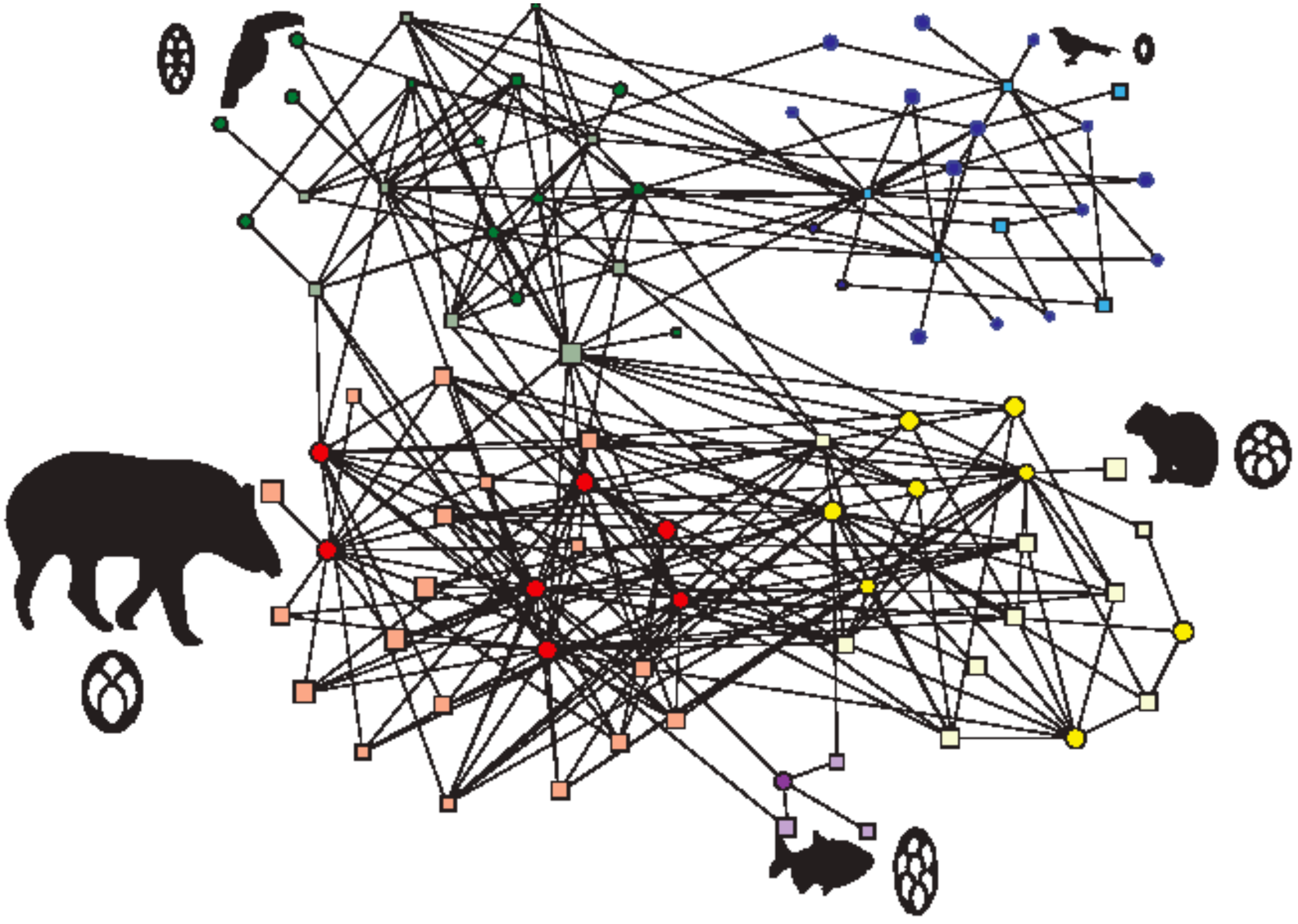
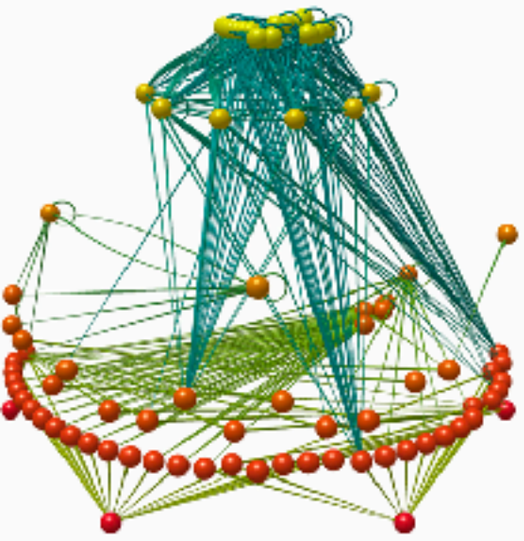
Understanding the ecology and evolution of communities through networks

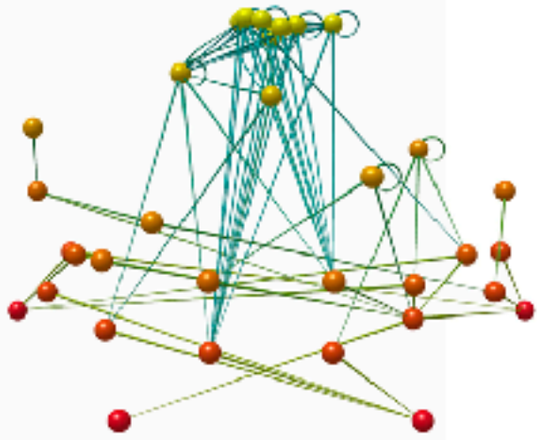
Lauren Ponisio and Marilia Gaiarsa
University of California Riverside



Chengjiang Shale

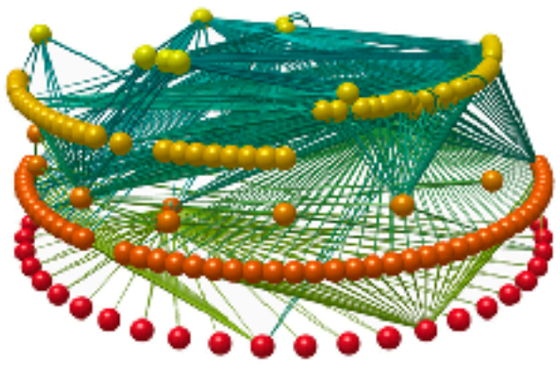


Original Species
S = 85, L = 559, C = 0.077
TL = 2.99, MaxTL = 5.15

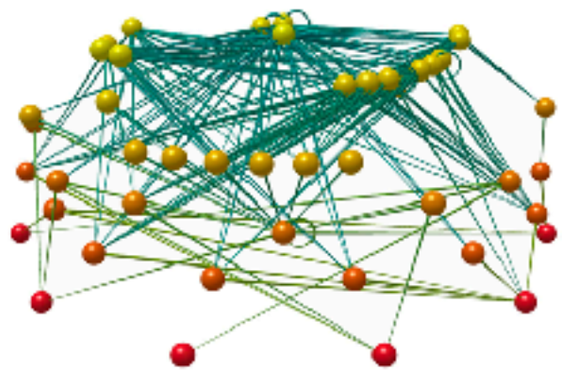


Trophic Species
S = 33, L = 99, C = 0.091
TL = 2.84, MaxTL = 4.36

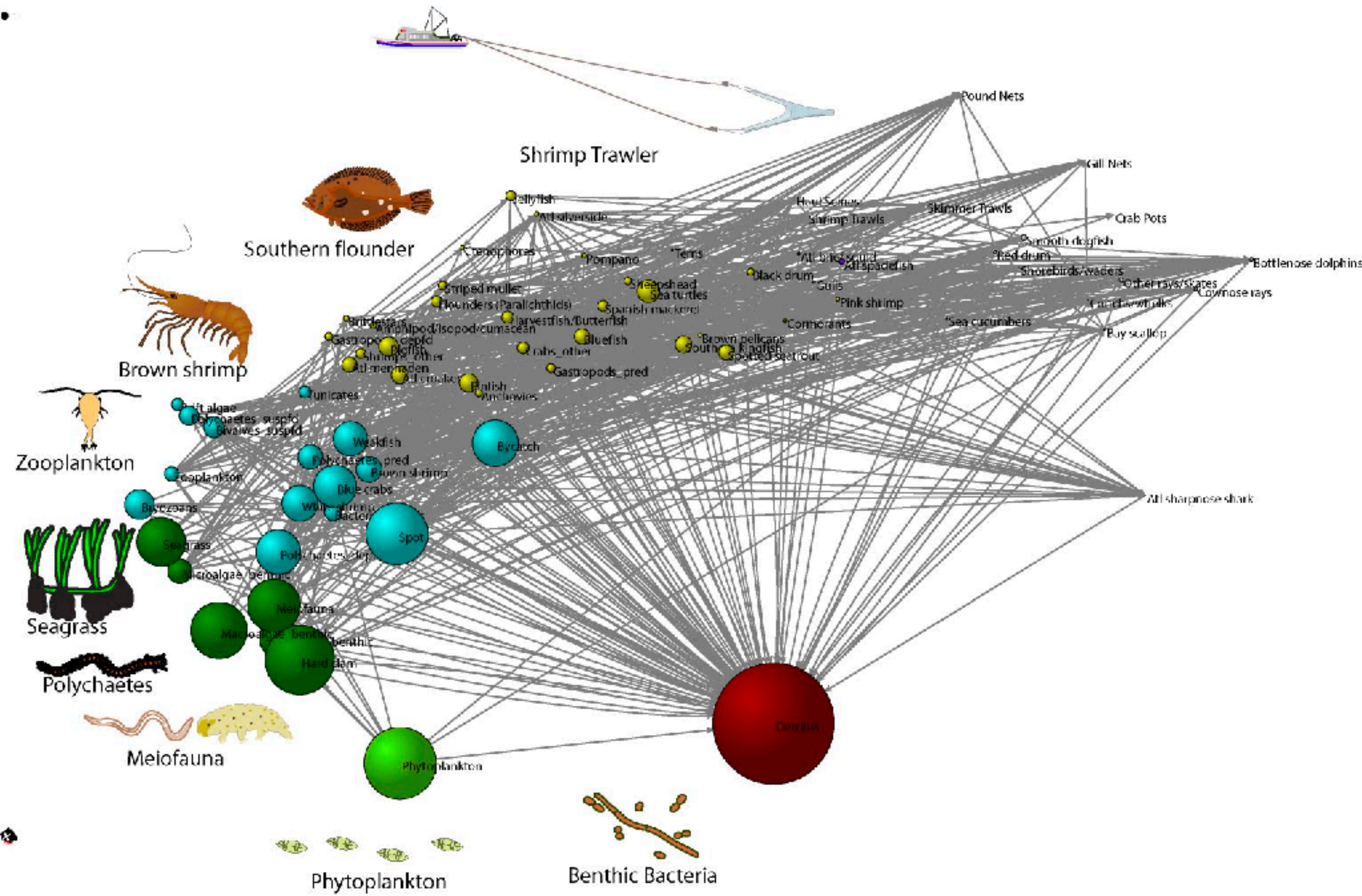
Burgess Shale



Original Species
S = 142, L = 771, C = 0.038
TL = 2.42, MaxTL = 3.67

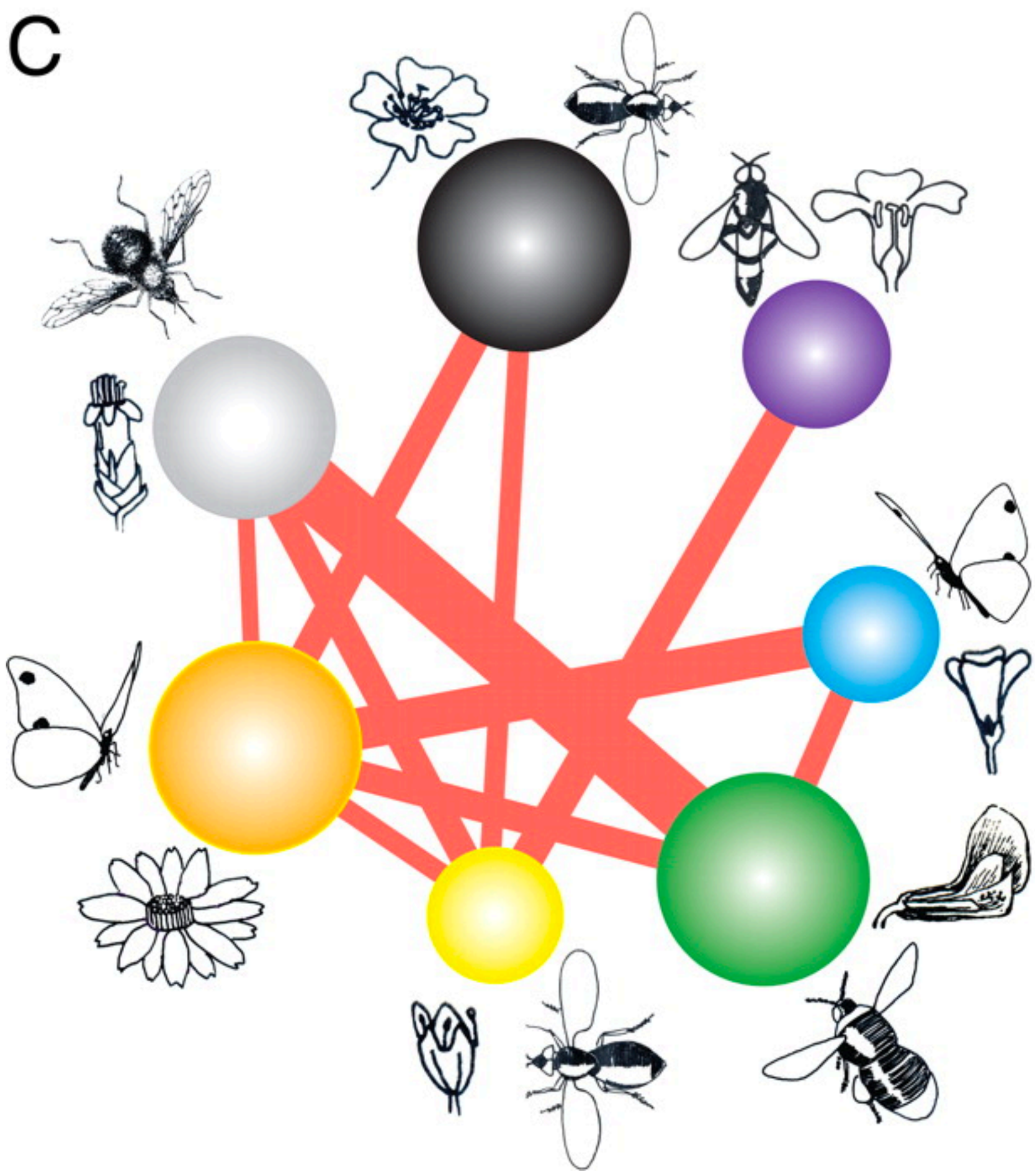


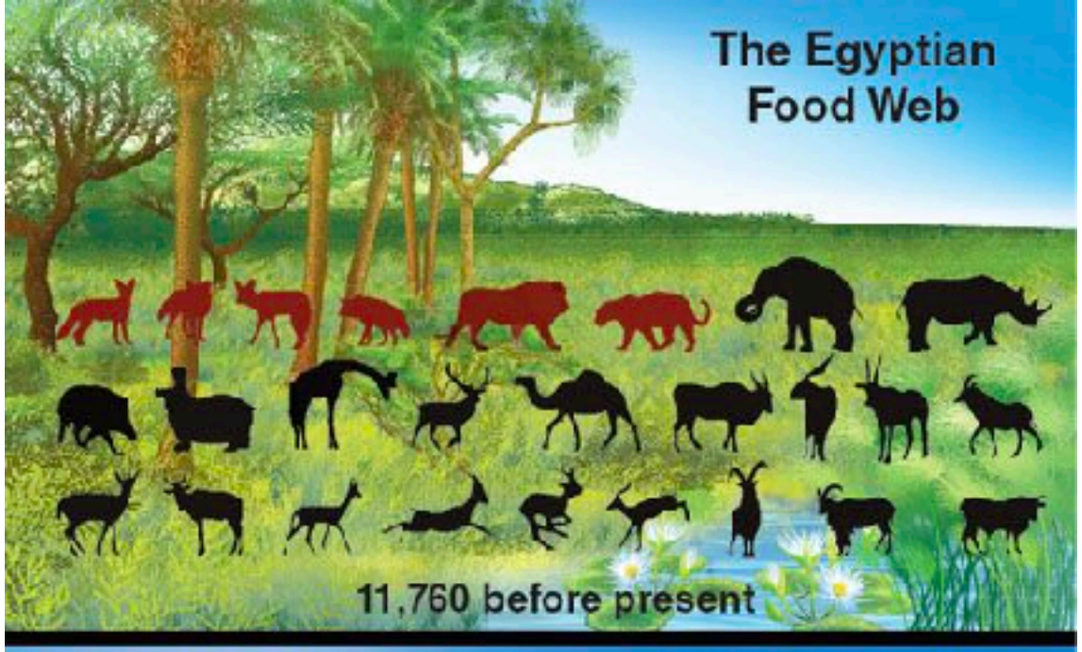
Trophic Species
S = 48, L = 249, C = 0.108
TL = 2.72, MaxTL = 3.78



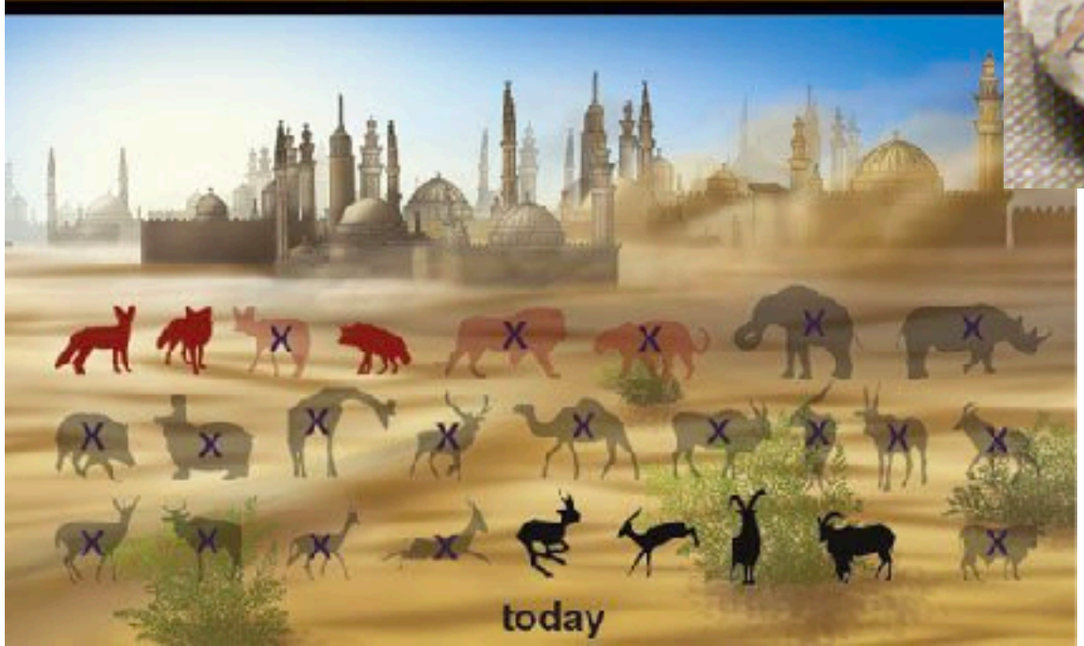
Shrimp Trawler
Southern flounder
Brown shrimp
Zooplankton
Seagrass
Polychaetes
Meiofauna
Phytoplankton
Benthic Bacteria
Pound Nets
Gill Nets
Skimmer Trawls
Shrimp Trawls
Crab Pots
Smooth dogfish
Red drum
Bottlenose dolphins
Shorebirds/waders
Cownose rays
Pink shrimp
Cormorants
Sea cucumbers
Bay scallop
Atl sharpnose shark
Jellyfish
Ctenophores
Pompano
Terns
Black drum
Gulls
Sheepshead
Sea turtles
Striped mullet
Flounders (Paralichthids)
Spanish mackerel
Harvestfish/Butterfish
Bluefish
Brown pelicans
Spotted seatrout
Gastropods_pred
Anchovies
Tunicates
Weakfish
Bycatch
Brown shrimp
Blue crabs
Zooplankton
Bryozoans
Seagrass
Spot
Meiofauna
Hard clam
Phytoplankton
Detritus

C




The Egyptian
Food Web
11,760 before present


4,640 before present

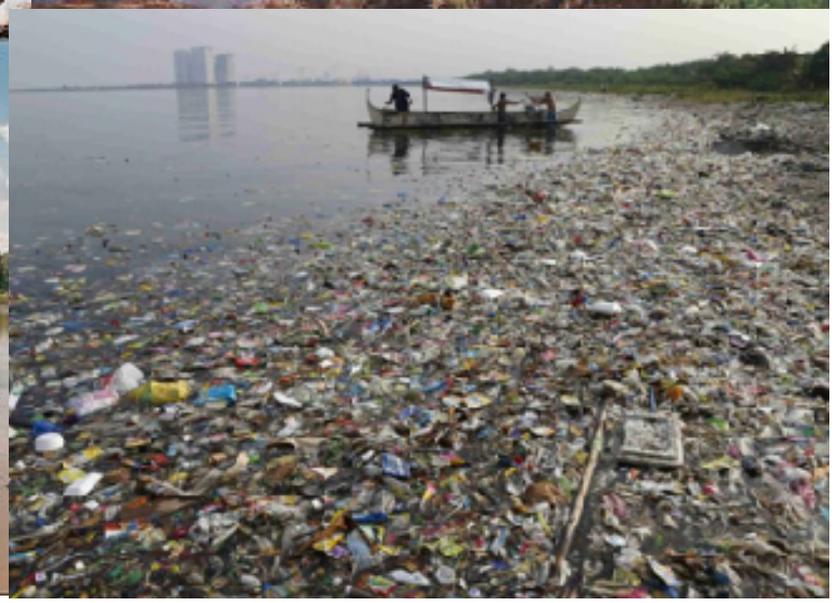

today









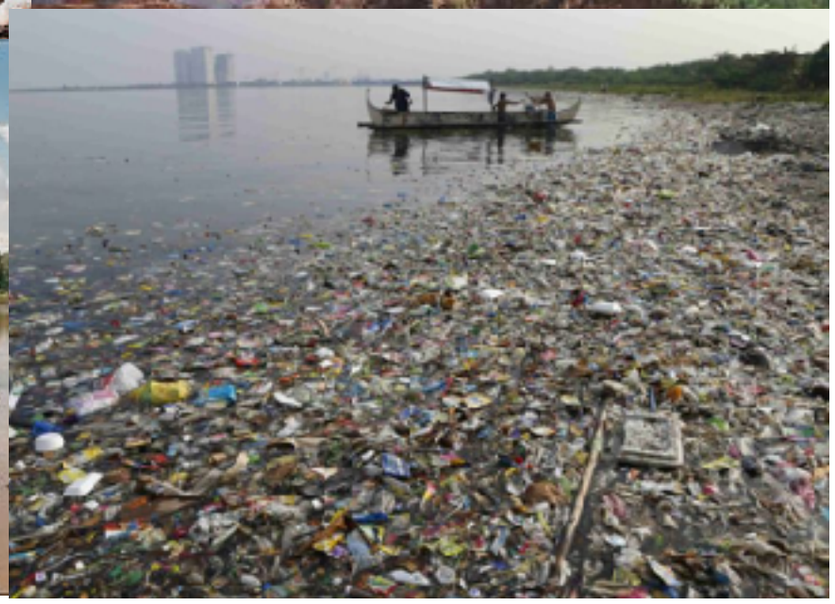




How can we re-assemble communities?







How can we re-assemble communities?

What enables communities to resist collapse?





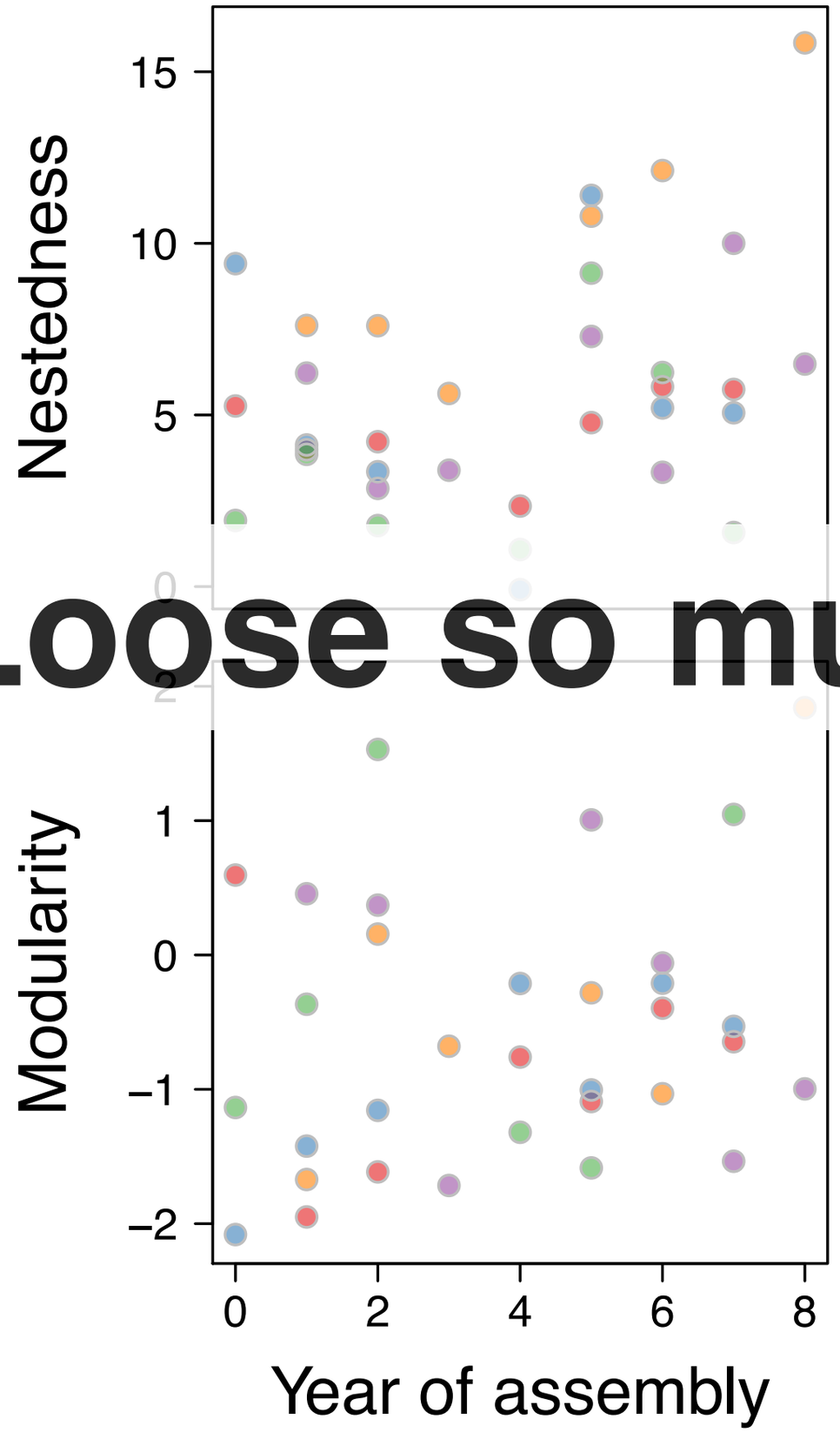


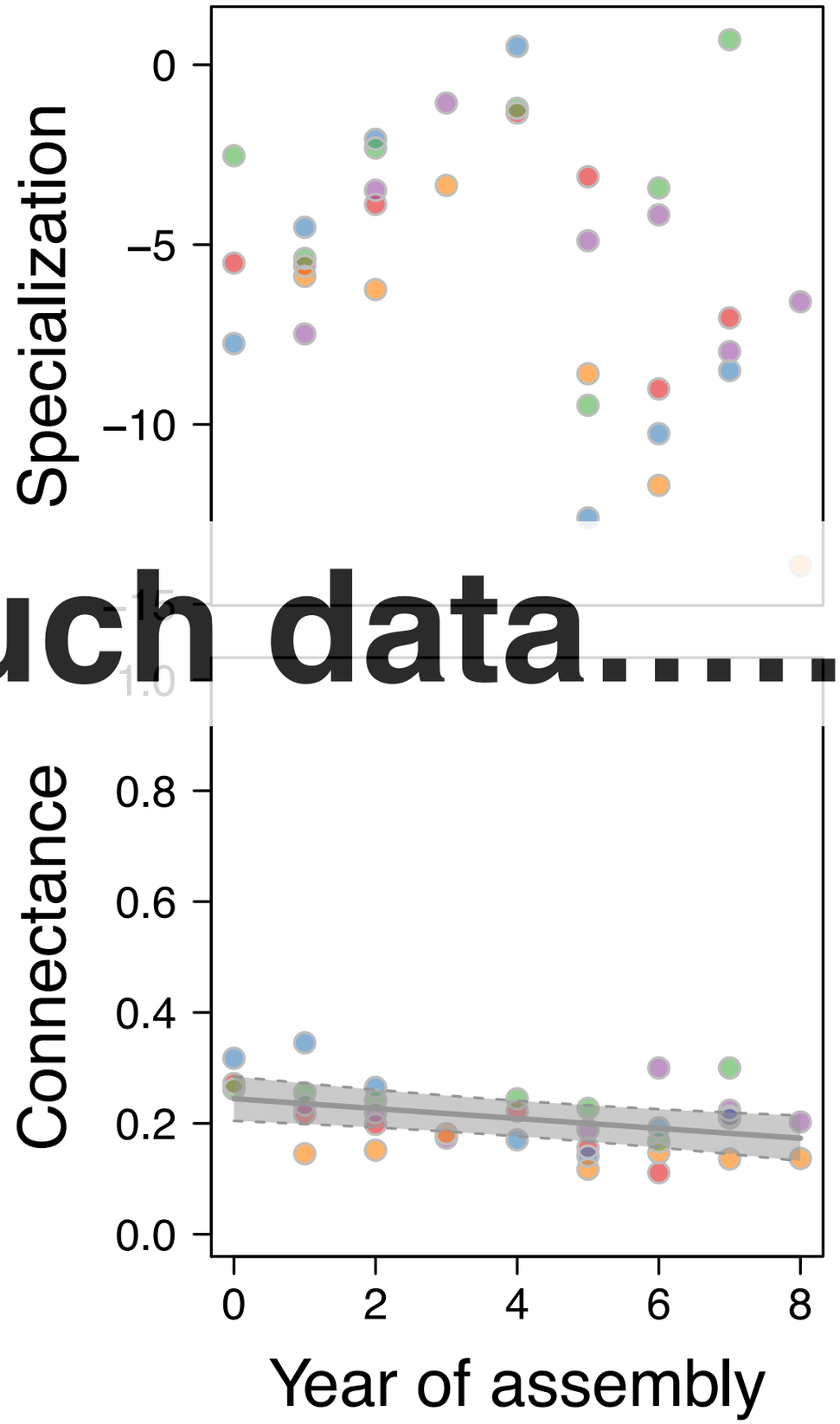

How can we re-assemble communities?

What enables communities to resist collapse?

How can we compare networks?







