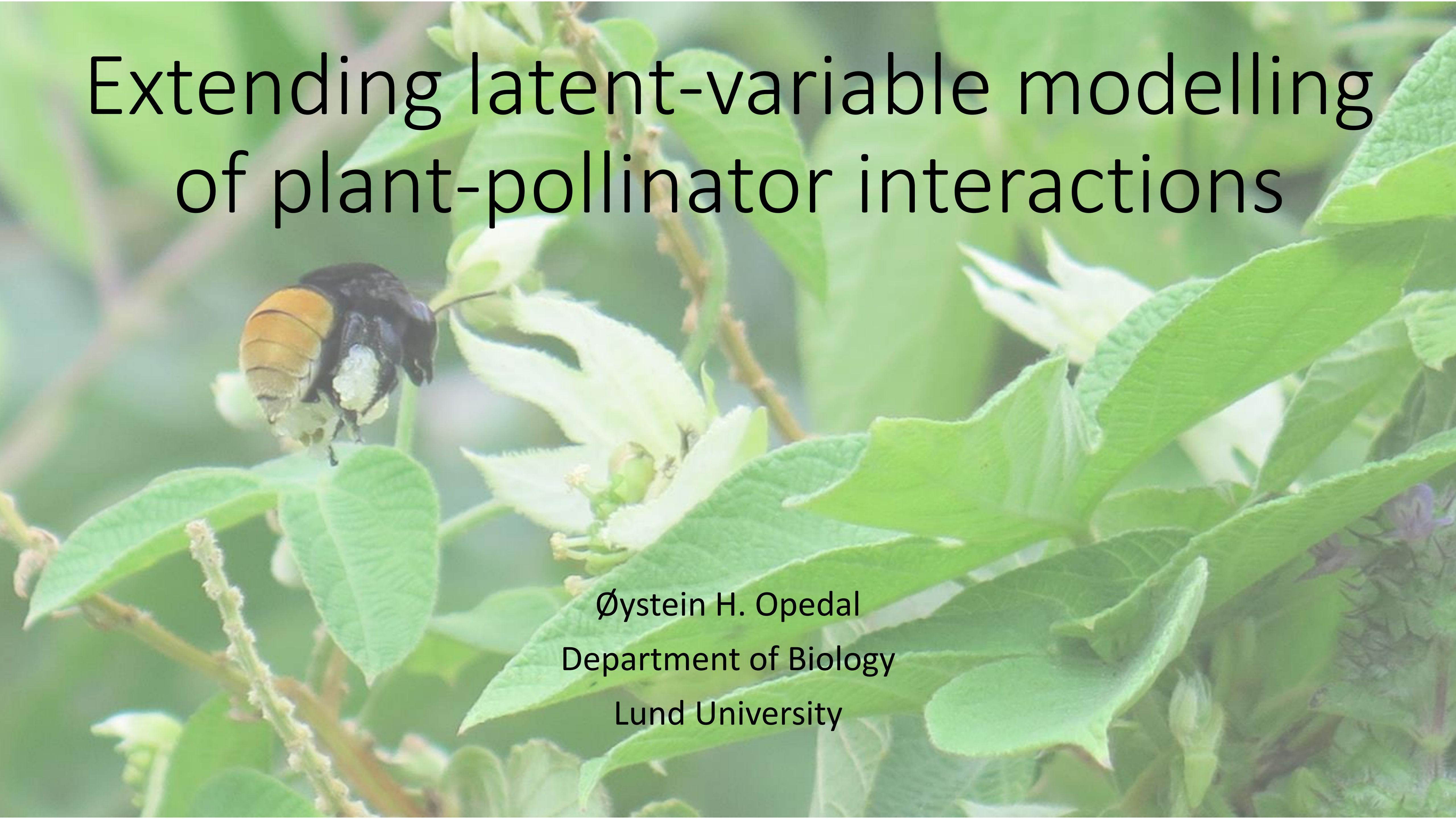
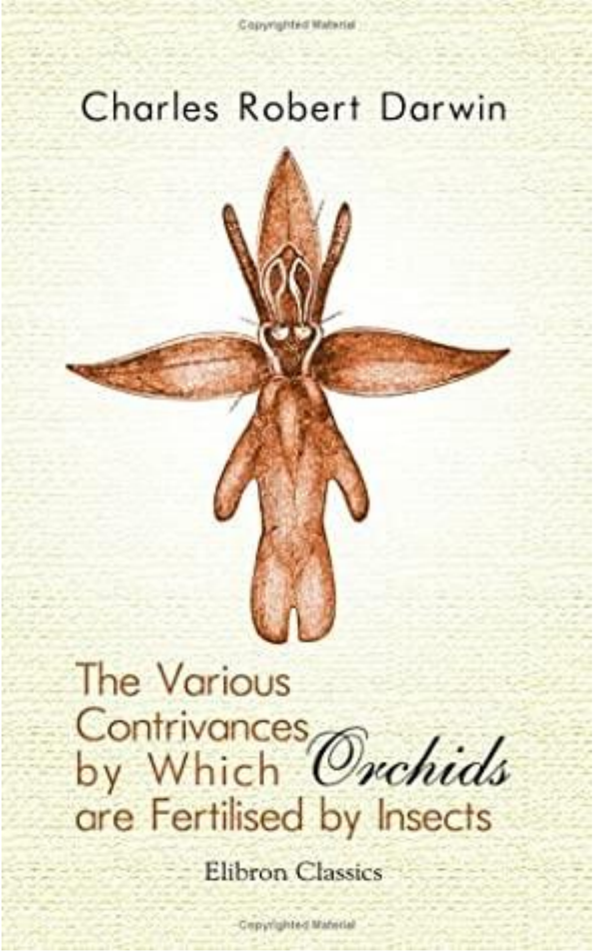


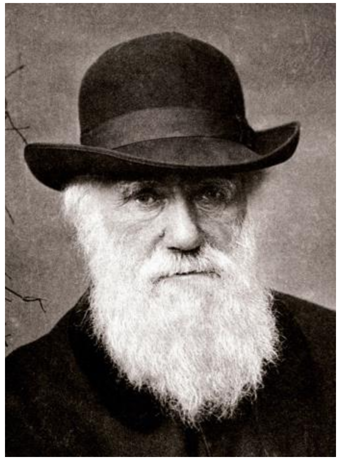
Extending latent-variable modelling of plant-pollinator interactions

Øystein H. Opedal
Department of Biology
Lund University

The study of floral evolution: Darwin’s ‘flank movement on the enemy’

