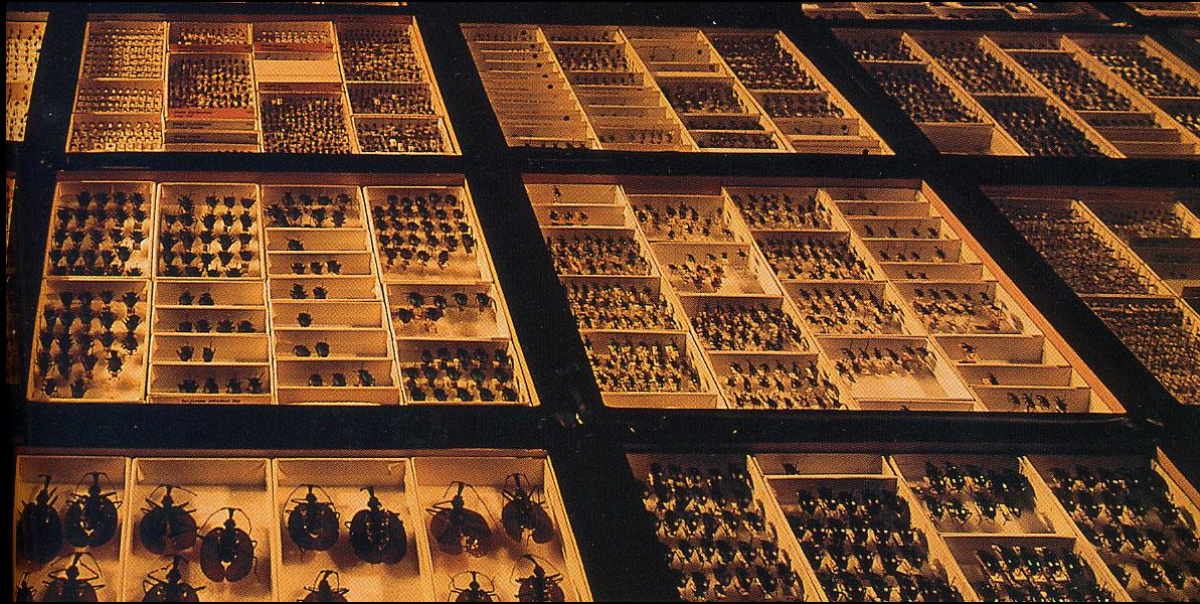


the Architecture of
Biodiversity:

A world of cooperation

Biodiversity

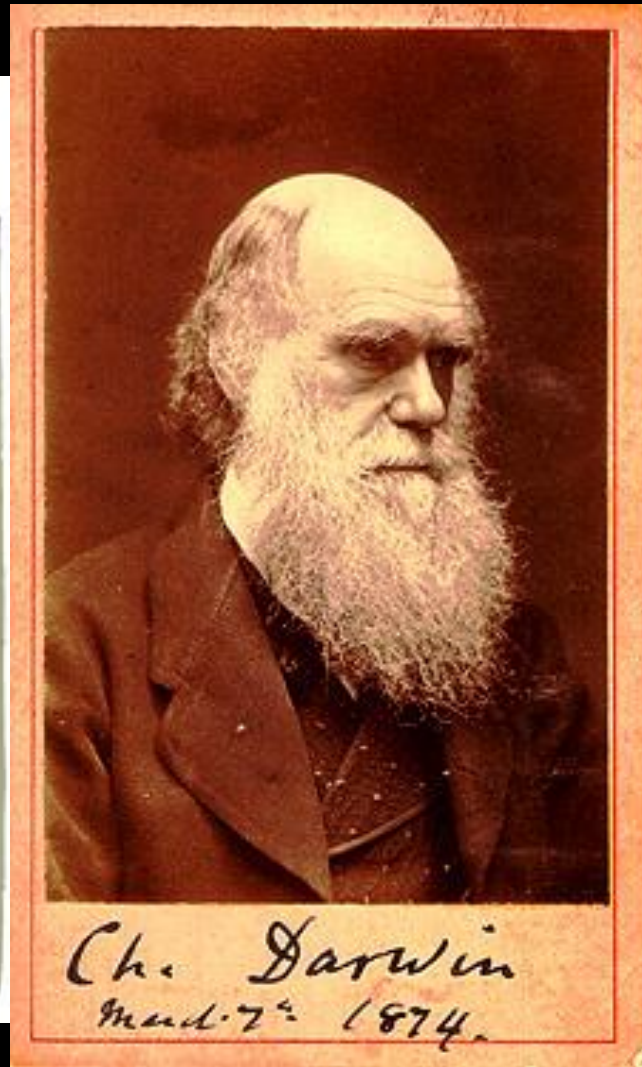
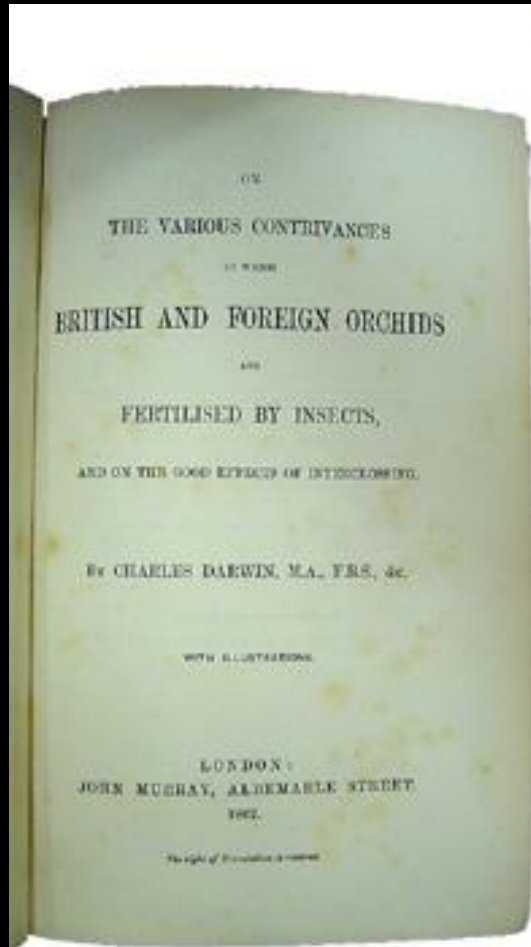


Interactions



Mutualistic Interactions

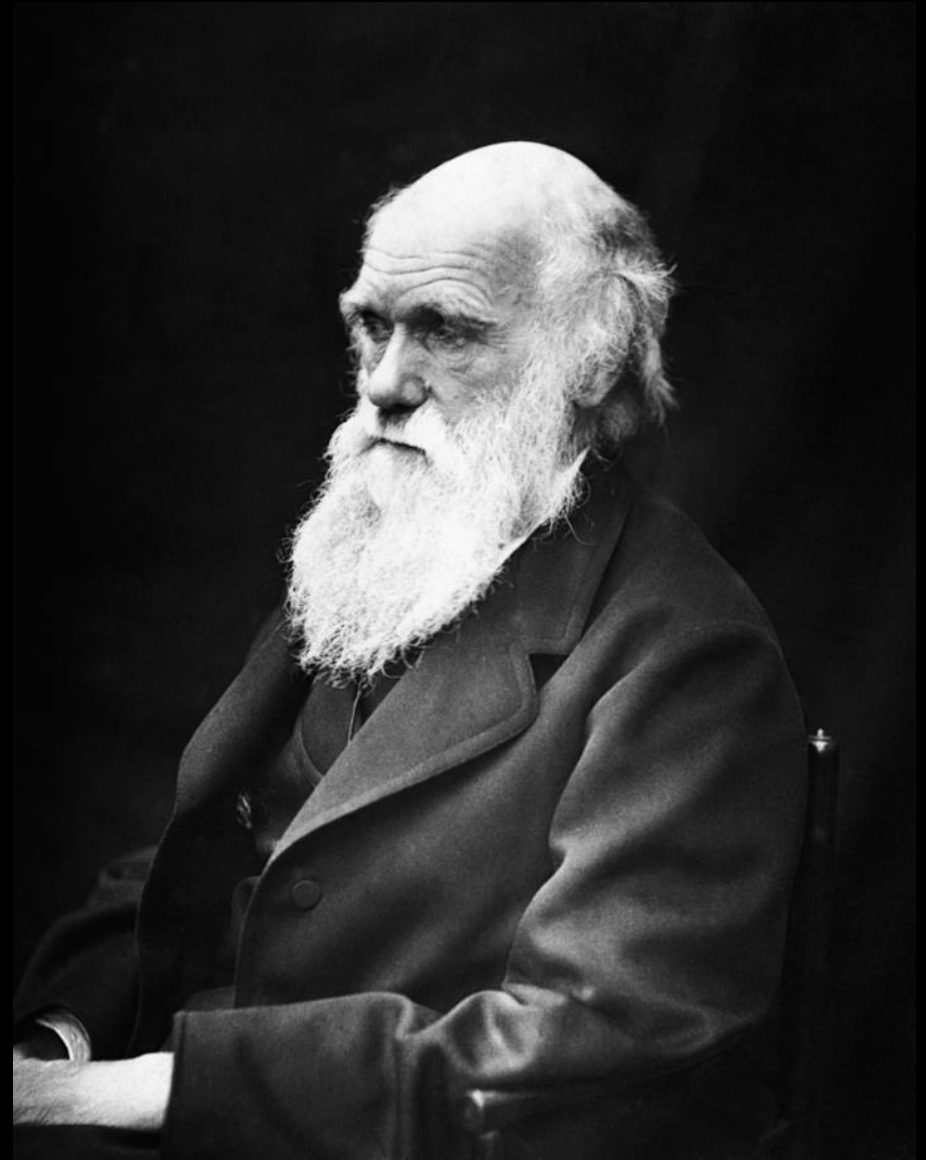




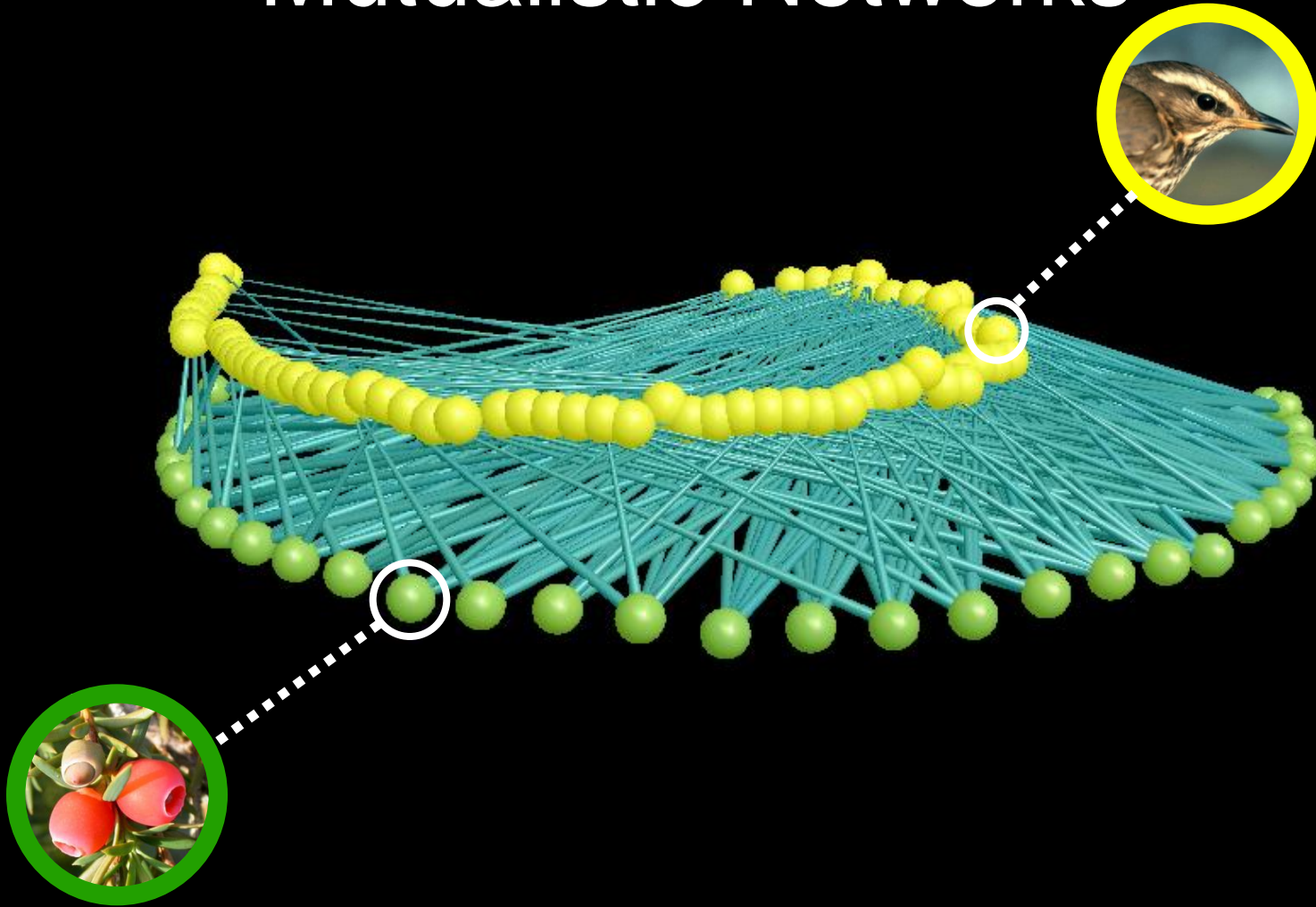


“I have deeply regretted that I did not proceed far enough at least to understand something of the leading principles of mathematics, for men thus endowed seem to have an extra sense.”