Loose so much data……

Ponisio et al. Ecol. Let. 2017

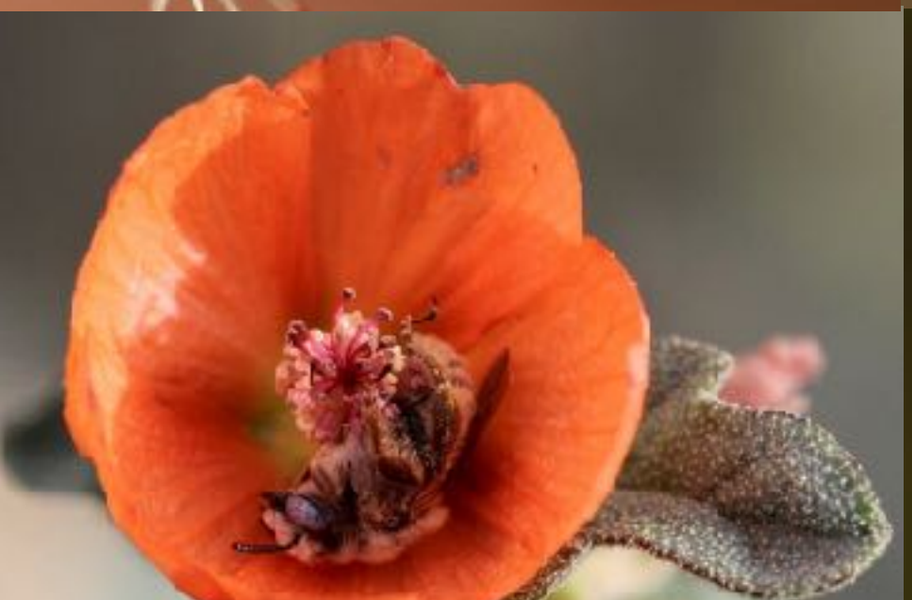
Case study in comparing networks

CA Central Valley





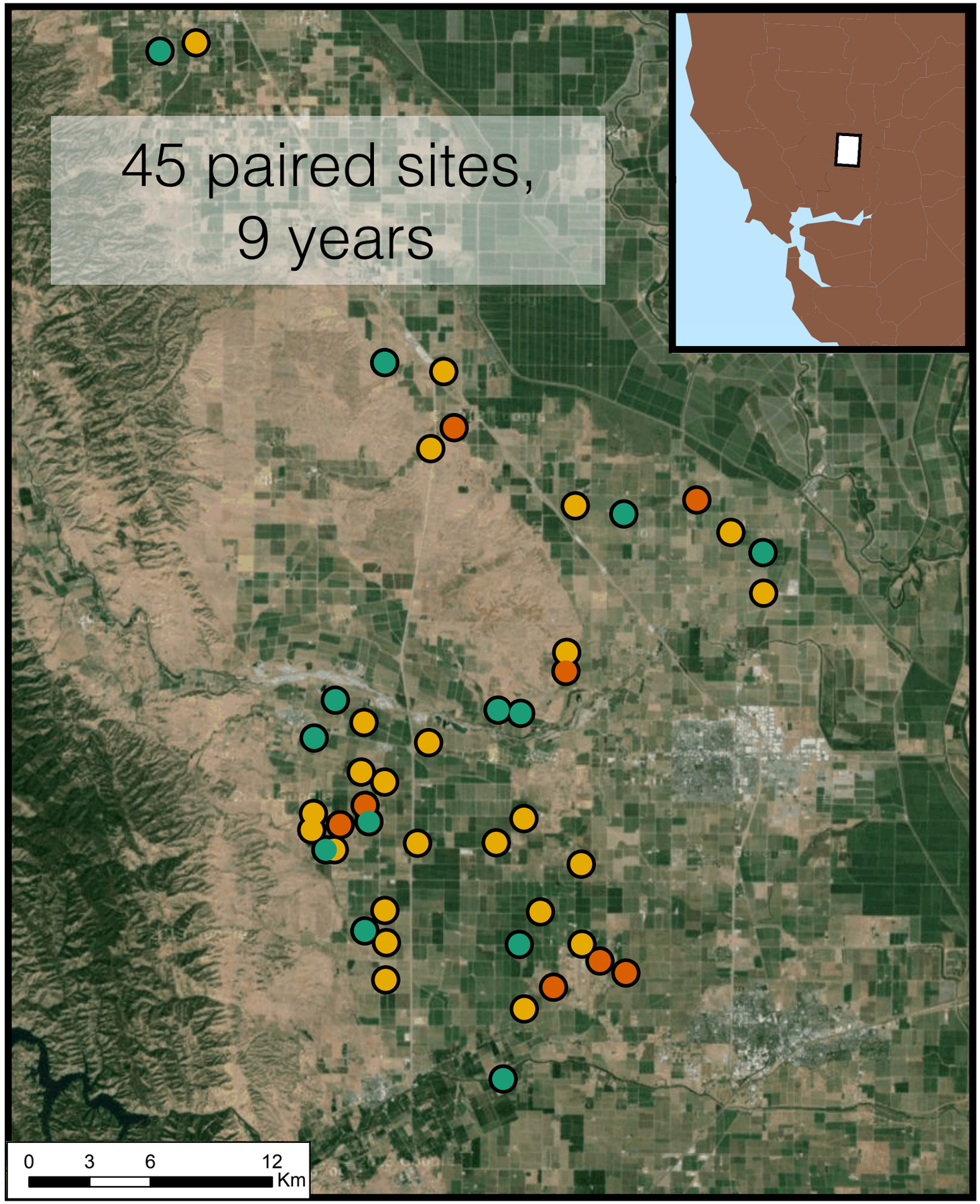




Assembling hedgerow

Non-assembling field margin

Non-assembling hedgerow



~20,000 hand netted specimens

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~500 sampling hours

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~170 pollinator species

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~170 pollinator species

~1500 interactions

What mechanisms underly re-assembly?

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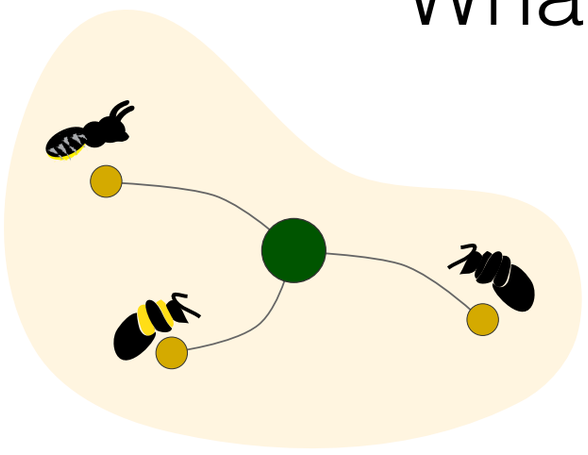
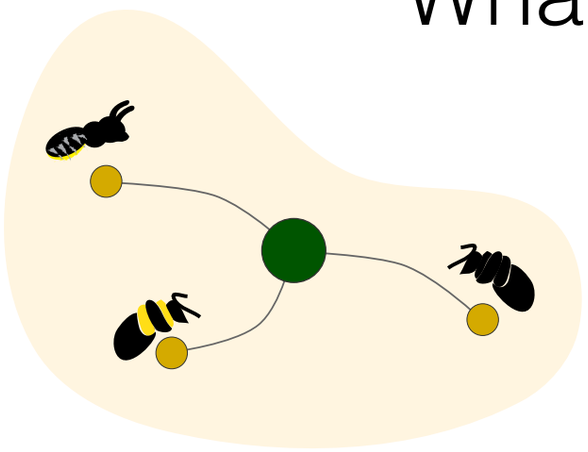


Preferential attachment

What mechanisms underly re-assembly?



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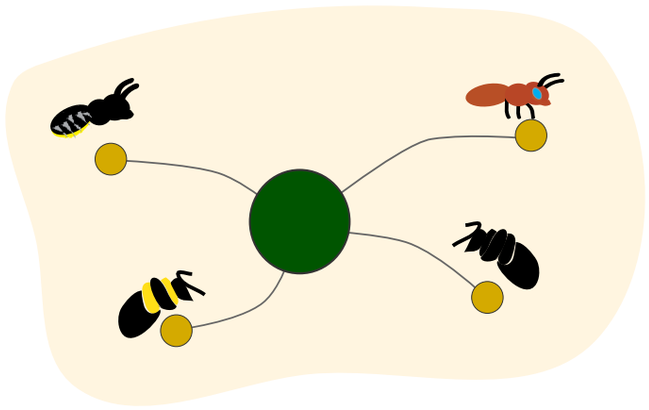

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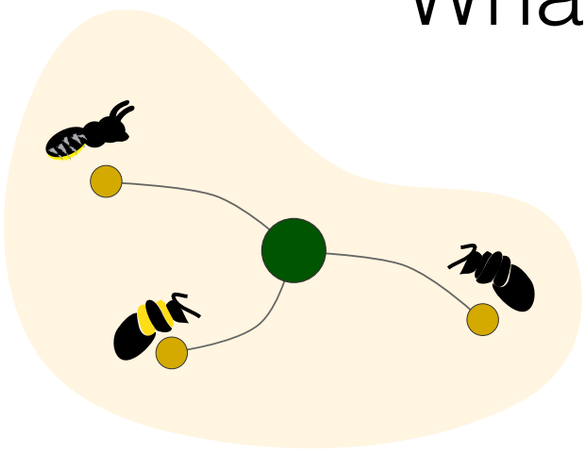

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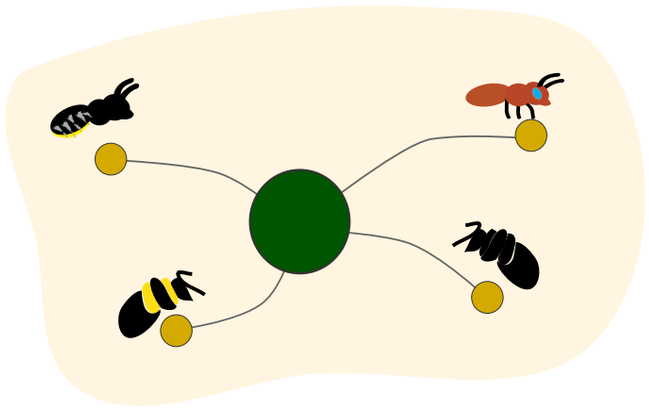

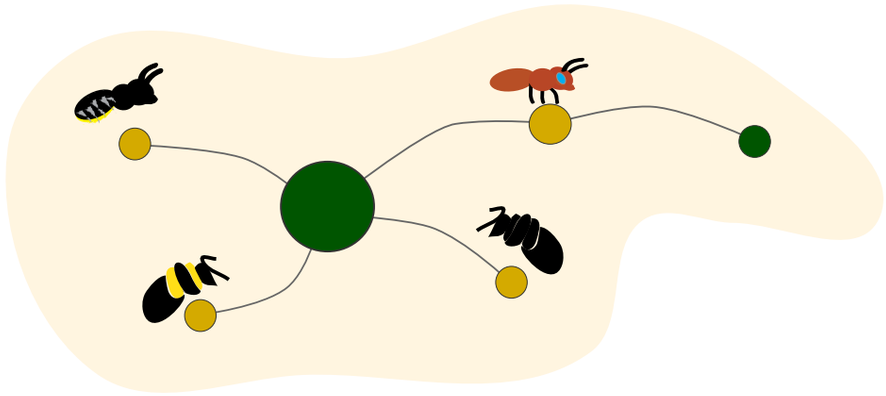

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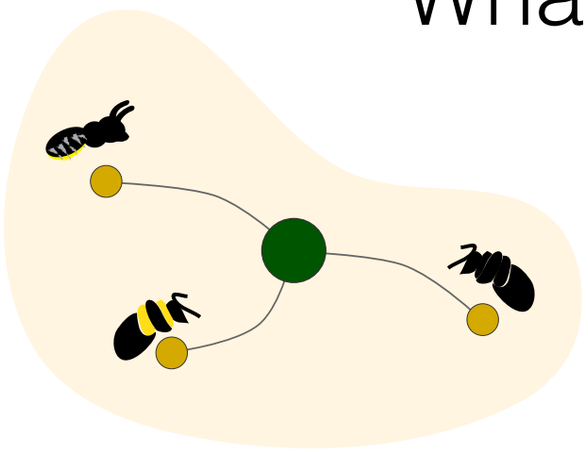

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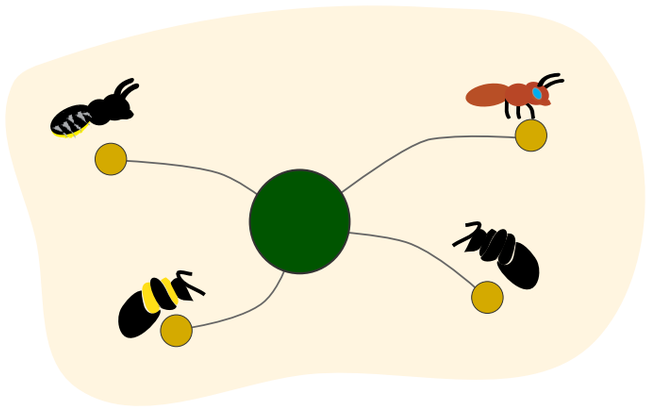

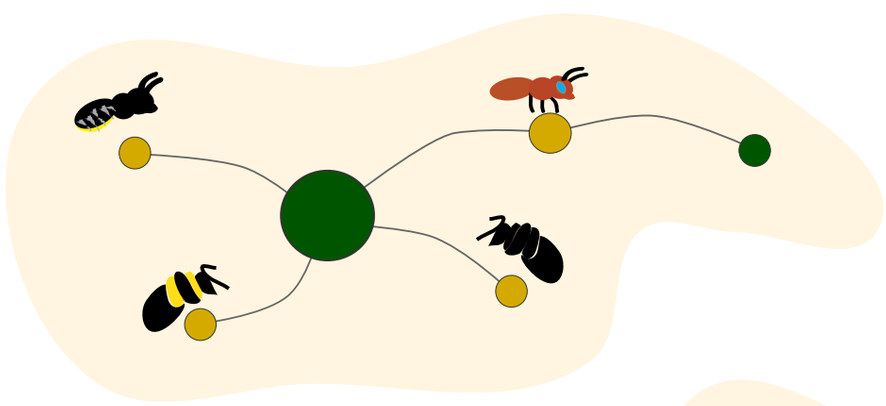

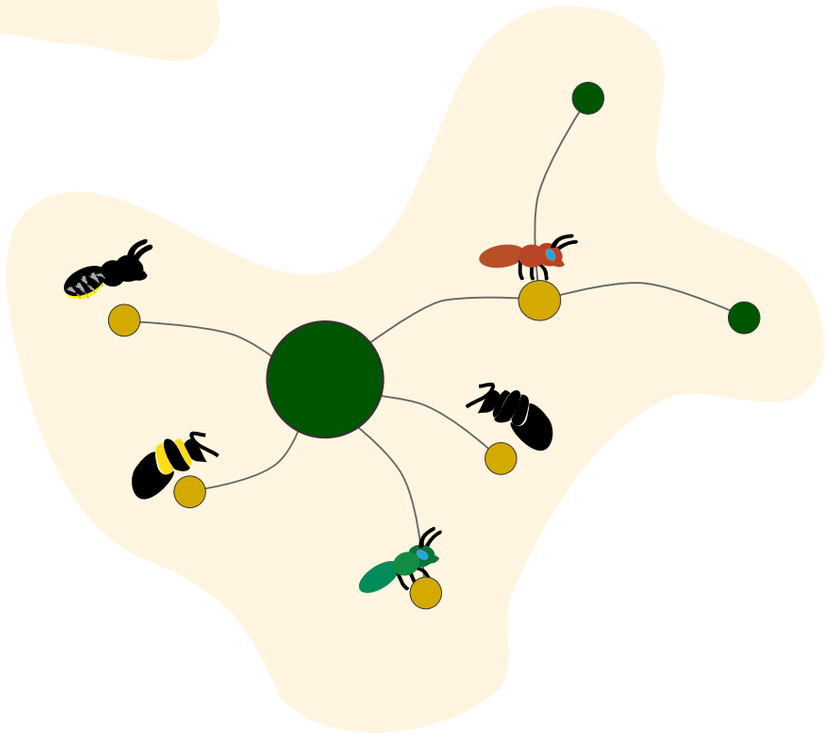

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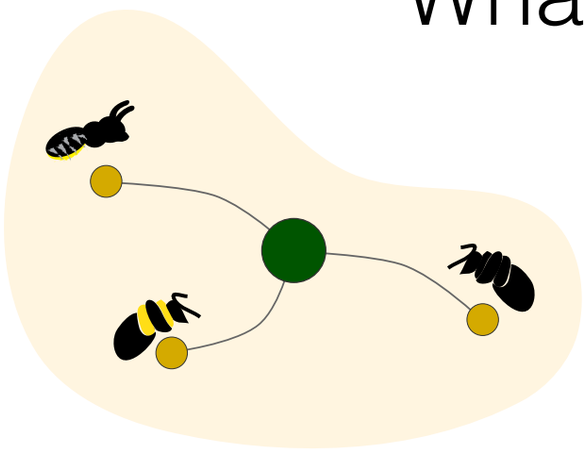

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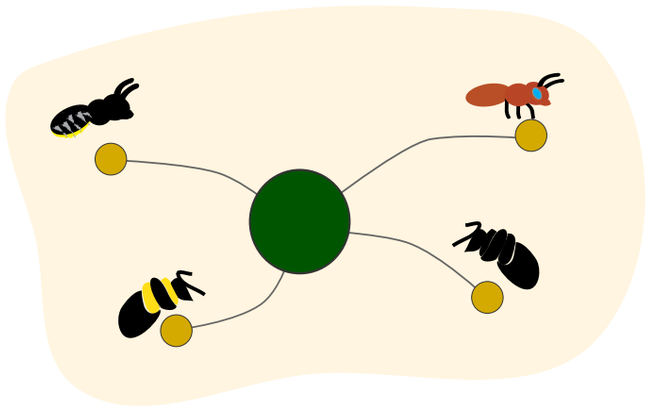
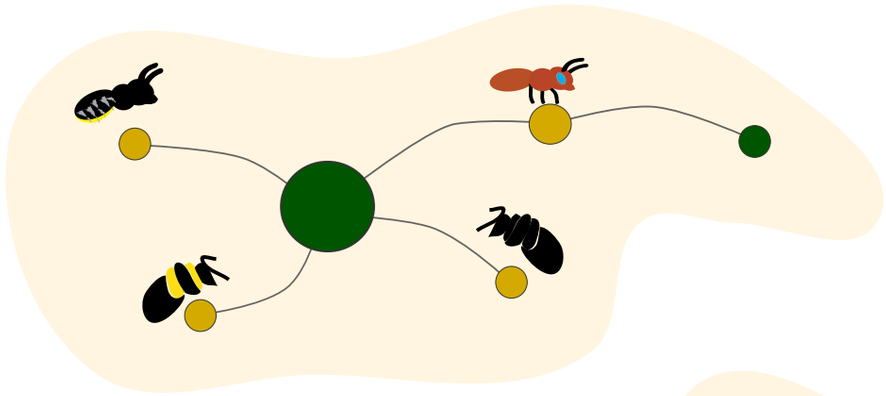
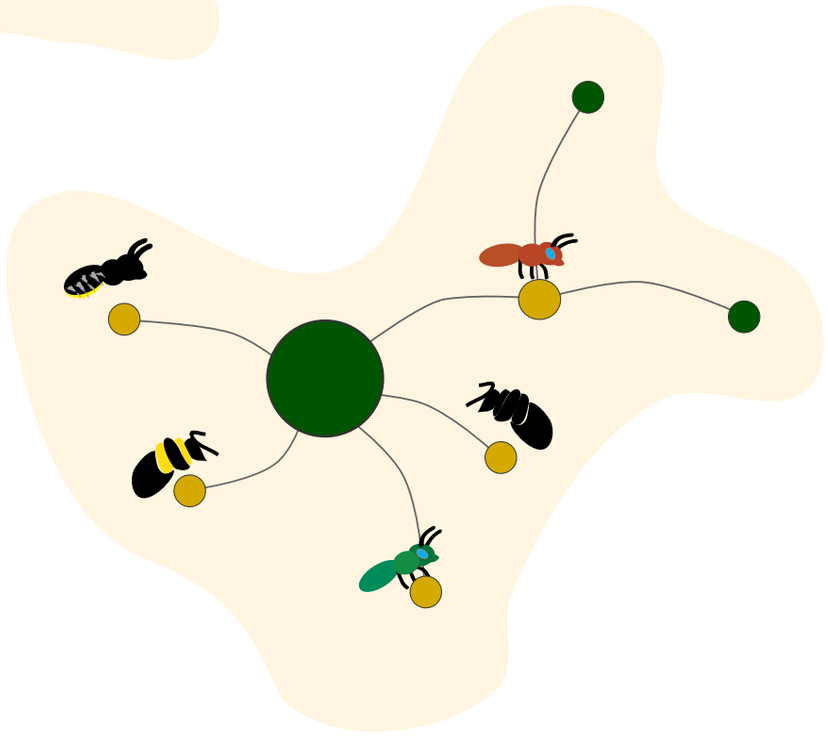


Persistent, generalist core
new species attach





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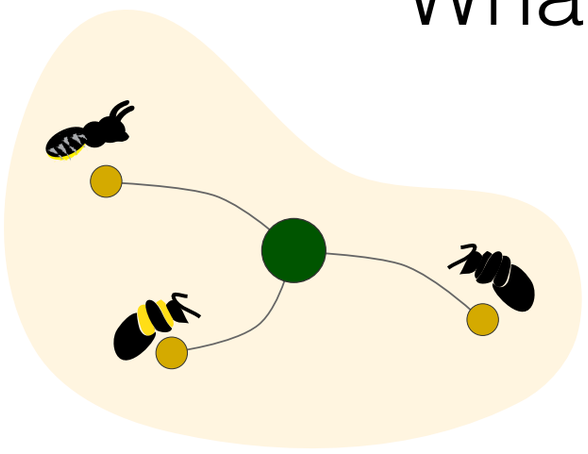

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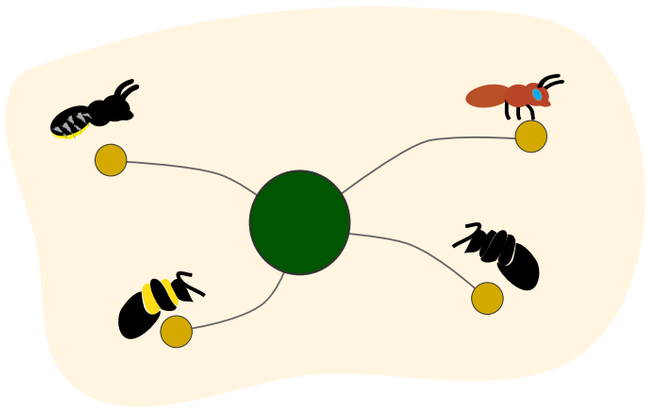
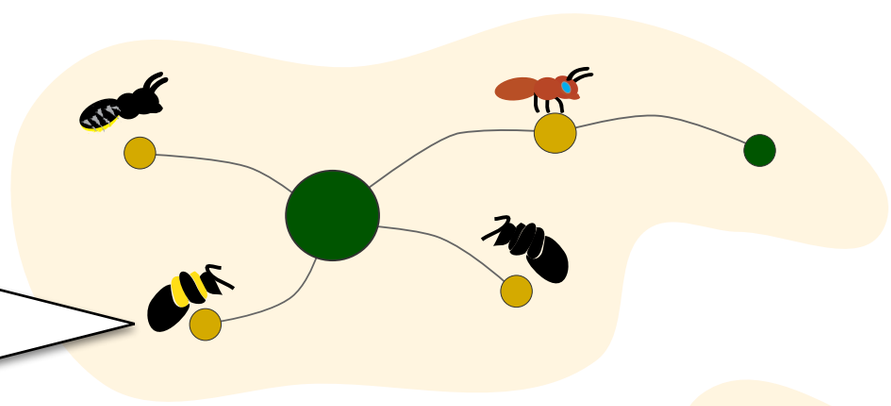
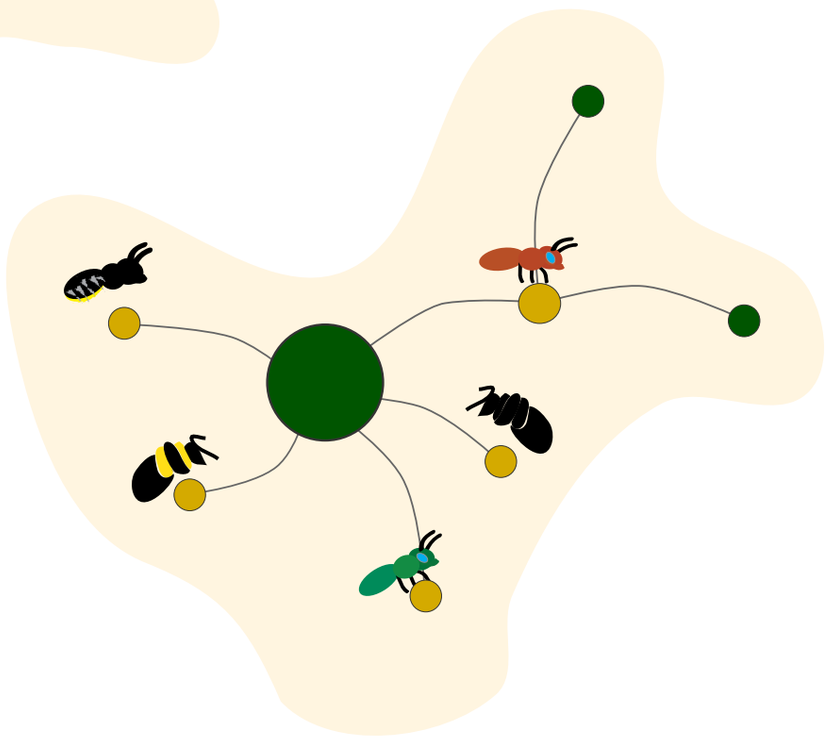


Persistent, generalist core
new species attach

Terrible idea…





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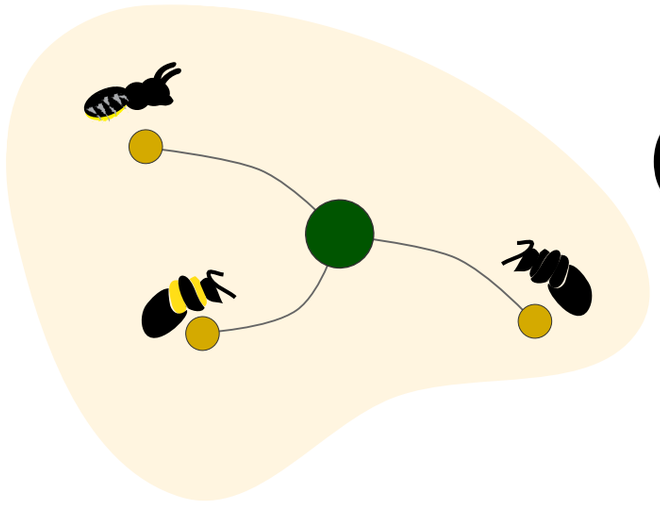

Opportunistic attachment

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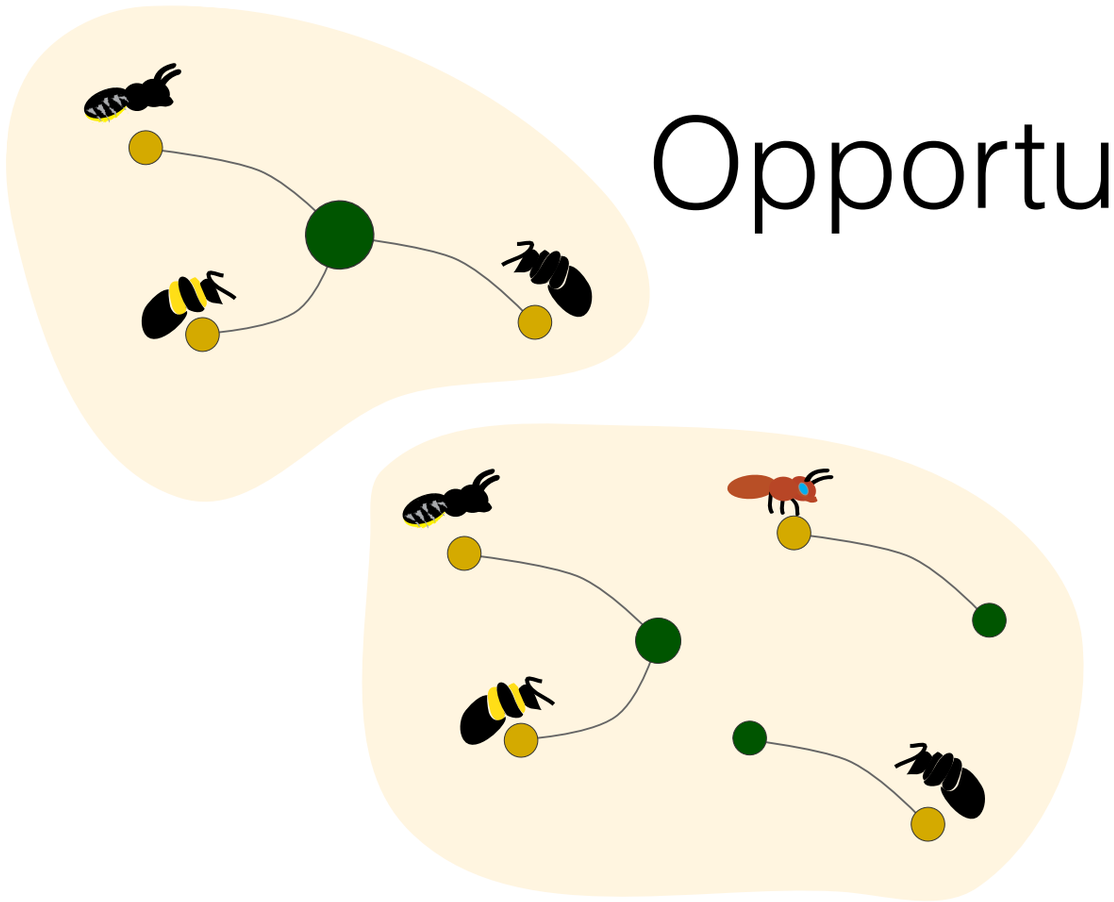

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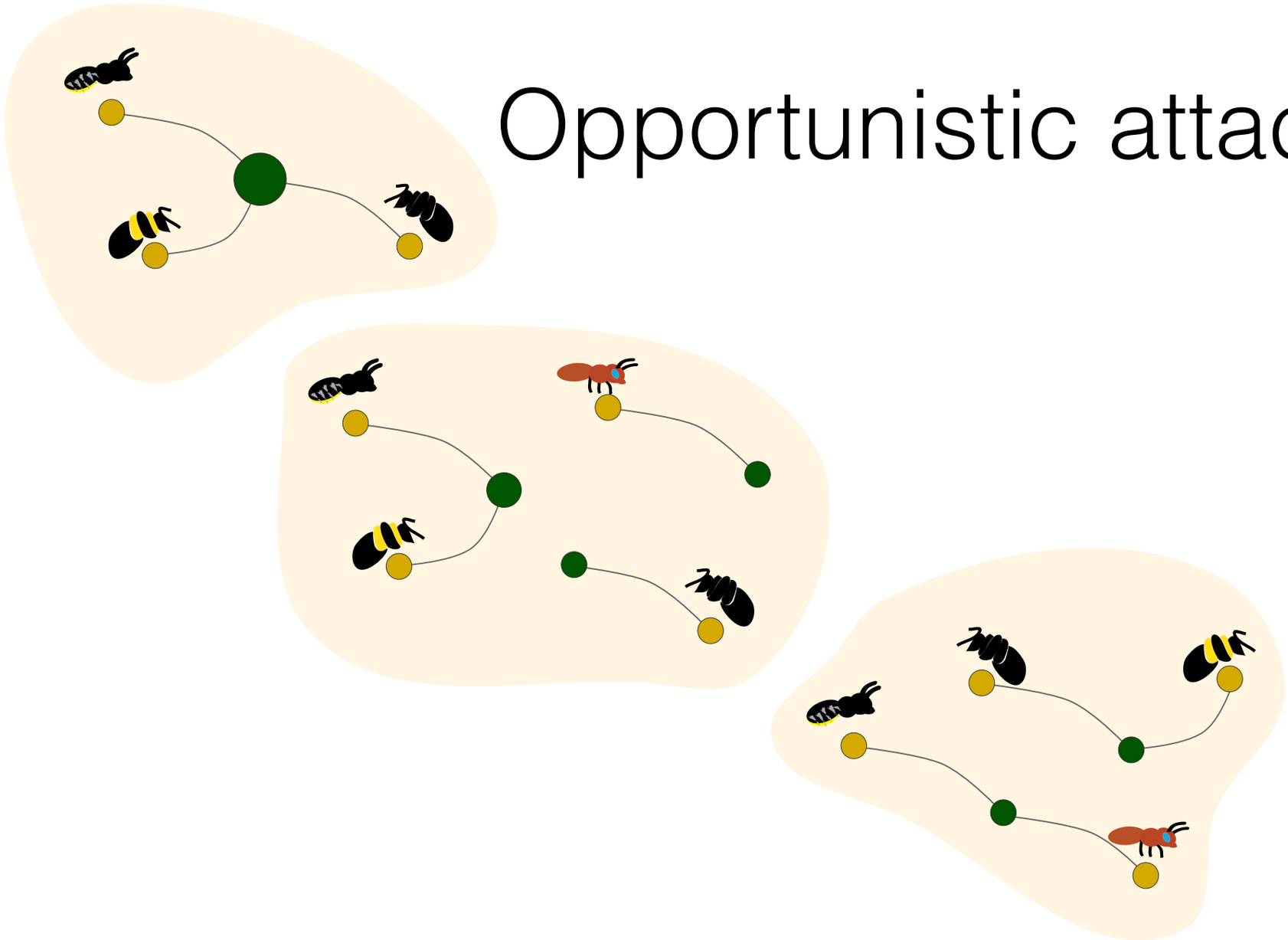

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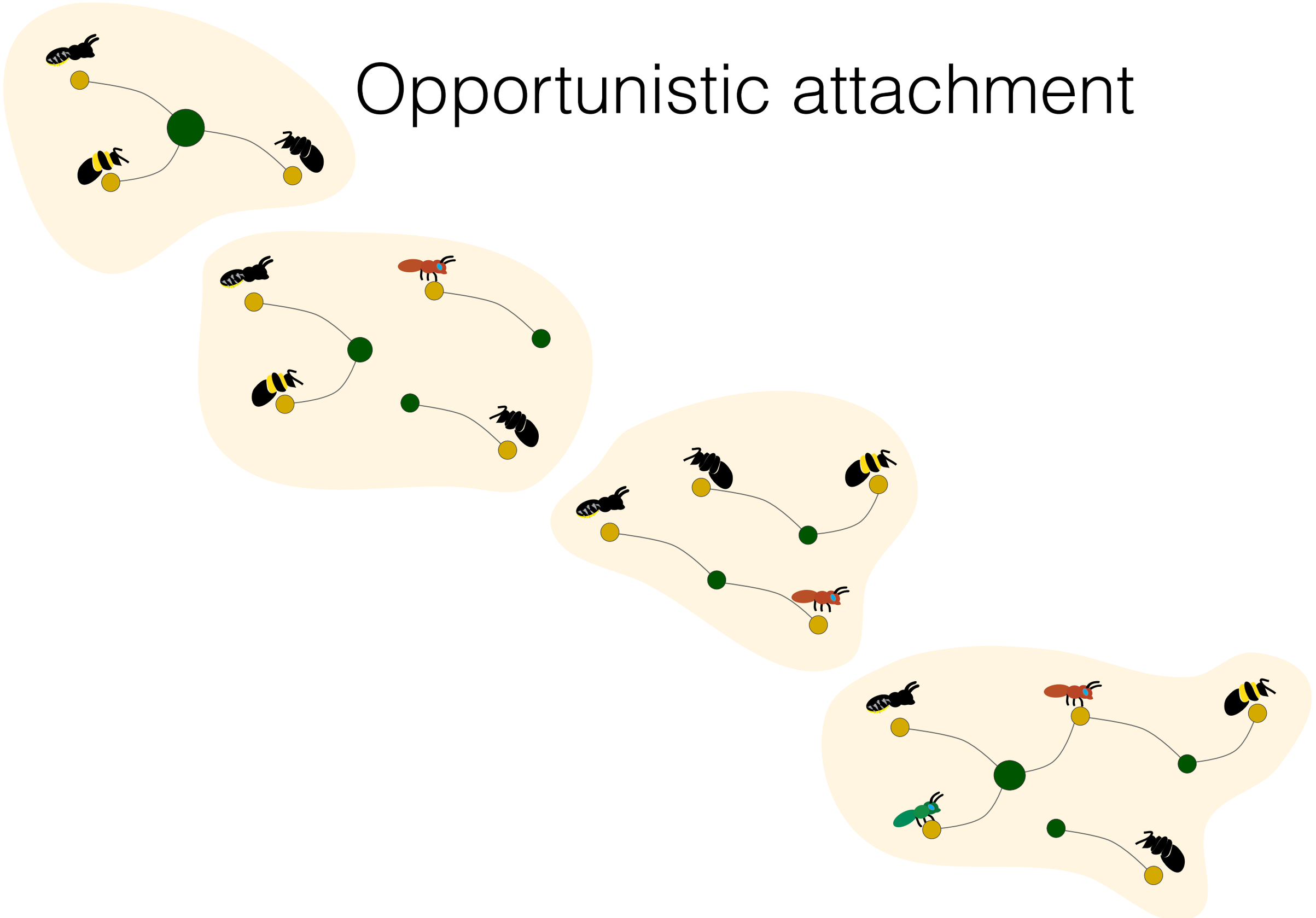