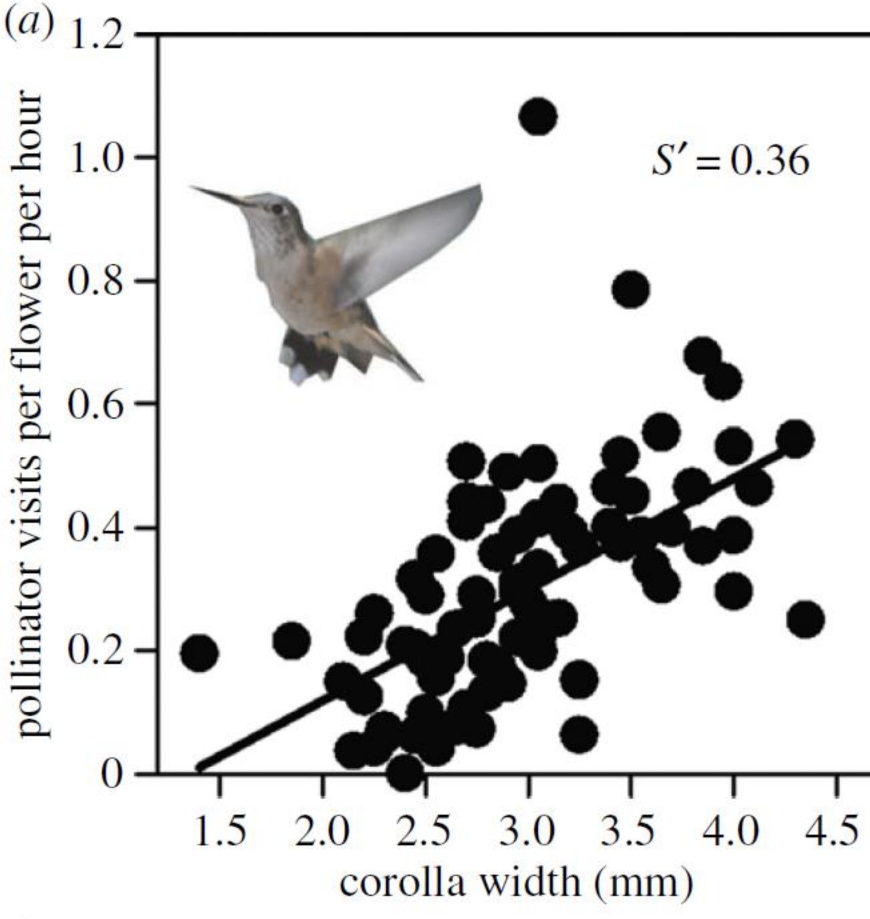
- ‘no one else has perceived that my chief interest in my orchid book, has been that it was a “flank movement” on the enemy’ (Darwin to Asa Gray, July 23rd 1862)
- ‘If you grant an intelligent designer anywhere in Nature, you may be confident that he has had something to do with the “contrivances” in your Orchids.’ (Gray to Darwin, July 2nd 1862)





Measuring Natural Selection

- Positive (or negative) relationship between a trait and a fitness component
- Pollinator-mediated selection arise when pollinators prefer some flowers over others, or when floral traits affect the efficiency of pollen transfer

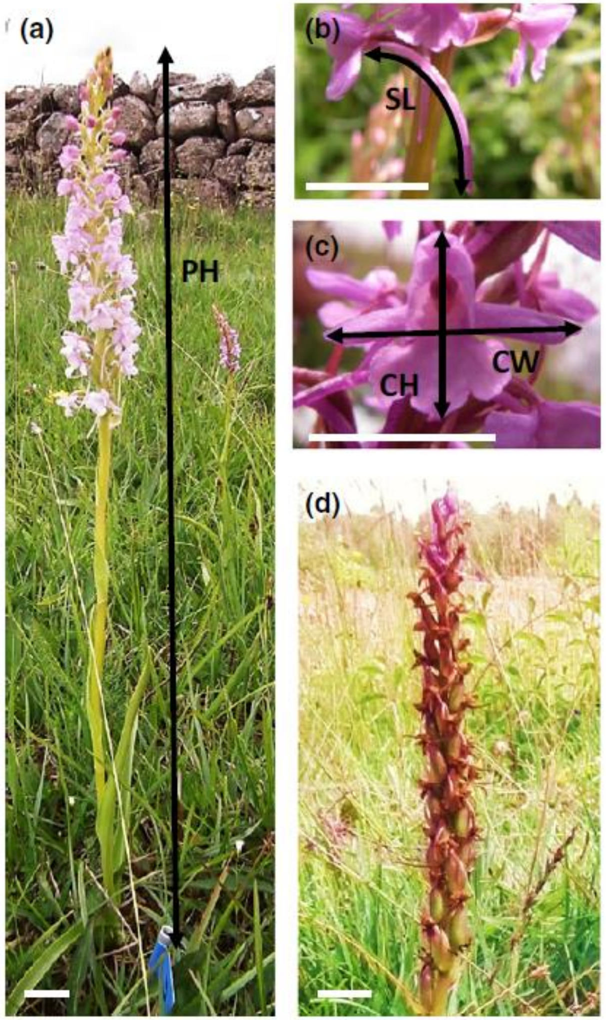


Campbell & Powers 2015 PRS

Traits are not independent

- To account for (measured) correlated traits, linear selection gradients are estimated as the partial regression coefficients of relative fitness on a set of traits.
- Relative fitness =

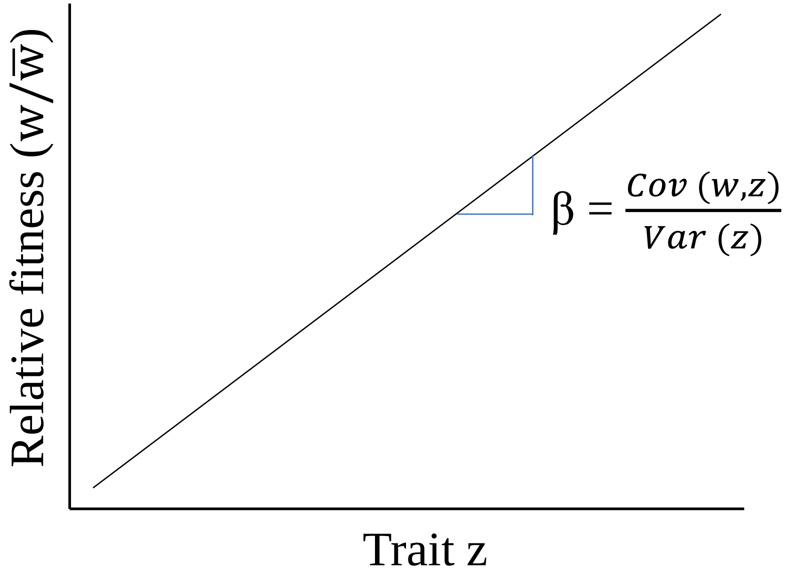
  individual fitness/population mean fitness
- In plants, we often know or can hypothesize the functions of specific traits in the pollination process

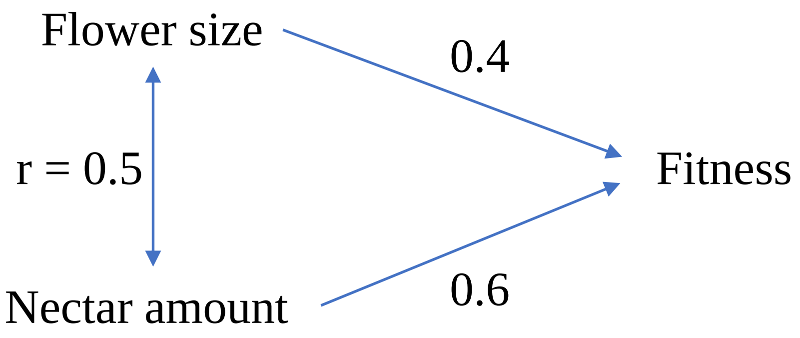


Chapurlat et al. 2015 New Phyt

The Lande-Arnold approach to measuring selection

- Total selection on a trait is the sum of direct selection on the focal trait, and indirect selection on phenotypically correlated traits