(The autobiography of Darwin, p. 13)



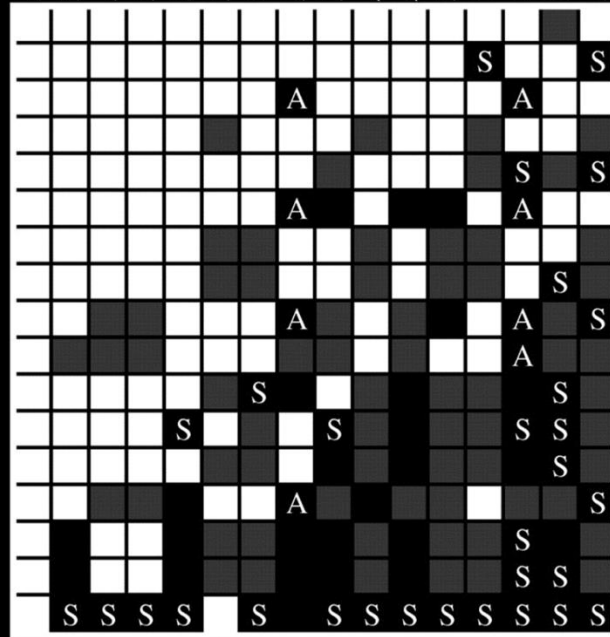
Mutualistic Networks





Sylvia atricapilla
Sylvia melanocephala
Turdus merula
Sylvia borin
Erithacus rubecula
Cyanopica cyanus
Sylvia hortensis
Sylvia communis
Saxicola torquata
Sturnus vulgaris
Ficedula hypoleuca
Sylvia cantillans
Phoenicurus phoenicurus
Turdus philomelos
Luscinia megarhynchos
Muscicapa striata
Sylvia undata

Pistacia lentiscus
Phillyrea angustifolia
Rhamnus lycioides
Rubus ulmifolius
Smilax aspera
Myrtus communis
Olea europaea
Daphne gnidium
Lonicera periclymenum
Asparagus aculeatus
Asparagus aphyllus
Rubia peregriana
Crataegus monogyna
Osyris alba
Tamus communis
Pyrus bourgaeana



no. links and cell colour code

for classification see ESM 1

141



observed links *I*

131



forbidden links *F*

68



— owing to phenological uncoupling

63



— owing to other constraints = (a) + (b) + (c)

8



(a) accessibility constraints

30



(b) size constraints

25

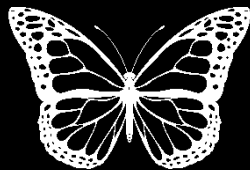


(c) unknown

272

total potential links *AP*

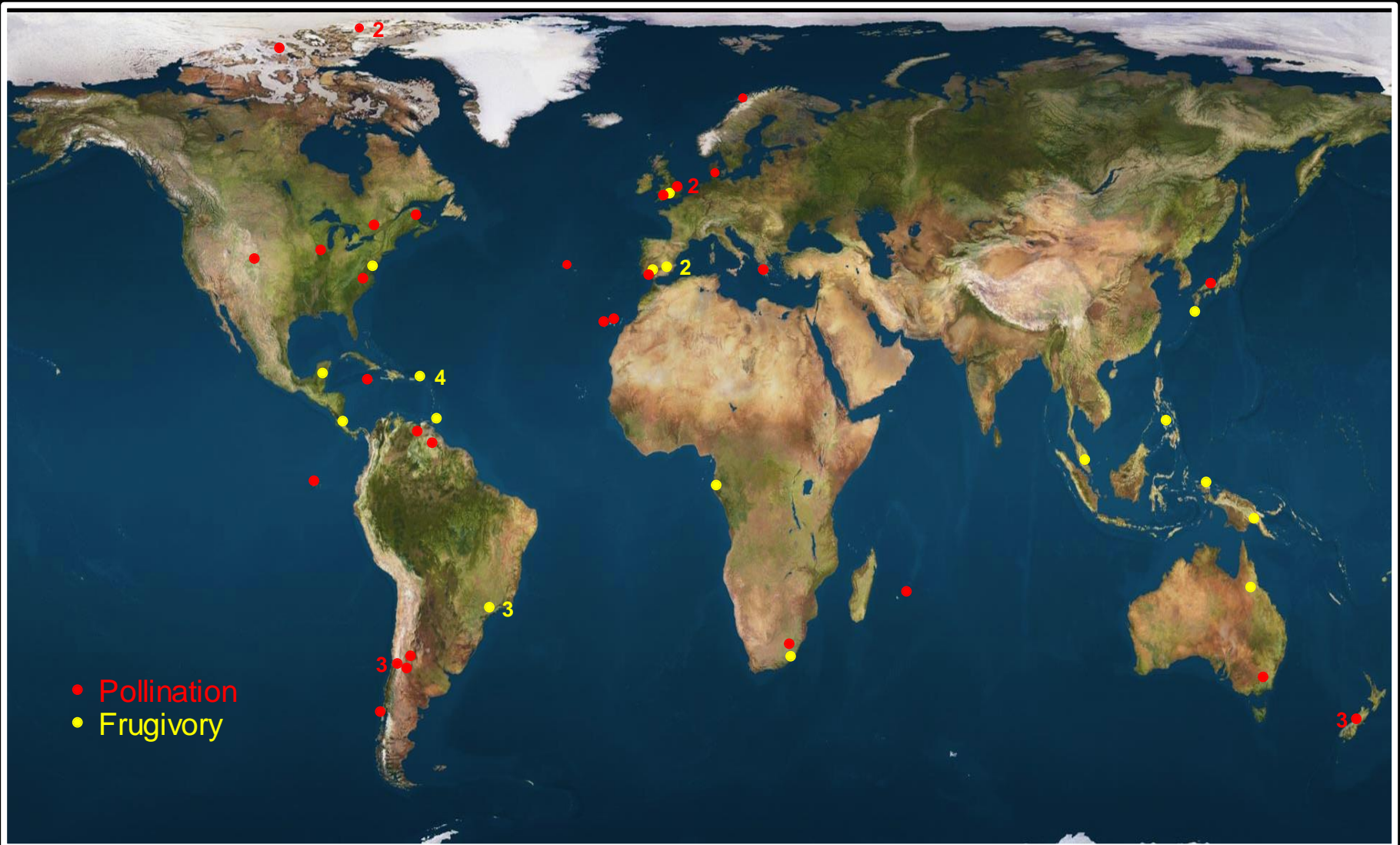
No mathematician left behind



$A =$

0	B
B'	0







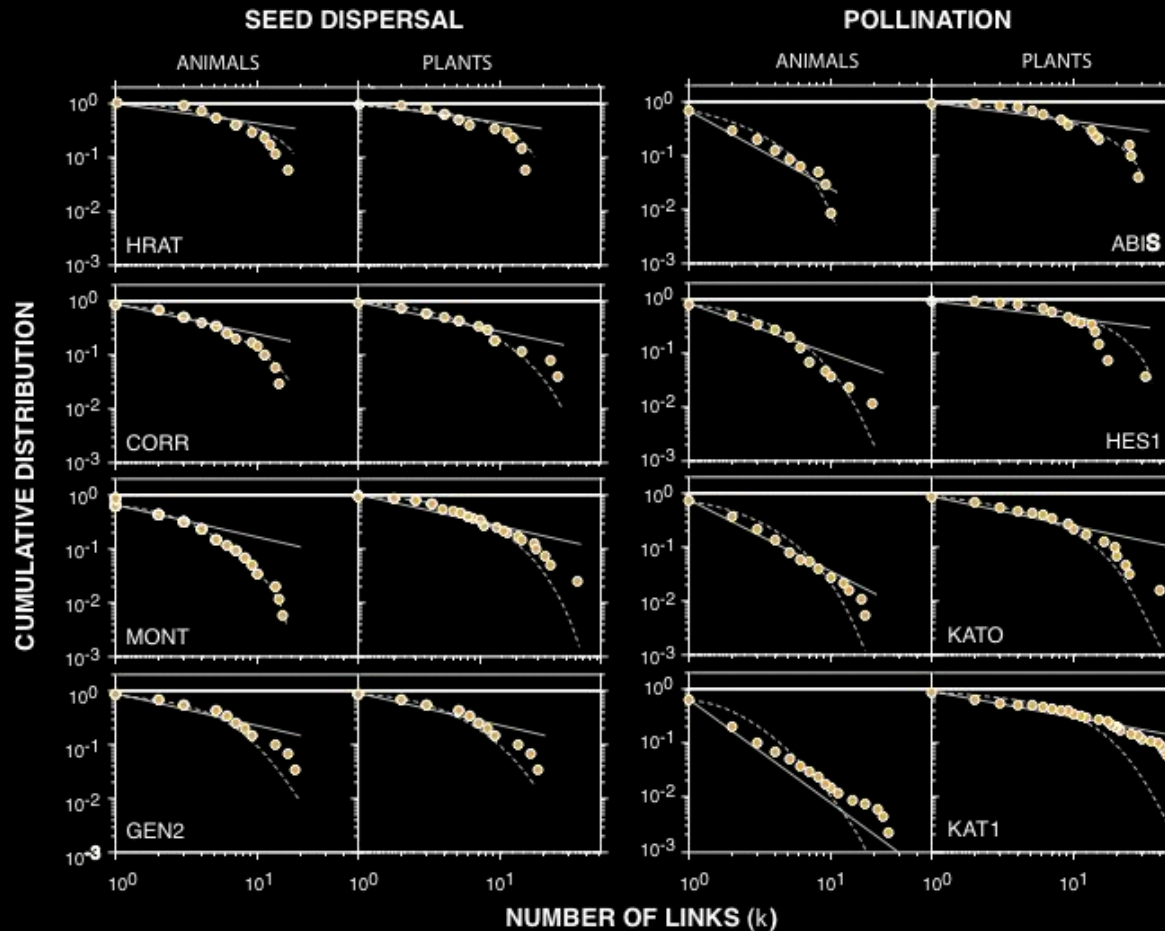
Outline

1. Describe network **architecture**.
2. Consequences for (i) network **robustness** to species extinctions and (ii) **species richness**.
3. Contribution of **species** to overall network architecture and robustness.



**Describe
Network Architecture**

1. Connectivity Distribution



Jordano, Bascompte, and Olesen (2003). *Ecol. Lett.* 6: 69-81.