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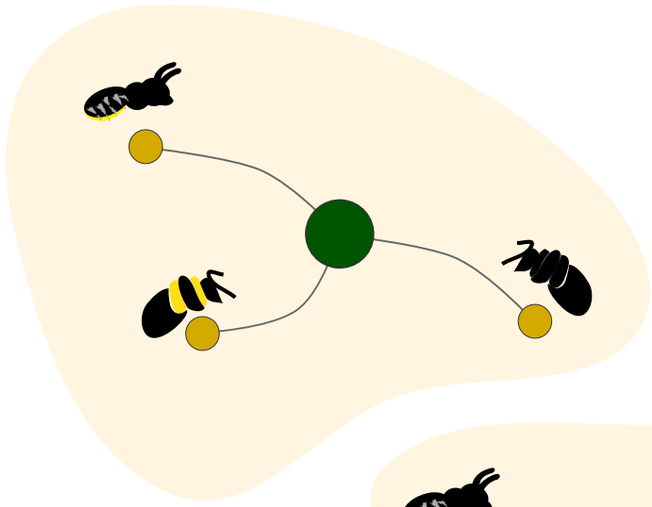
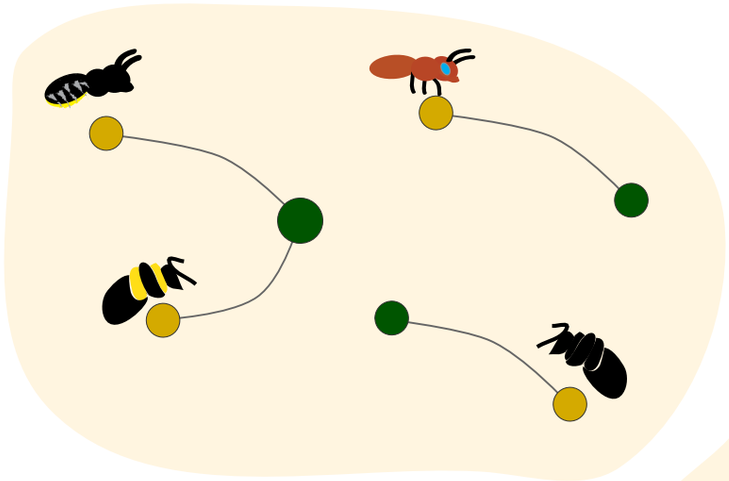
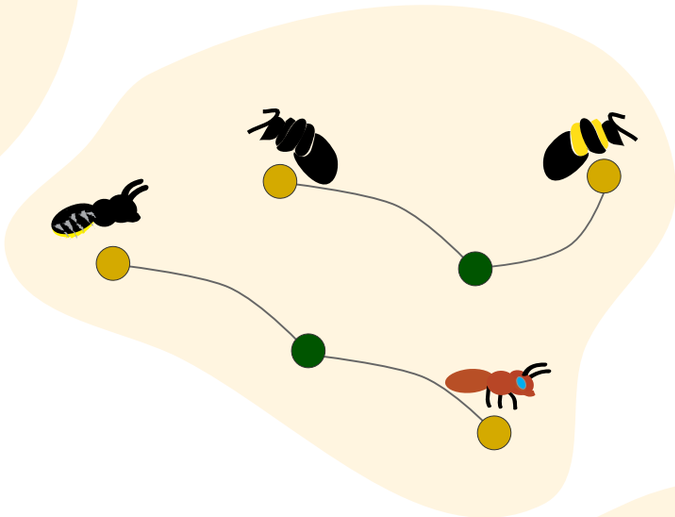
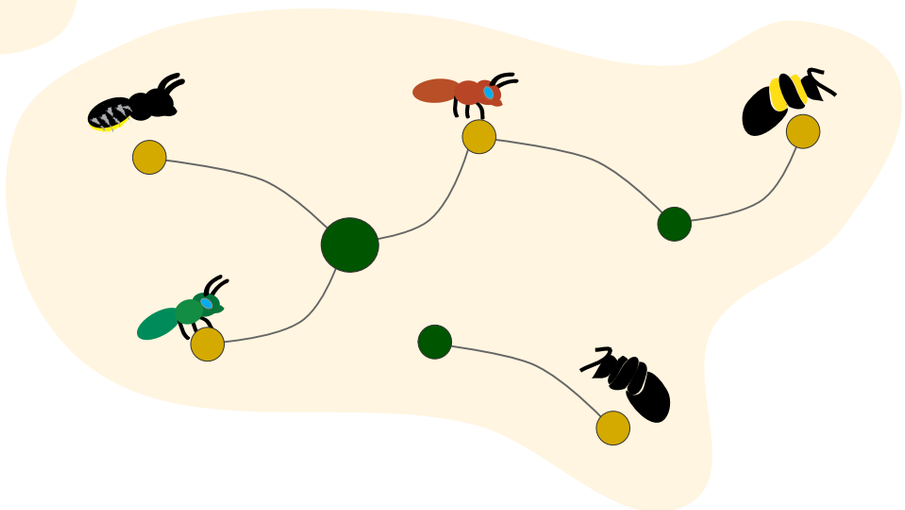


Opportunistic attachment

Dynamic position of generalist species => major reorganizations







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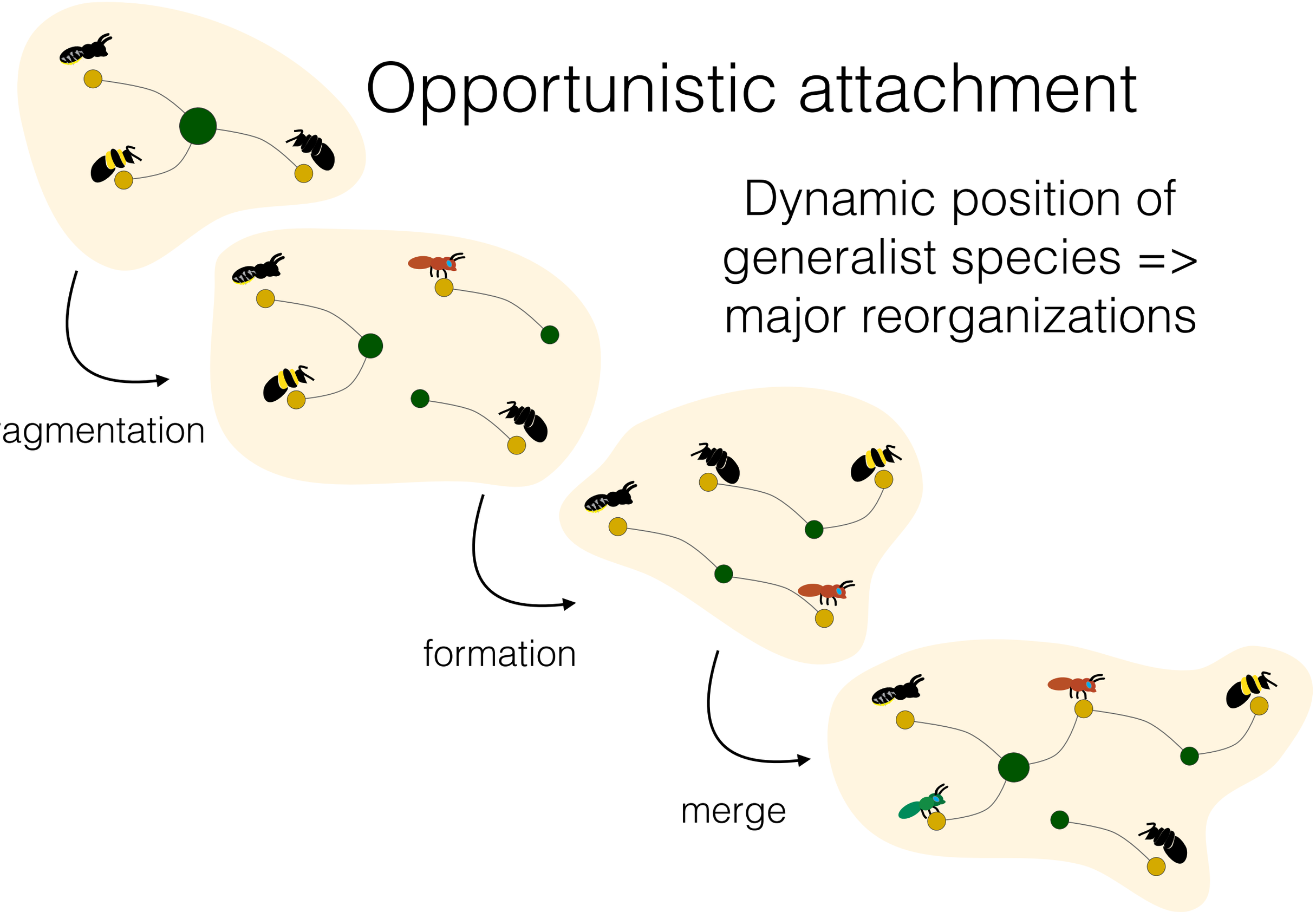
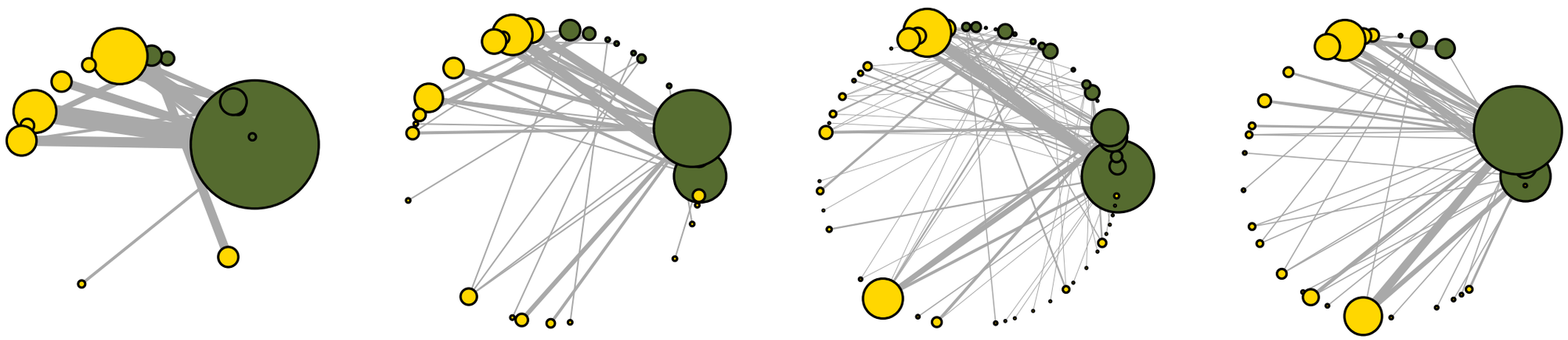
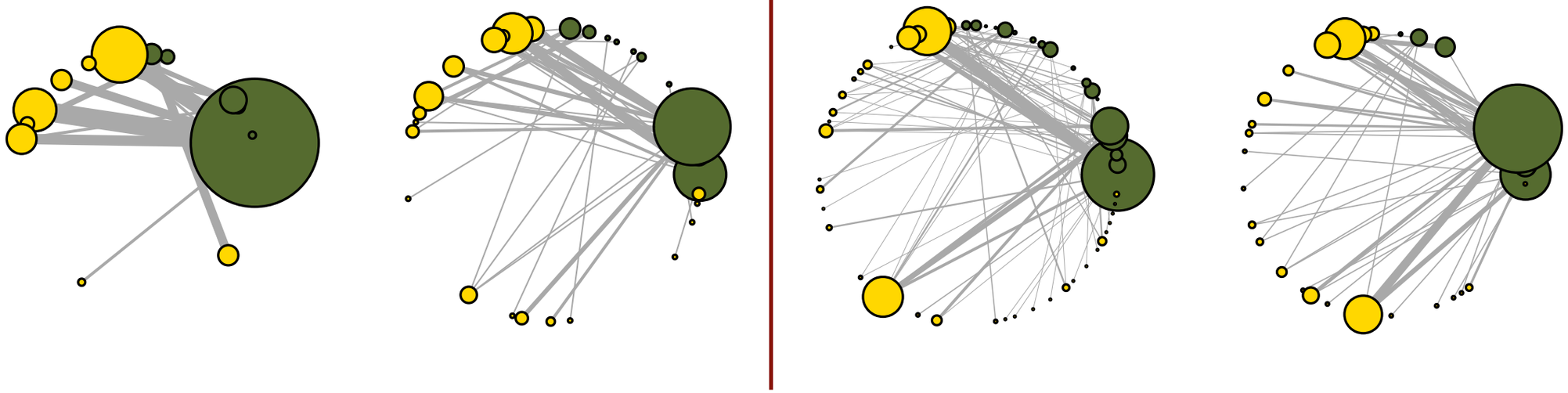




Assembling hedgerow

Change point?



Assembling hedgerow

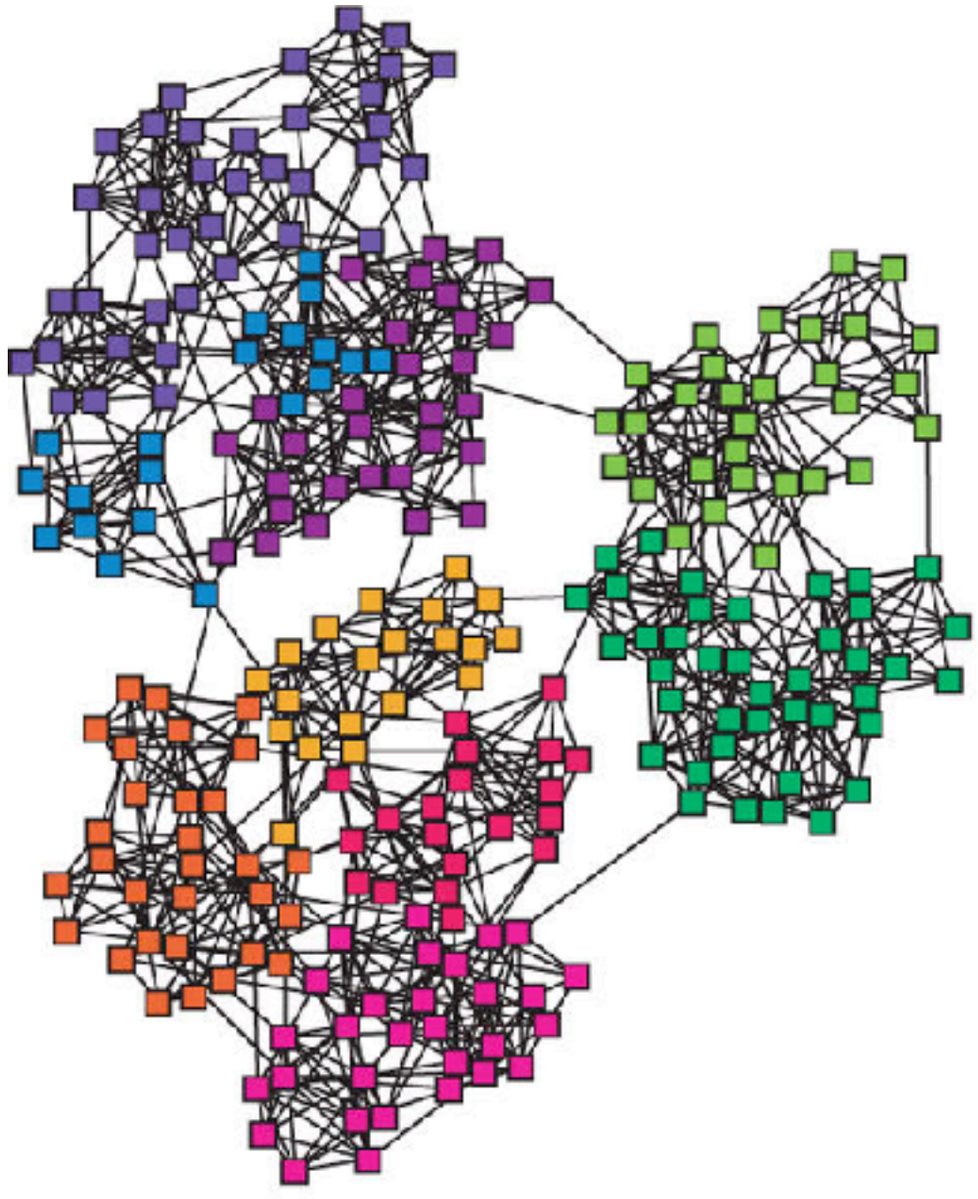
Change point analysis

Peel & Clauset, 2014

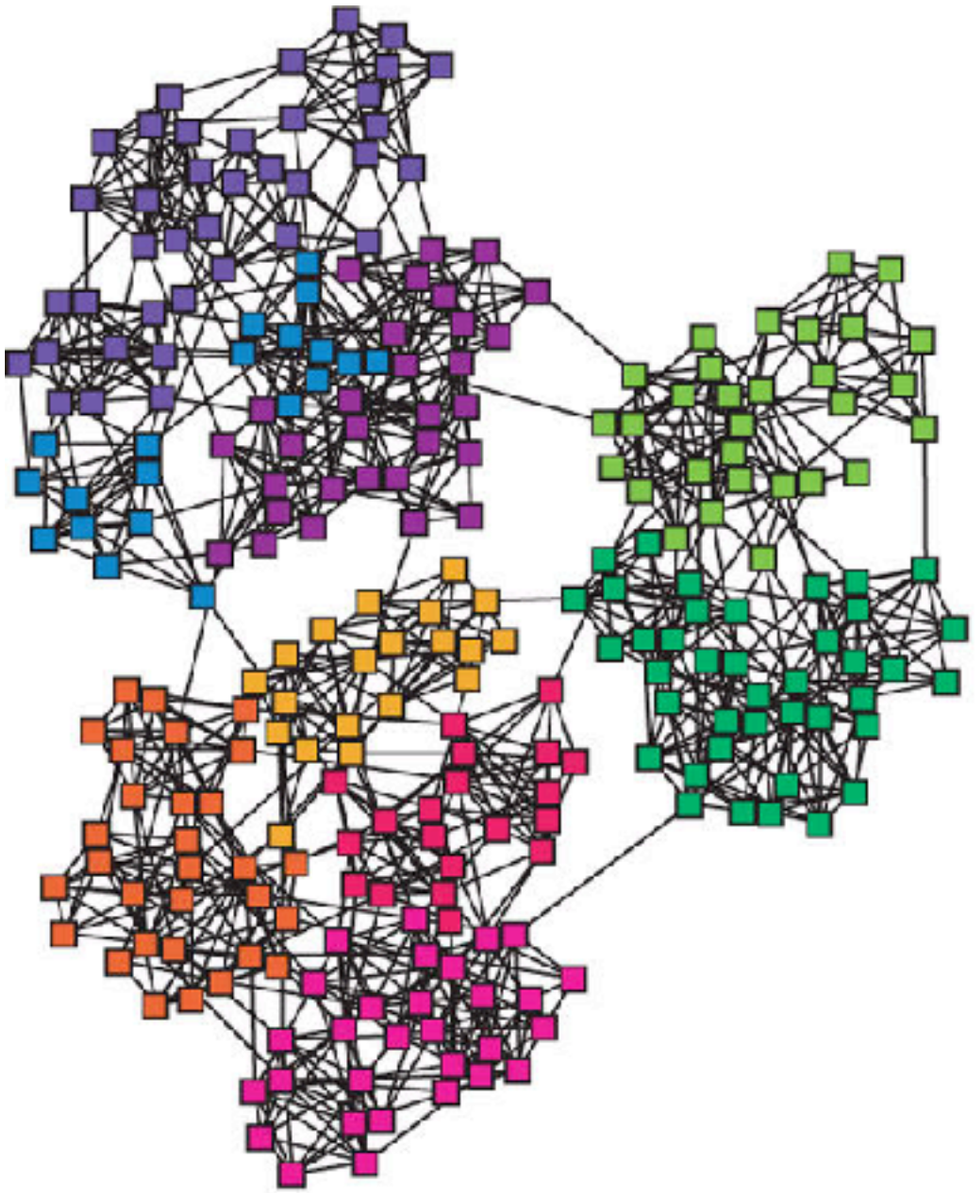
Change point analysis

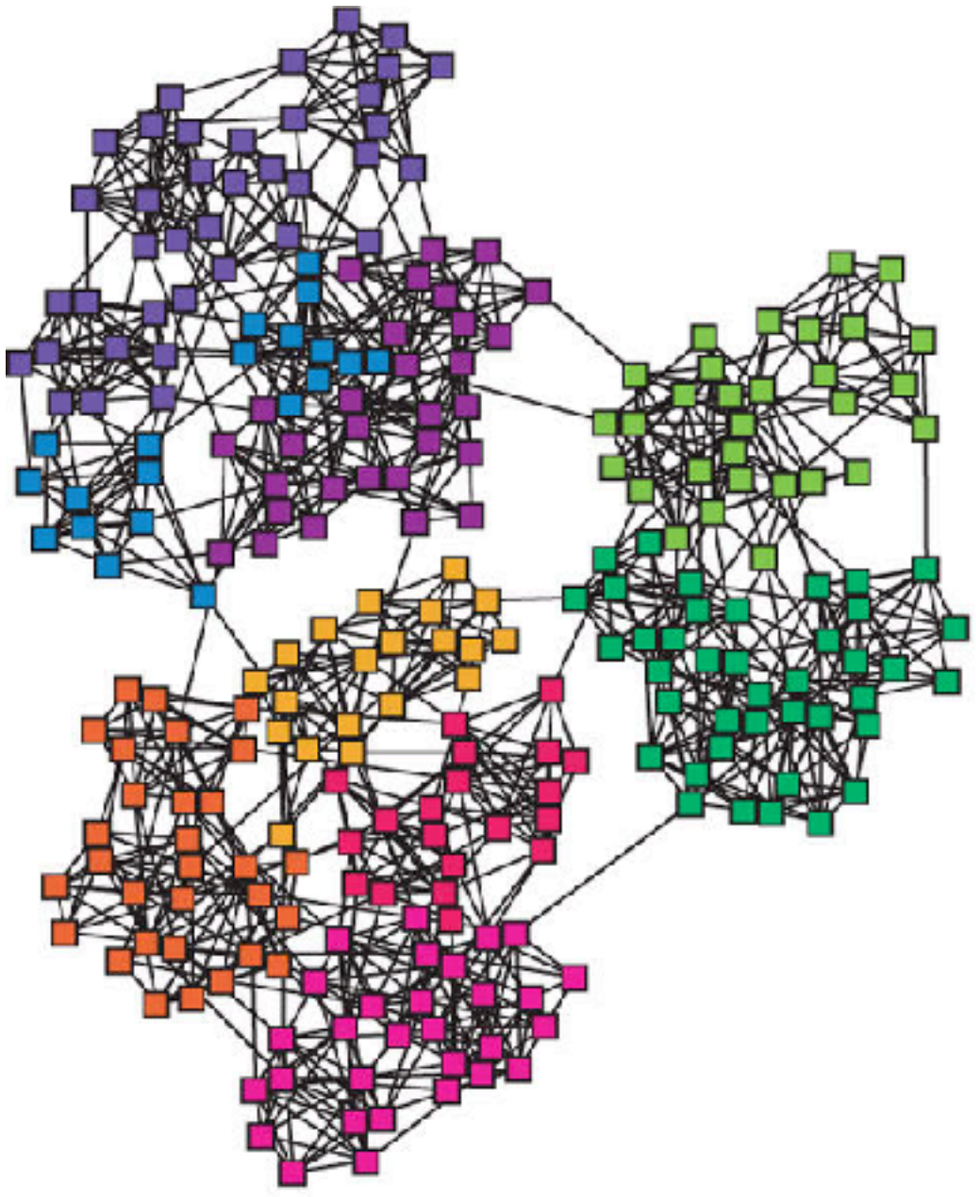
1. Fit model to network structure

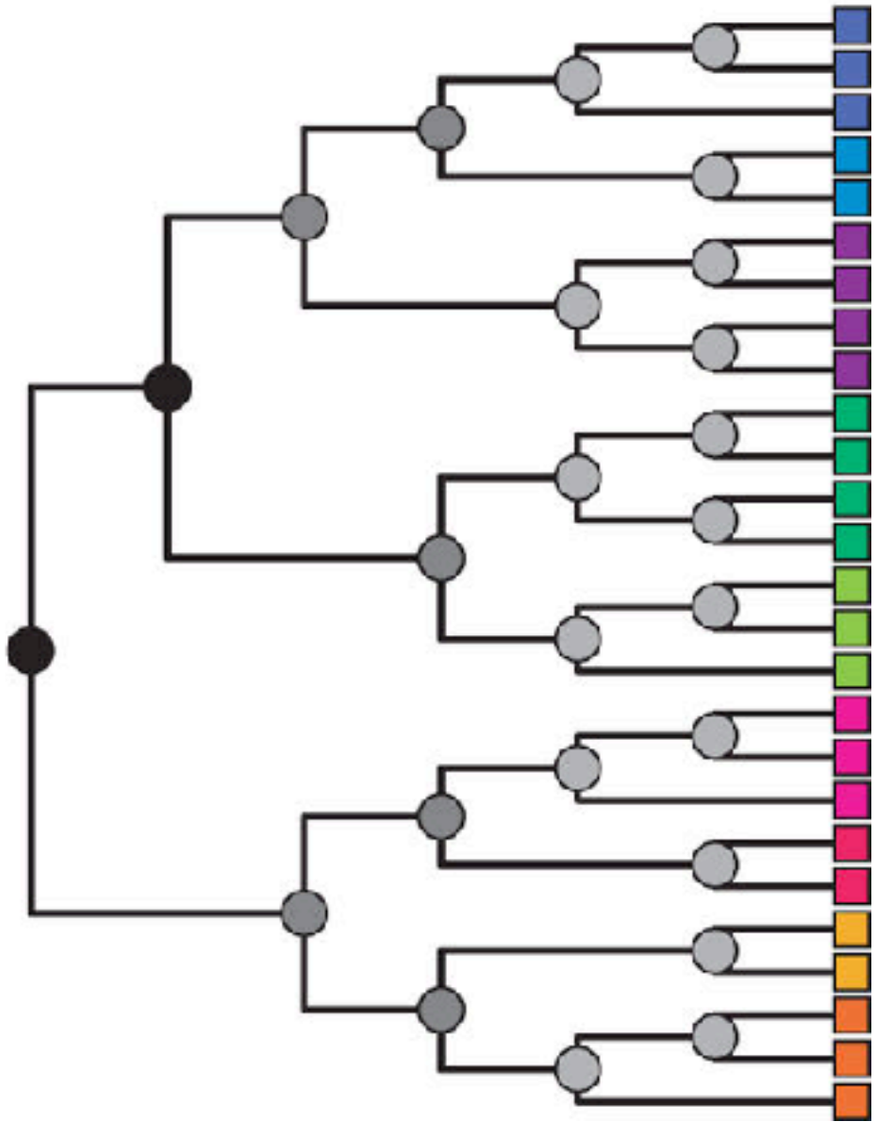
Peel & Clauset, 2014



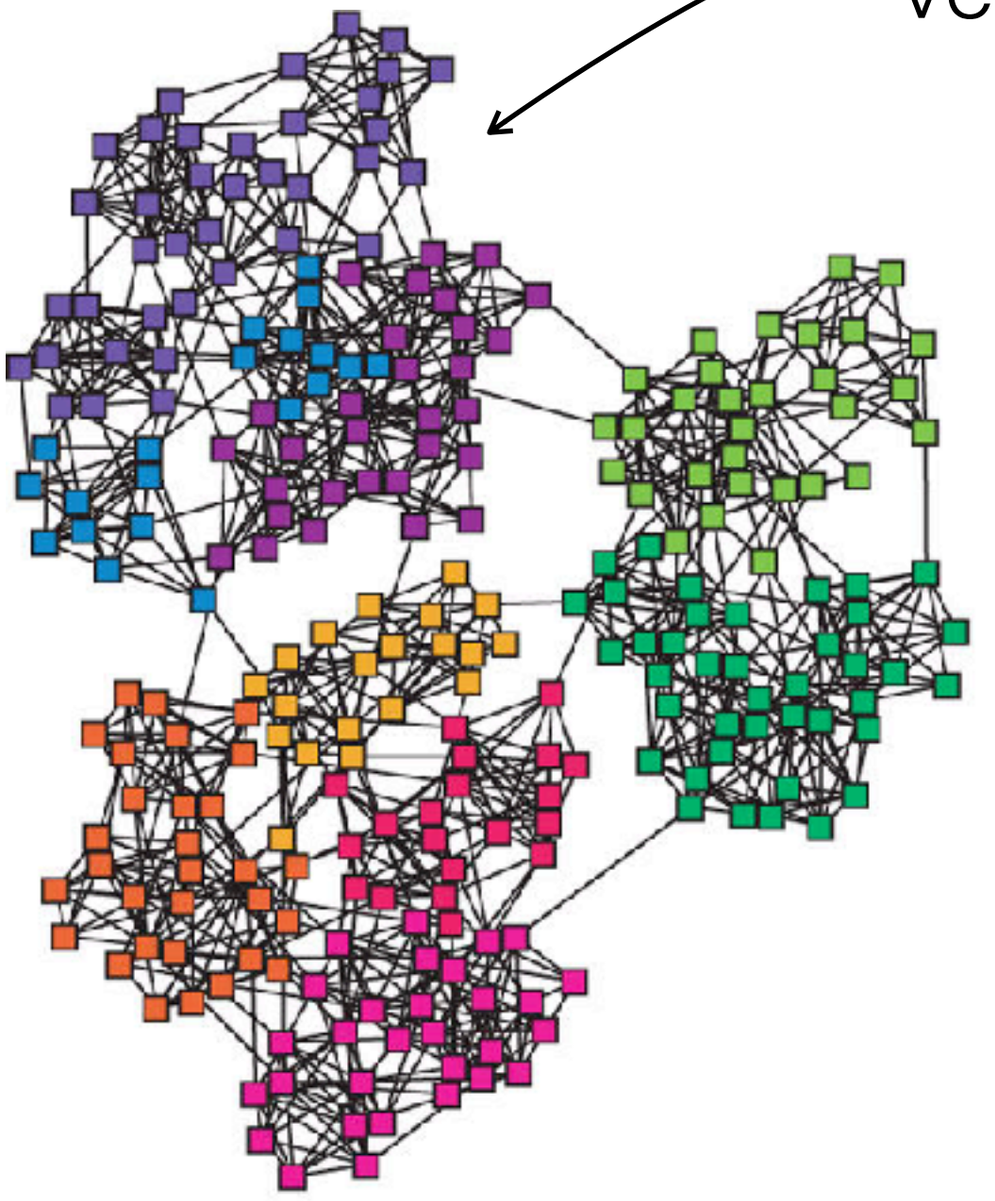
How could we simulate a random network with the same hierarchy?