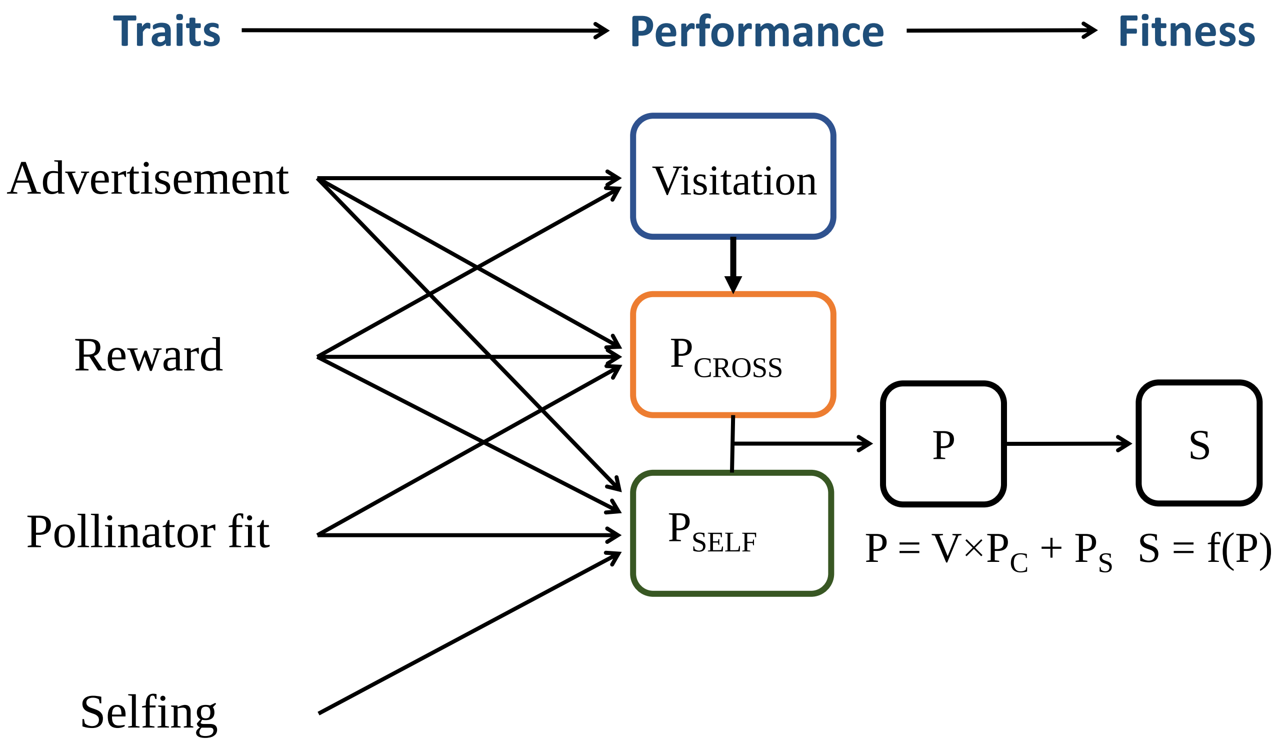




Net selection on flower size = 0.4 + 0.5 × 0.6 = 0.7

Lande & Arnold 1983 Evolution

Building a fitness function



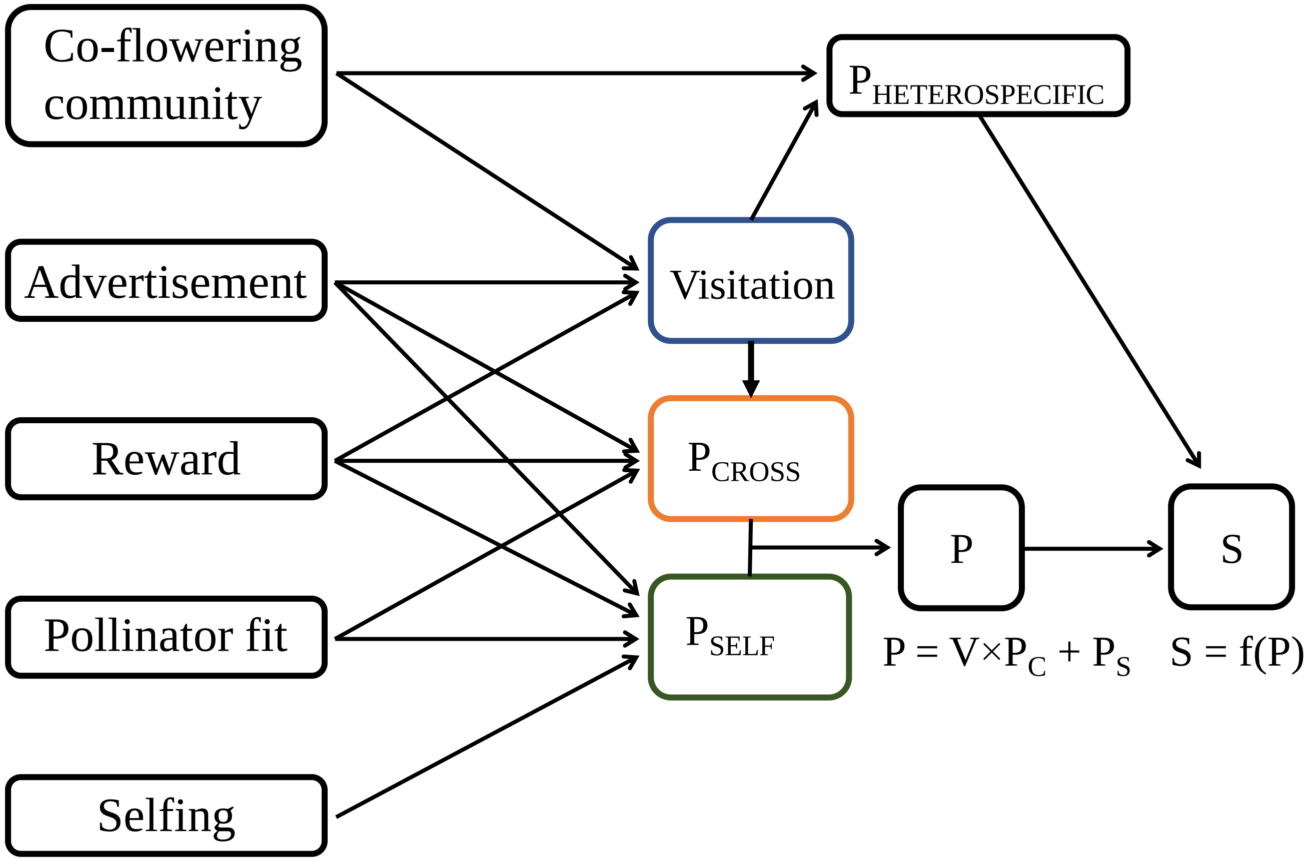
Visitation (V) = f(Advertisement, Reward)