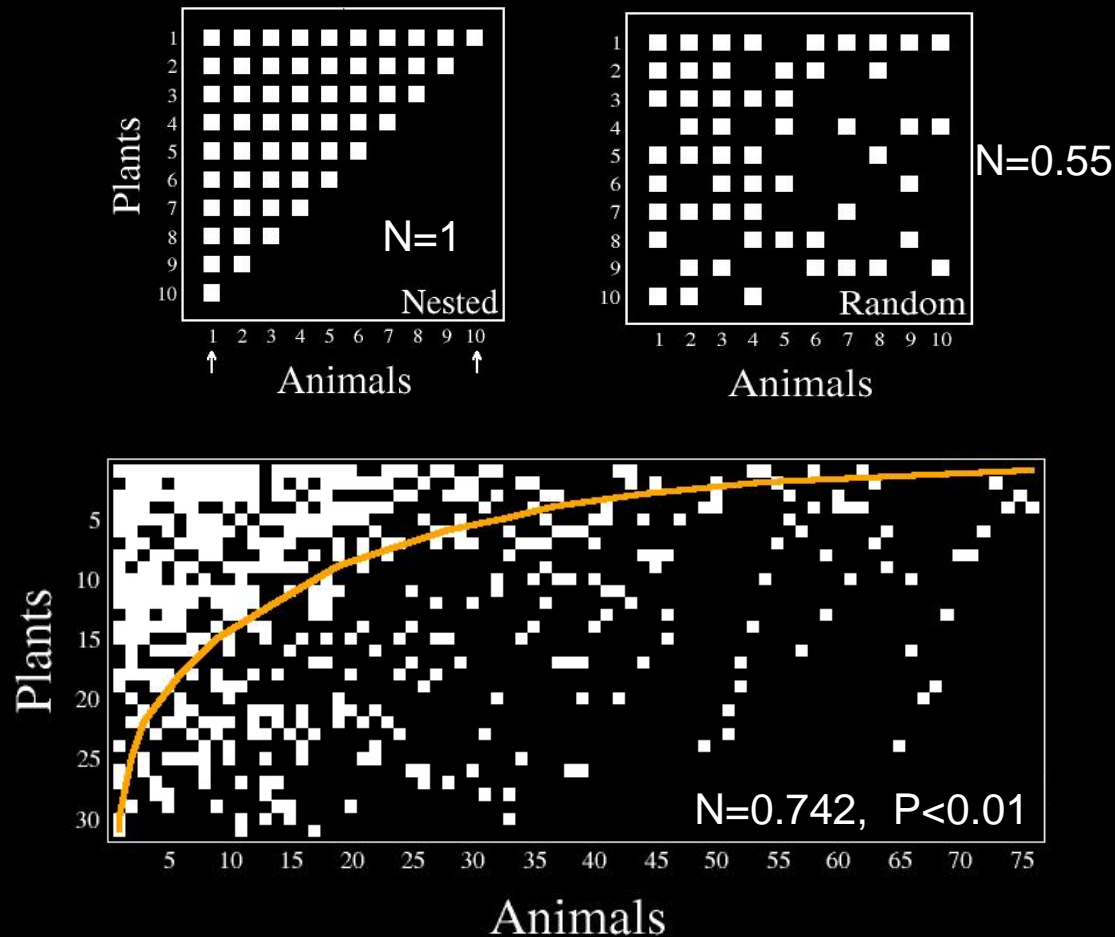
Is degree distribution
everything that matters?

Is degree distribution
everything that matters?

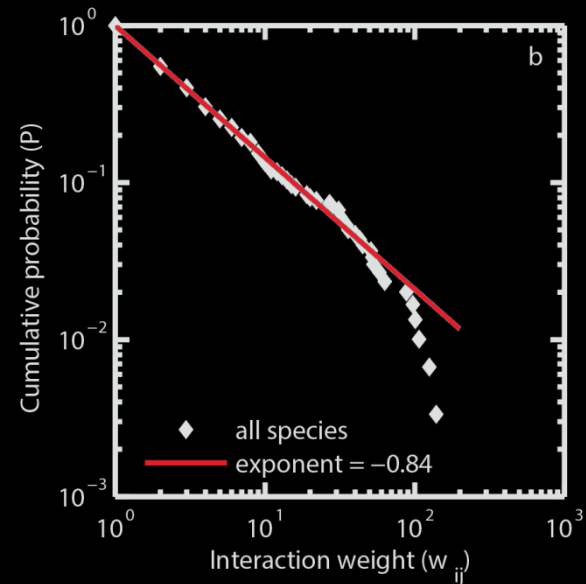
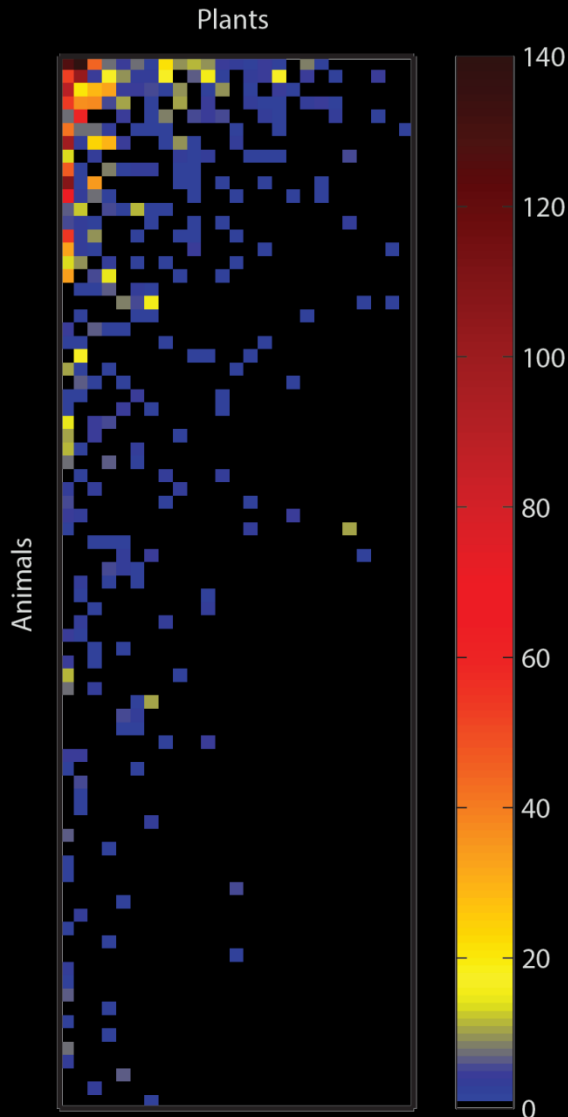
NO

With the correct null model
we can go beyond
degree distribution

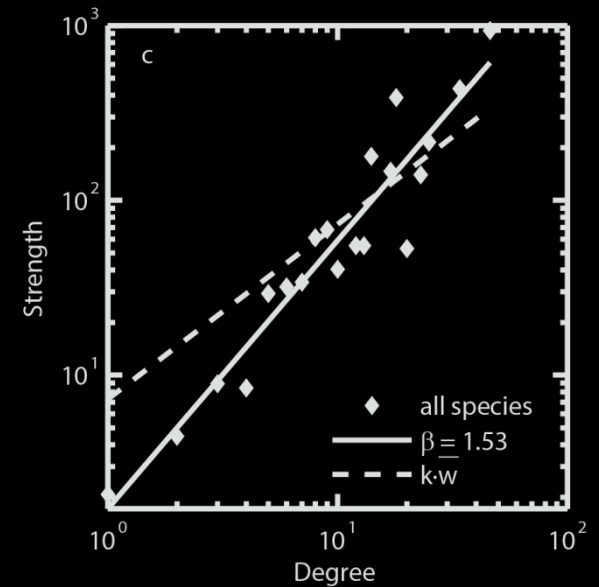
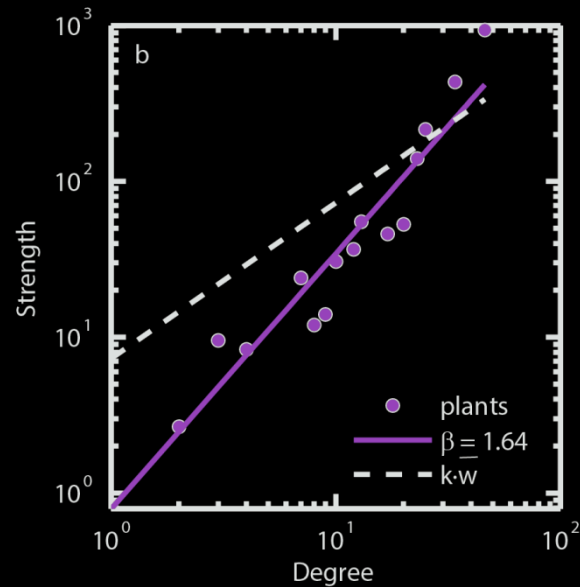
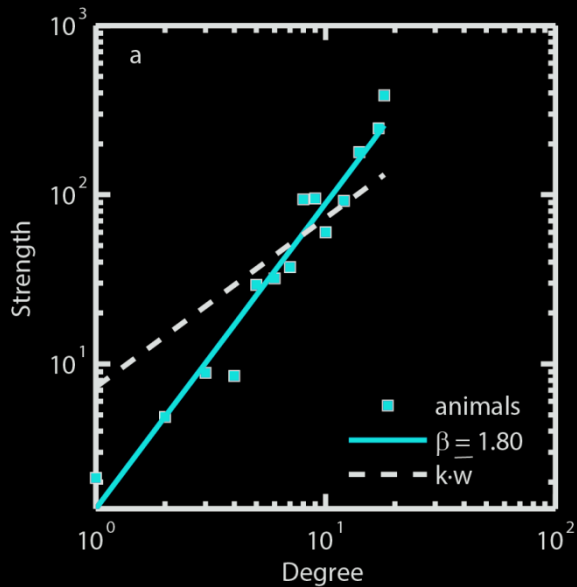
2. Mutualistic networks are Nested



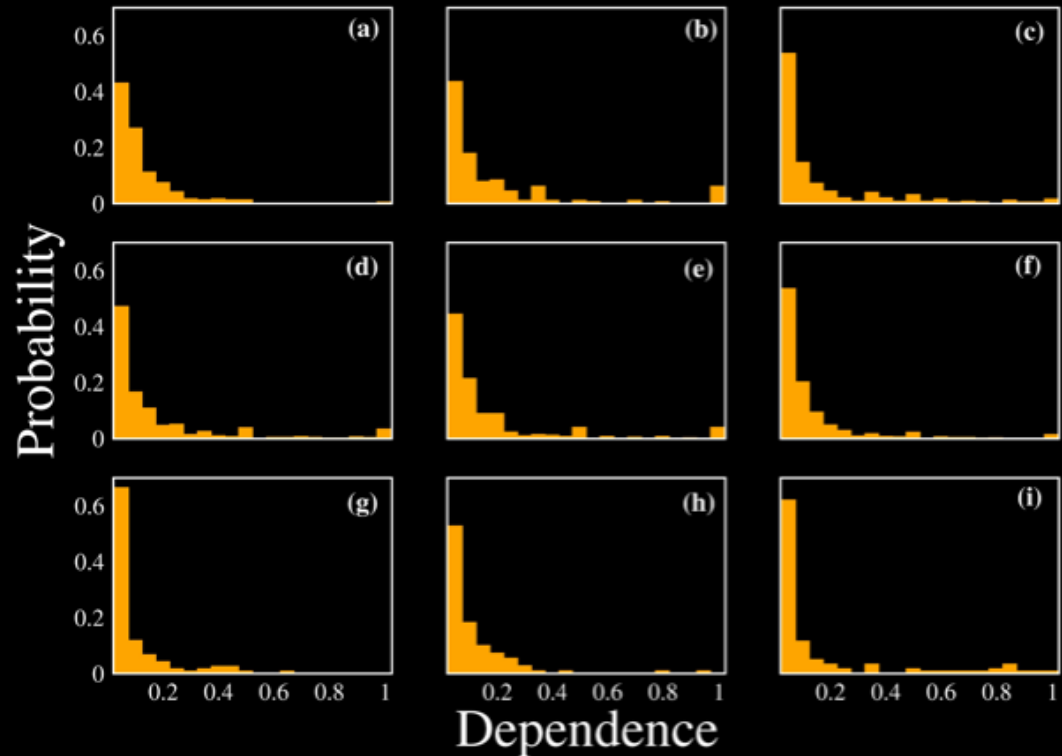
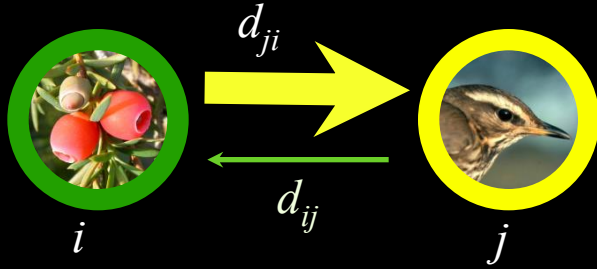
3. Interaction strength is not evenly distributed