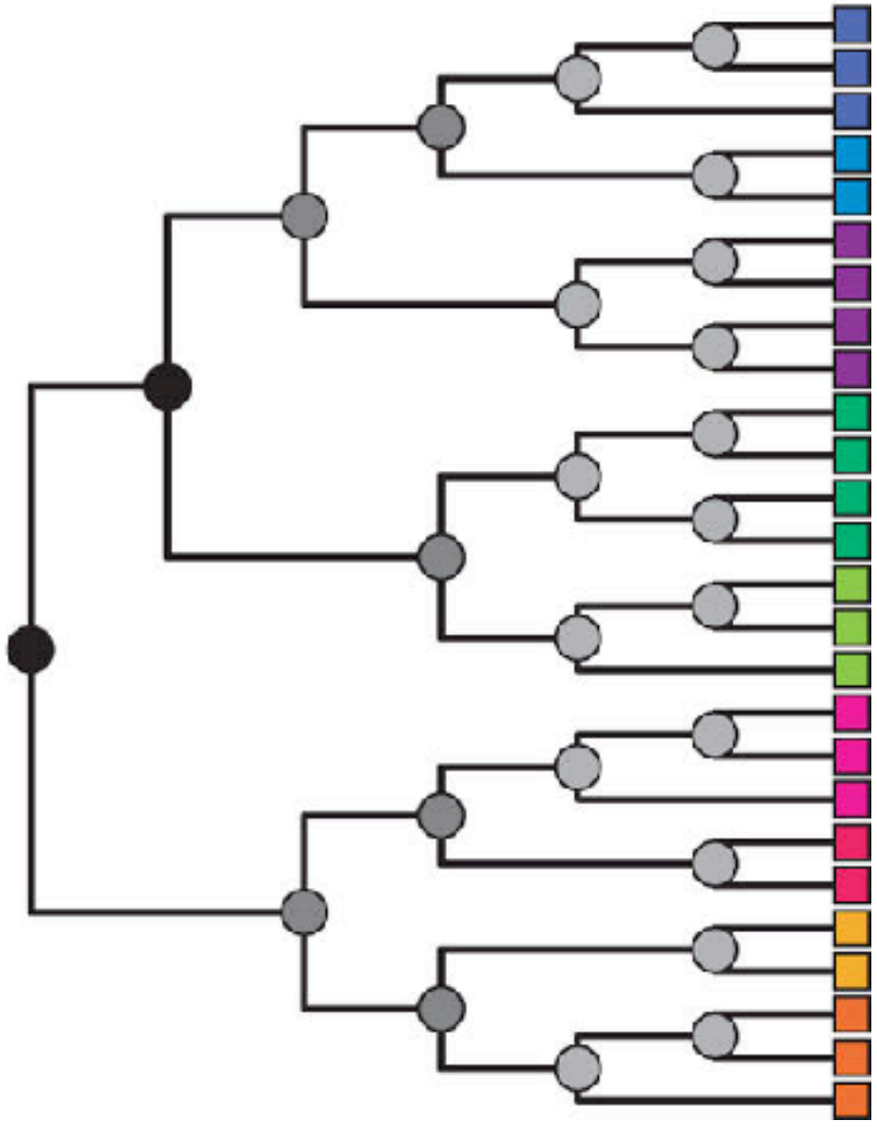






vertices of network





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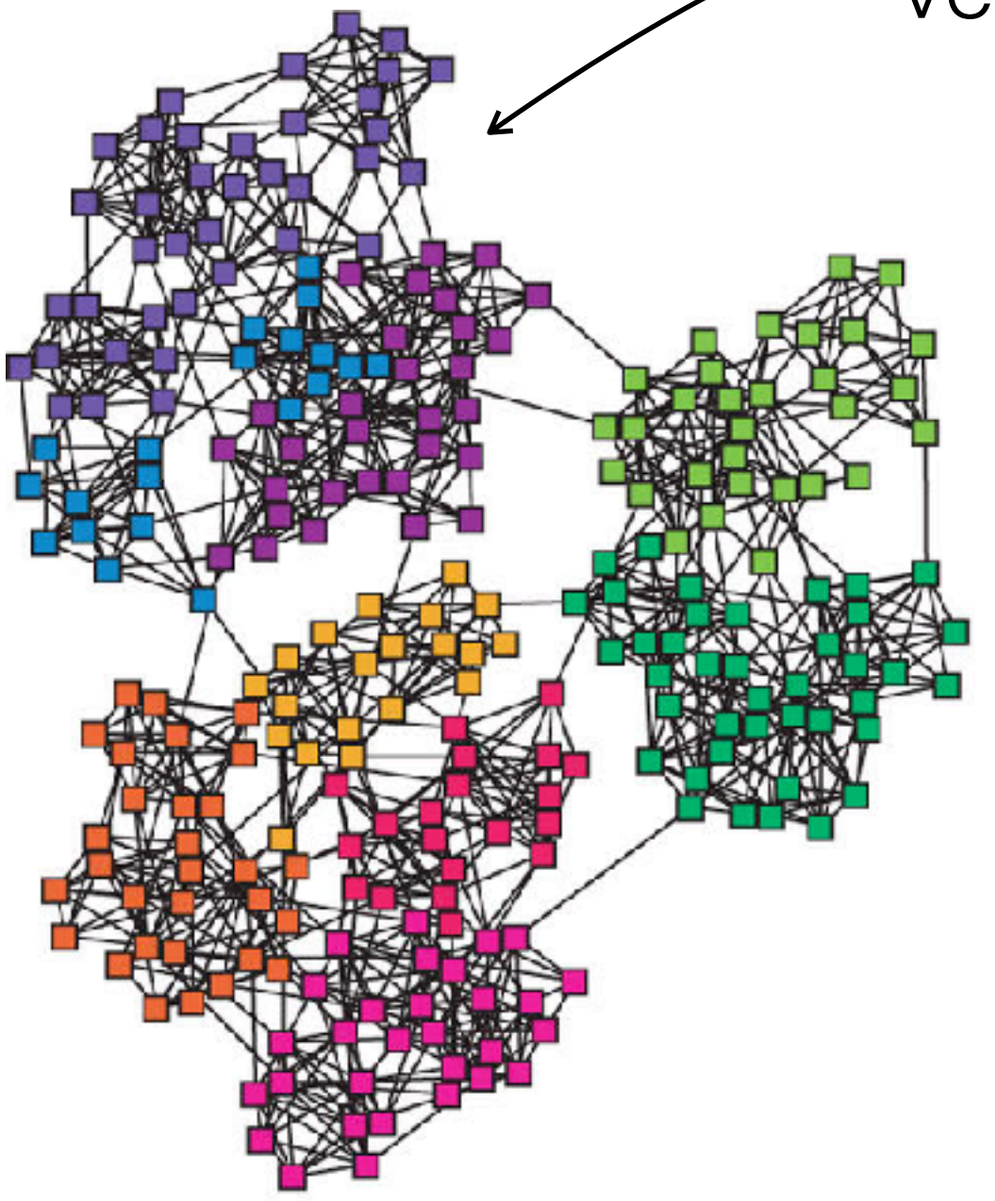

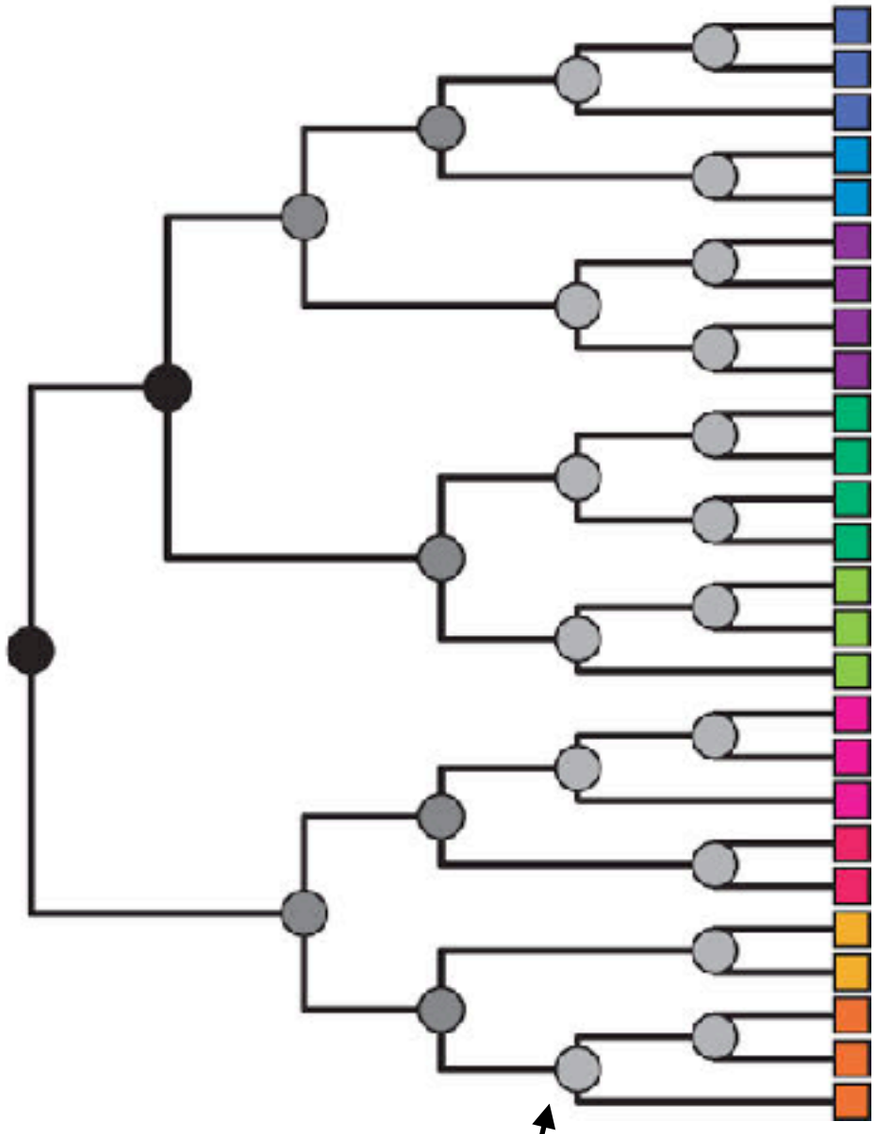

vertices share a common ancestor r
with probability p_r

Estimate the distribution from which the P_rs are drawn

Peel & Clauset, 2014

Estimate the distribution from which the P_rs are drawn

$$P(G|T,p_r) =$$

Peel & Clauset, 2014

Estimate the distribution from which the P_rs are drawn

Dendrogram

$$P(G|T,p_r) =$$

Graph

Peel & Clauset, 2014

Estimate the distribution from which the P_rs are drawn

Dendrogram

$$P(G|T,p_r) = \prod_r p_r^{E_r}(1-p_r)^{N_r-E_r}$$

Graph

Peel & Clauset, 2014

Estimate the distribution from which the P_rs are drawn

edges between vertices with the common ancestor r

Dendrogram

$$P(G|T,p_r) = \prod_r p_r^{E_r}(1-p_r)^{N_r-E_r}$$

Graph

Peel & Clauset, 2014

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Graph

total number of edges

Peel & Clauset, 2014

Estimate the distribution from which the P_rs are drawn

edges between vertices with the common ancestor r

Dendrogram

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Graph

total number of edges

Peel & Clauset, 2014

Estimate the distribution from which the P_rs are drawn

edges between vertices with the common ancestor r

Dendrogram

$$P(G|T,p_r) = \prod_r p_r^{E_r}(1-p_r)^{N_r-E_r}$$

Graph

total number of edges

Peel & Clauset, 2014

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Peel & Clauset, 2014

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$$Beta(\alpha,\beta)$$

Peel & Clauset, 2014

Change point analysis

1. Fit model to network structure

Peel & Clauset, 2014

Change point analysis

1. Fit model to network structure (Generalized Hierarchical Random Graph Model)

Peel & Clauset, 2014

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2. Infer two versions of the model:
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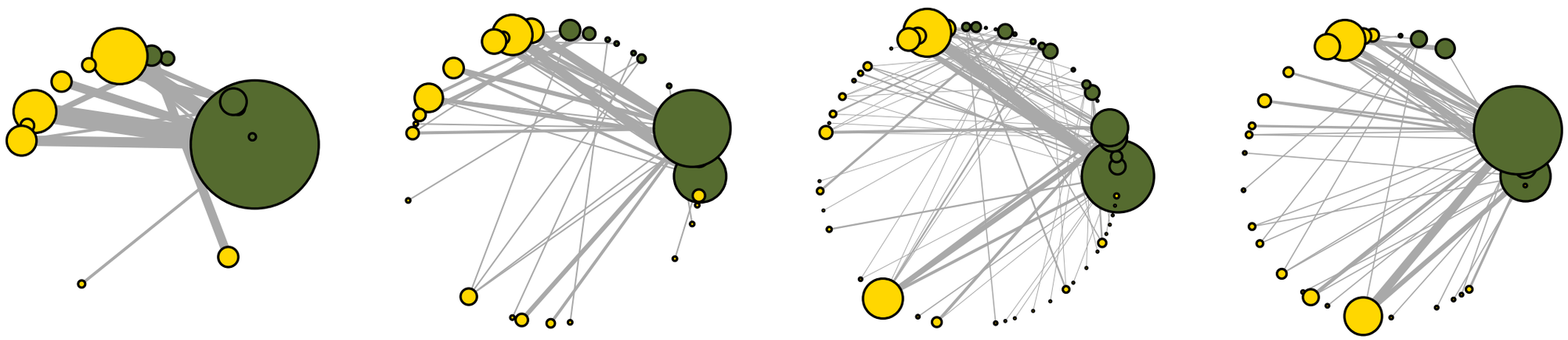
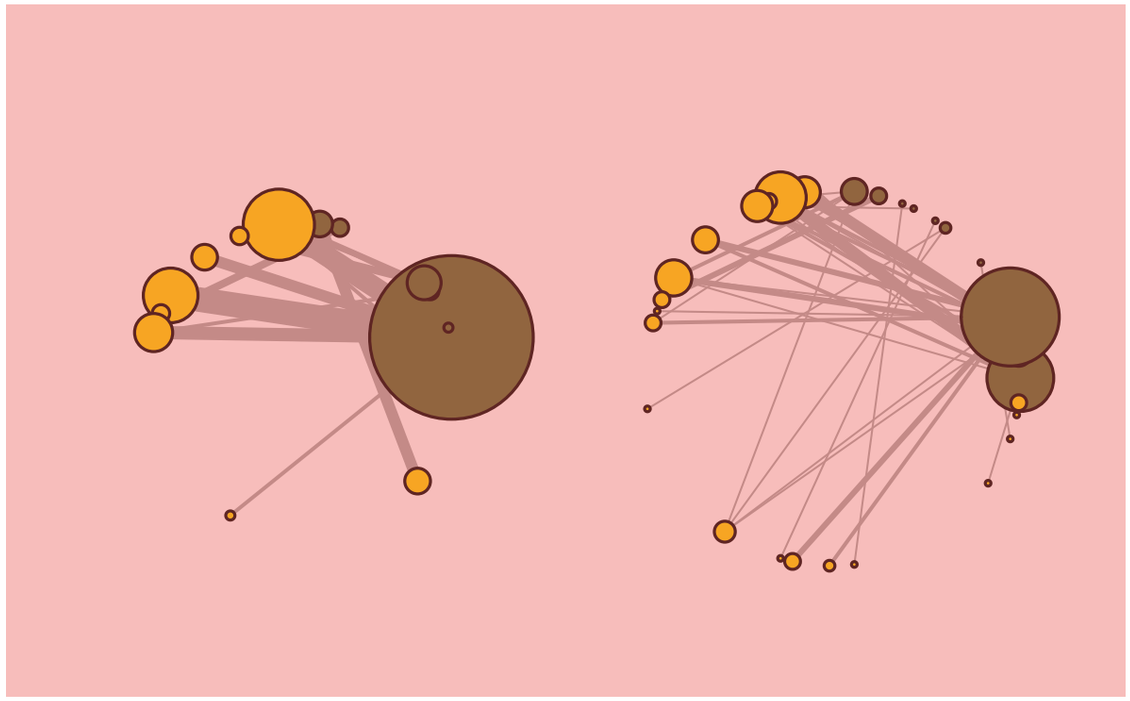
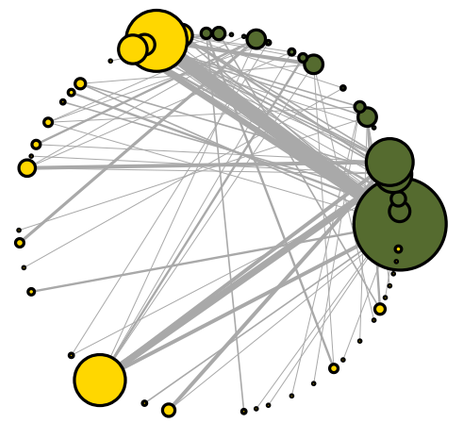
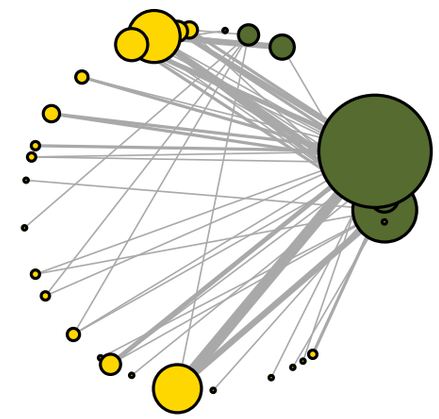
Peel & Clauset, 2014

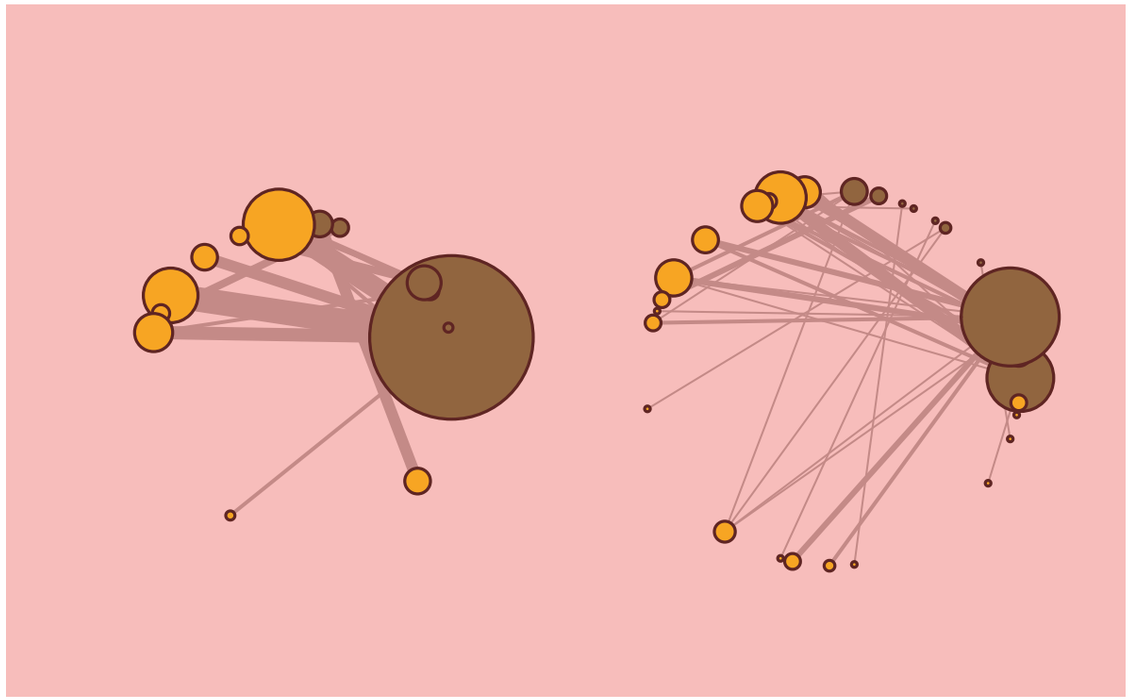


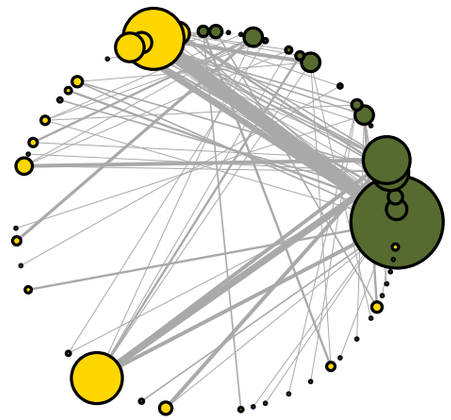
Assembling hedgerow

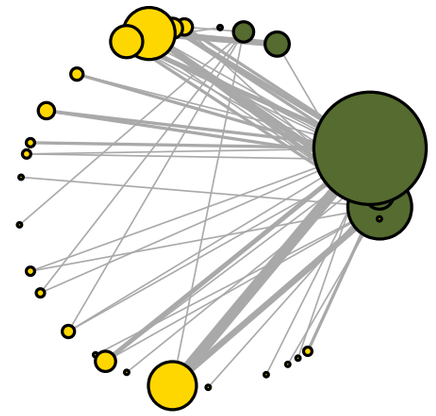


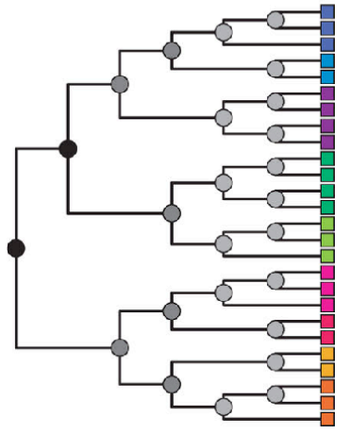






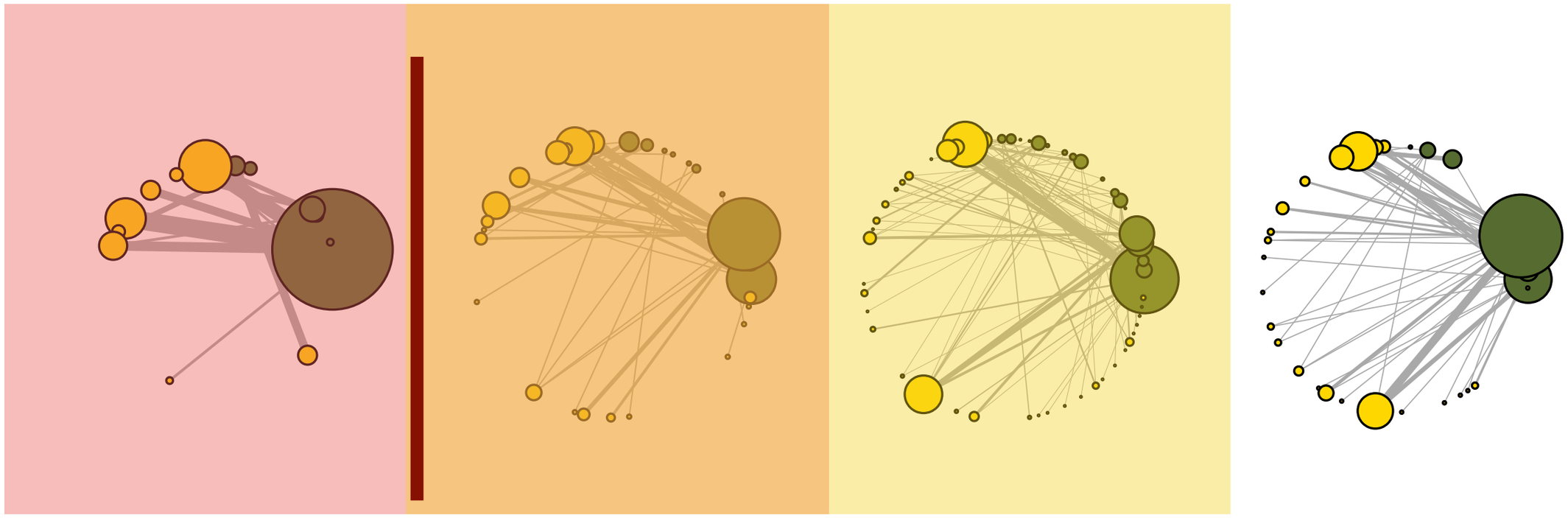


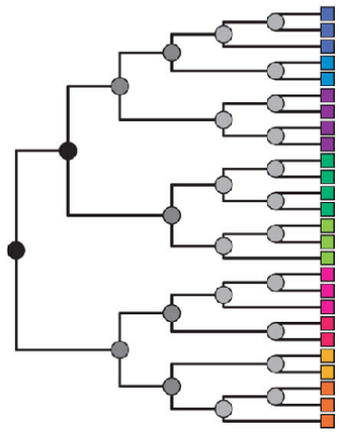




$$Beta(\alpha, \beta)$$

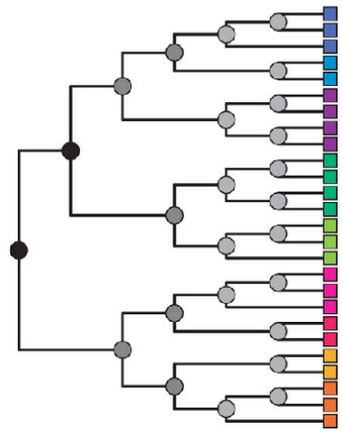
Change point?





$Beta(\alpha, \beta)$

!=



$Beta(\alpha, \beta)$

Change point analysis

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Peel & Clauset, 2014

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3. Use Bayes factors to choose which model, change or no-change, is the better

Peel & Clauset, 2014

$$\frac{\overbrace{\mathcal{L}(G_{\leq t^*} \mid \theta_{\leq t^*})}^{\text{likelihood up to } t^*} \times \overbrace{\mathcal{L}(G_{>t^*} \mid \theta_{>t^*})}^{\text{likelihood after}}}{\underbrace{\mathcal{L}(G_{\text{all}} \mid \theta_{\text{all}})}_{\text{likelihood of no change point}}}$$

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Peel & Clauset, 2014

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Peel & Clauset, 2014

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leto.peel@uclouvain.be

Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.

Results

Assembling hedgerow

Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.

Results

Assembling hedgerow

~ 20% pairs of years

Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.

Results

Assembling hedgerow

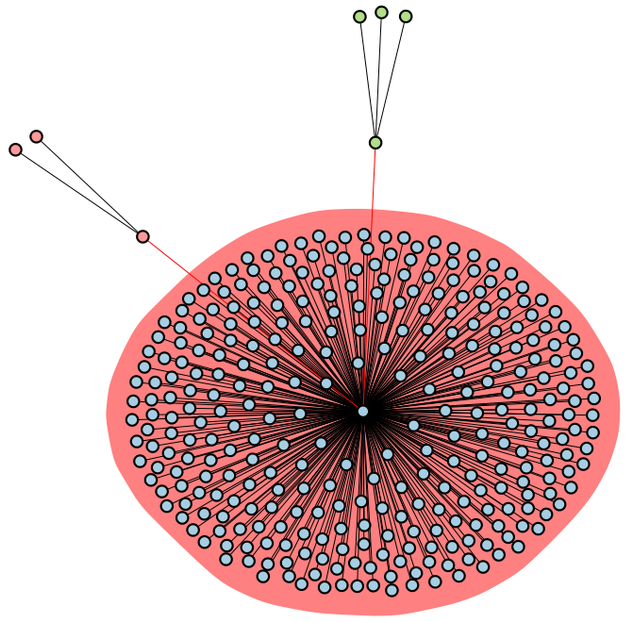
~ 20% pairs of years**

Non-assembling communities

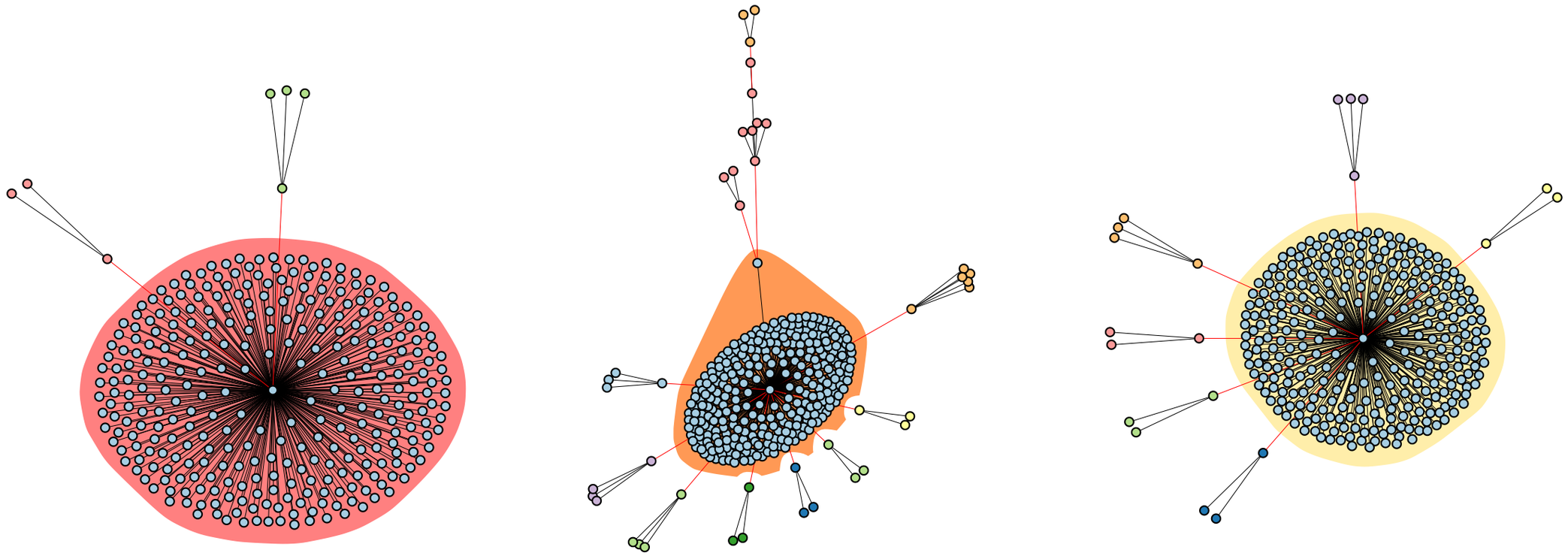
~ 5% pairs of years

Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.

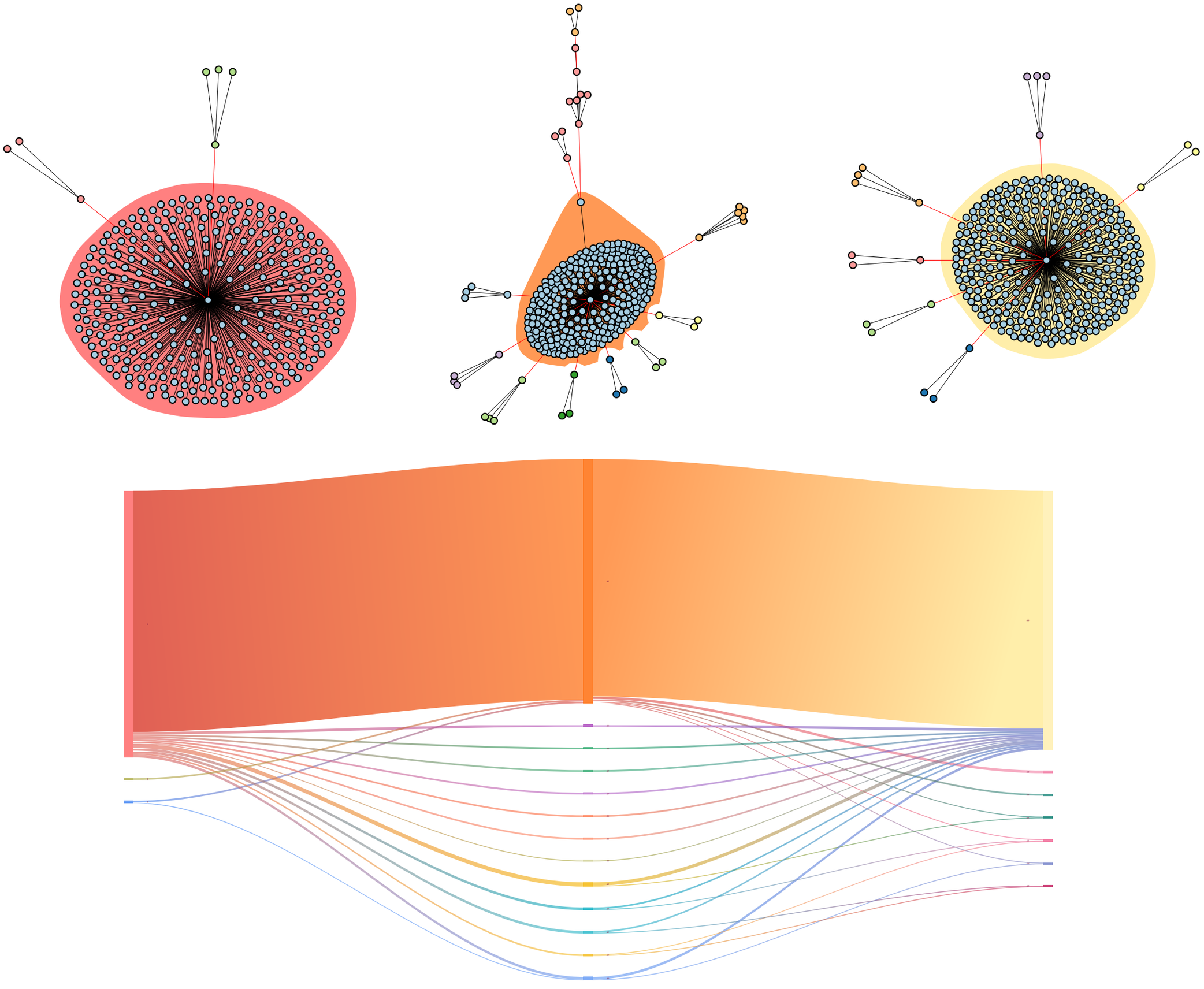
Results



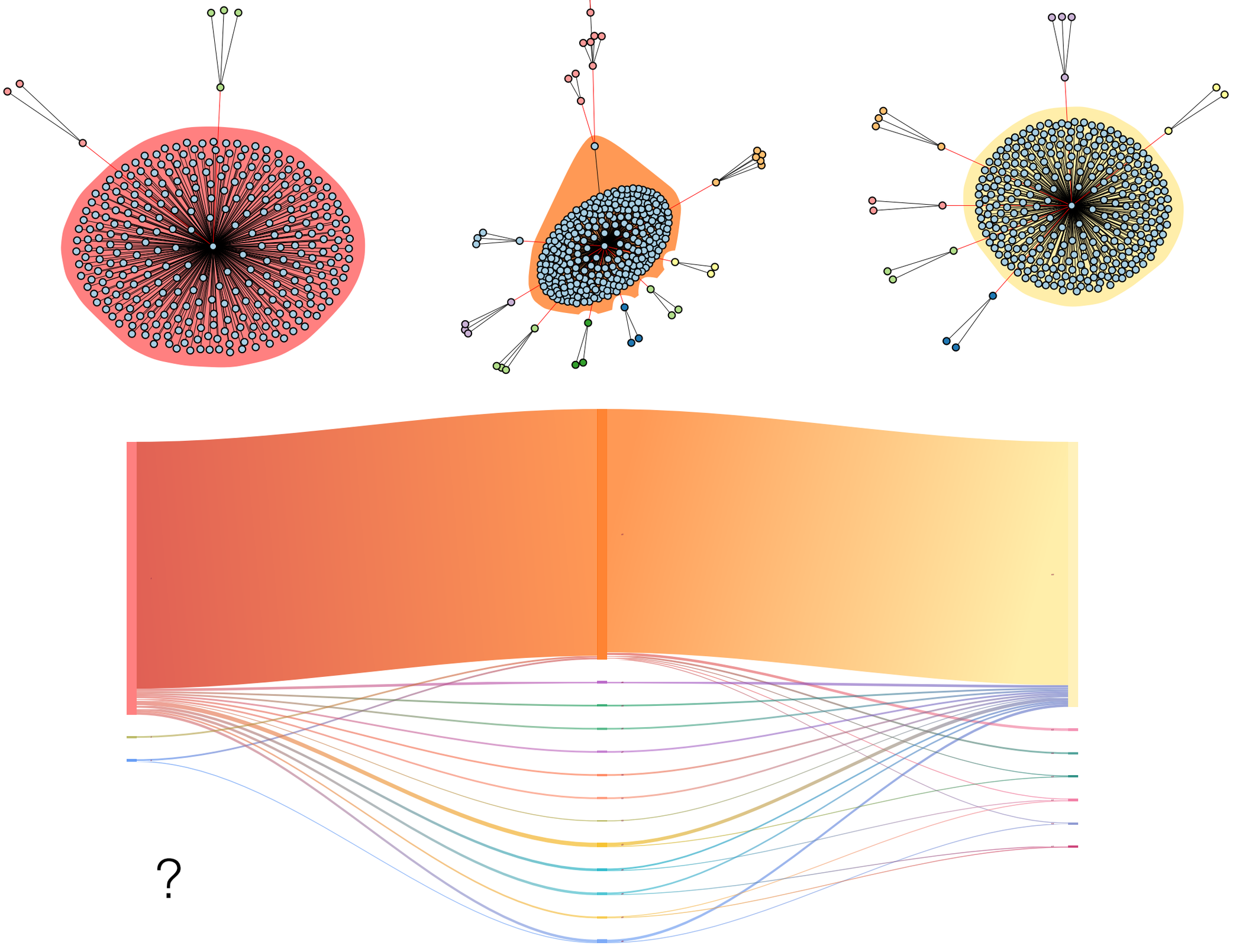
Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.