Cross-pollen arrival (P_{CROSS}) = f(Advertisement, Reward, Fit)

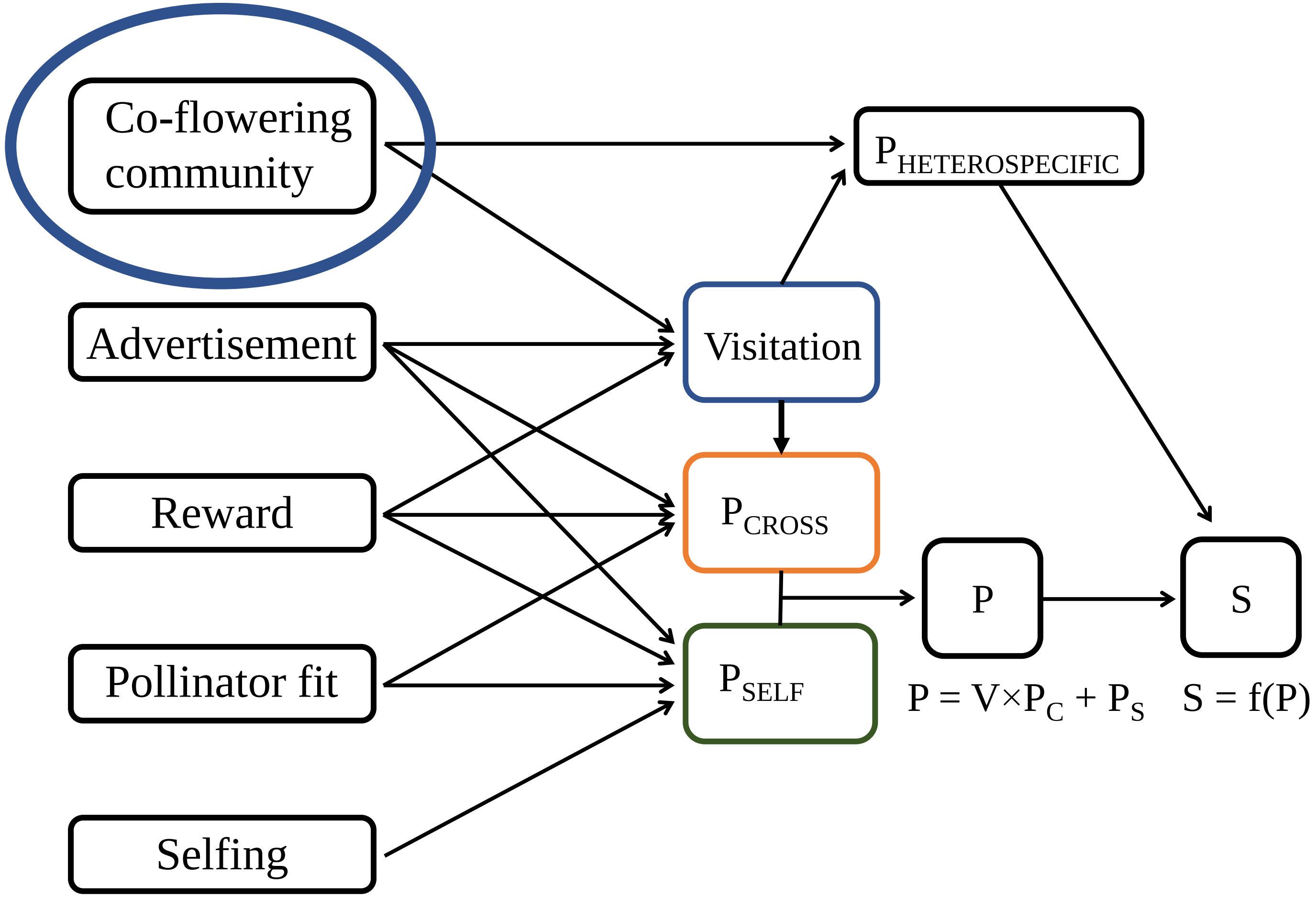
Self-pollen arrival (P_{SELF}) = f(Advertisement, Reward, Fit, Herkogamy)

Opedal 2021 J Poll Ecol


Plants do not interact with their pollinators in isolation
How can we extend single-species analyses to the community level?



Co-flowering community
Advertisement
Reward
Pollinator fit
Selfing
Visitation
P HETEROSPECIFIC
P CROSS
P SELF
P
S
P = V×P C + P S
S = f(P)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P = V×P C + P S
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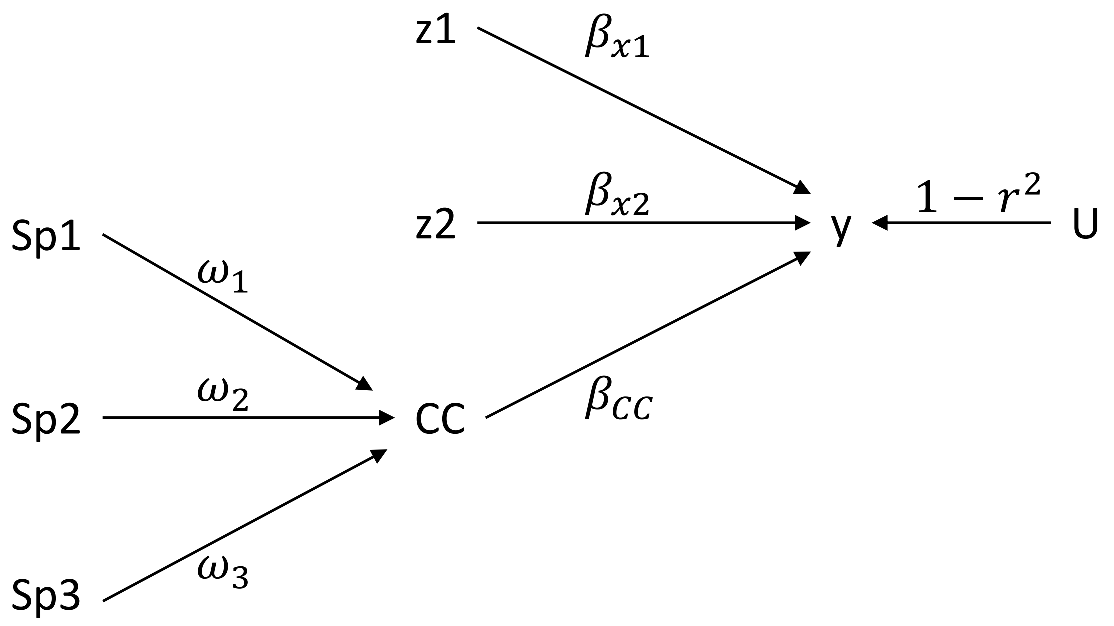
Treating the coflowering community as a unmeasured (latent) variable

- With many coflowering species, it becomes untractable to model the effect of each separately
- Alternative approach is to consider the community as a composite variable representing all coflowering species



Opedal et al. 2022 JEB

Theory: selection analysis with reduced-rank regression

- Reduced-rank regression (Anderson 1951; Izenman 1975) achieves dimension reduction of multivariate problems by projecting an original set of covariates onto a reduced set of composite variables that best explains variance in the response variable. In our case, **the composite scent trait under selection**