3. Interaction strength is not evenly distributed

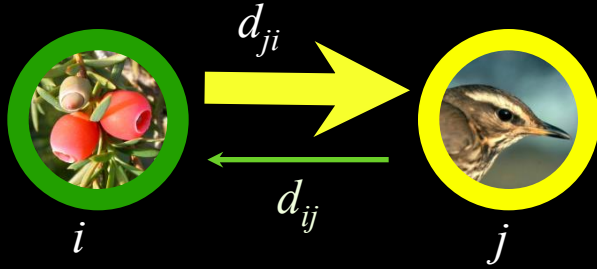


4. Mutualistic dependences are Asymmetric

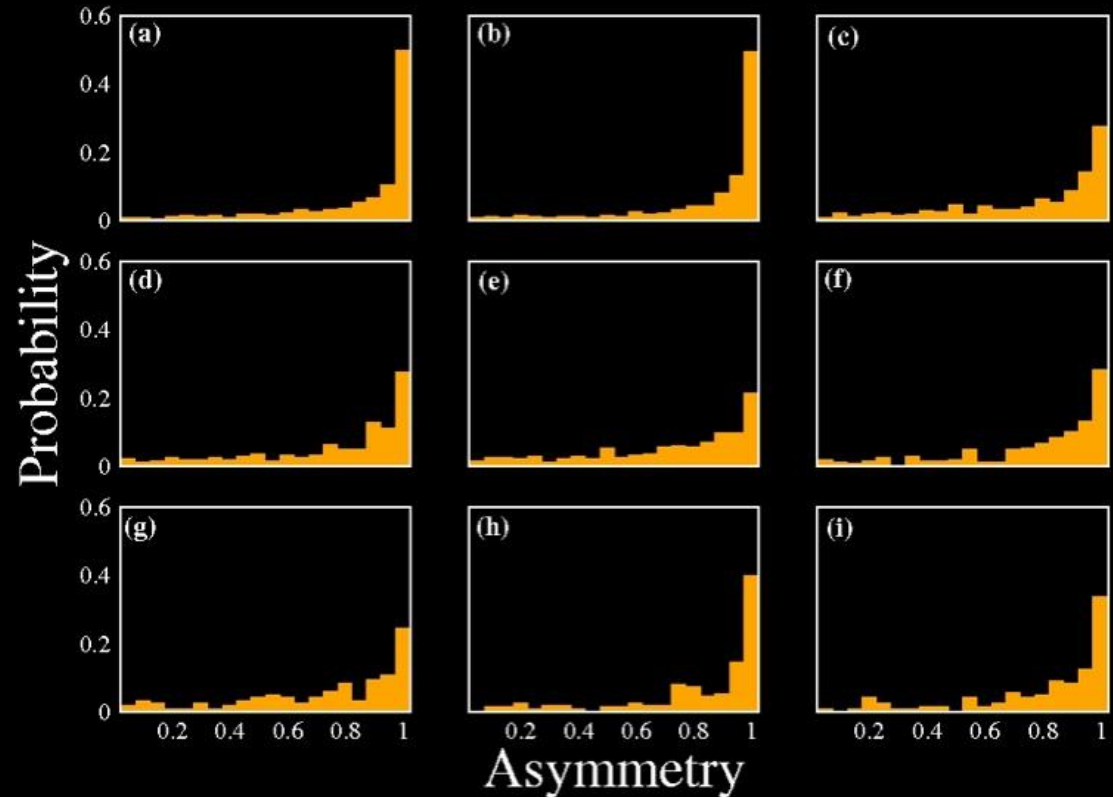


Bascompte, Jordano, and Olesen (2006). *Science* 312: 431-433.

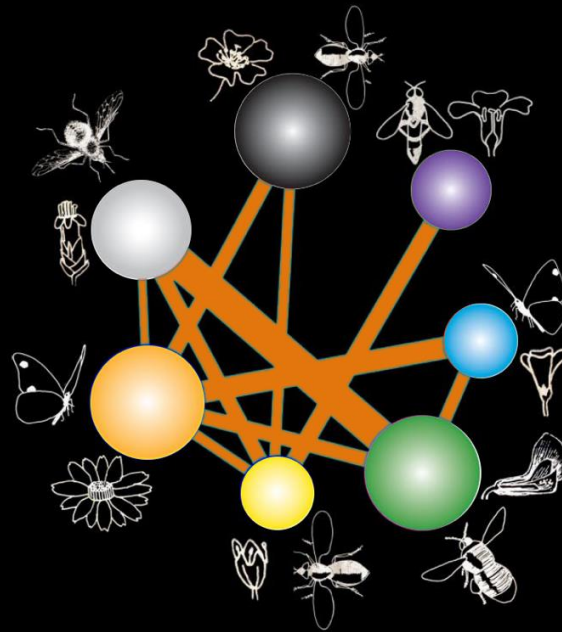
4. Mutualistic dependences are Asymmetric



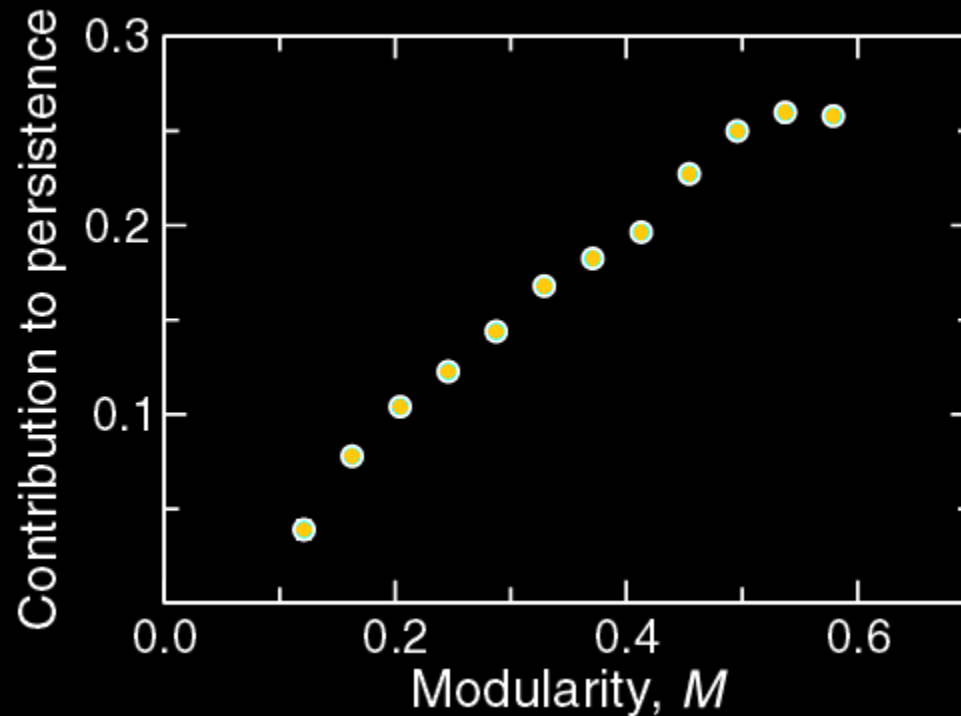
$$AS(i, j) = \frac{|d_{ij} - d_{ji}|}{\max(d_{ij}, d_{ji})}$$



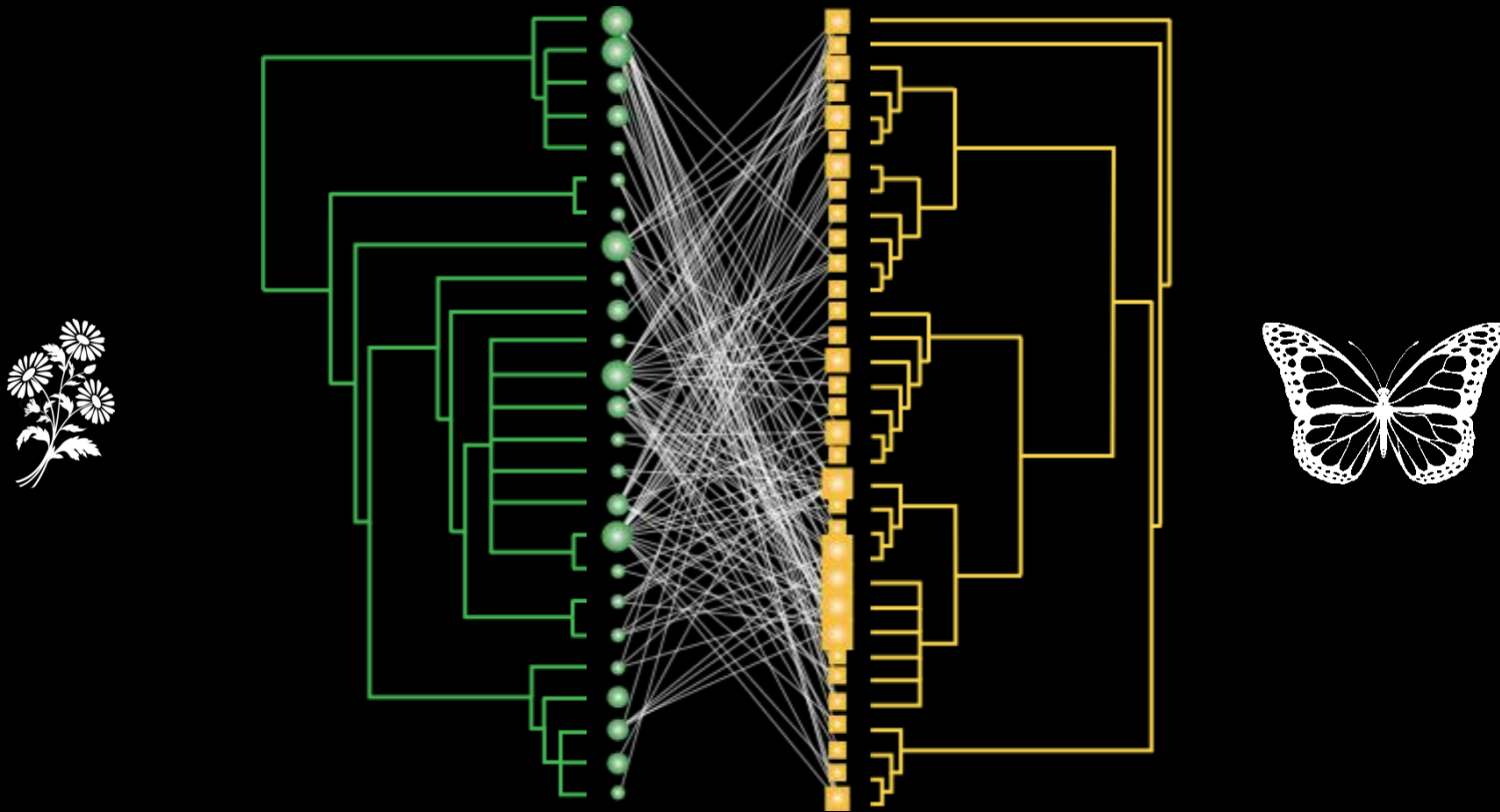
5. Mutualistic networks are also Modular