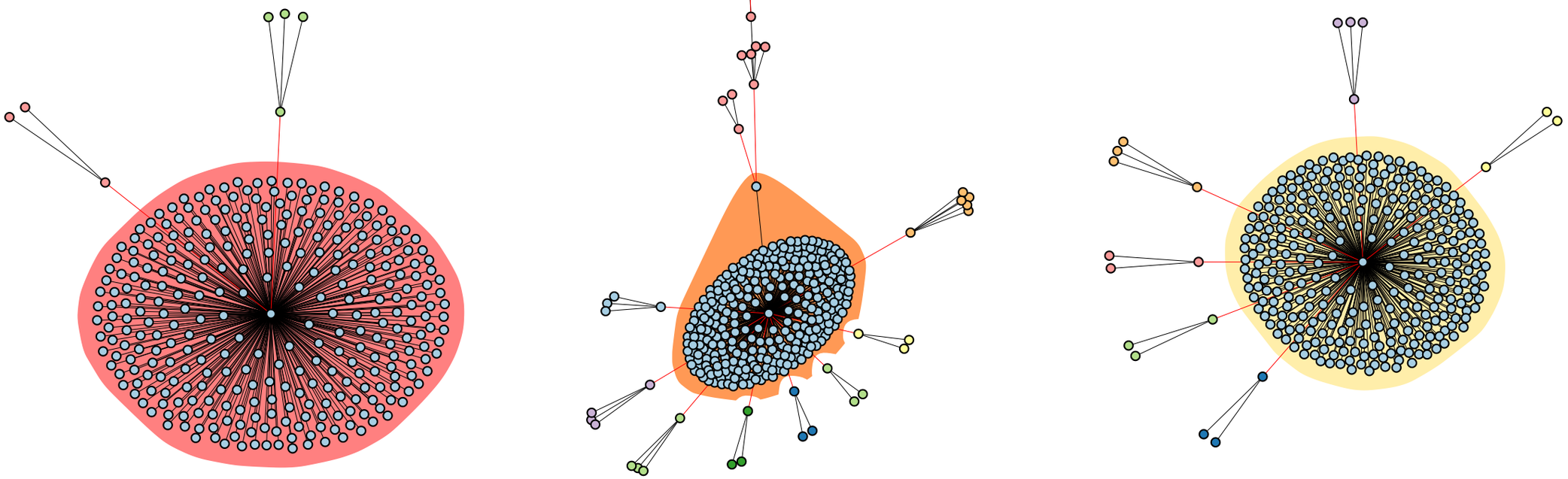
Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.



Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.



Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.



How do communities resist collapse?

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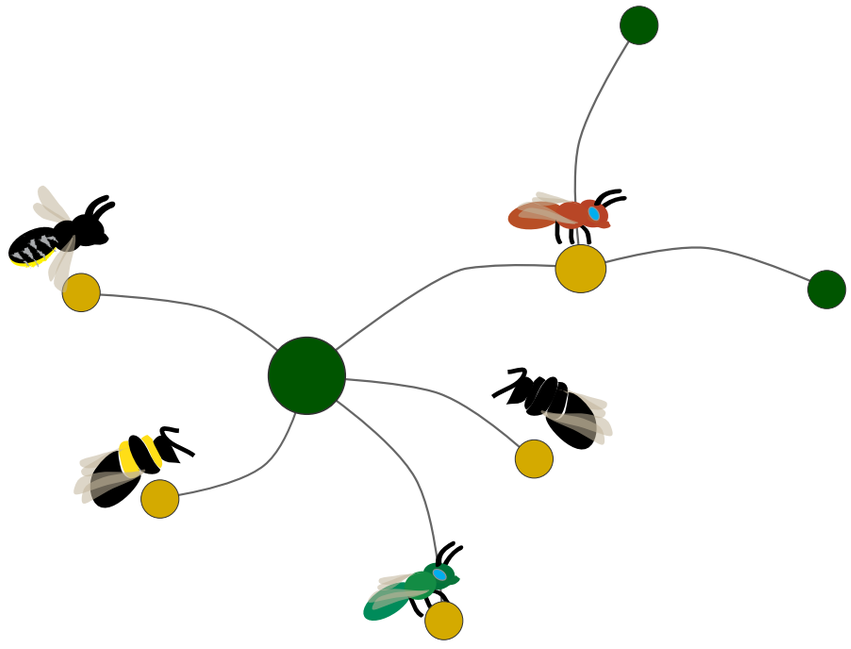
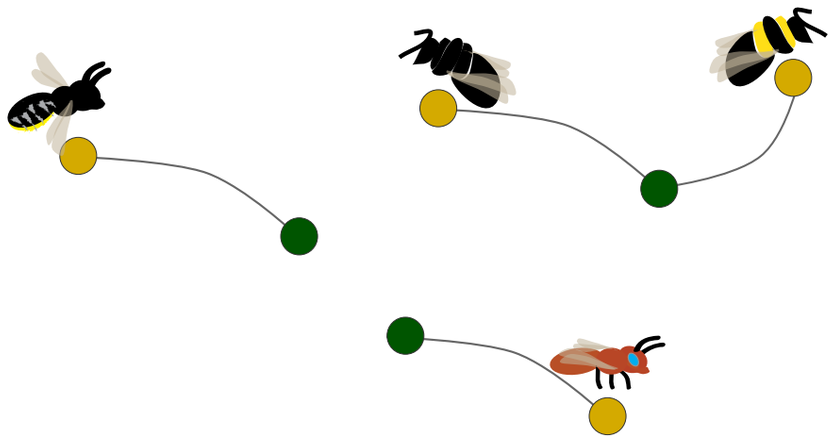
Ponisio, Gaiarsa and Kremen, 2017 Ecol. Lett.

Interaction flexibility

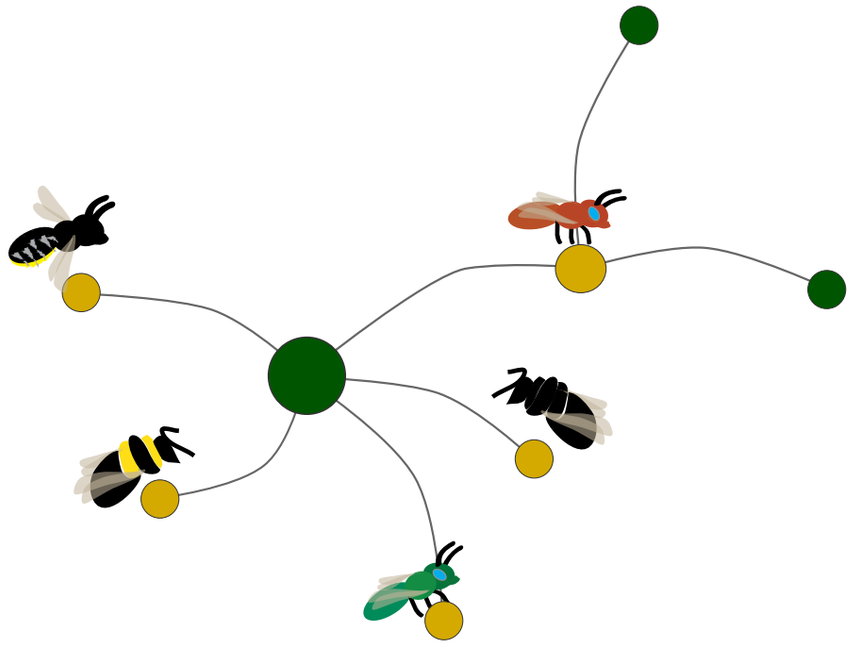


Year 1

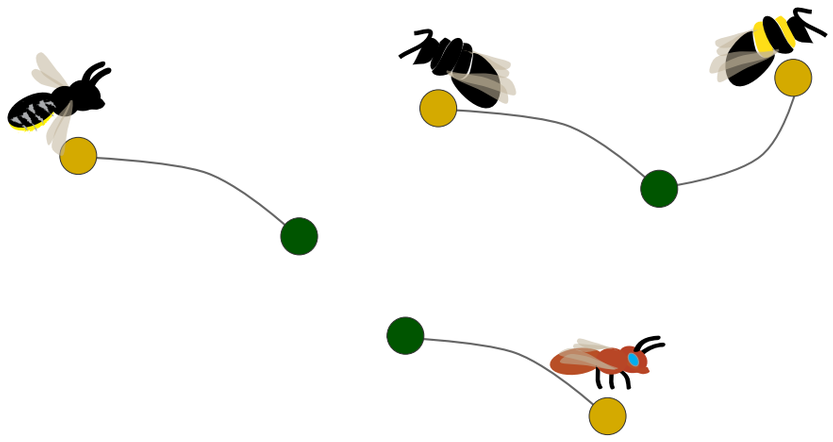


Year 2

Microscale: who are your partners?

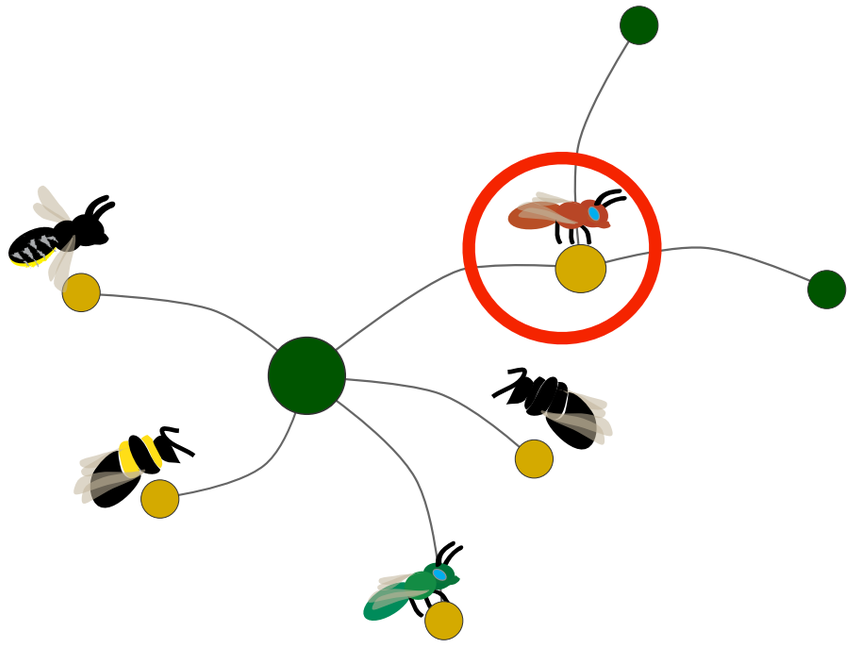


Year 1

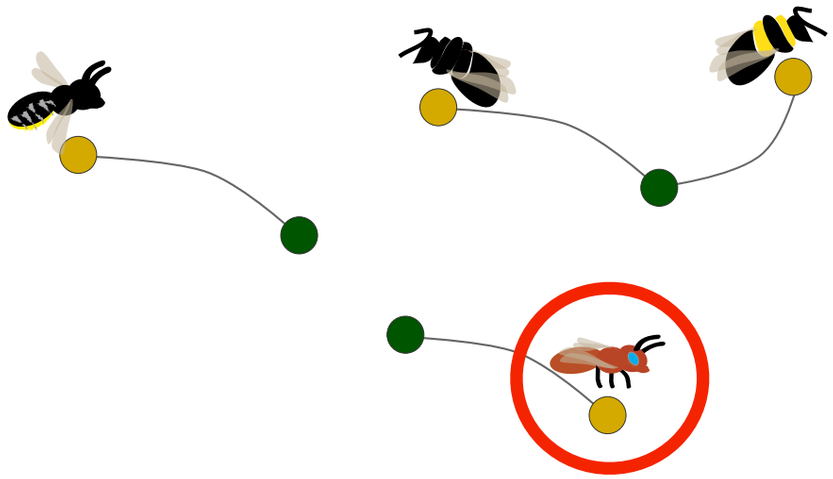


Year 2

Microscale: who are your partners?

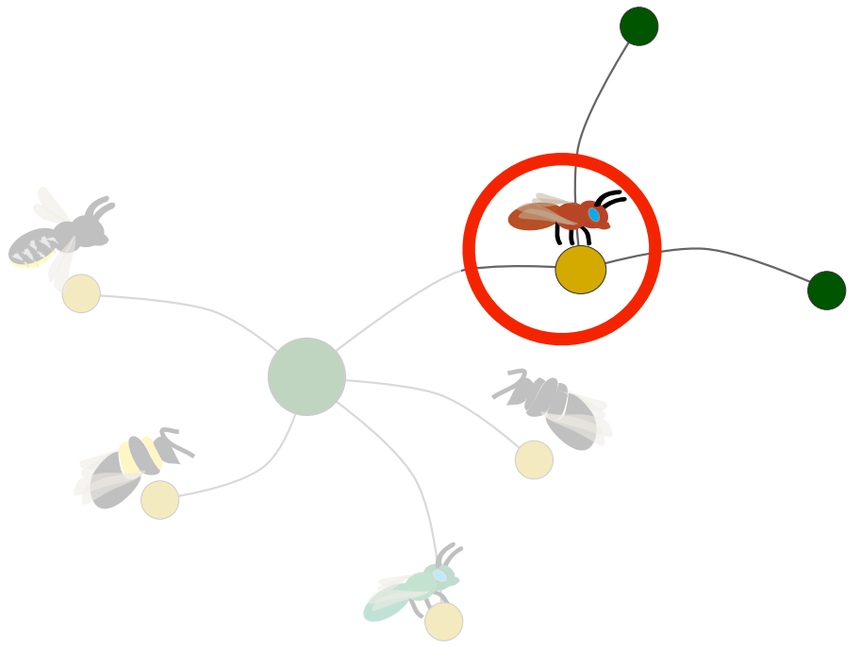


Year 1

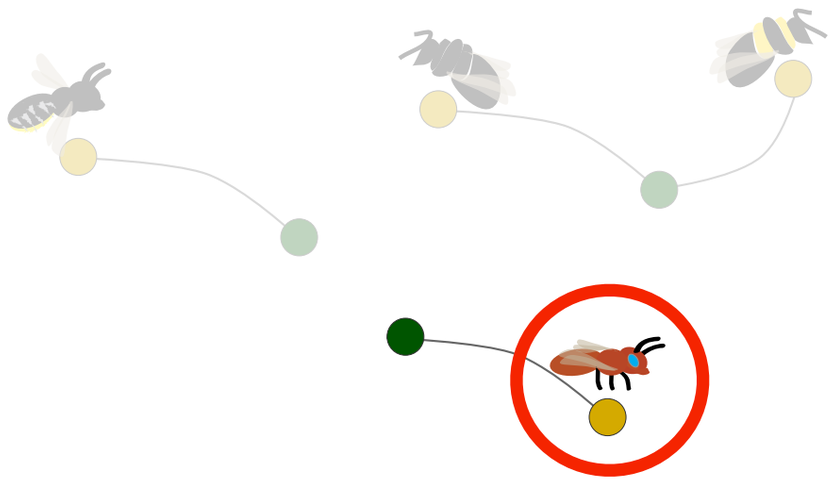


Year 2

Microscale: who are your partners?



Year 1



Year 2

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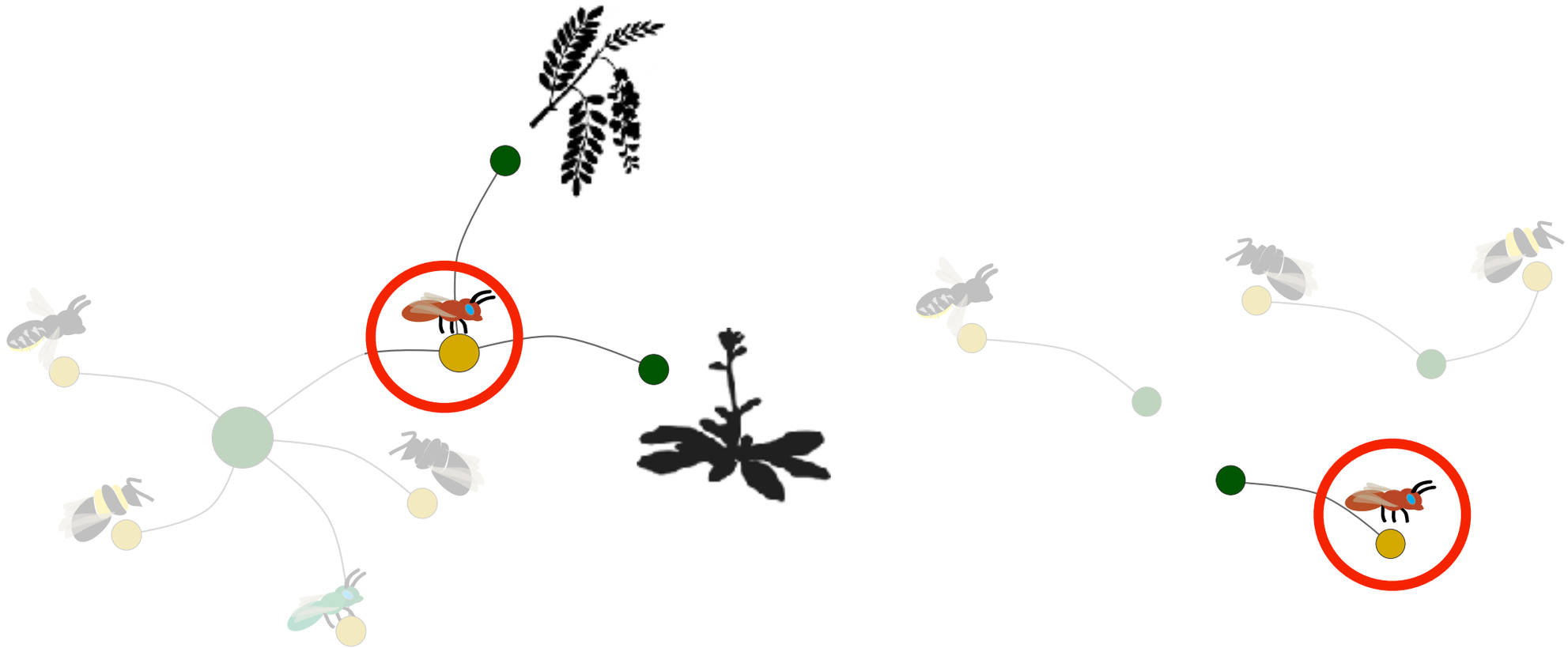
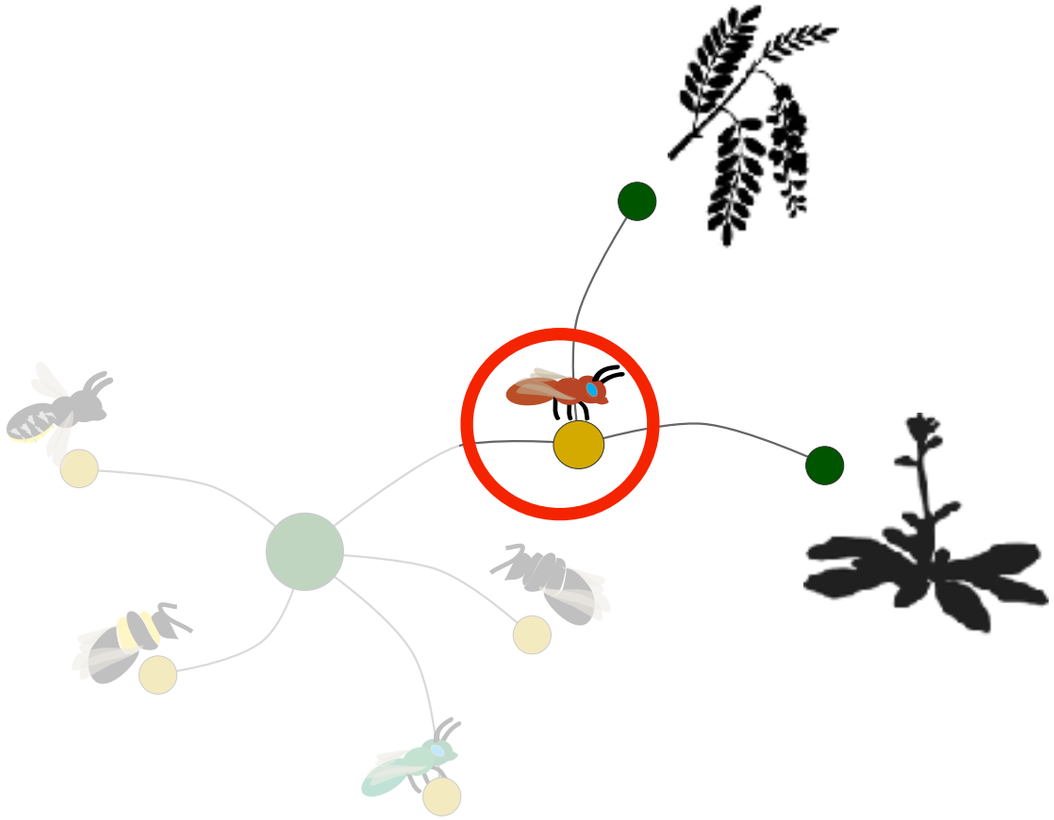


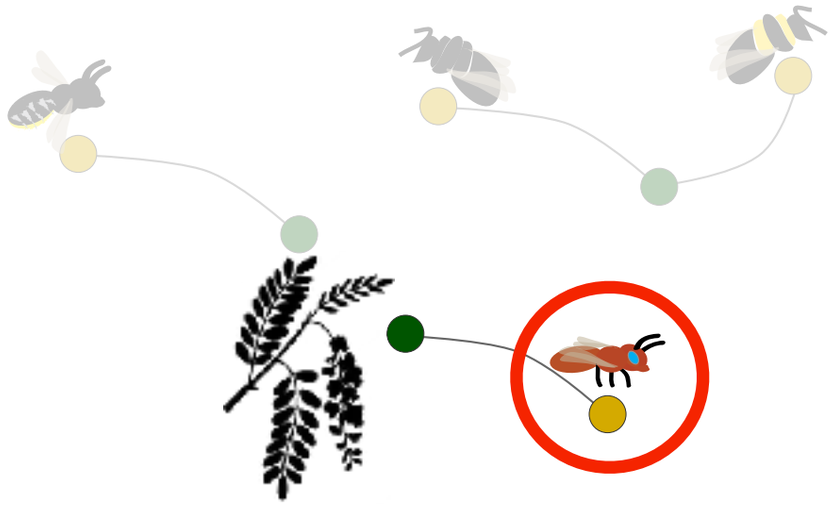
Year 1

Year 2

Microscale: who are your partners?



Year 1



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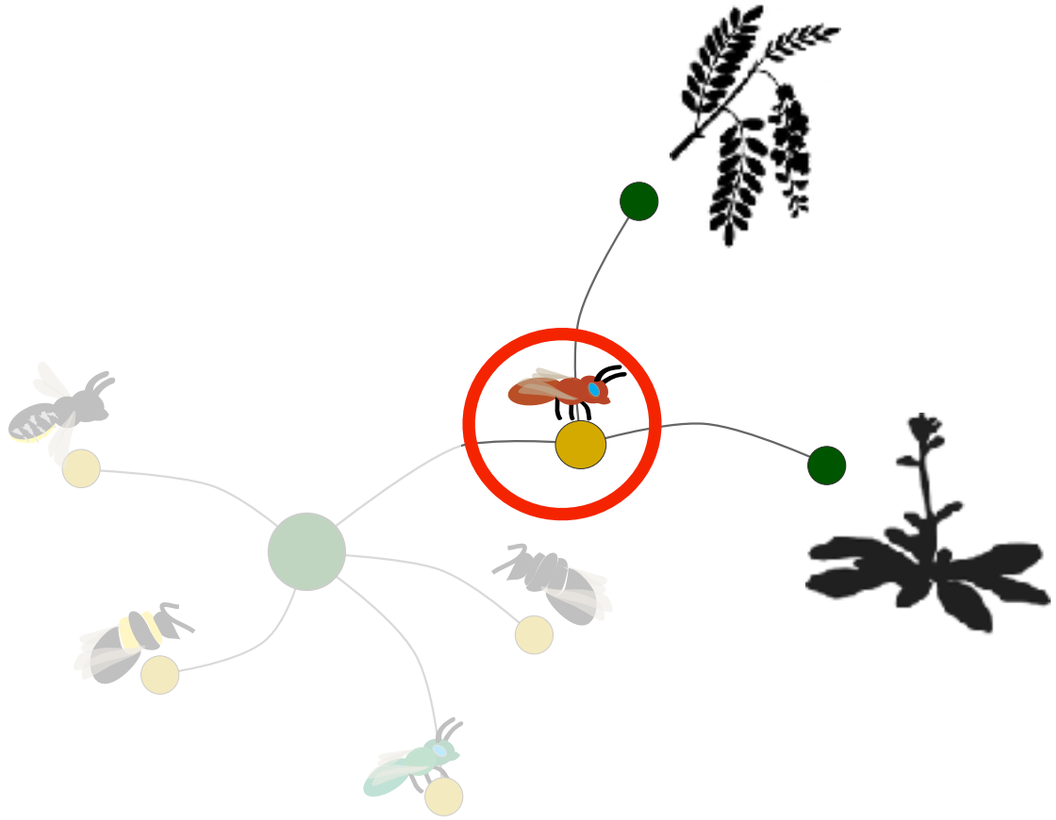
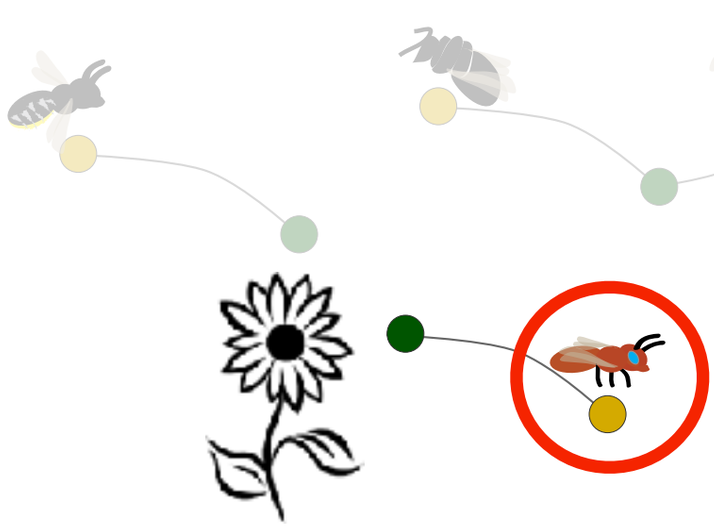
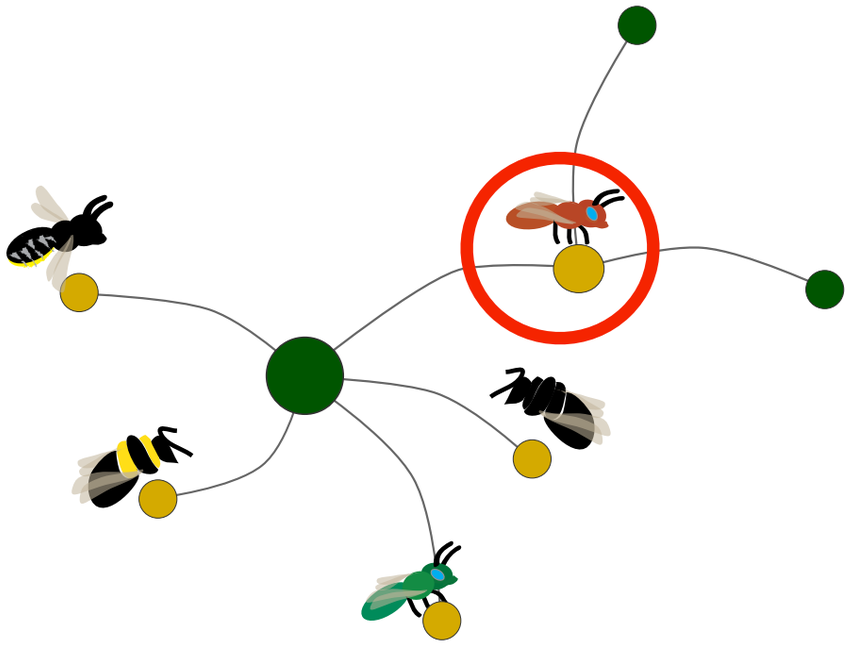


Year 1

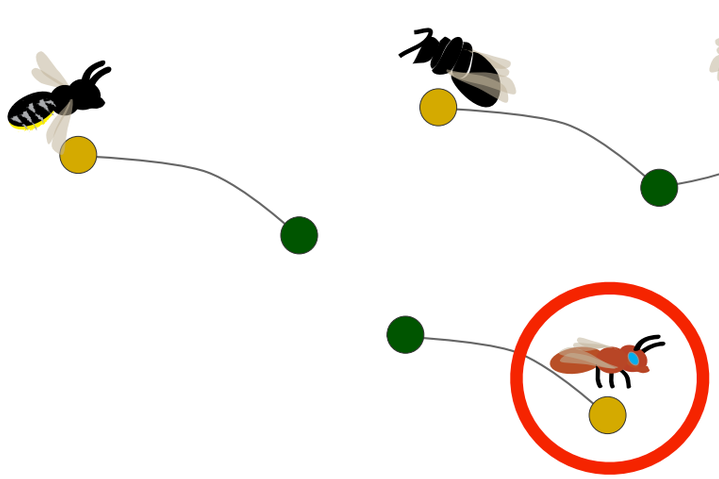


Year 2

Mesoscale: what is your network role?



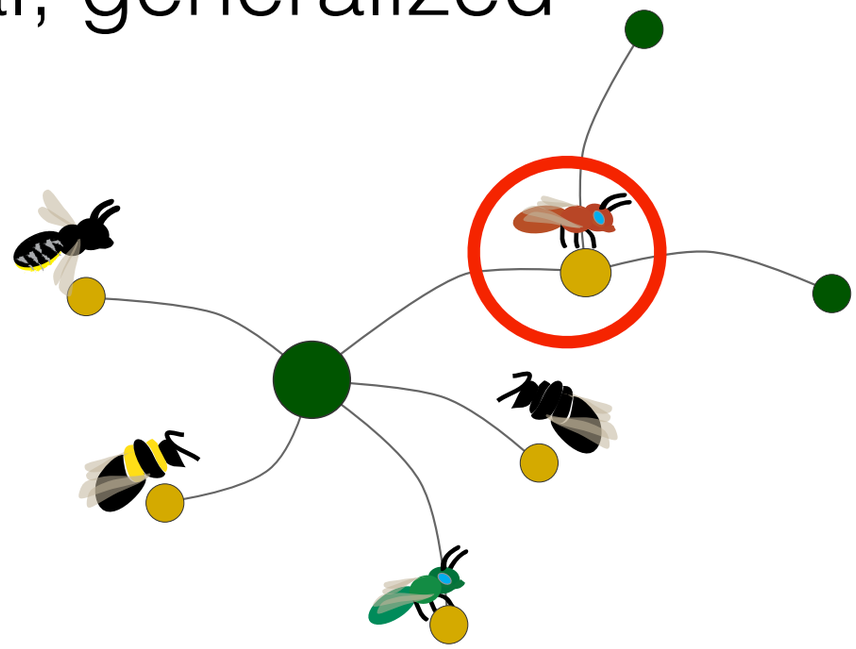
Year 1



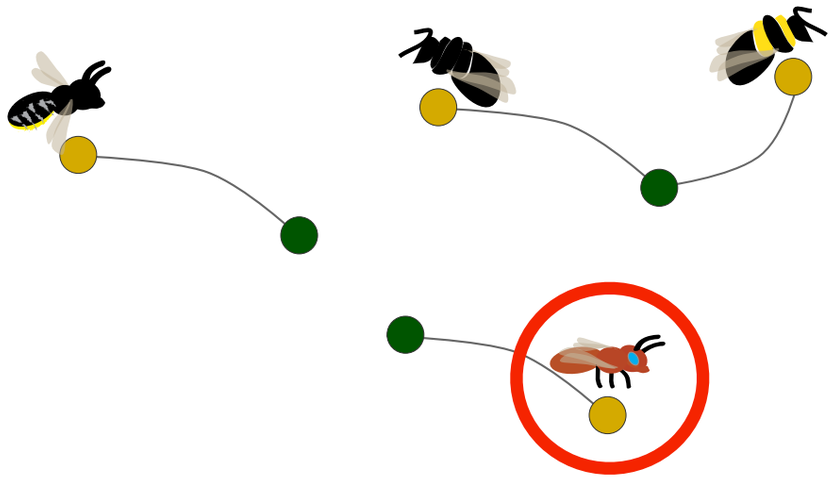
Year 2

Mesoscale: what is your network role?