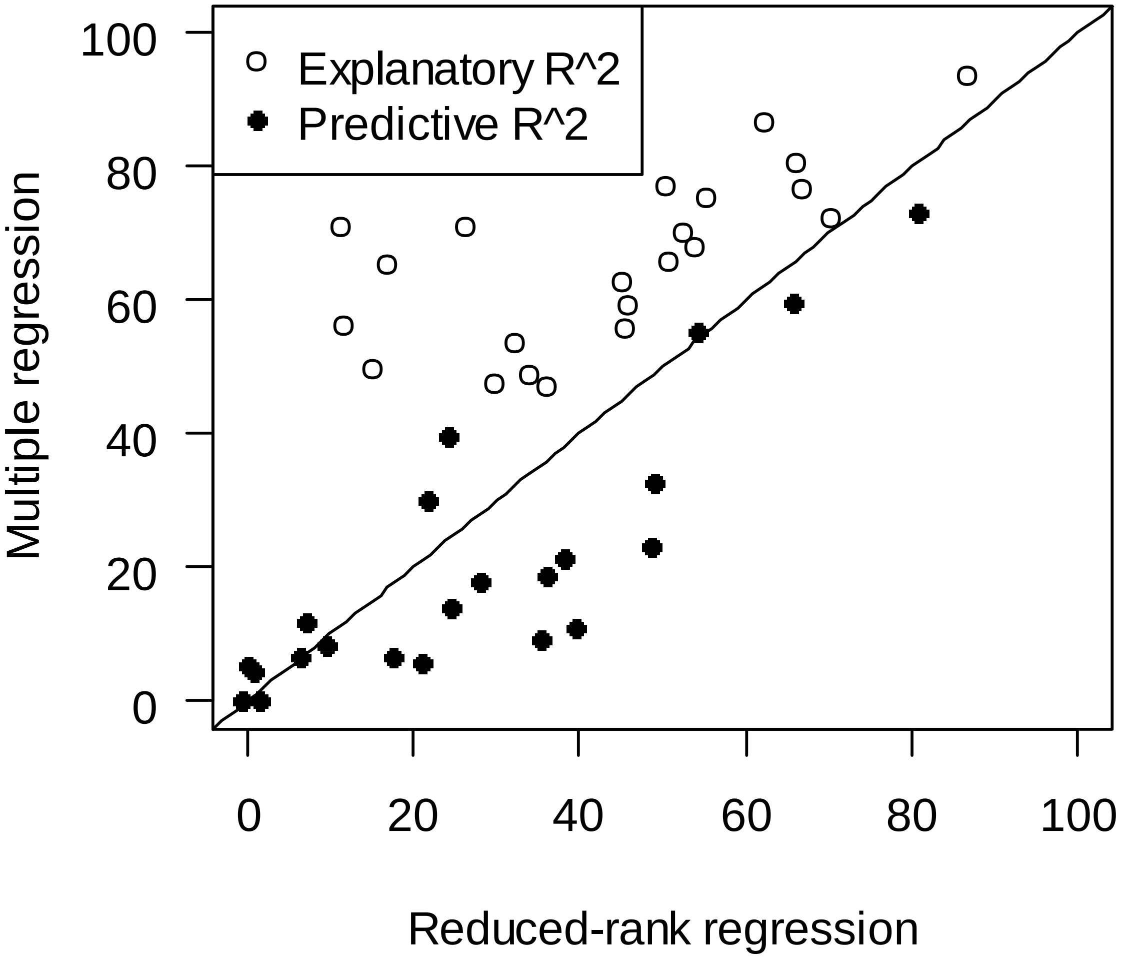
- The reduced-rank regression covariates (**scent selection axis**) are obtained as linear combinations of the original covariates, $x_{i(n_c+k)} = \sum_{l=1}^{n_c^{O,RRR}} w_{kl}\tilde{x}_{il}$, where the weights w_{kl} determine the contribution of the original covariates (**volatiles**) $\tilde{x}_{il}$ to the new covariate $x_{i(n_c+k)}$.

- The weights w_{kl} and the regression coefficients β_{kj} are estimated during model fitting (posterior sampling). For the weights, we apply a multiplicative Gamma process shrinkage prior to ensure that the leading axis explains the most variation. Thus, **our approach jointly estimates the structure of the scent selection axis, and selection acting on it**.

Opedal et al. 2022 JEB

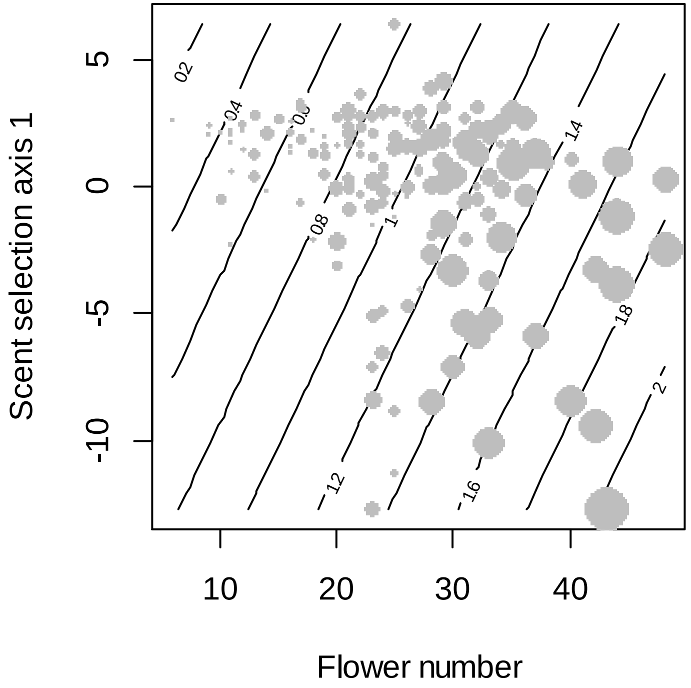
Is the 'scent selection axis' a reasonable approximation?

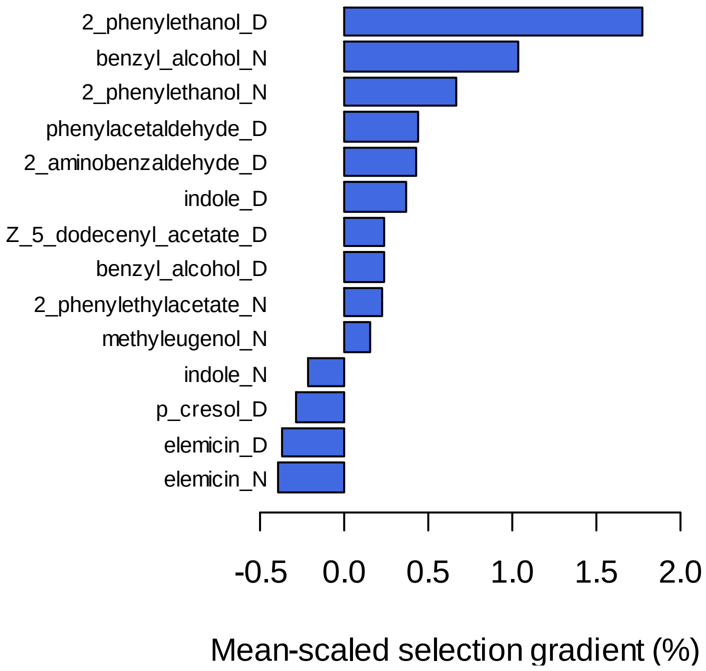
- Explanatory power always higher for multiple-regression: fully expected
- Predictive power tends to be higher for reduced-rank regression: less overfitting