5. Mutualistic networks are also Modular

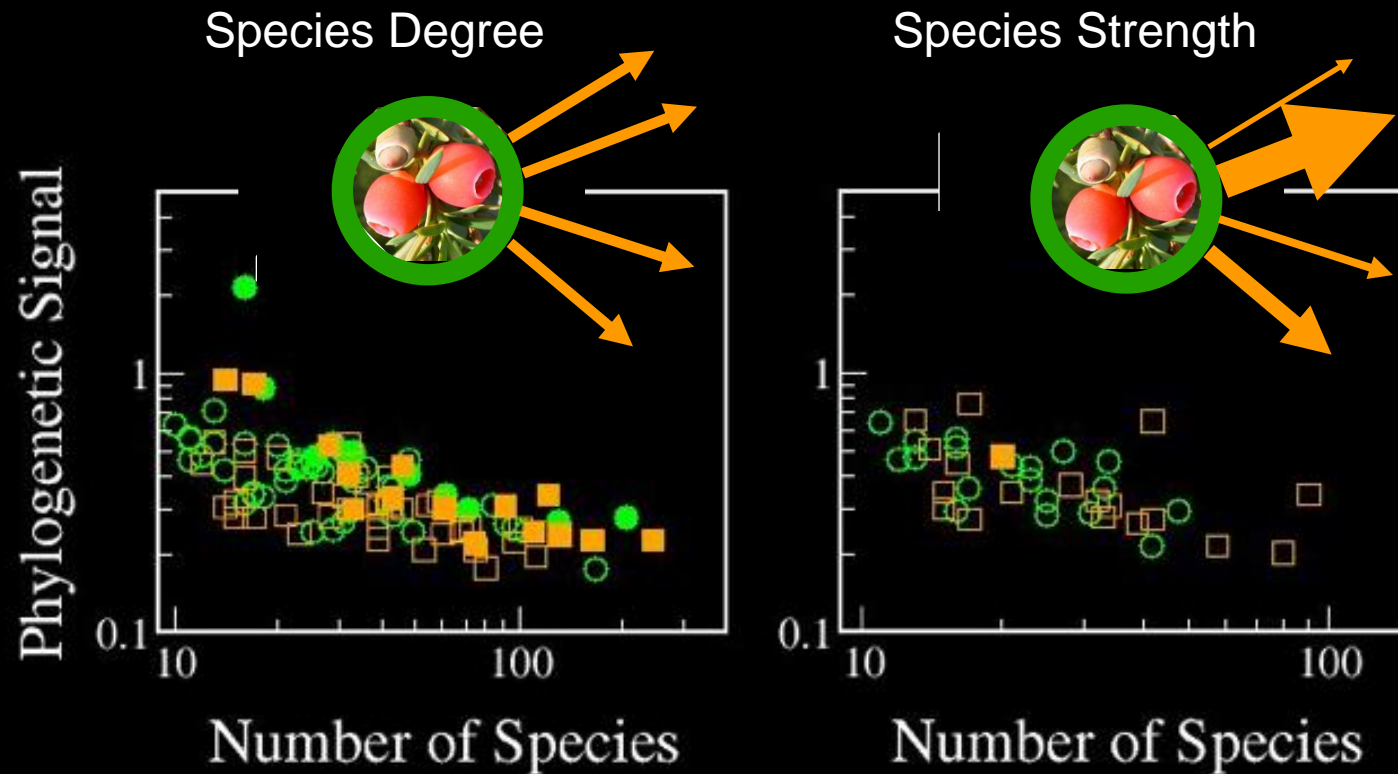


6. Evolutionary History



Rezende, Lavabre, Guimaraes, Jordano, and Bascompte (2007). *Nature* 448: 925-928.

7. Phylogenetic Signal

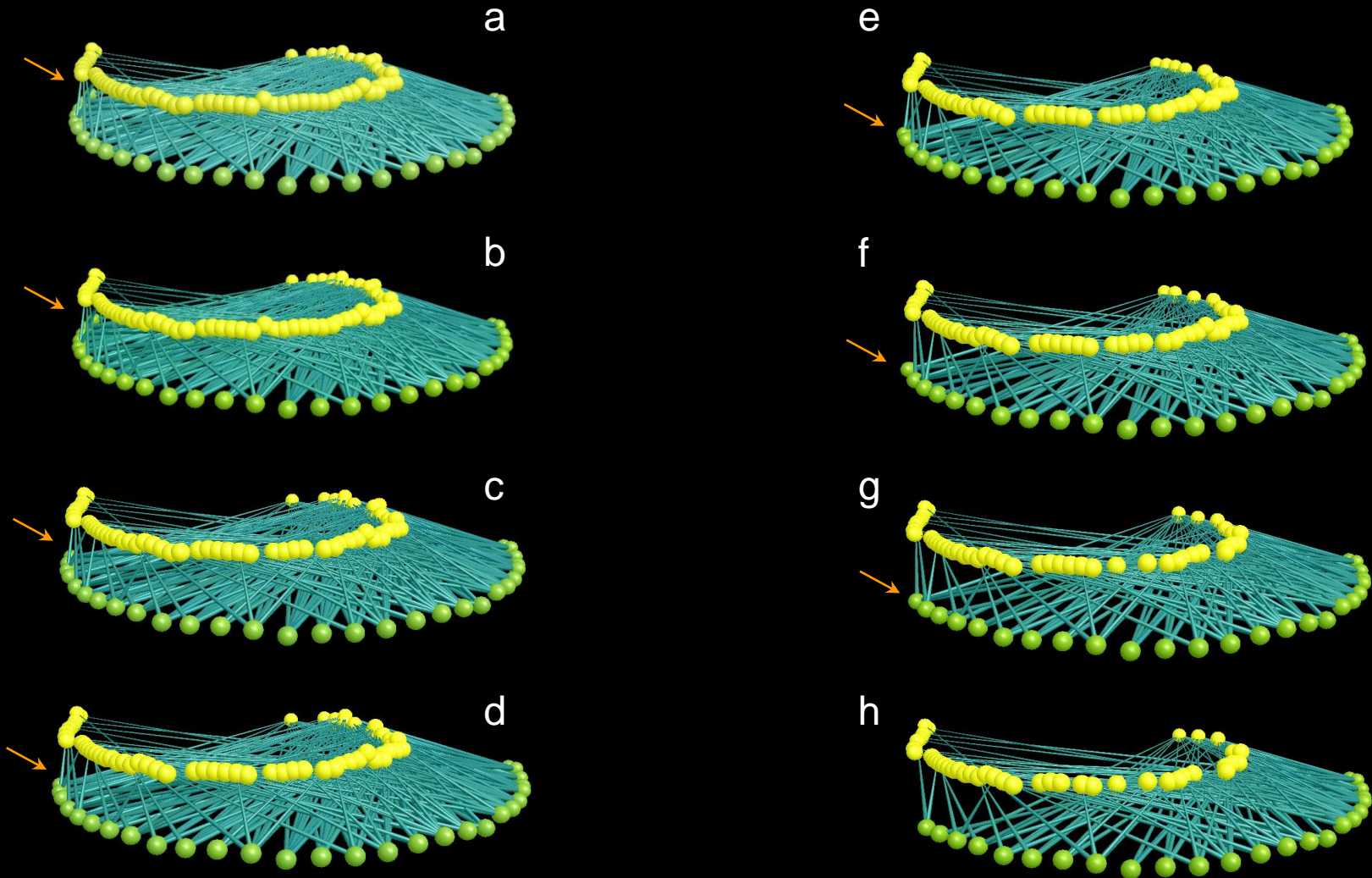


Consequences for:

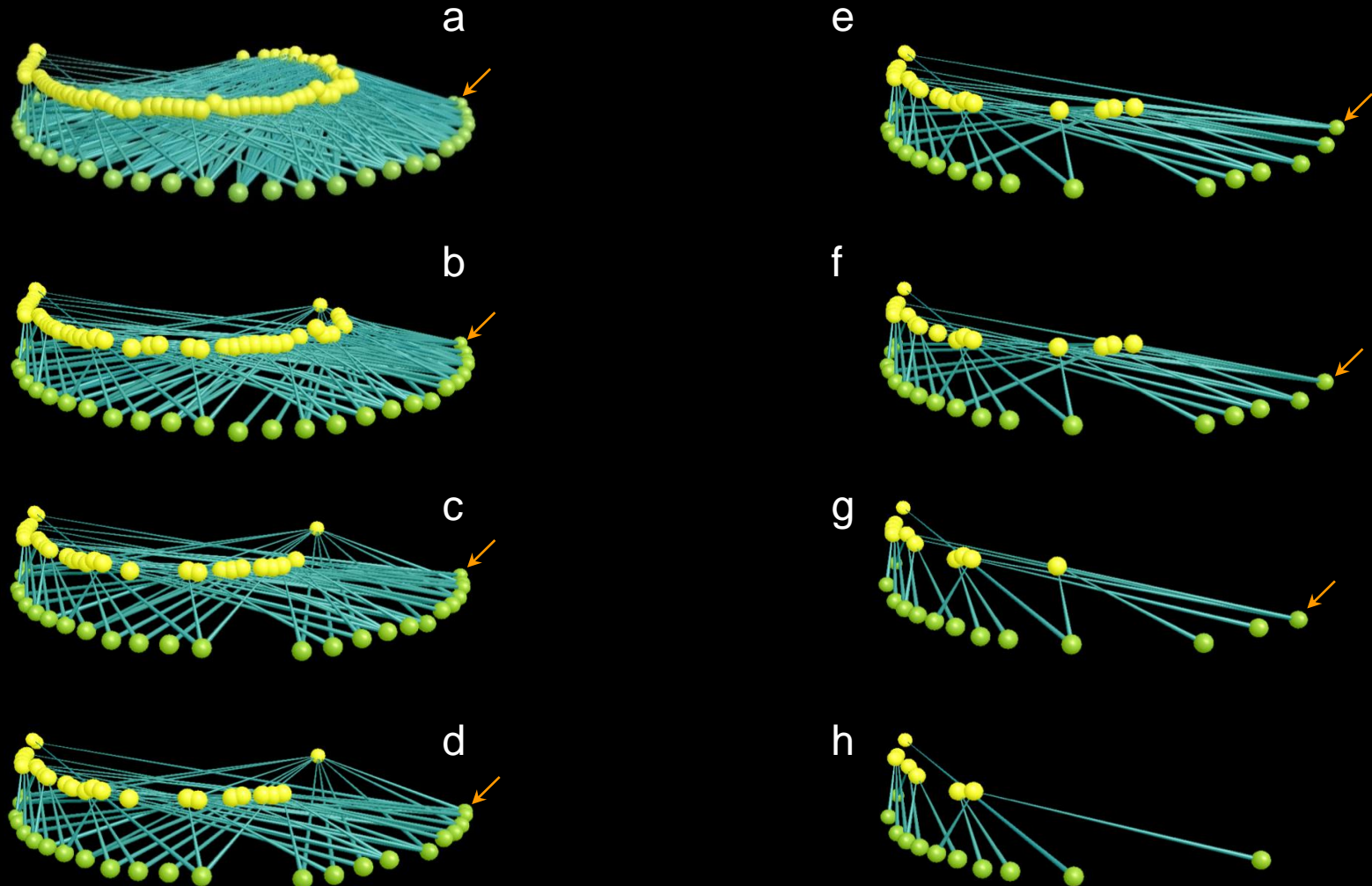
**Network robustness to
species extinctions.**

Species richness.

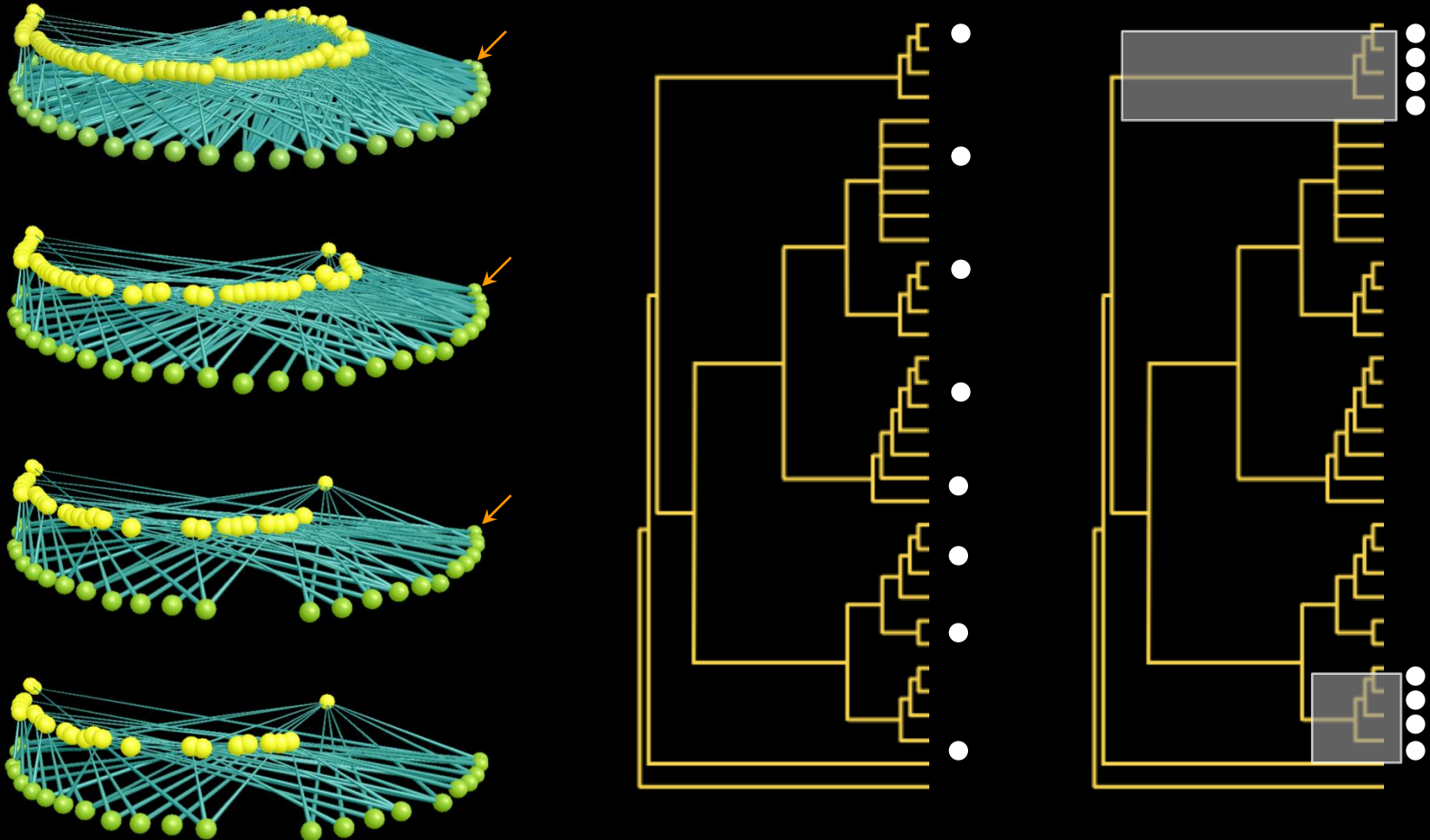
1. Degree distribution and Network Robustness