Central, generalized



Year 1

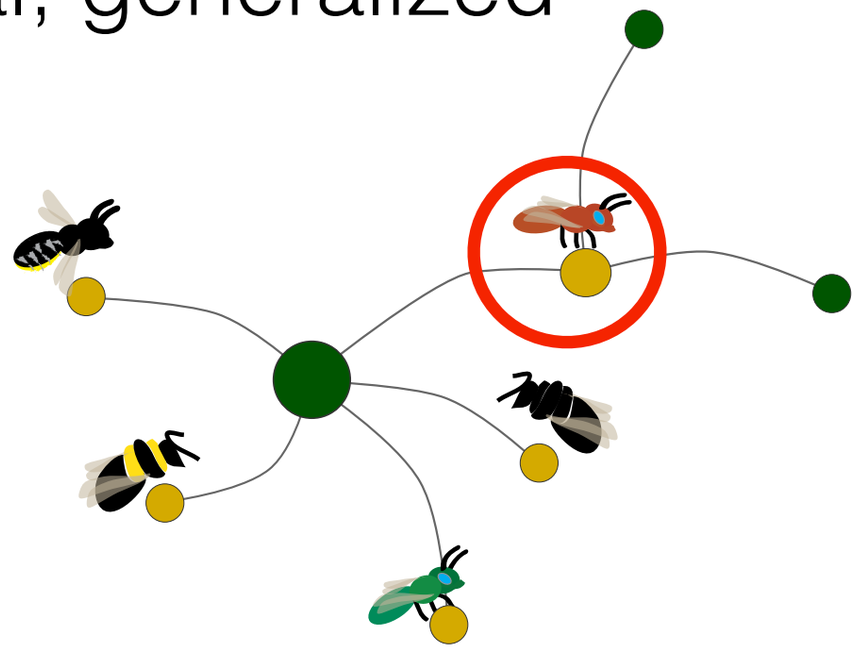


Peripheral, specialized

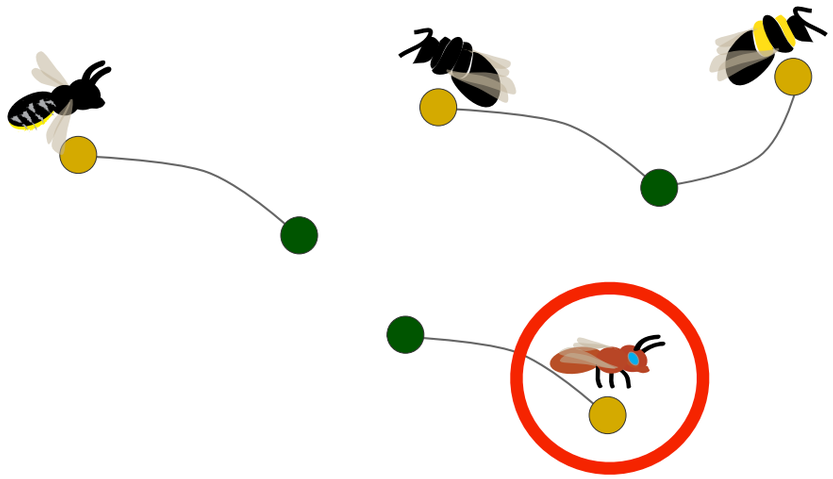
Year 2

Macroscale: what is your contribution to network organization?

Central, generalized



Year 1



Peripheral, specialized

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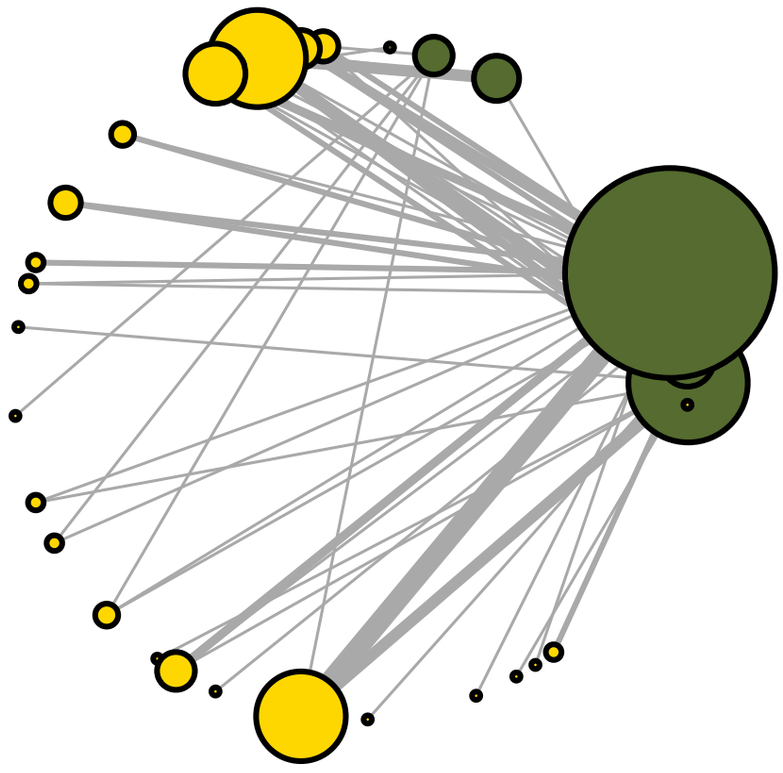

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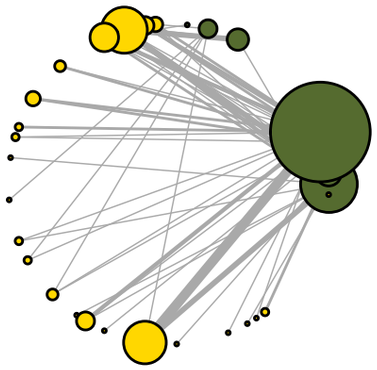
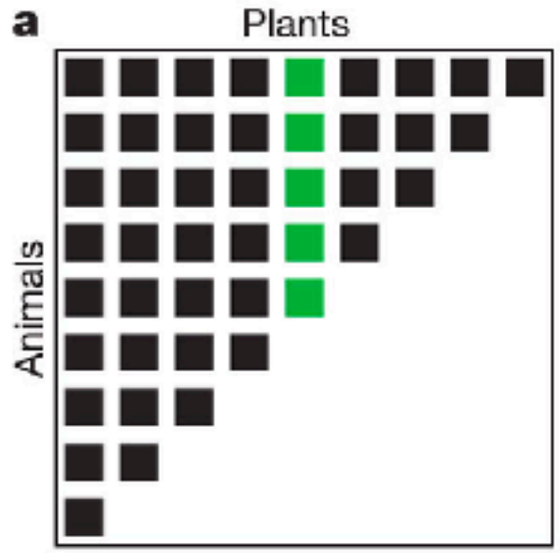
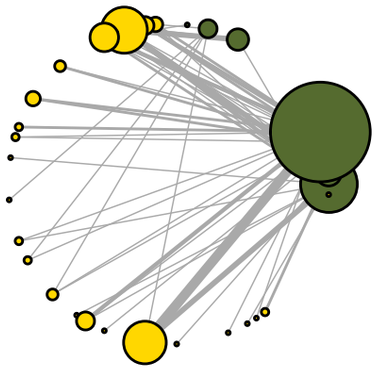
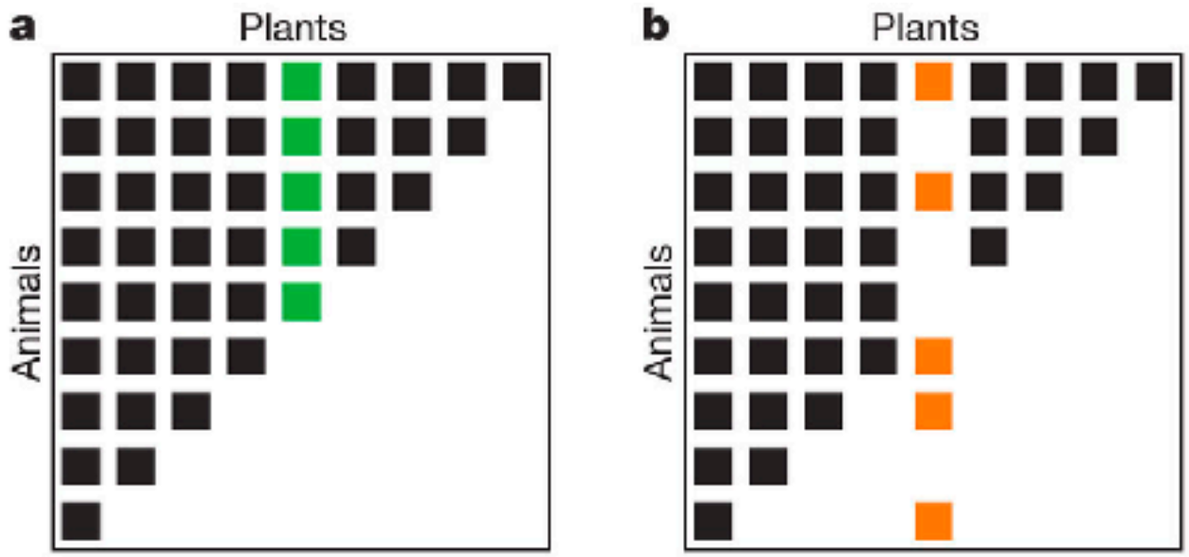




Saavedra et al. 2011

Macroscale: what is your contribution to network organization?





Saavedra et al. 2011

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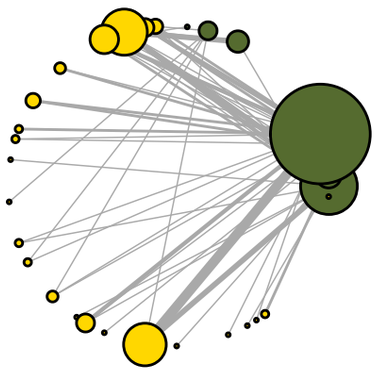

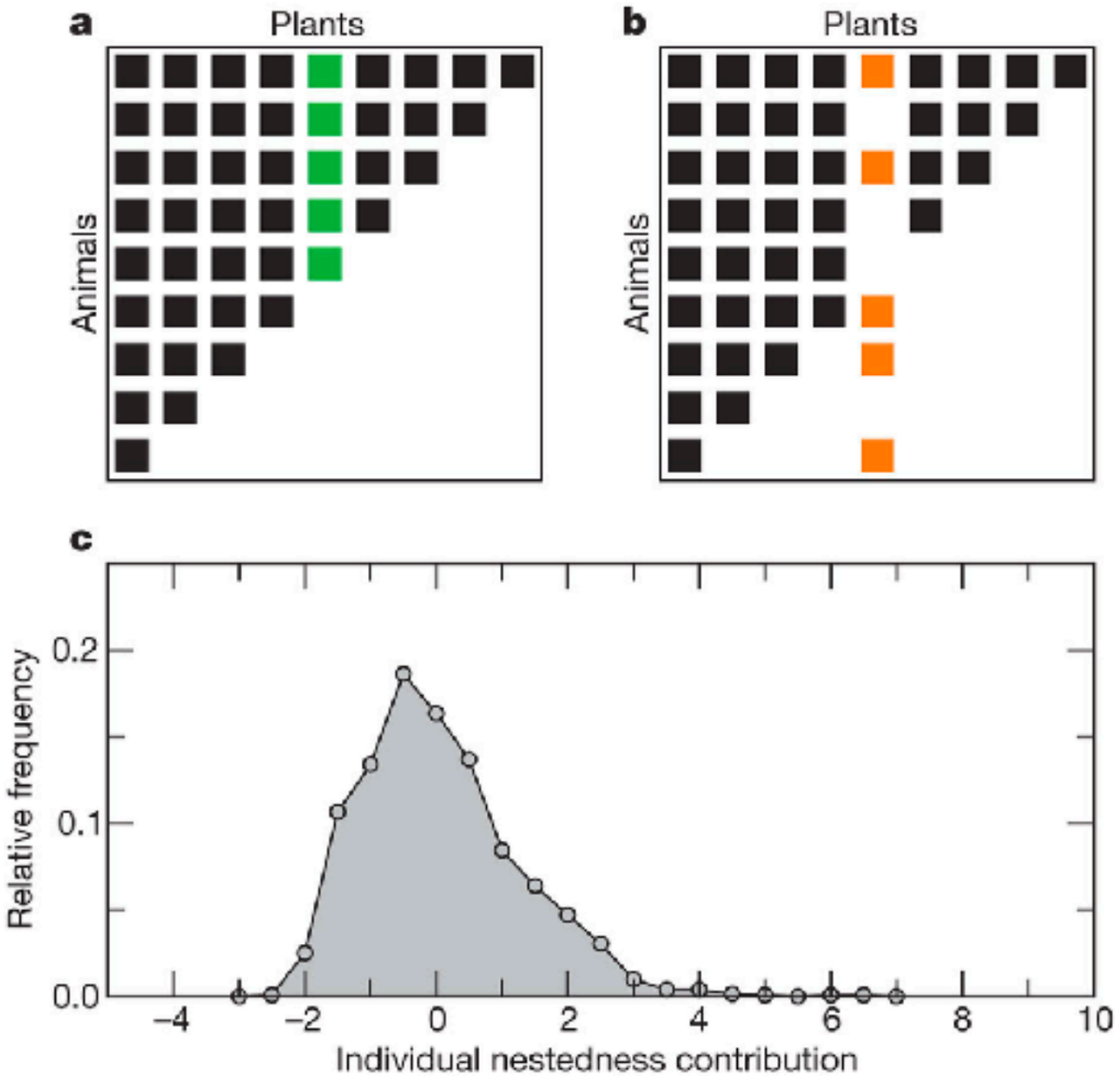

Saavedra et al. 2011

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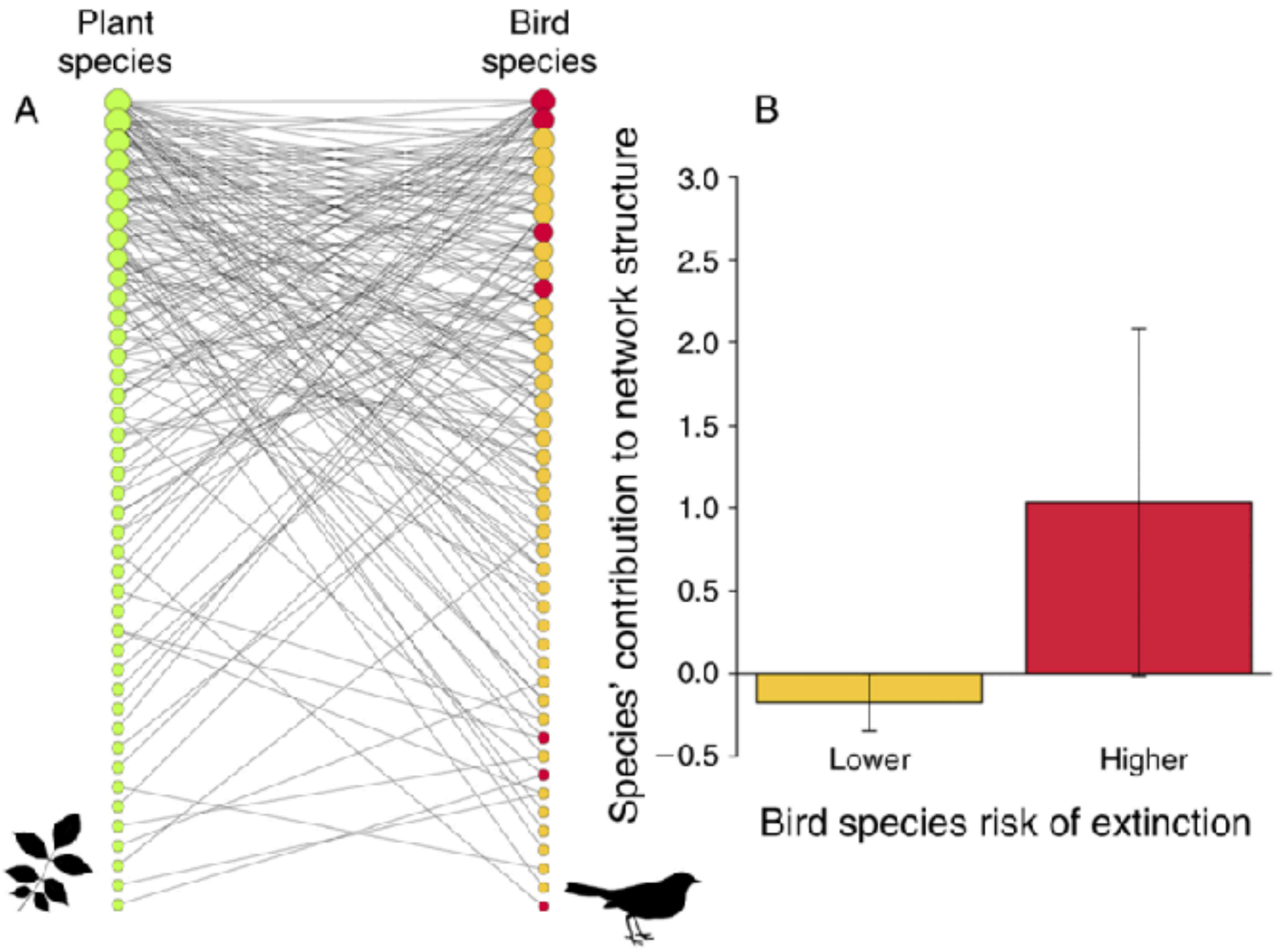


Vidal et al. 2014

Interaction flexibility

Interaction flexibility

Abundance

Interaction flexibility

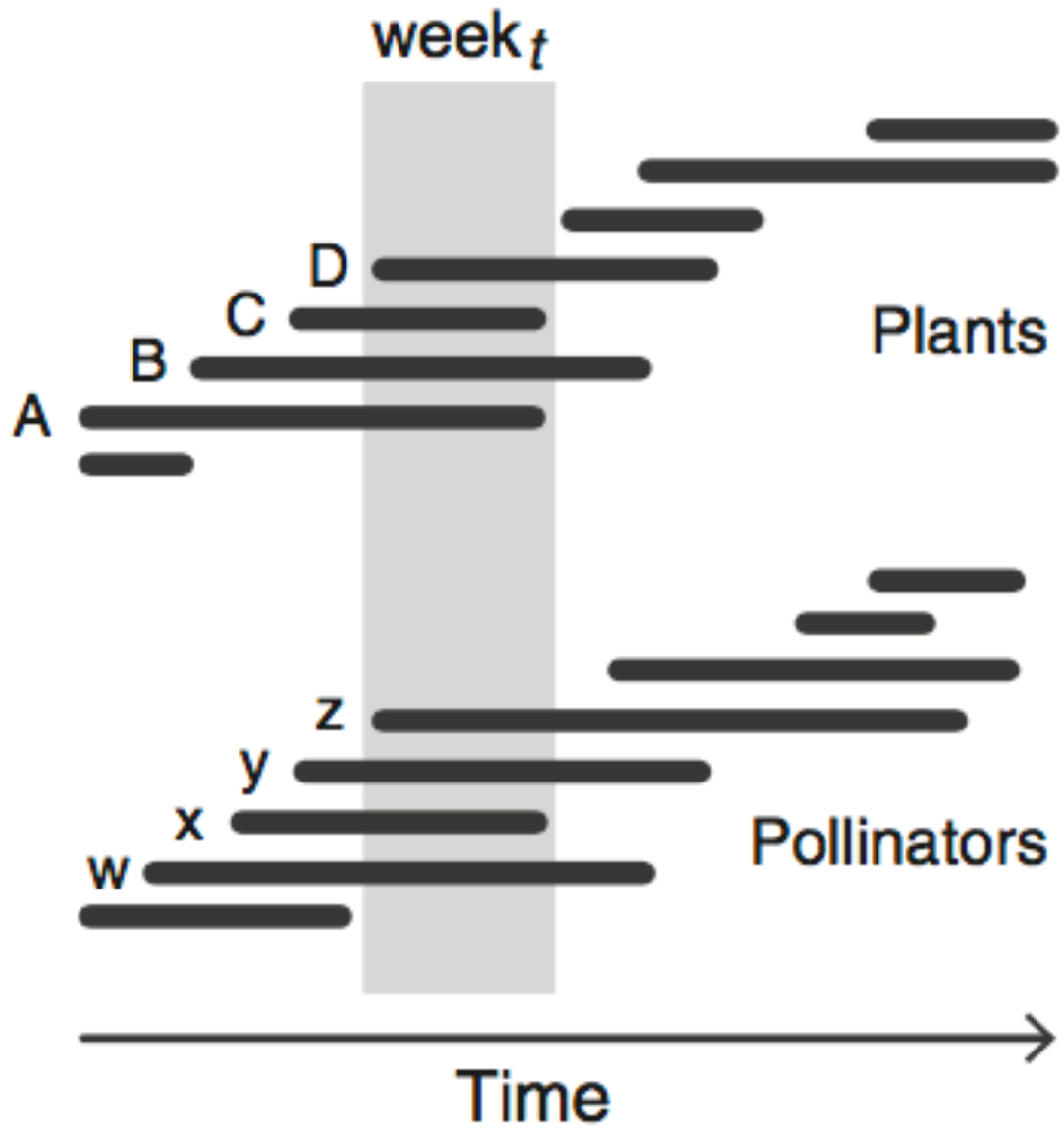
Abundance

Individuals as “samplers”

Interaction flexibility

Abundance

Phenological range



Caradonna et al., 2017

Interaction flexibility

Abundance

Phenological range

Degree


(a)
(d)
(b)
(e)
(c)
(f)

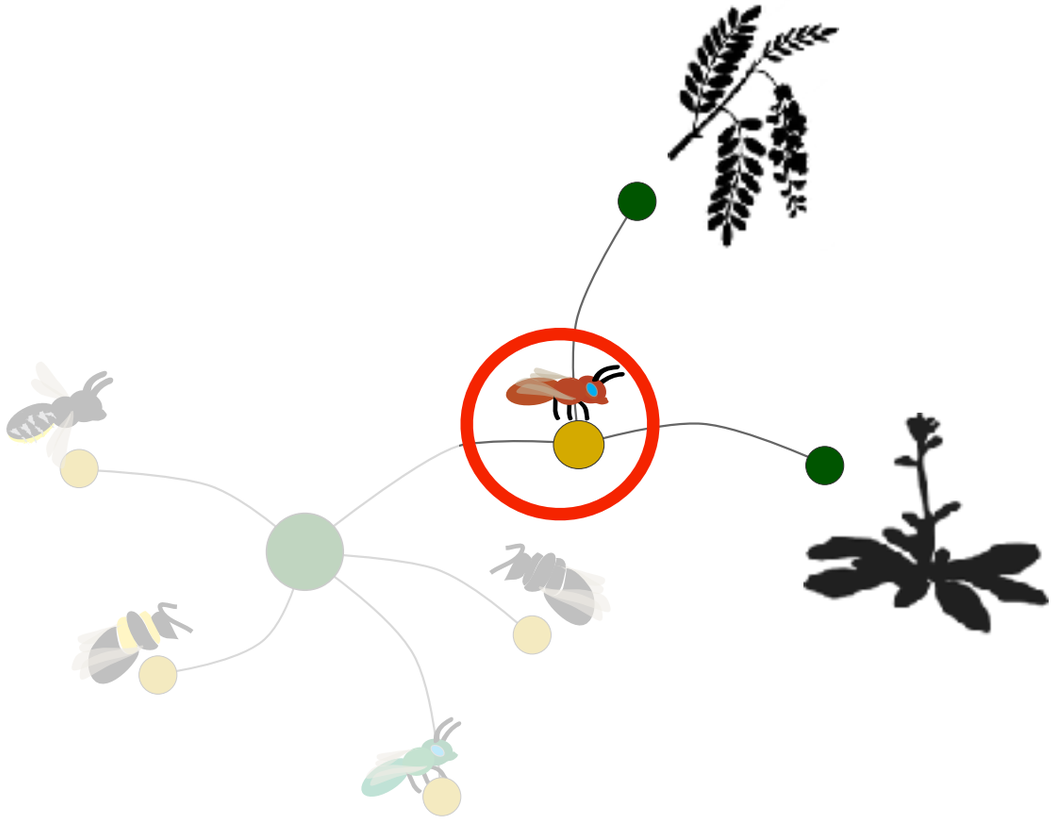
Interaction flexibility

Abundance

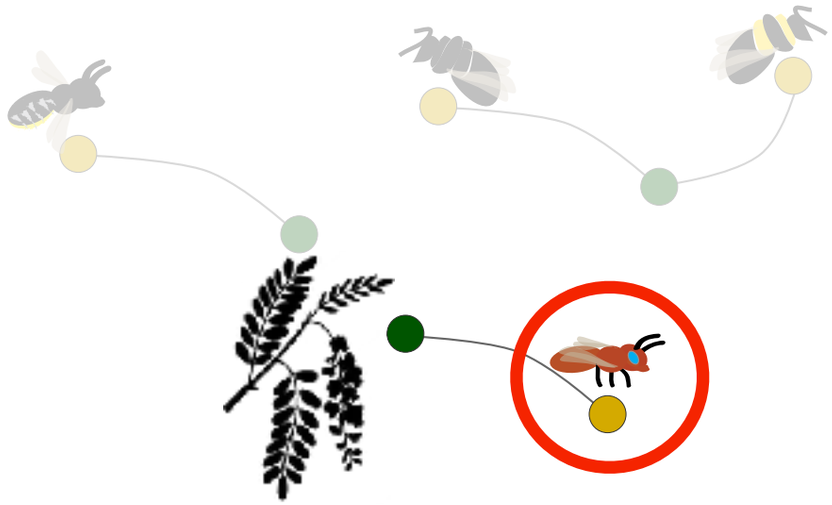
Phenological range

Degree

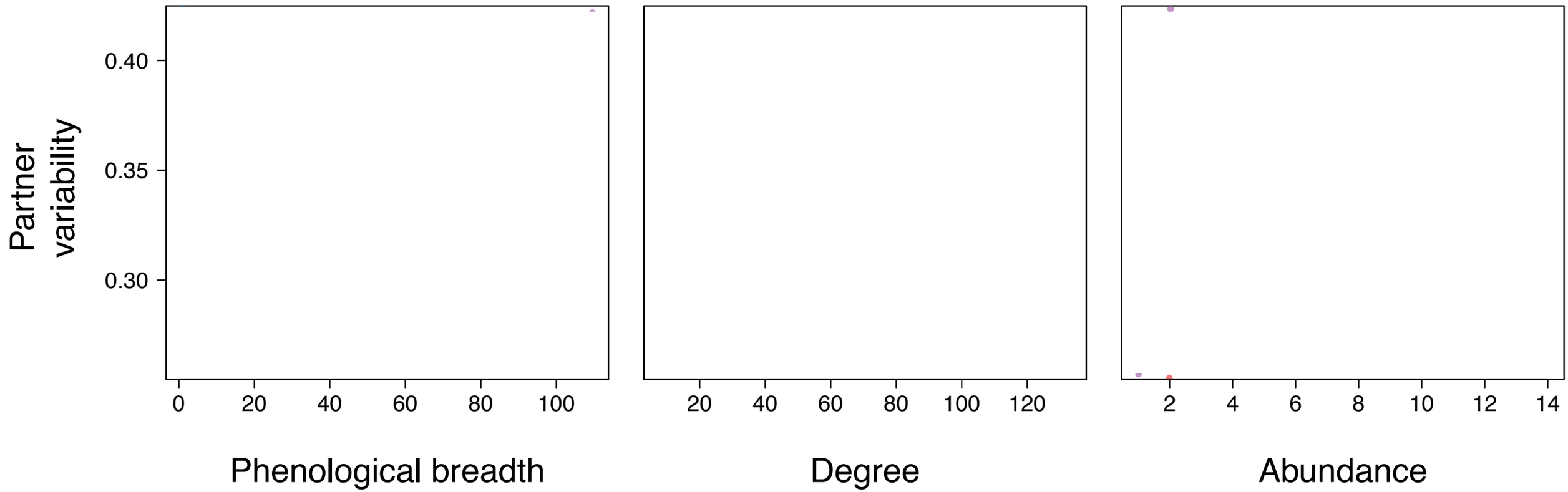
Microscale: who are your partners?

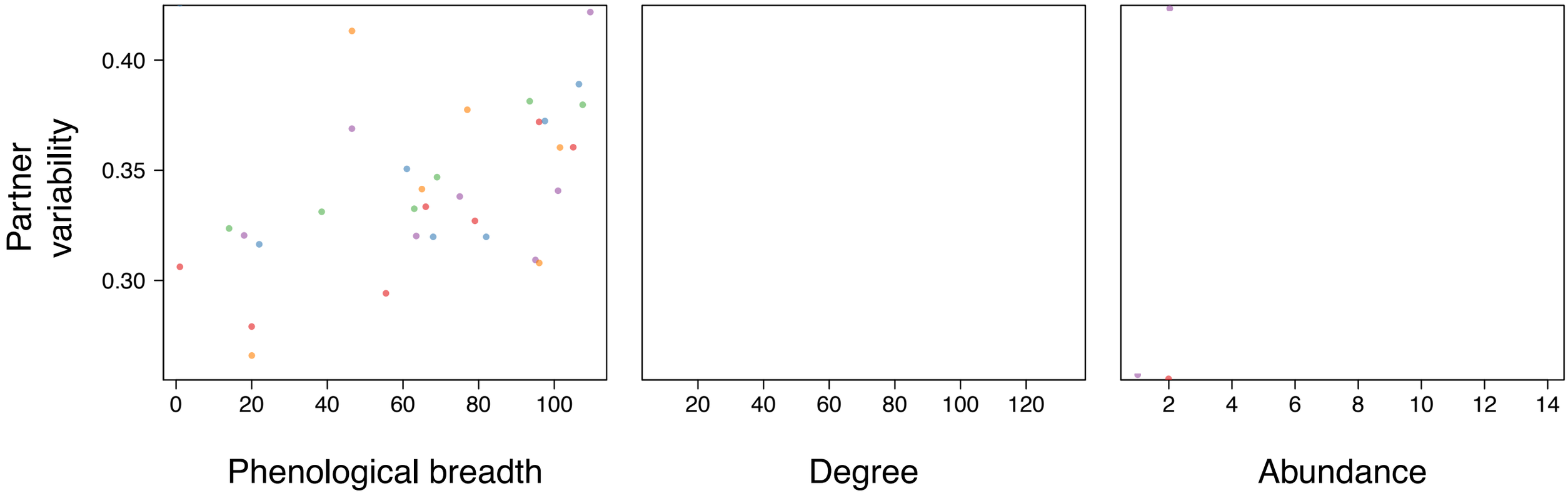


Year 1



Year 2


Partner variability
0.40
0.35
0.30
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
4
6
8
10
12
14
Abundance


Partner variability
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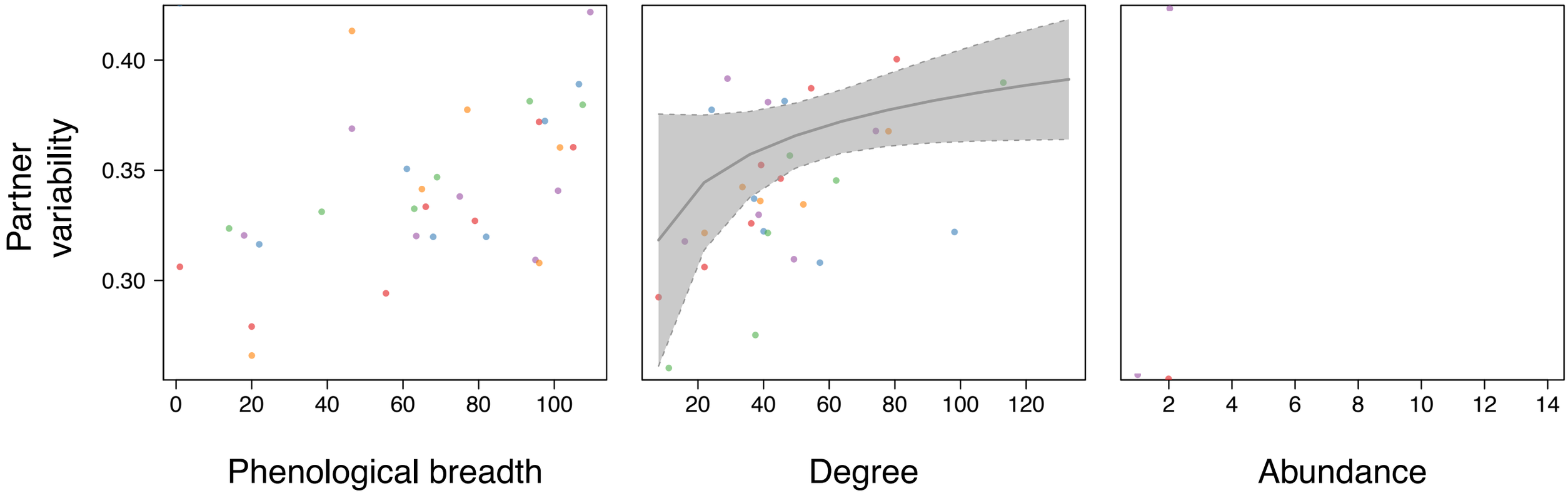
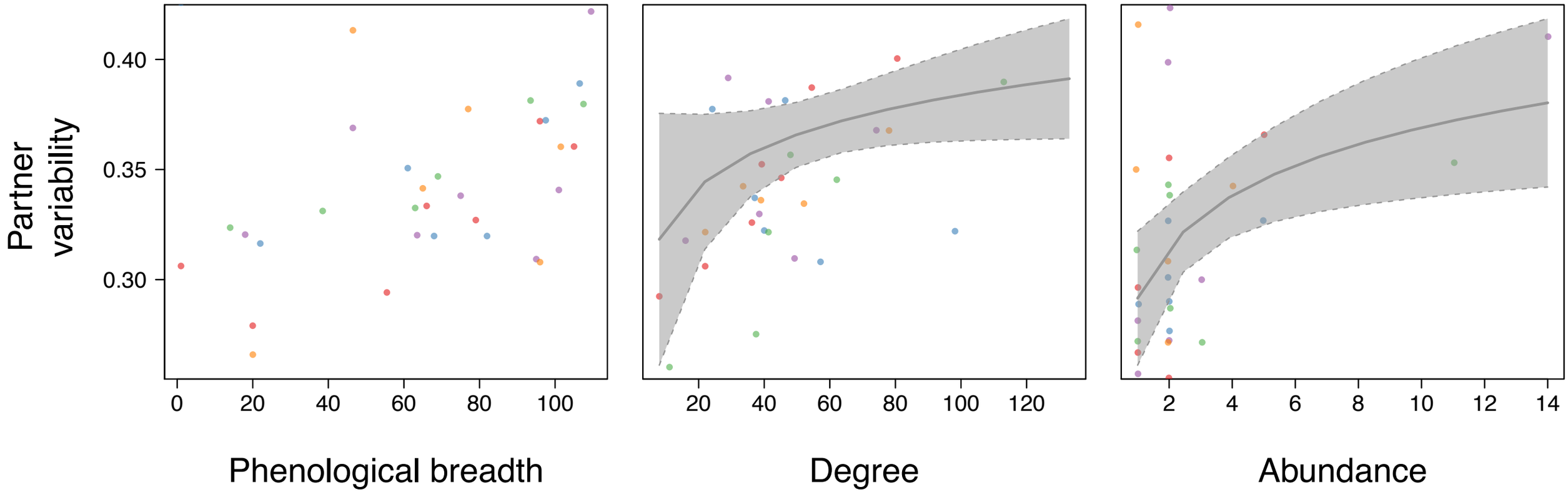
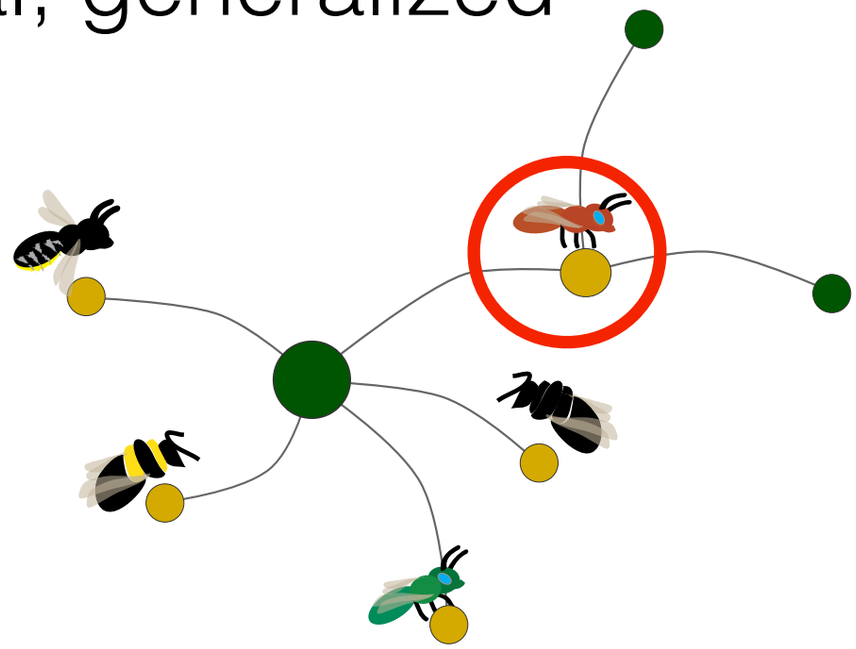
12
14
Abundance


Partner variability
0.40
0.35
0.30
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
4
6
8
10
12
14
Abundance

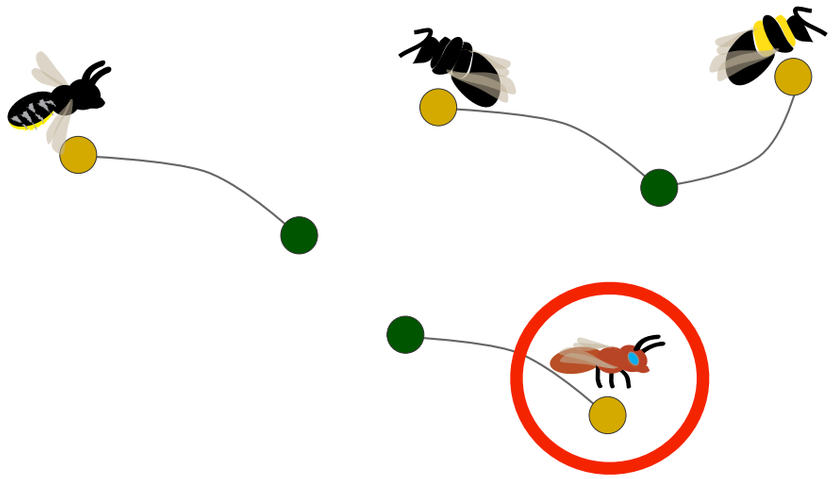

Partner variability
0.40
0.35
0.30
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
4
6
8
10
12
14
Abundance

Mesoscale: what is your network role?