Opedal et al. 2022 JEB

Characterizing the scent selection axis





Opedal et al. 2022 JEB

Theory: co-flowering community analysis with reduced-rank regression

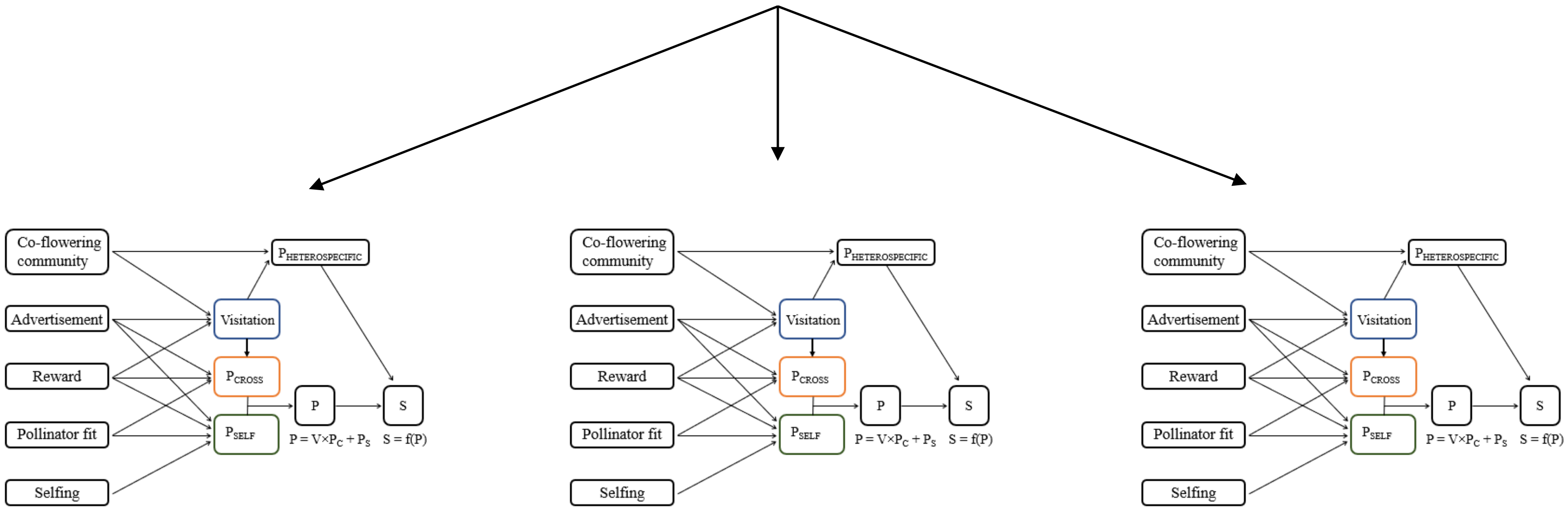
- Reduced-rank regression (Anderson 1951; Izenman 1975) achieves dimension reduction of multivariate problems by projecting an original set of covariates onto a reduced set of composite variables that best explains variance in the response variable. In our case, **the combination of co-flowering species associated with pollination success of a focal plant**

- The co-flowering community variables are obtained as linear combinations of the original covariates, $x_{i(n_c+k)} = \sum_{l=1}^{n_c^{O,RRR}} w_{kl}\tilde{x}_{il}$, where the weights w_{kl} determine the contribution of the original covariates (**species**) $\tilde{x}_{il}$ to the new covariate $x_{i(n_c+k)}$.

- The weights w_{kl} and the regression coefficients β_{kj} are estimated during model fitting (posterior sampling). For the weights, we apply a multiplicative Gamma process shrinkage prior to ensure that the leading axis explains the most variation. Thus, **our approach jointly estimates the structure of the community variable, and its effect on a focal species**

Still a single focal species, what about multiple?

“Hierarchical structure linking species together”



Methodological advances towards community-level analyses

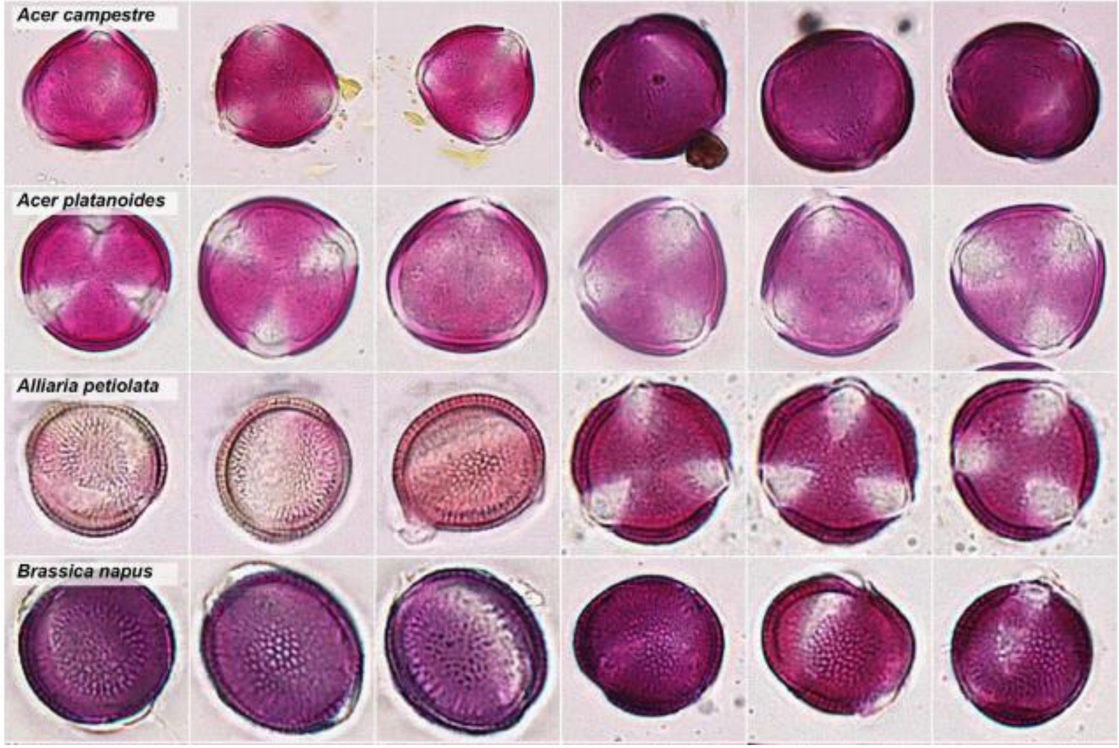
- Analysing plant-pollinator interactions and selection at the community level is complex
- Advances in automated pollen identification and joint modelling paves the way forward