1. Degree distribution and Network Robustness



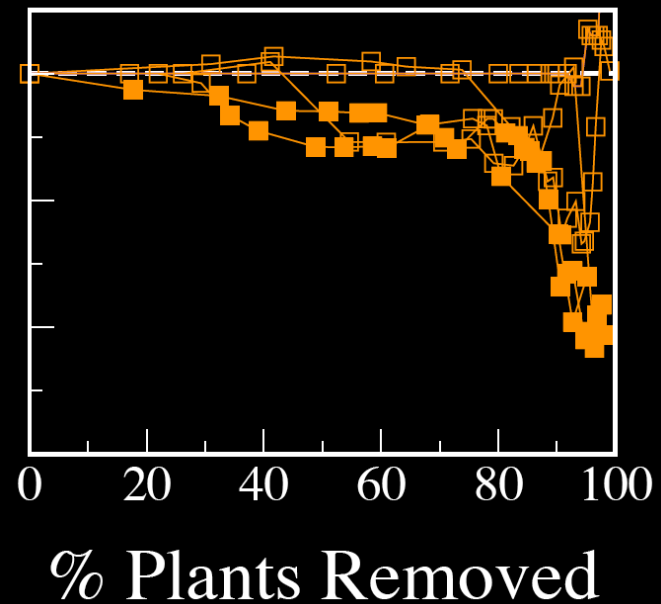
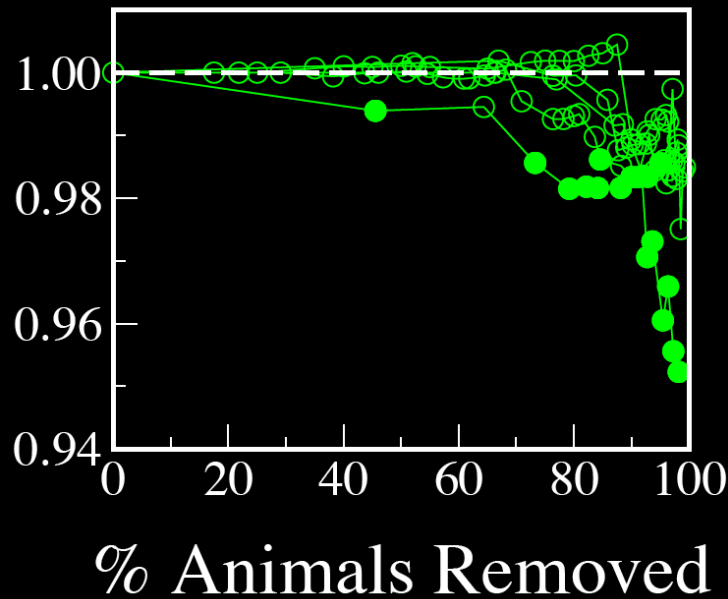
2. Phylogenetic Signal and Non-random coextinctions



Rezende, Lavabre, Guimaraes, Jordano, and Bascompte (2007). *Nature* 448: 925-928.

2. Phylogenetic Signal and Non-random coextinctions

Taxonomic Diversity



Ok, this is very nice but is starting to be kind of boring, and I've spend the last two days wondering...

Why do we observe in nature these patterns?



d



dt

Pollinator Abundance

Interspecific Competition

Intrinsic Growth Rate

Mutualistic Strength

$$\begin{cases} \frac{dP_i}{dt} = P_i \left(\alpha_i^{(P)} - \sum_j \beta_{ij}^{(P)} P_j + \frac{\sum_j \gamma_{ij}^{(P)} A_j}{1+h \sum_j \gamma_{ij}^{(P)} A_j} \right) \\ \frac{dA_i}{dt} = A_i \left(\alpha_i^{(A)} - \sum_j \beta_{ij}^{(A)} A_j + \frac{\sum_j \gamma_{ij}^{(A)} P_j}{1+h \sum_j \gamma_{ij}^{(A)} P_j} \right) \end{cases}$$

Plant Abundance

3. Network Size, i.e. Biodiversity

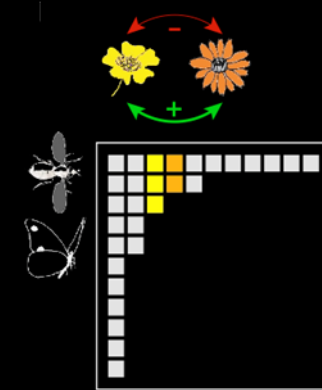
effective competition

Number of shared interactions between i and j

$$c_{ij}^{(P)} = \delta_{ij} + \frac{1}{\bar{S}^{(P)}} + R \left(\frac{1}{S^{(A)} + \bar{S}^{(A)}} \underbrace{n_i^{(P)} n_j^{(P)} - n_{ij}^{(P)}} \right)$$

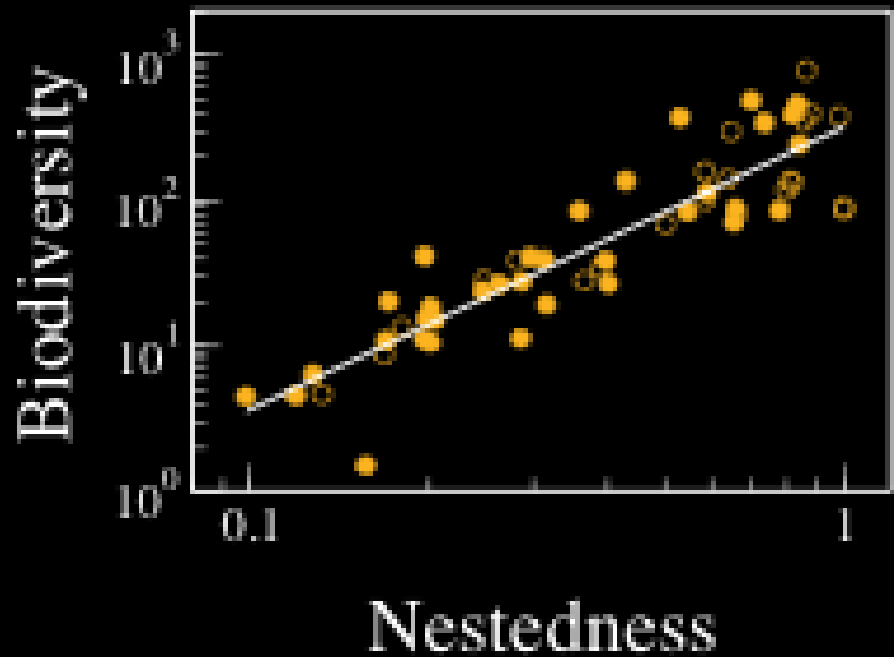
$$\rho^{(P)} = f(\lambda_1)$$

$$\bar{S}^{(P)} = \frac{1 - \rho^{(P)}}{\rho^{(P)}}$$

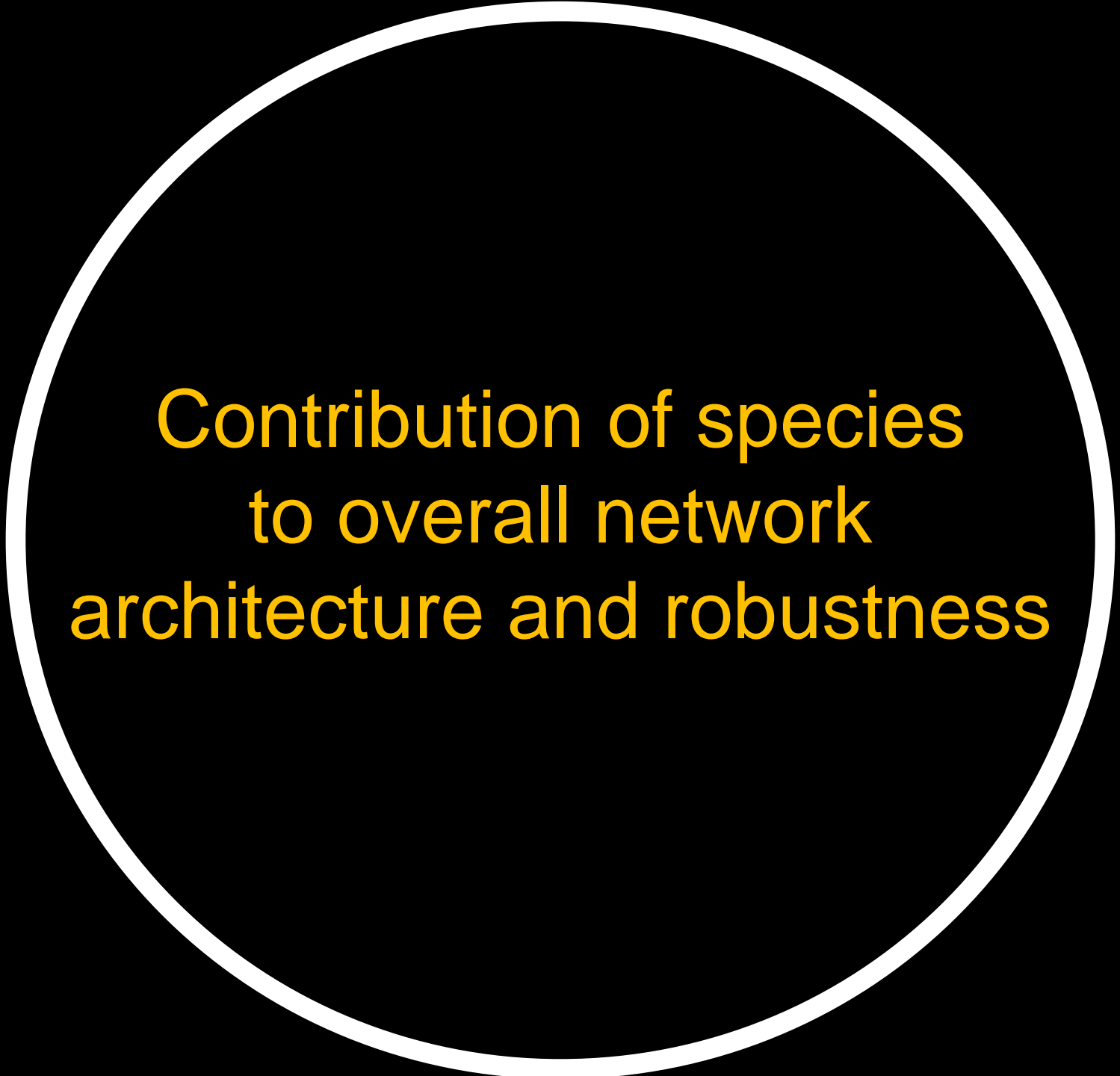


The higher nestedness, the lower the effective interspecific competition, and the higher the maximum biodiversity