Central, generalized

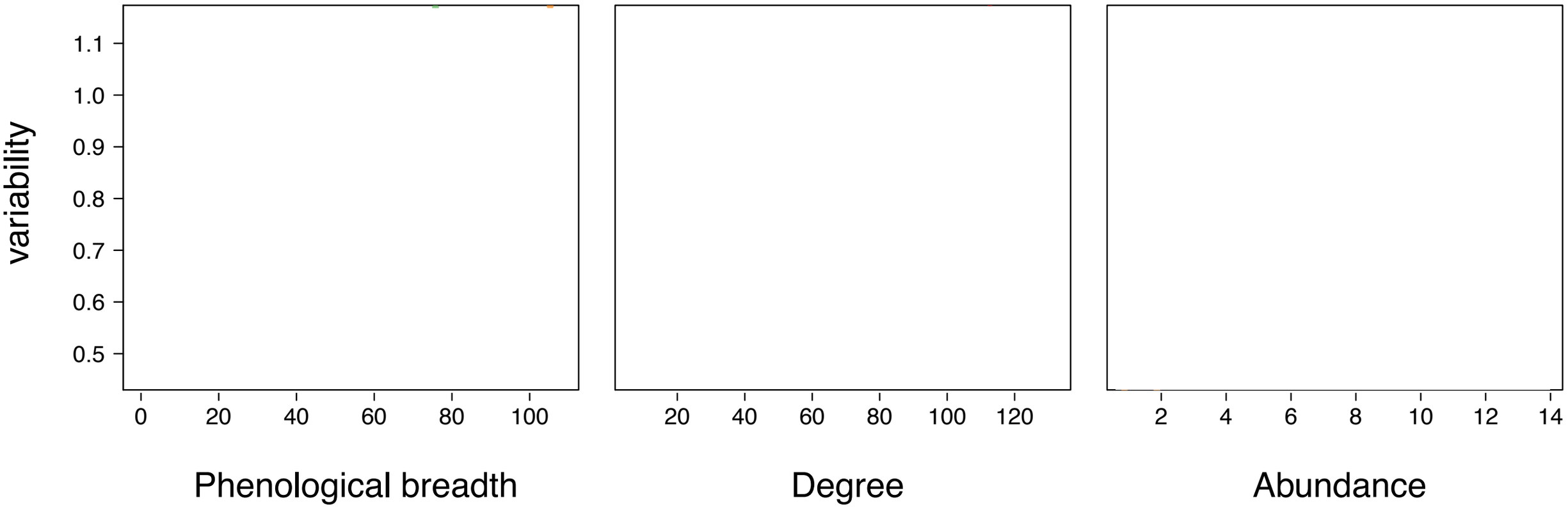


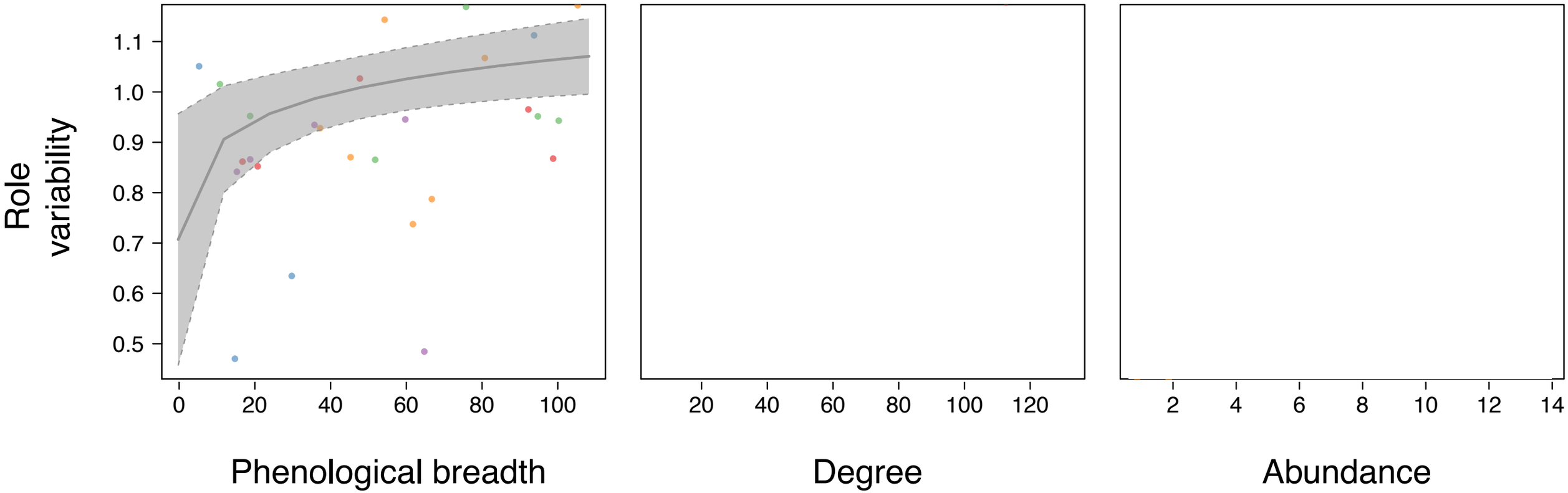
Year 1



Peripheral, specialized

Year 2


Role variability
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
4
6
8
10
12
14
Abundance


Role variability
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0
20
40
60
80
100
Phenological breadth
20
40
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120
Degree
2
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12
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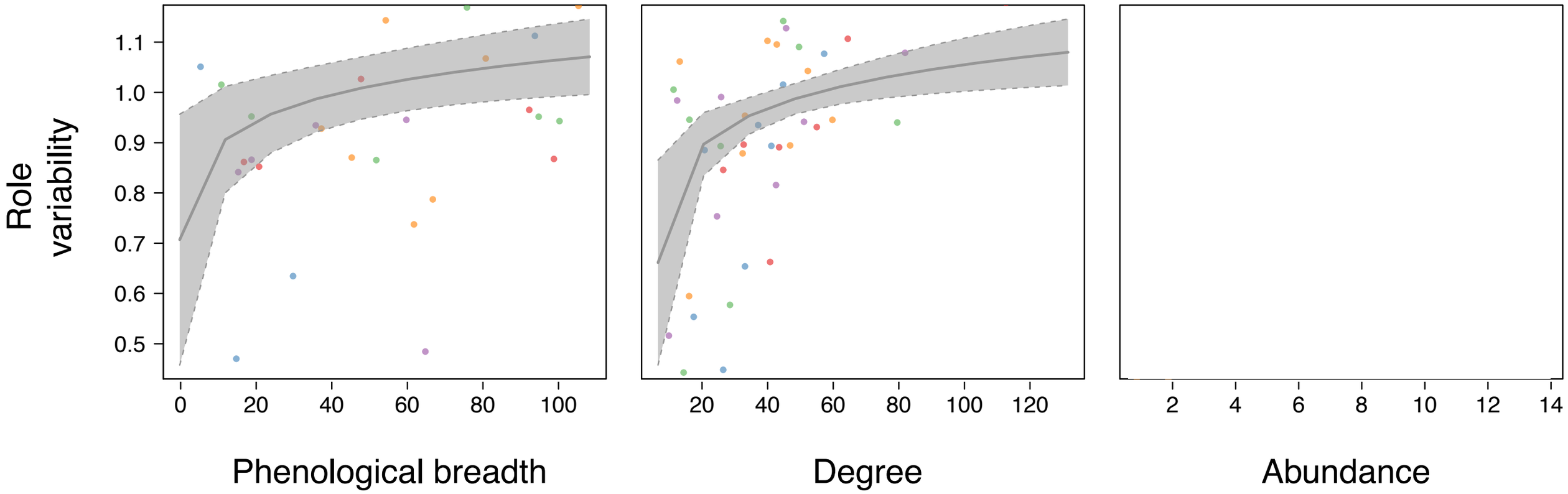
Abundance


Role variability
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0
20
40
60
80
100
Phenological breadth
20
40
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100
120
Degree
2
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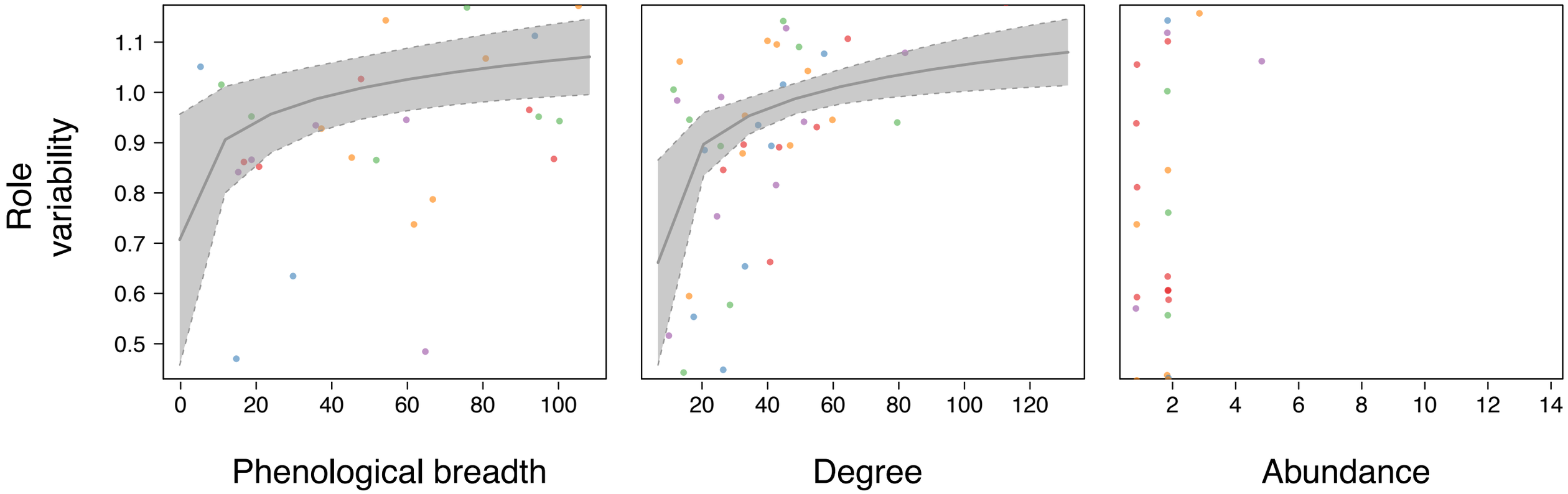
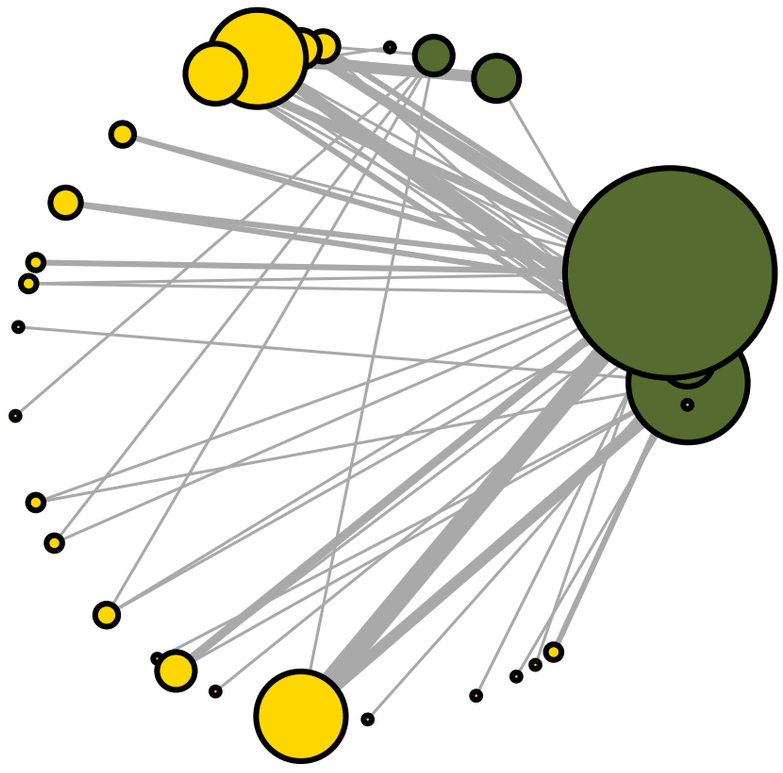
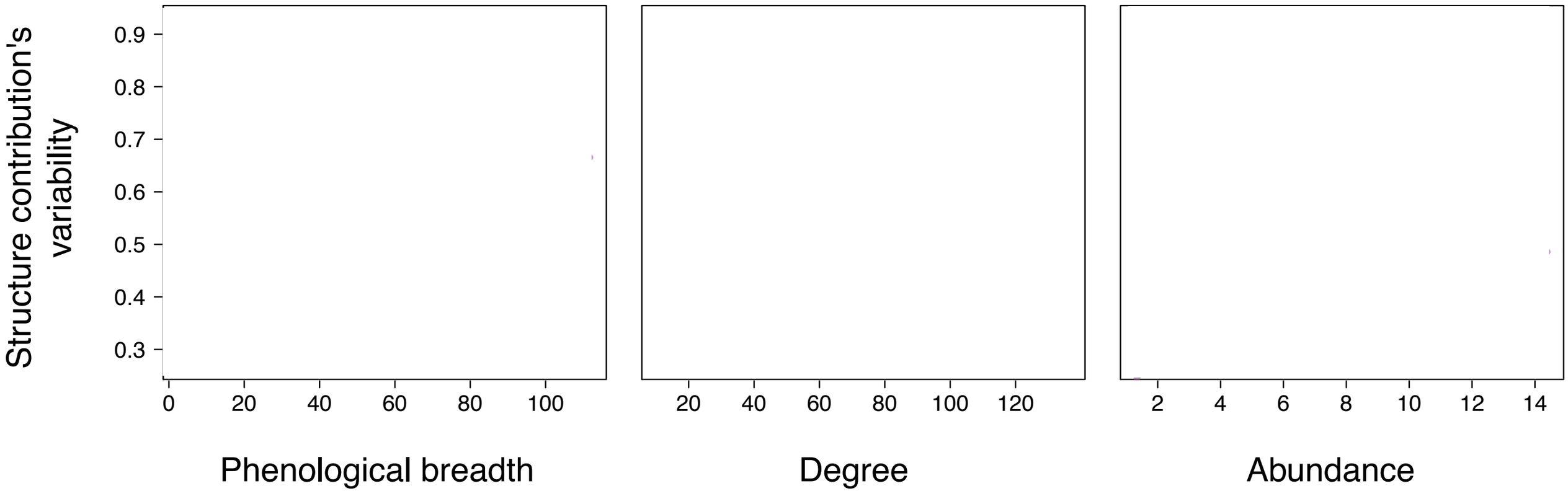
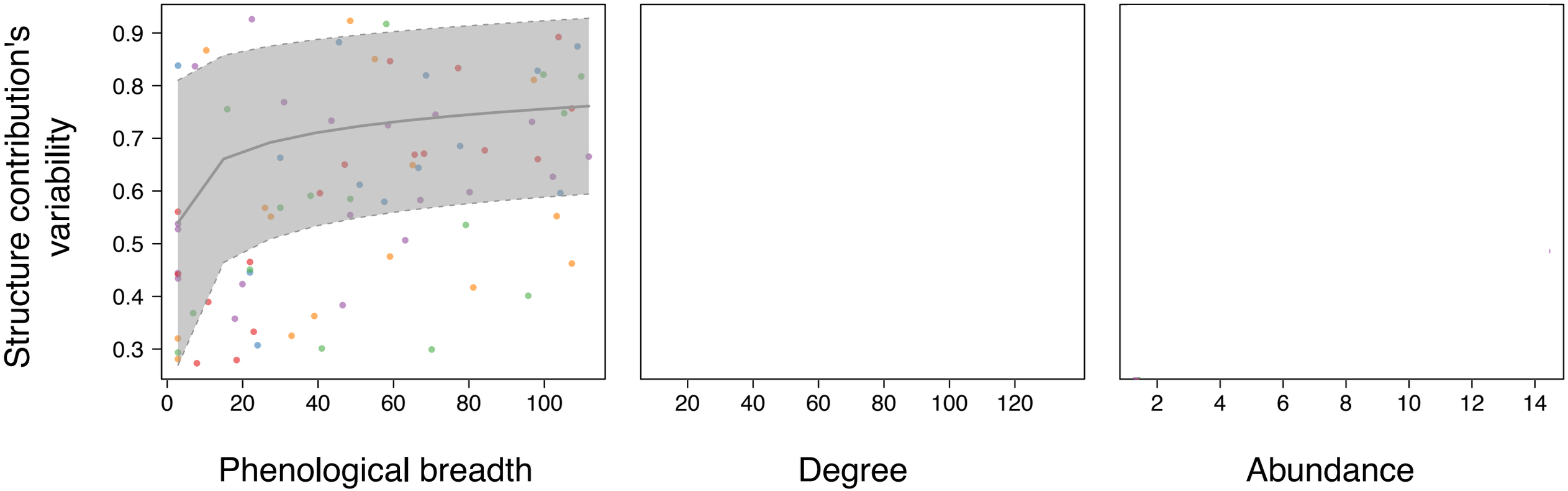
12
14
Abundance

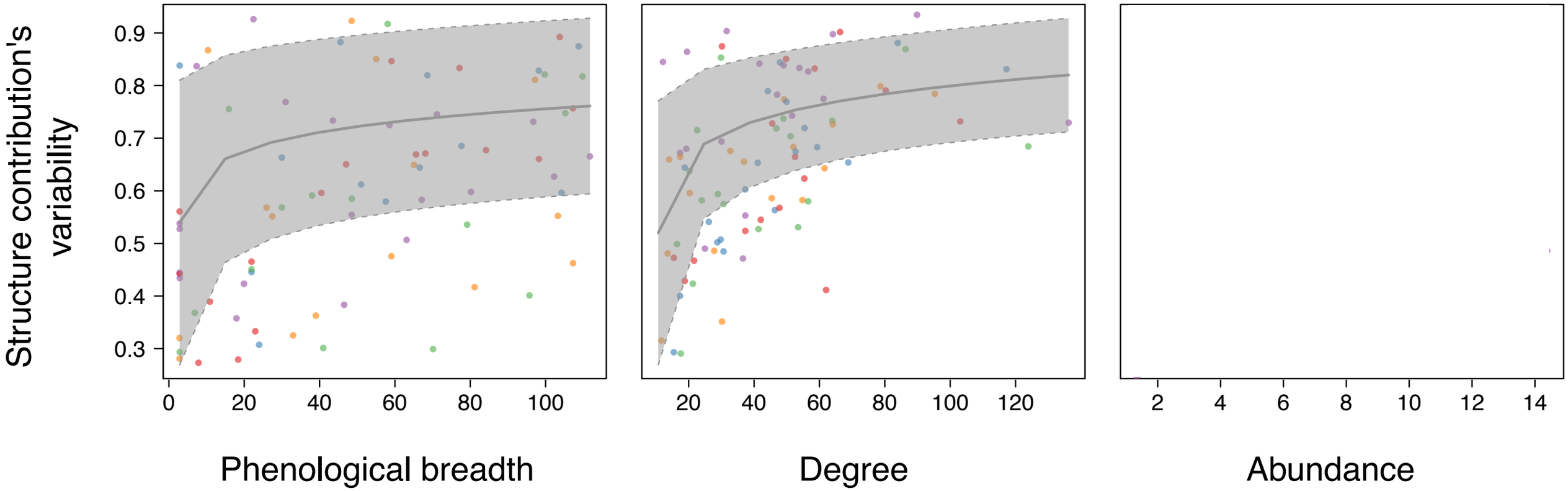

Role variability
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
4
6
8
10
12
14
Abundance

Macroscale: what is your contribution to network organization?




Structure contribution's variability
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
4
6
8
10
12
14
Abundance


Structure contribution's variability
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
4
6
8
10
12
14
Abundance


Structure contribution's variability
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
20
40
60
80
100
Phenological breadth
20
40
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100
120
Degree
2
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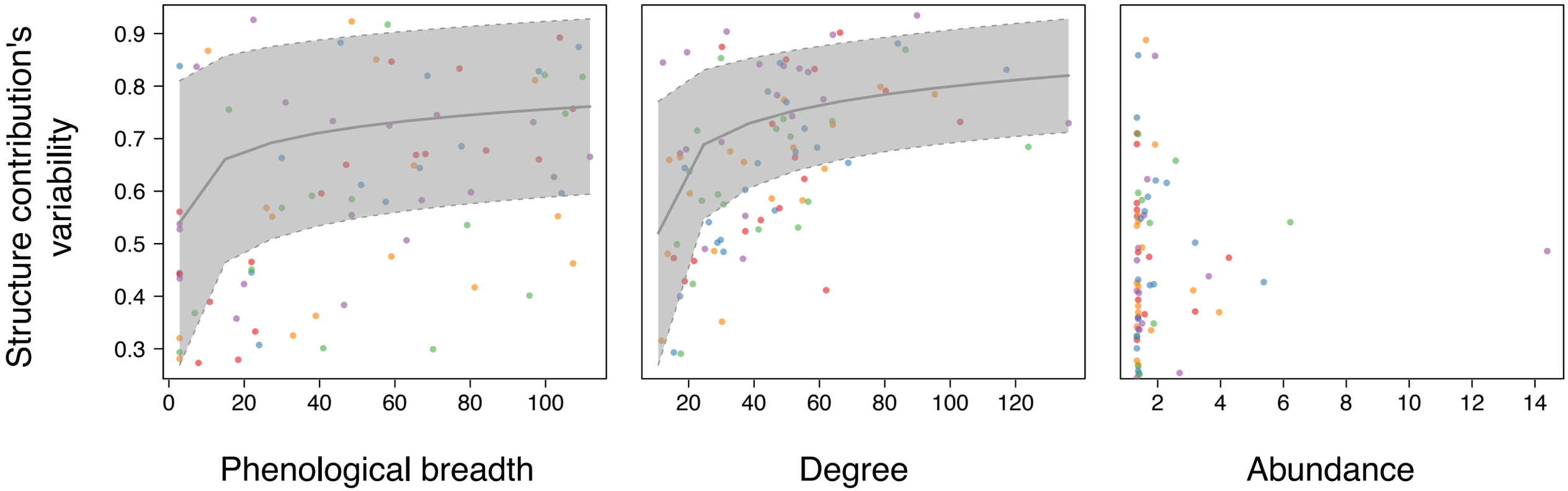
10
12
14
Abundance


Structure contribution's variability
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
20
40
60
80
100
Phenological breadth
20
40
60
80
100
120
Degree
2
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6
8
10
12
14
Abundance

Structure contribution's variability

Role variability

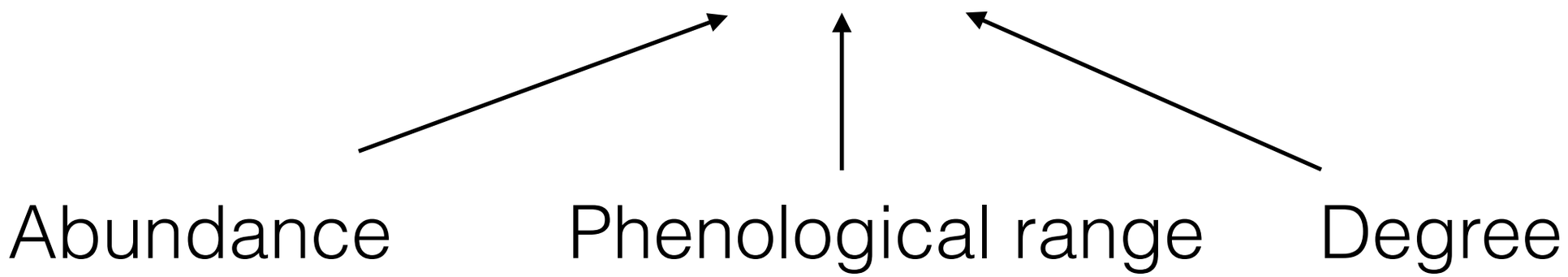
Partner variability

Phenological breadth

Degree

Abundance

Interaction flexibility



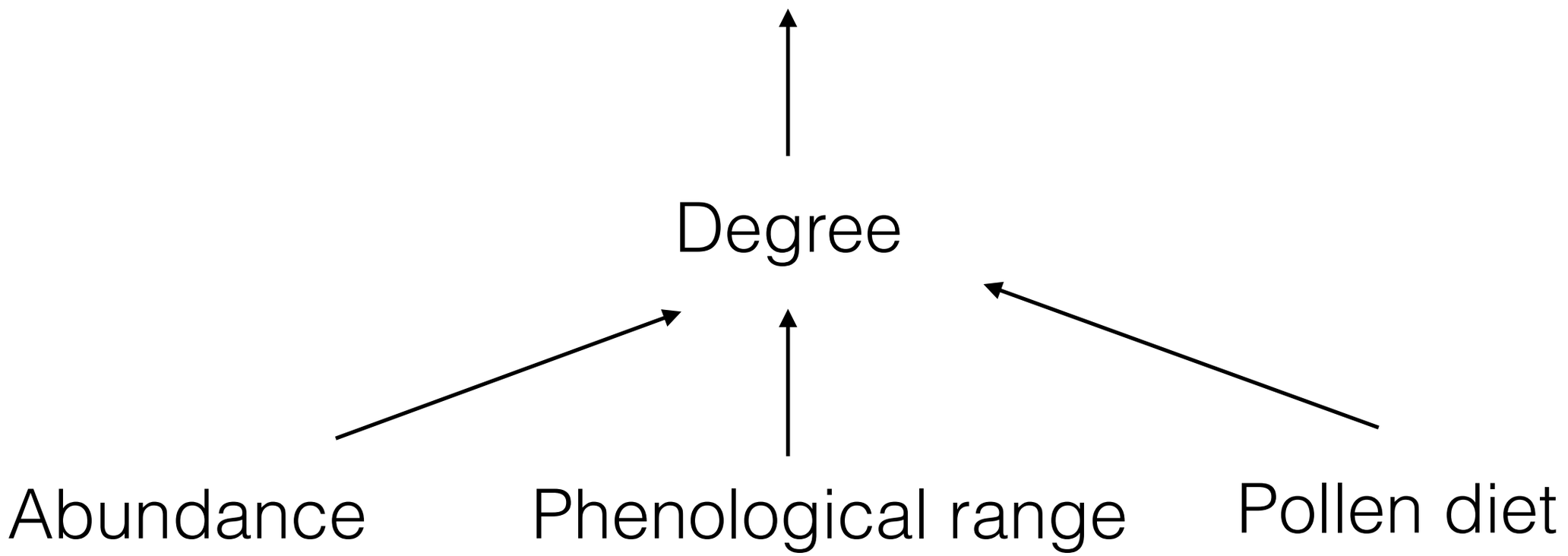
Interaction flexibility

Degree

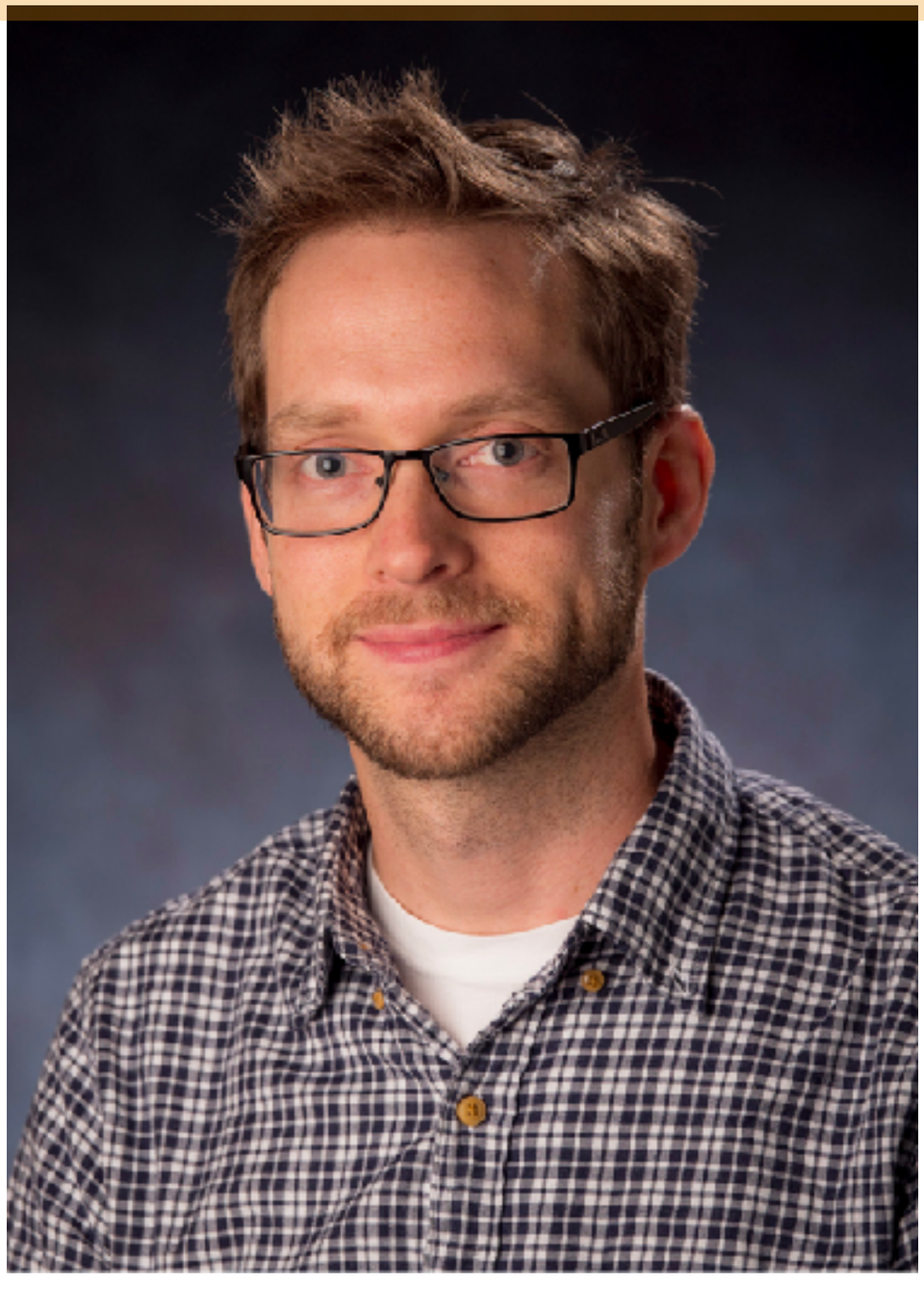
Abundance

Phenological range

Interaction flexibility



What’s next?