RESEARCH ARTICLE

Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

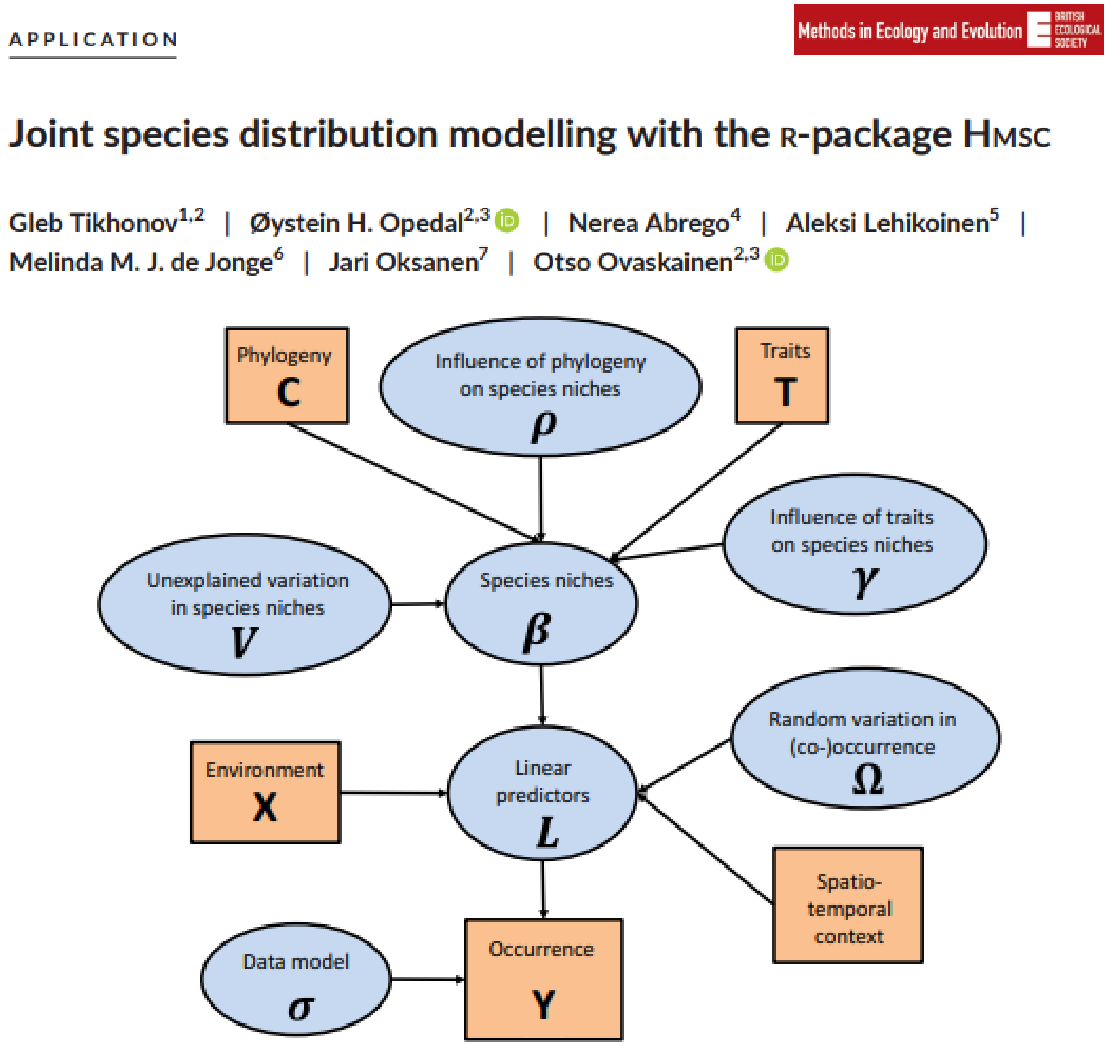
Efficient, automated and robust pollen analysis using deep learning

Ola Olsson[1] | Melanie Karlsson[2] | Anna S. Persson[2] | Henrik G. Smith[1,2] | Vidula Varadarajan[1] | Johanna Yourstone[1] | Martin Stjernman[1]



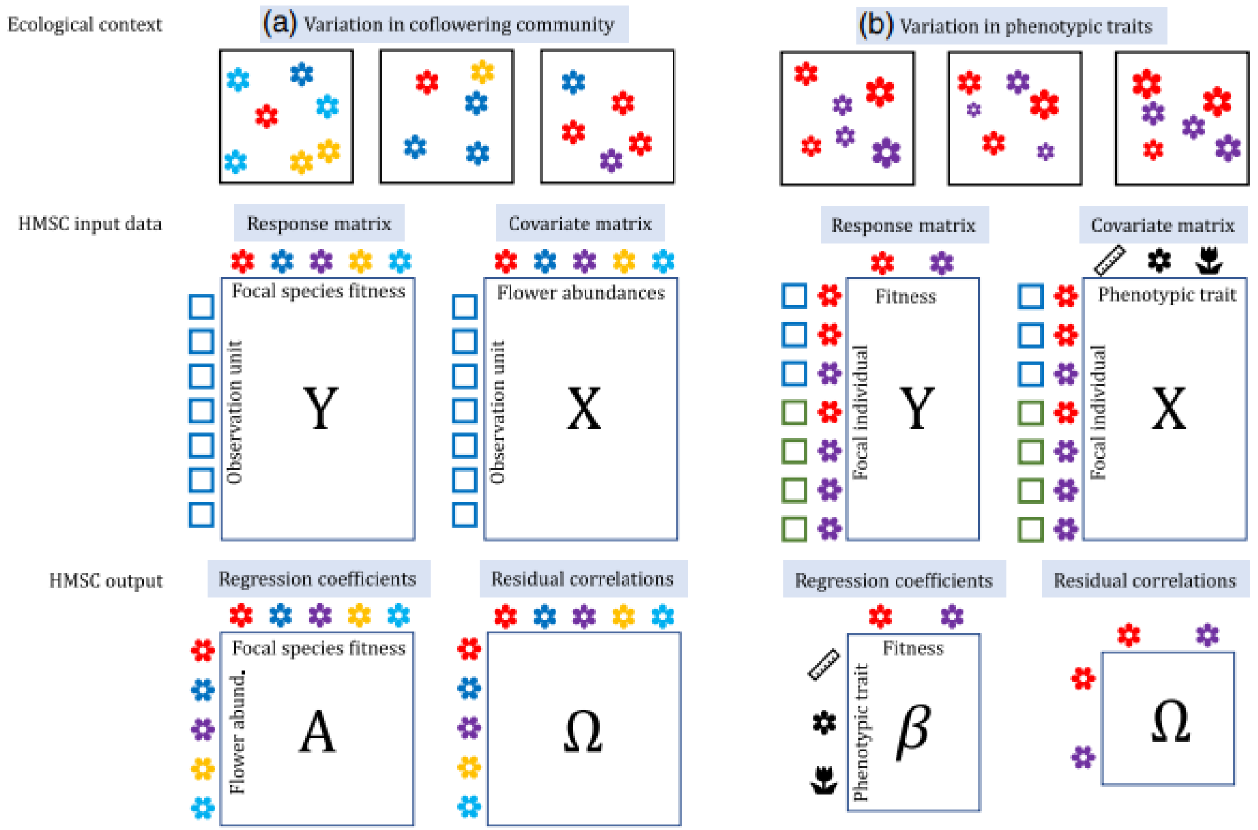
Methodological advances towards community-level analyses