3. Network Size, i.e. Biodiversity

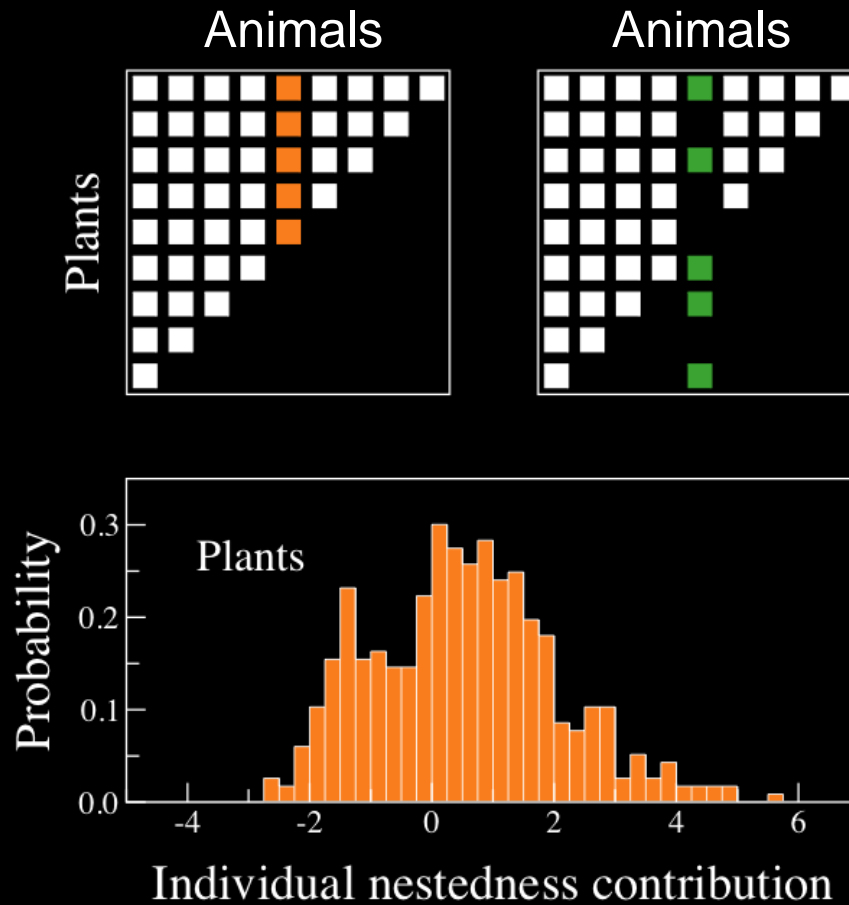


Bastolla, Fortuna, Pascual-García, Ferrera, Luque and Bascompte (2009). *Nature* 458:1018-1020

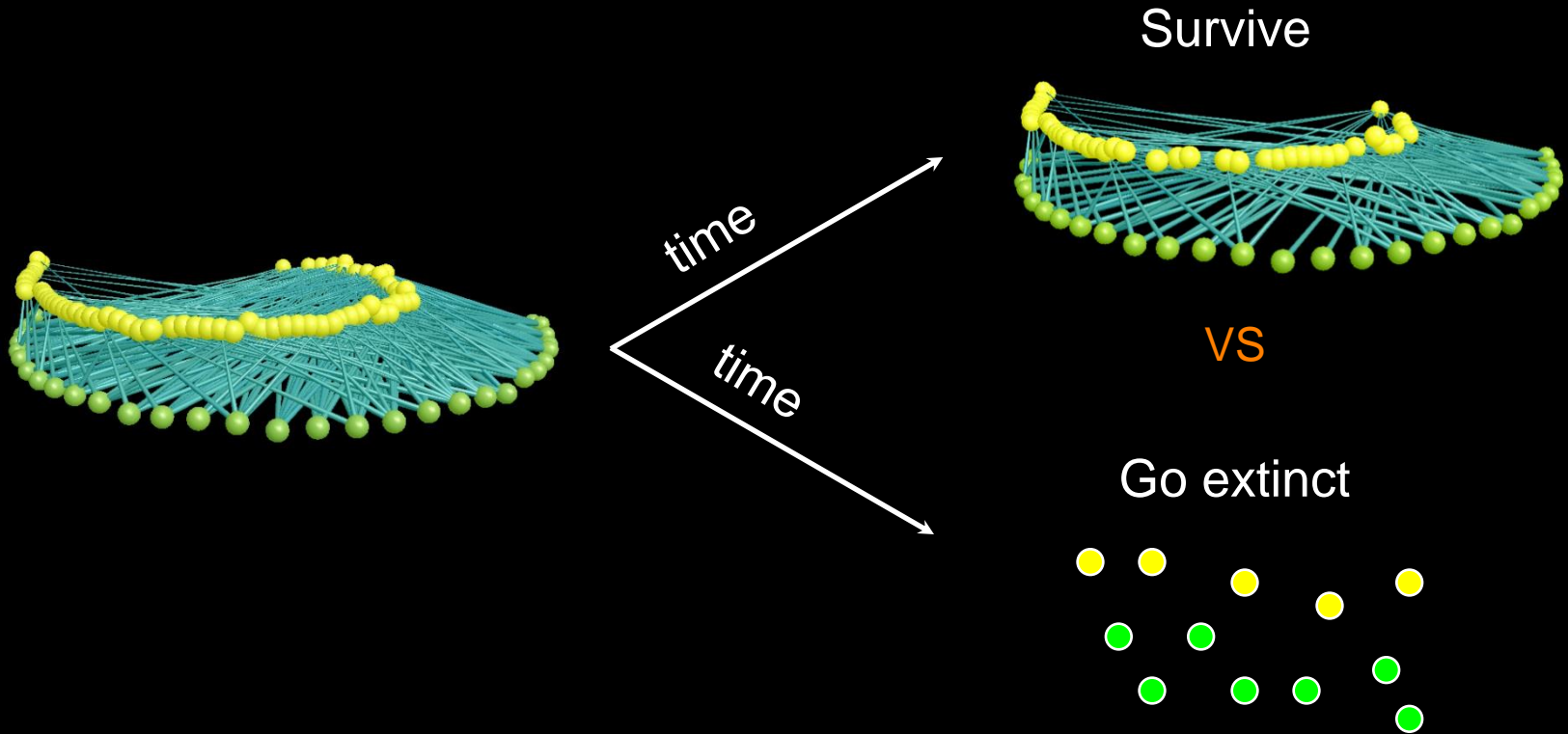


**Contribution of species
to overall network
architecture and robustness**

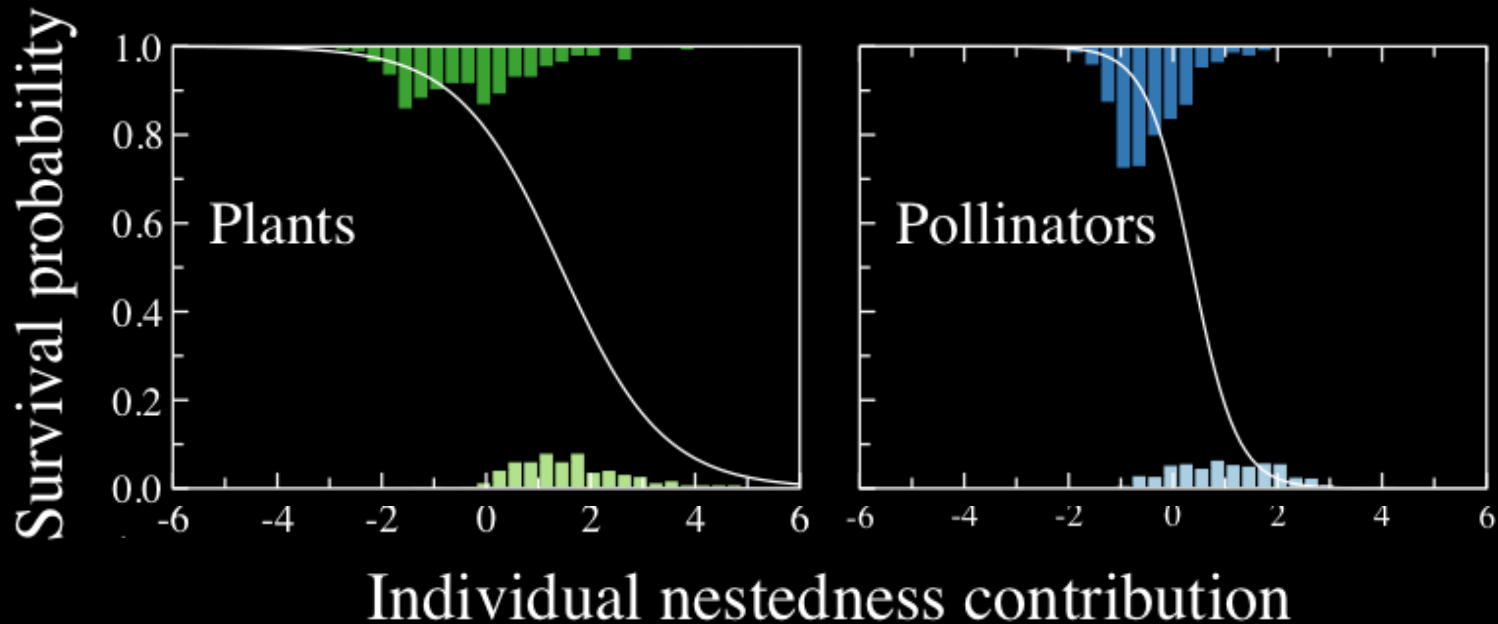
1. Species Contribution



2. Species Survival



3. Trade-offs in Persistence



LETTERS

A simple model of bipartite cooperation for ecological and organizational networks

Serguei Saavedra^{1,2,3}, Felix Reed-Tsochas^{1,4} & Brian Uzzi^{1,6}

Vol 451 | 21 February 2008

nature

NEWS & VIEWS

COMPLEX SYSTEMS

Ecology for bankers

Robert M. May, Simon A. Levin and George Sugihara

There is a condition:

Tipping point regime shift the flip of a coin state to a financial inst of 1929 and I such an even complicated cial markets systems wide (cla sub-prime loa Well before US National Council and t York collabo late fresh th main event w in May 2006, from various betwee syst and in selecte ogy and the report' was p stimulating n Catastroph a system can organiz—f it, and from l unrecognized some obvious is more usual happenstance Once set in m become explo exhibit some f ery is much sh cases, the cha

As the repr such large sc applicable f greenhouse l service, as s at stocks are grids or the In placed on bot banking syst possibility of lessons learne For instance,

PERSPECTIVE

doi:10.1038/nature09659

Systemic risk in banking ecosystems

Andrew G. Haldane¹ & Robert M. May²

In the run-up to the recent financial crisis, an increasingly elaborate set of financial instruments emerged, intended to optimize returns to individual institutions with seemingly minimal risk. Essentially no attention was given to their possible effects on the stability of the system as a whole. Drawing analogies with the dynamics of ecological food webs and with networks within which infectious diseases spread, we explore the interplay between complexity and stability in deliberately simplified models of financial networks. We suggest some policy lessons that can be drawn from such models, with the explicit aim of minimizing systemic risk.

In the 1960s, the notion of the 'balance of nature' played a significant part as ecologists sought a conceptual foundation for their subject. In particular, Evelyn Hutchinson¹, following Elton², suggested that "oscillations observed in arctic and boreal fauna may be due in part to the communities not being sufficiently complex to damp out oscillations". He went on to state, based on a misunderstanding of MacArthur's³ paper, that there was now a "formal proof of the increase in stability of a community as the number of links in its food web increases".

To the direct contrary, however, a closer examination of model ecosystems showed that a random assembly of N species, each of which had feedback mechanisms that would ensure the population's stability were it alone, showed a sharp transition from overall stability to instability as the number and strength of interactions among species increased. More explicitly, for $N \gg 1$ this transition occurs once $m^2 \gg 1$, where m is the average number of links per species, and $(\pm) \pm$ their average strength⁴. In ecology this has, since the 1970s, prompted a search for special food-web structures that may help reconcile complexity with persistence or stability^{5,6}. Along these lines there is, for example, tentative evidence for modularity⁷ (particularly in plant-pollinator associations, where linkages tend to be overlapping or disassortative), and more generally for nested hierarchies in food webs^{8,9}. The fact that some features of the network structure of interactions (such as predator/prey ratios) inferred from the Burgess Shale communities are similar to those in present day ones¹⁰ reinforces hopes that this is a meaningful area of research.

In the wake of the global financial crisis that began in 2007, there is increasing recognition of the need to address risk at the systemic level, as distinct from focusing on individual banks^{11,12}. This quest to understand the network dynamics of what might be called 'financial ecosystems' has interesting parallels with ecology in the 1970s. Implicit in much economic thinking in general, and financial mathematics in particular, is the notion of a 'general equilibrium'. Elements of this belief underpin, for example, the pricing of complex derivatives. But, as shown below, deeper analysis of such systems reveals explicit analogies with the concept that too much complexity implies instability, which was found earlier in model ecosystems.