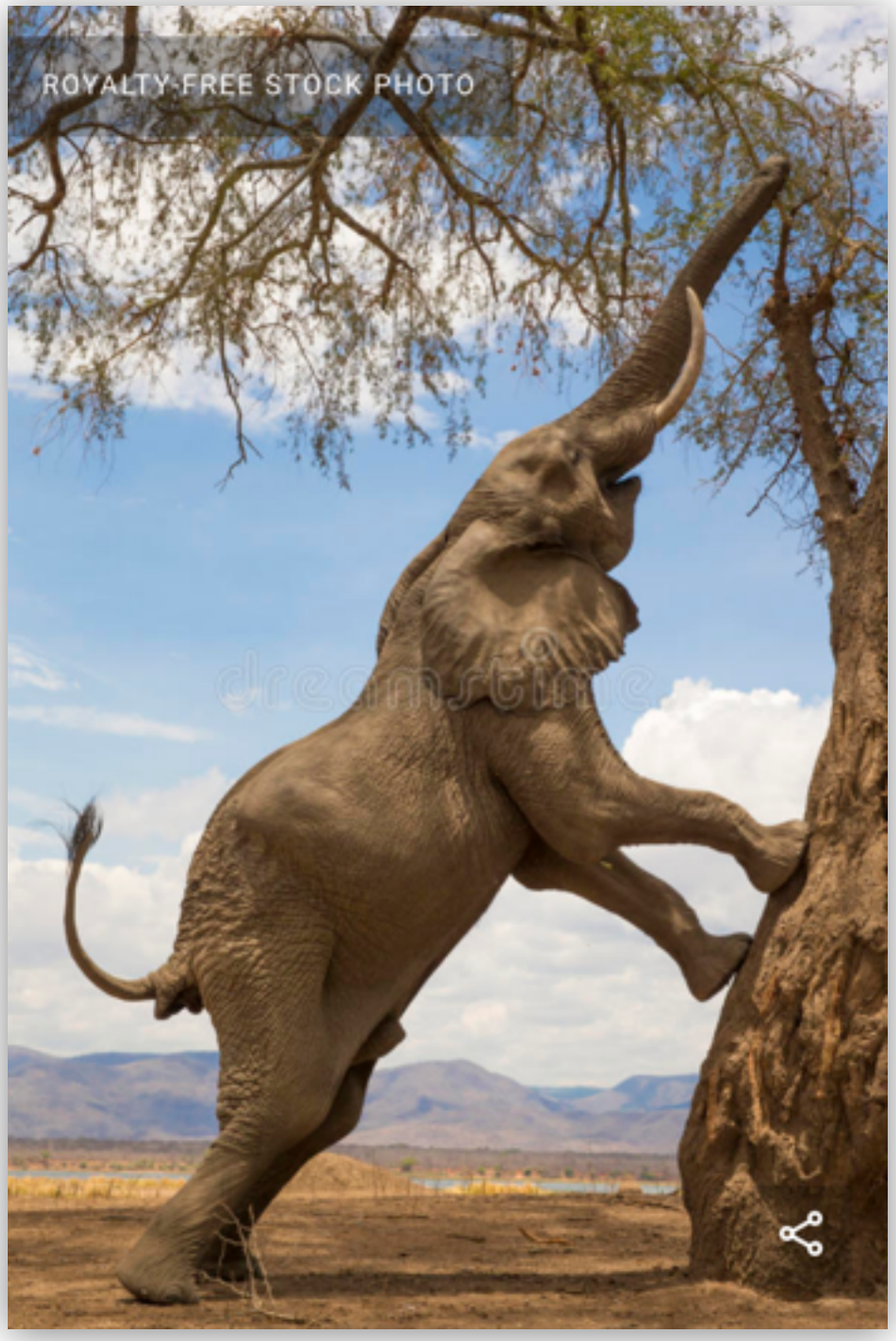
What’s next?

More data!!

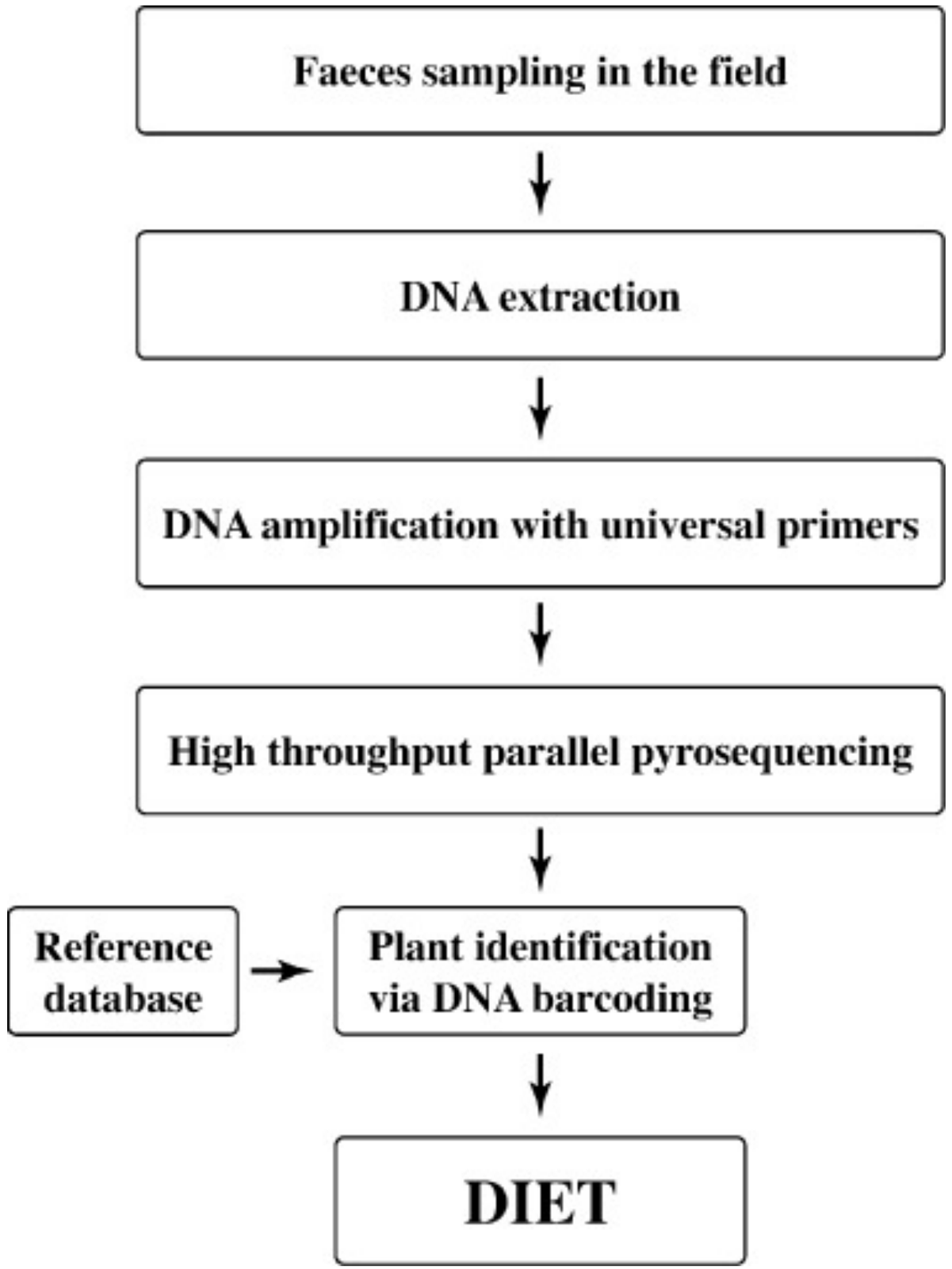
What's next?

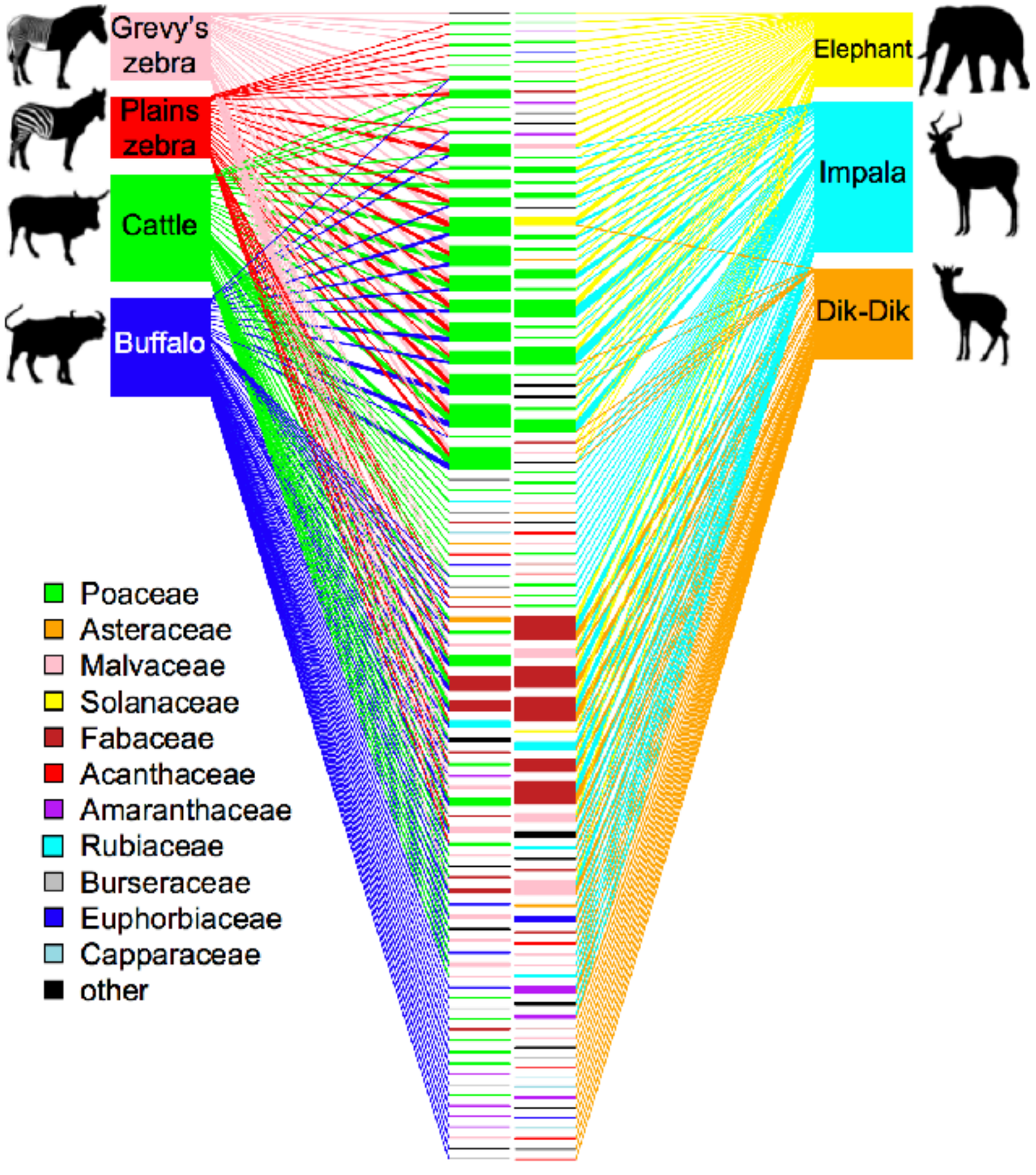
More data!!

POLICE PUBLIC BOX


ROYALTY-FREE STOCK PHOTO


M.C. Hutchinson


Faeces sampling in the field
DNA extraction
DNA amplification with universal primers
High throughput parallel pyrosequencing
Reference database
Plant identification via DNA barcoding
DIET

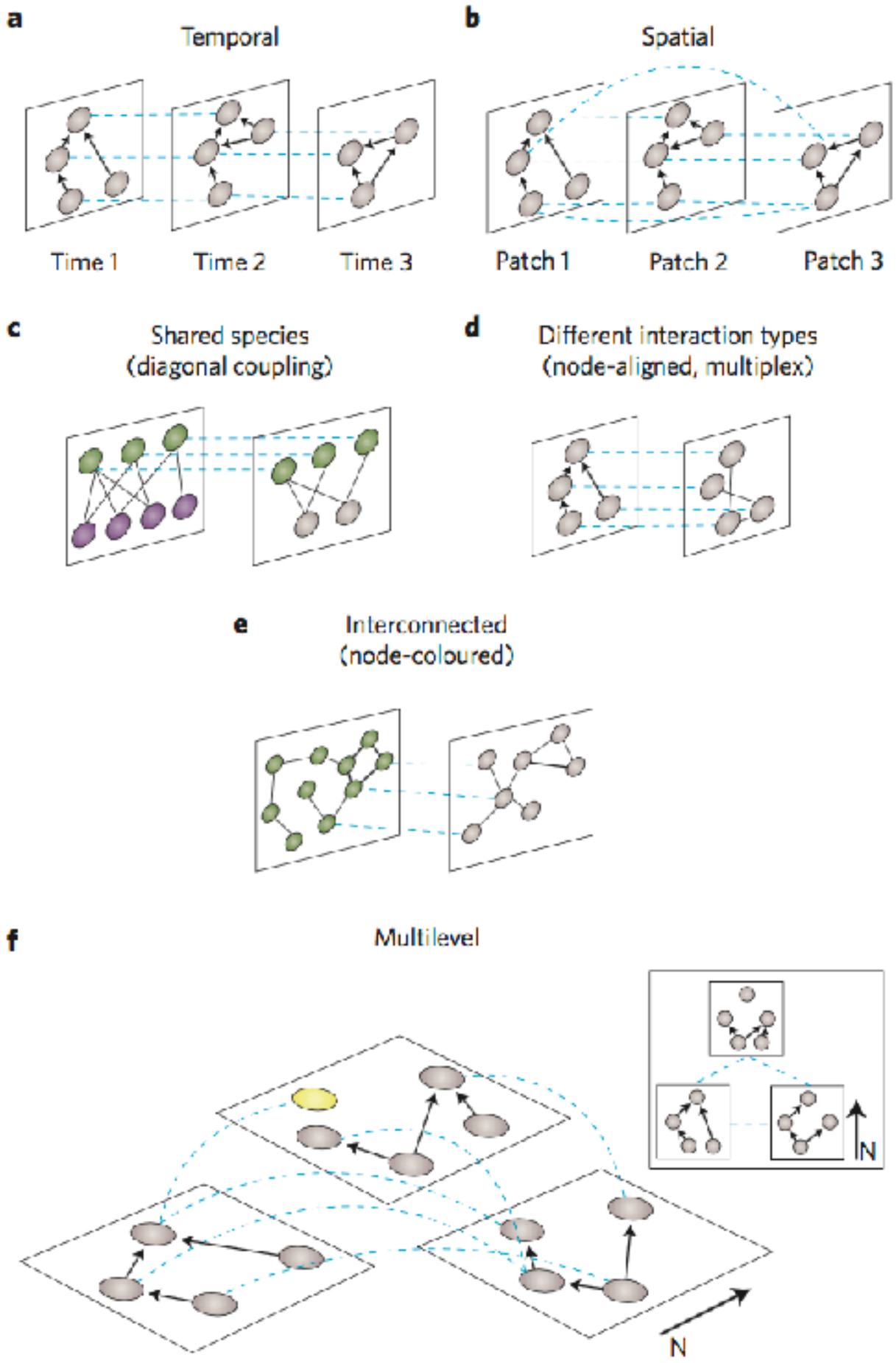


Kartzinel et al. 2015

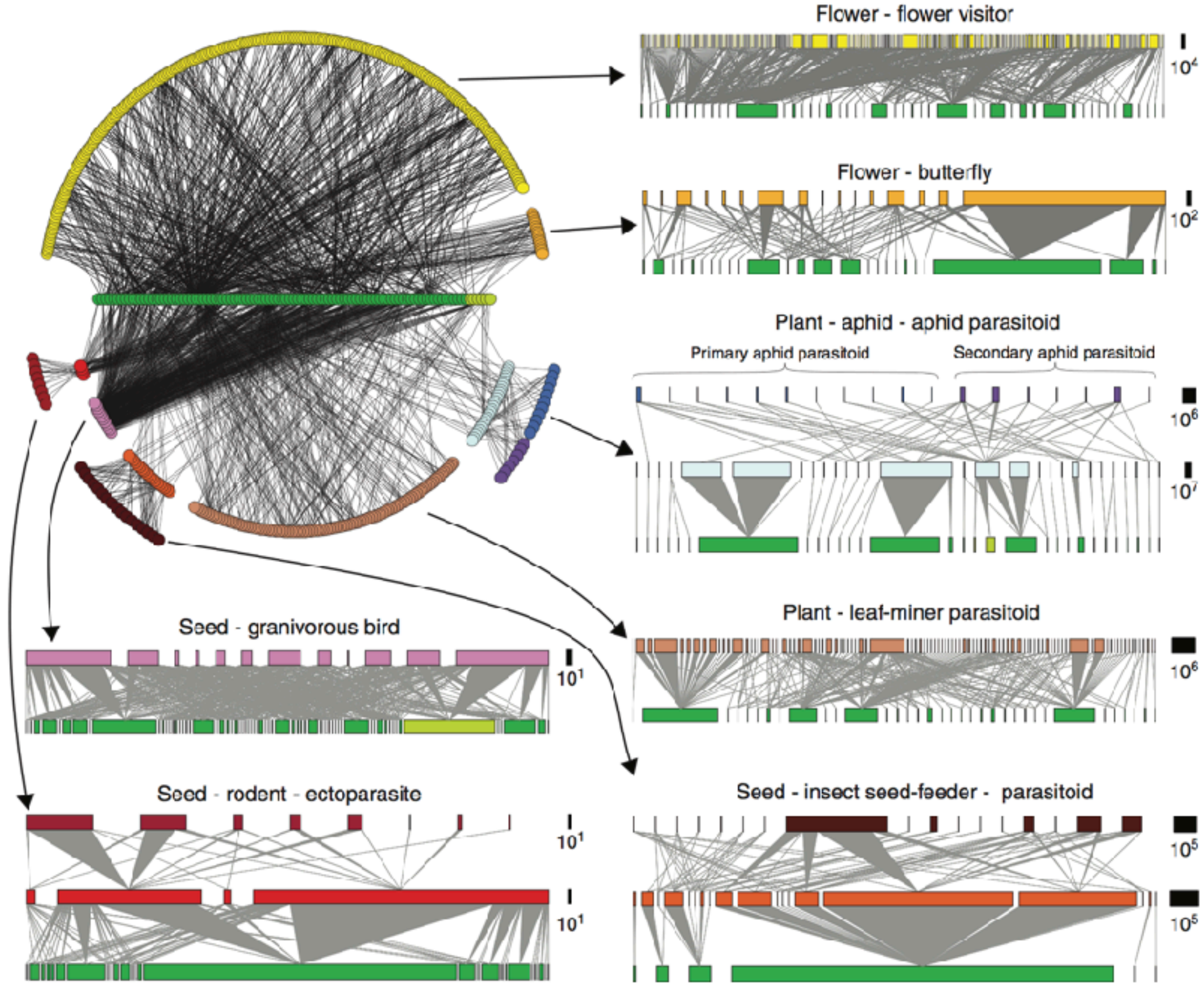
What’s next?

What's next?

Multilayer networks



Pilosof et al. 2017



Pocock et al. 2012

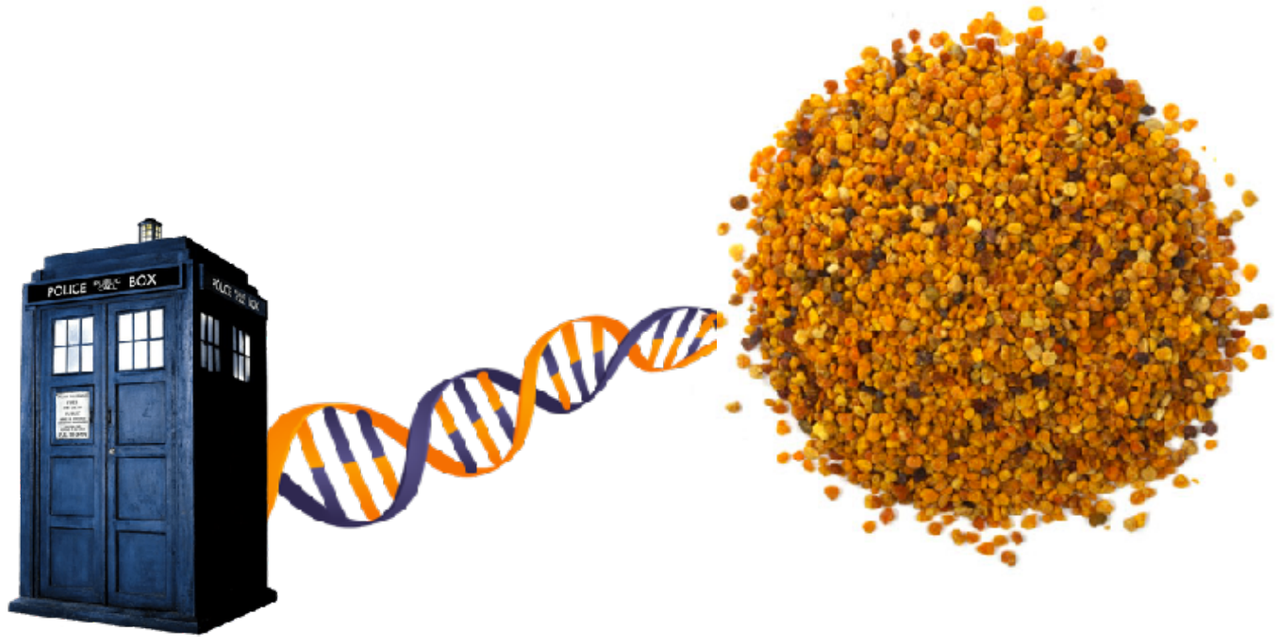
What’s next?

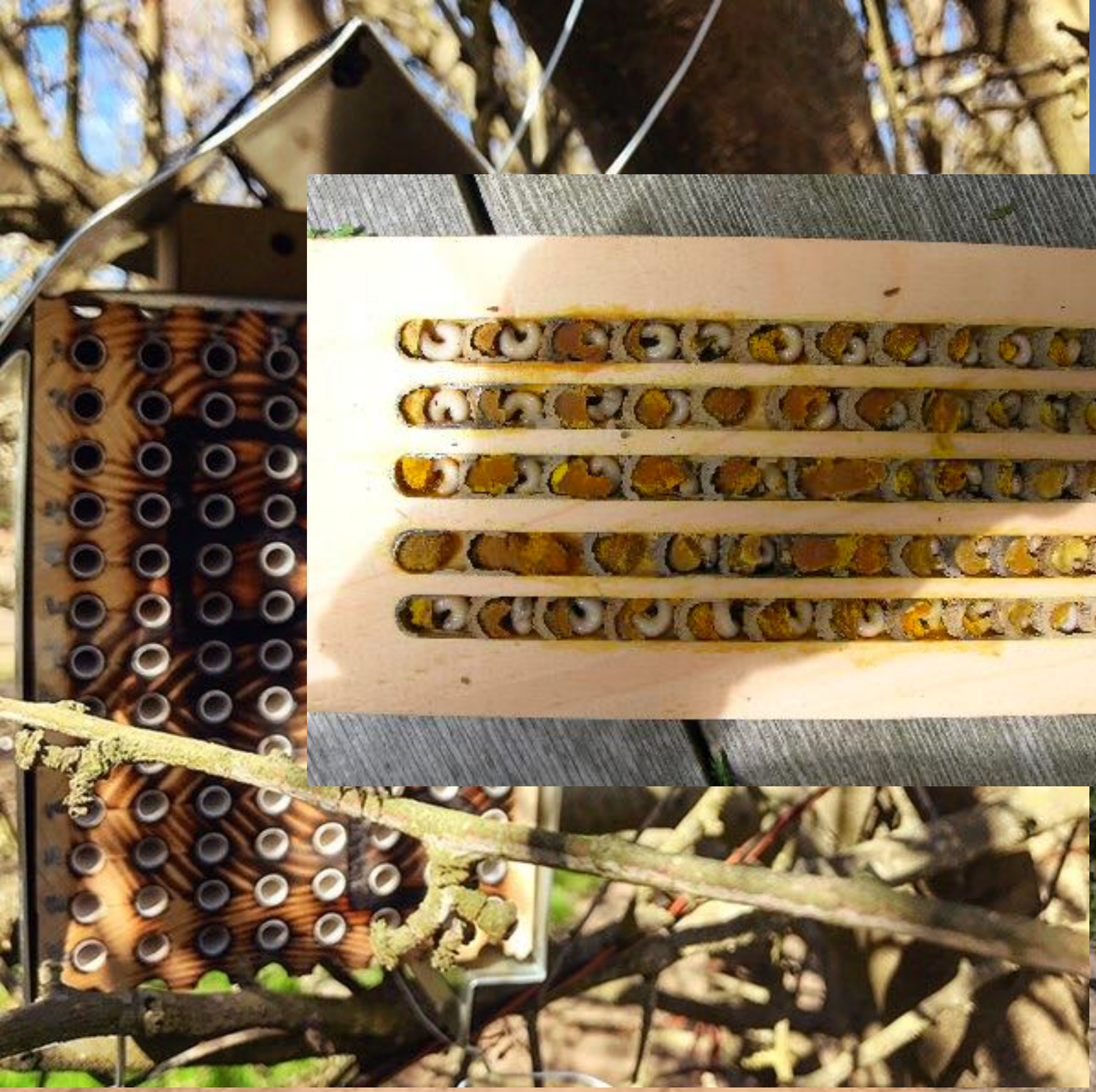
Meta-data

What's next?

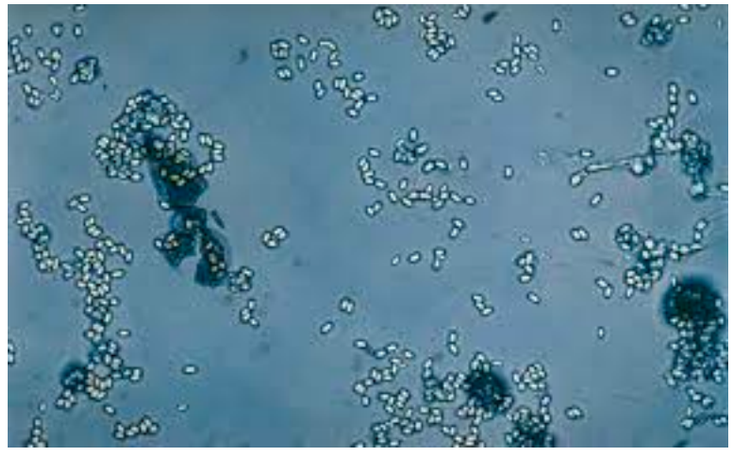
Meta-data

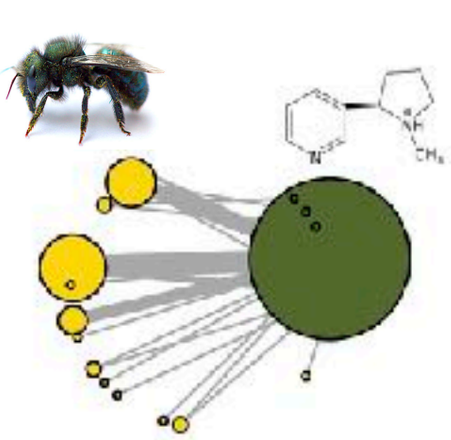
interaction frequency, strength, character, outcome, etc



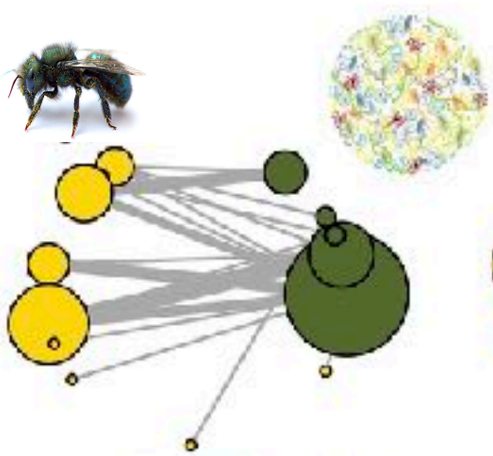



MUSCLE
MILK

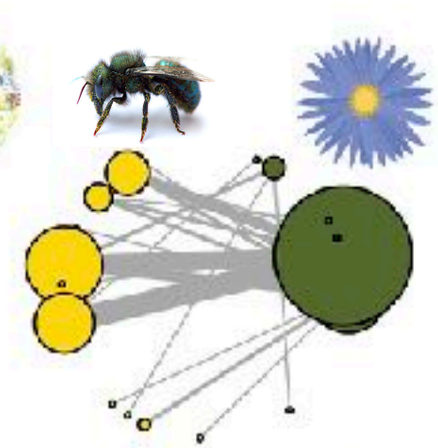




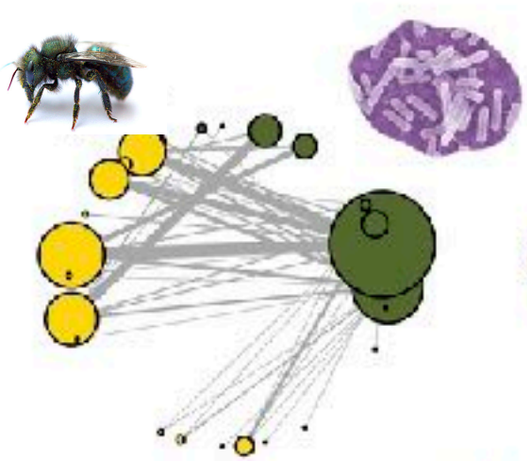
Pollinator-Pesticide



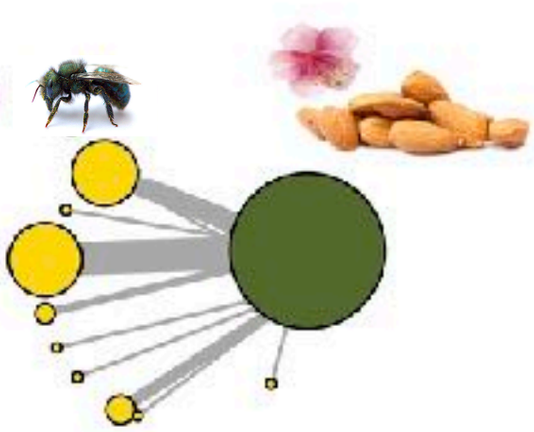
Pollinator-Parasite



Pollinator-Plant



Pollinator-Gut microbe



Almond pollination

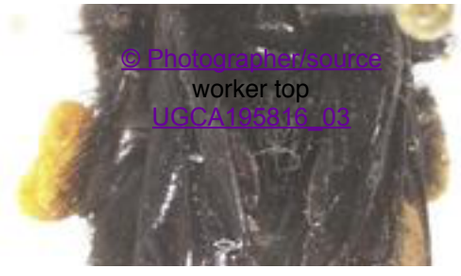
But…

The hardest part of all of this is identifying the individuals to species….

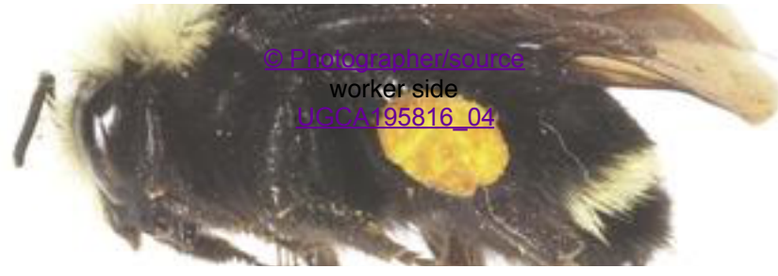

SIMMS

© Photographer/source
worker front
UGCA195816_01

© Photographer/source
worker front top
UGCA195816_02



© Photographer/source
worker top
UGCA195816_03

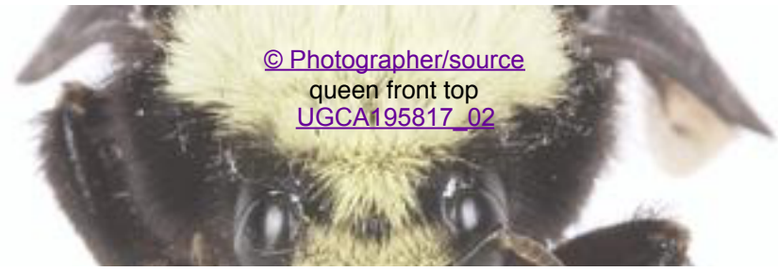


© Photographer/source
worker side
UGCA195816_04

© Photographer/source
worker rear
UGCA195816_05

© Photographer/source
worker rear tip
UGCA195816_06

© Photographer/source
queen front
UGCA195817_01



© Photographer/source
queen front top
UGCA195817_02

www.ponisiolab.com

Thank you!

Networks + ecology and evolution

1. Moving past summarizing networks with metrics
2.Possibilities to look at change through time
- change point analysis
3. Soon:
    - more data due to new sequencing technologies
    - more data due to image recognition (right Stefan?)
    - Combine different types of networks
    - Incorporate meta data