There are, of course, major differences between ecosystems and financial systems. For one thing, today's ecosystems are the winnowed survivors of long-lasting evolutionary processes, whereas the evolution of financial systems is a relatively recent phenomenon¹³. Nor have selective pressures been entirely dispassionate, with the hand of government a constant presence shaping financial structures, especially among institutions deemed 'too big to fail'¹⁴. In financial ecosystems, evolutionary forces have often been driven of the fittest rather than the fittest.

In what follows, we first consider the role of the growth in intrafinancial system claims in generating bank failure and instability, focusing on the problems inherent in prevailing methods of pricing complex derivatives, or arbitrage pricing theory (APT). Second, we sketch various ways in which such an initial bank failure, or 'shock', may propagate to cause cascades of subsequent failure. Third, we outline some tentative policy lessons that might be drawn from these deliberately oversimplified models. Last, we ask how we might reshape the financial system to realize the economic benefits individual banks can deliver, while at the same time paying deliberate and explicit attention to their system-wide stability.

Potential causes of an initial shock

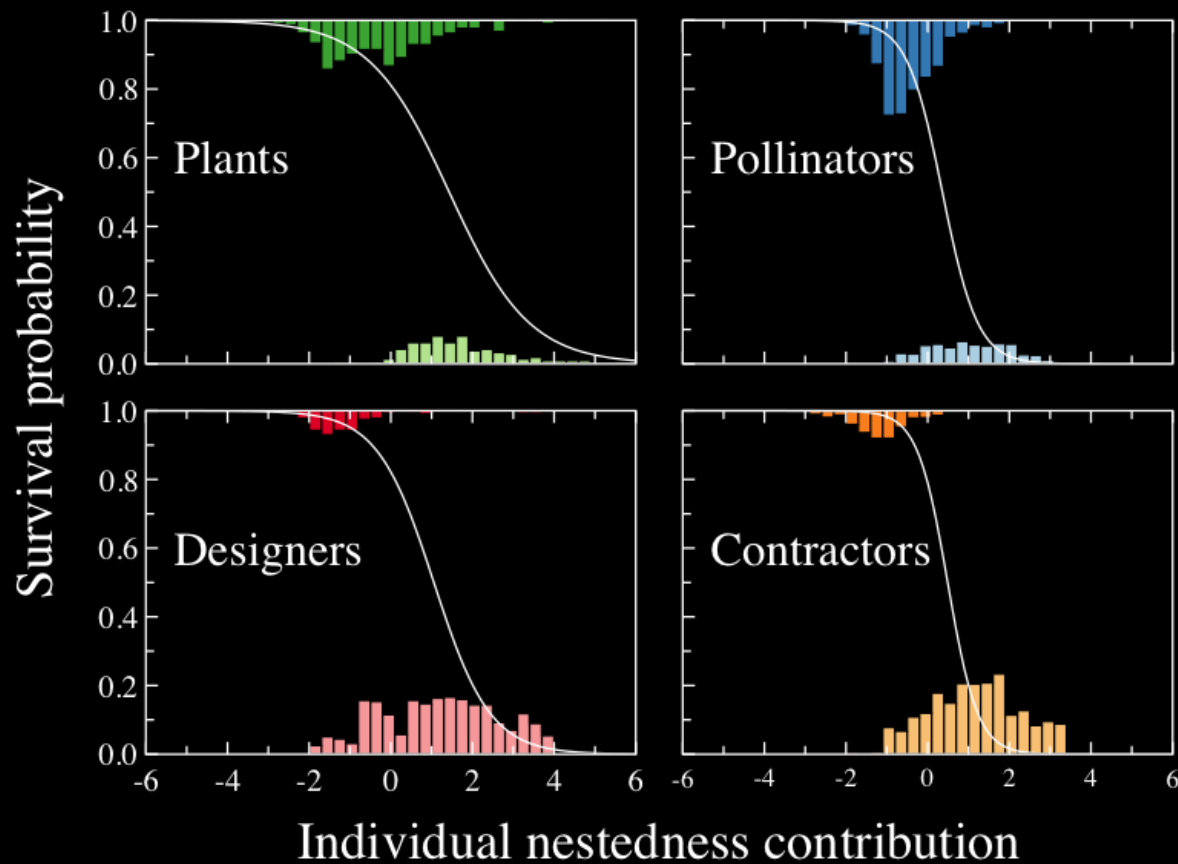
Events external to the banking system, such as recessions, major wars, civil unrest or environmental catastrophes, clearly have the potential to depress the value of a bank's assets so severely that the system fails. Although probably exacerbated by such events, including global imbalances (China as producer and saver, the United States as consumer and debtor), the present crisis seems more akin to self-harm caused by overexuberance within the financial sector itself. Perhaps as much as two-thirds of the spectacular growth in banks' balance sheet over recent decades reflected increasing claims within the financial system, rather than with non-financial agents. One key driver of this explosive intrasystem activity came from the growth in derivative markets.

In 2002, when Warren Buffet first expressed his view that "derivatives are financial weapons of mass destruction"¹⁵, markets—although booming—seemed remarkably stable. Their subsequent growth, illustrated in Fig. 1, has been extraordinary, outpacing the growth in world gross domestic product (GDP) by a factor of three. In some derivatives markets, such as credit default swaps (CDS), growth has outpaced Moore's Law. These developments contributed significantly towards an unprecedented influx of mathematically skilled people (quantitative analysts) into the financial/banking industry. These people produced very sophisticated techniques (including APT), which seemingly allowed you to put a price on future risks, and thus to trade increasingly complex derivative contracts—bundles of assets—with risks apparently decreasing as the bundles grew.

However, recent empirical and theoretical studies have indicated that the trading activity associated with derivatives can have significant effects on markets^{16–19}. More specifically, Brock and colleagues¹⁶ have shown that proliferation of hedging instruments can destabilize markets. Building on this, Caccioli and colleagues¹⁷ note that APT makes several conventional assumptions upon which everything else depends: "perfect competition, market liquidity, no arbitrage and market completeness". Crucially, this adds up to the implicit assumption that trading activity has no feedback on the dynamical behaviour of markets. And indeed, in the APT-fuelled

¹Bank of England, Threadneedle Street, London EC2R 8AH, UK; ²Zoology Department, Oxford University, Oxford OX1 3PS, UK.

3. Trade-offs in Persistence



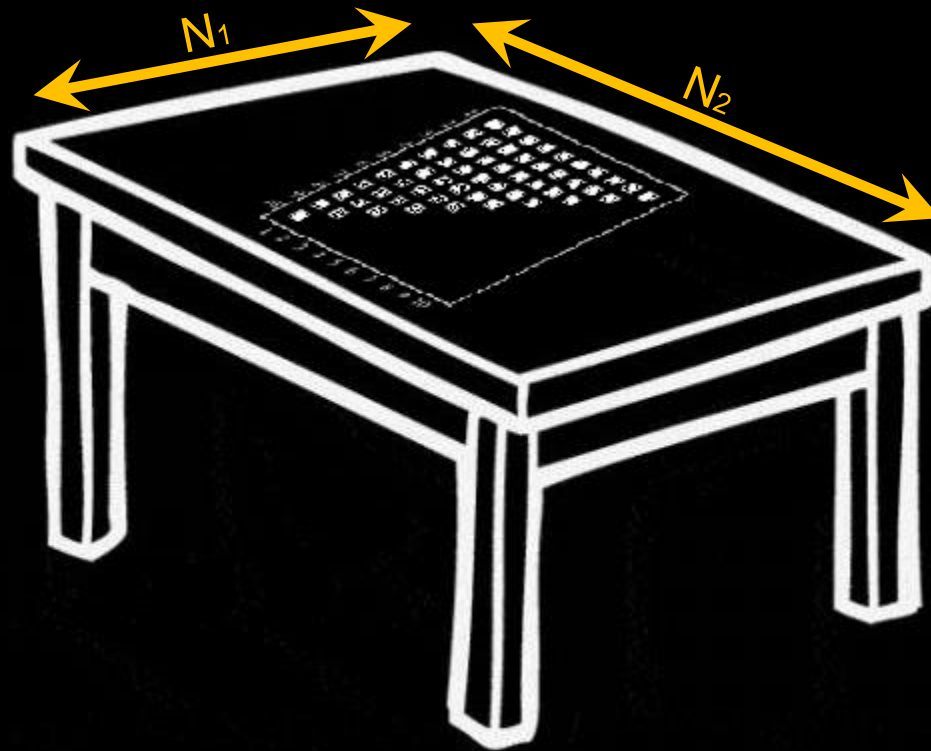
The species that contribute
the most to the nested pattern
are more likely going to go extinct!



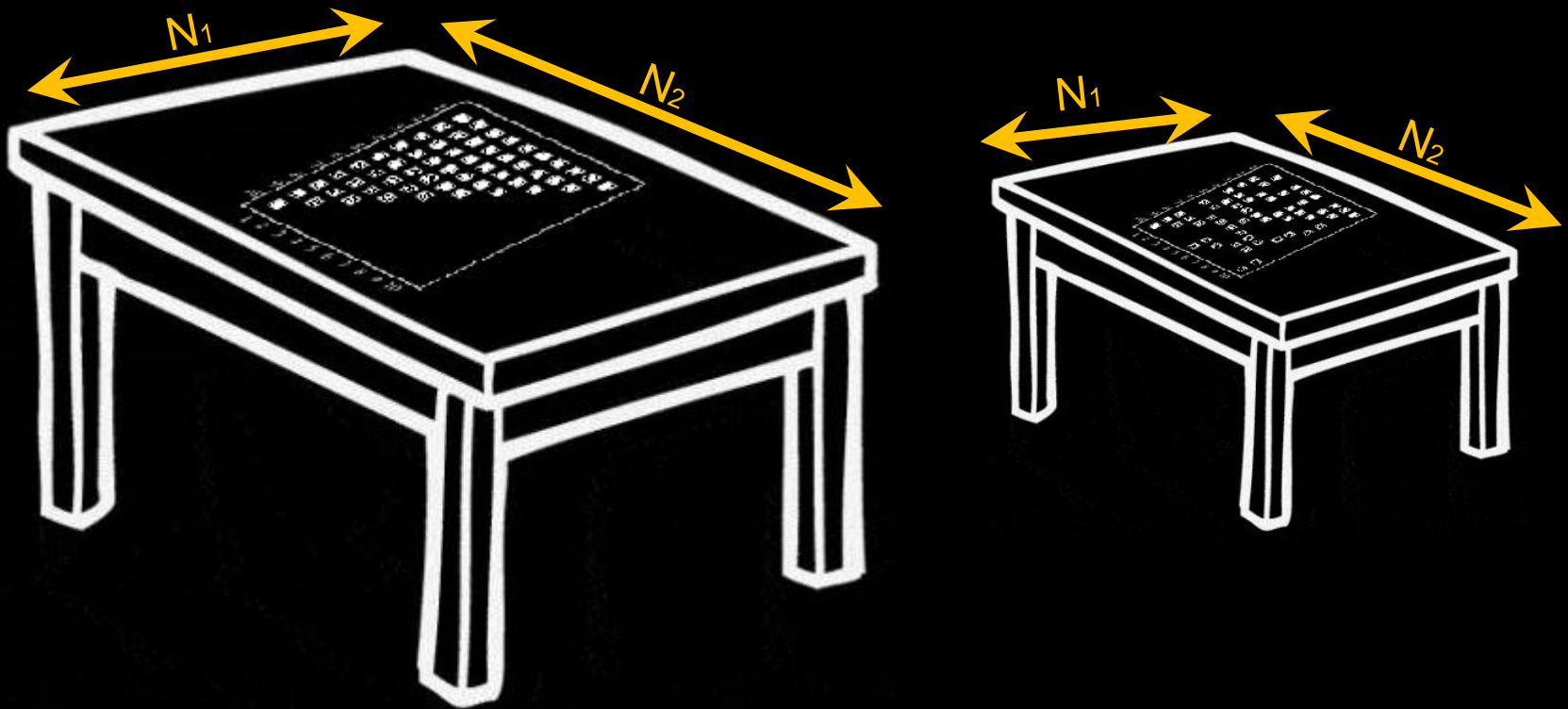
Bonus track 1

Structural Stability

1. Range of Feasibility



2. Nested networks can allocate more noise \rightarrow will resist better changing conditions





Bonus track 2

Spatial Distribution