- Analysing plant-pollinator interactions and selection at the community level is complex
- Advances in automated pollen identification and joint modelling paves the way forward



Hierarchical joint models

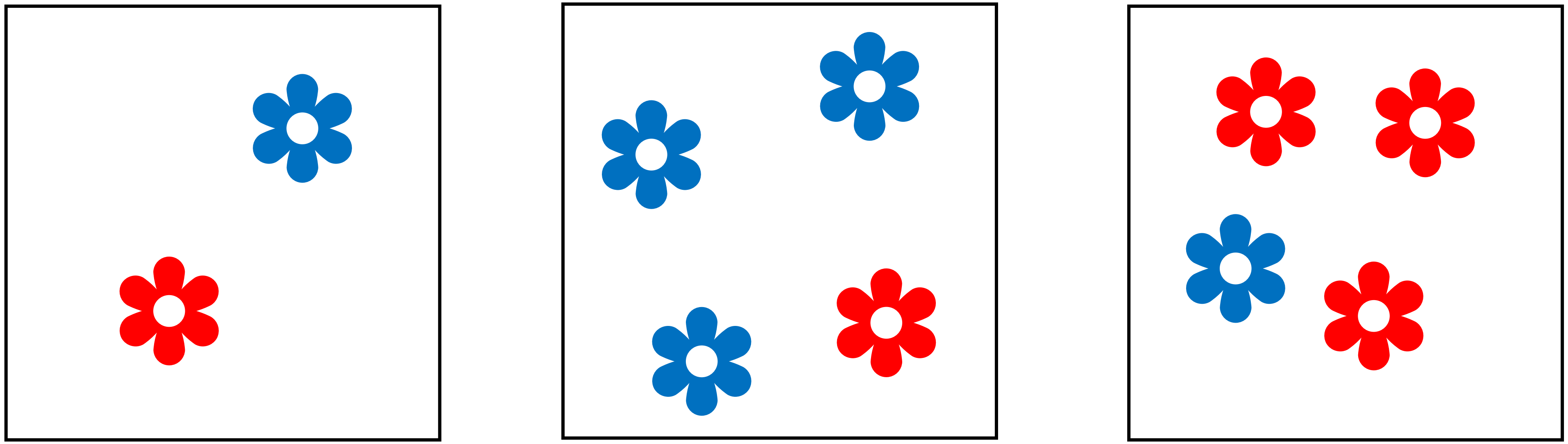
- Hierarchical joint models allows analysing multiple response variables (e.g. pollinator species) while inferring joint responses
- Also allows inferring residual associations after accounting for relevant covariates (e.g phenotype)



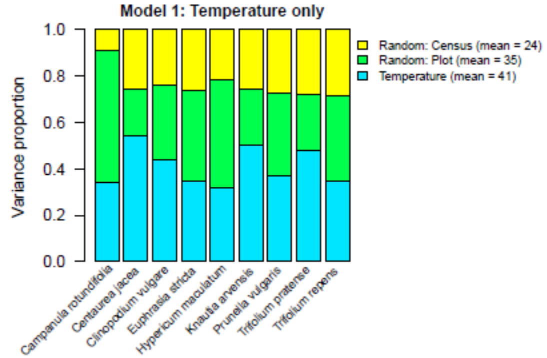
Opedal & Hegland 2020 J Ecol

The Rudsviki data

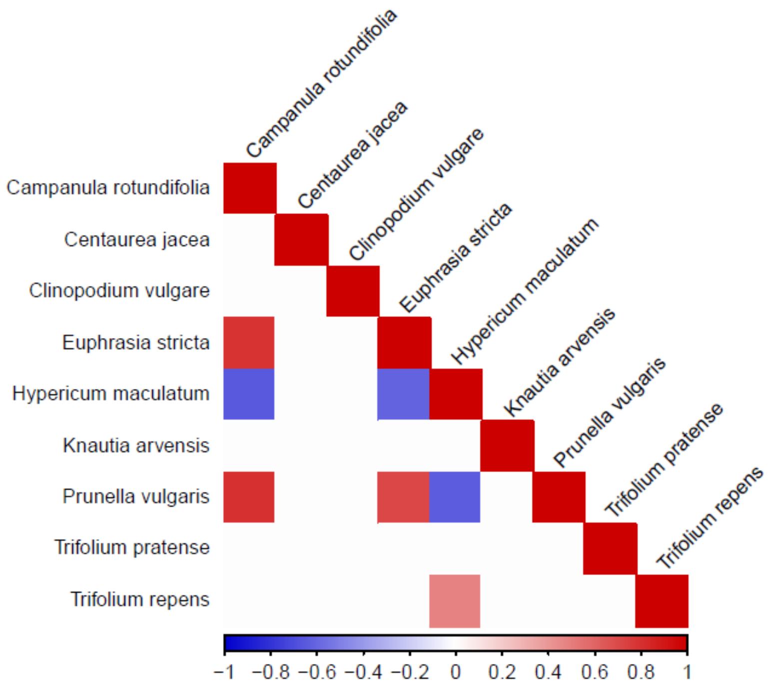
- 20 plots
- 9 bumblebee-pollinated plant species
- 200 censuses, each 10 min
- Number of visits to each species



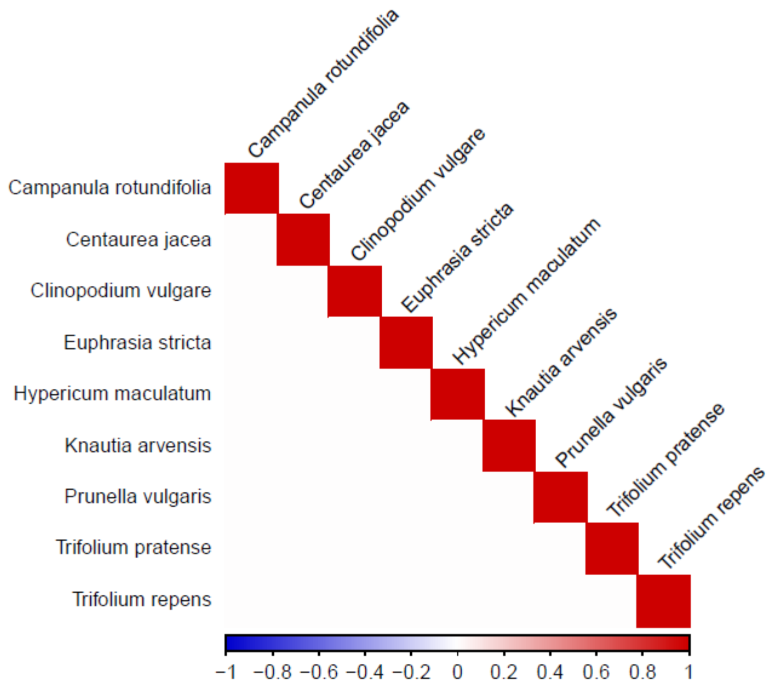
Model 1: Latent variables only



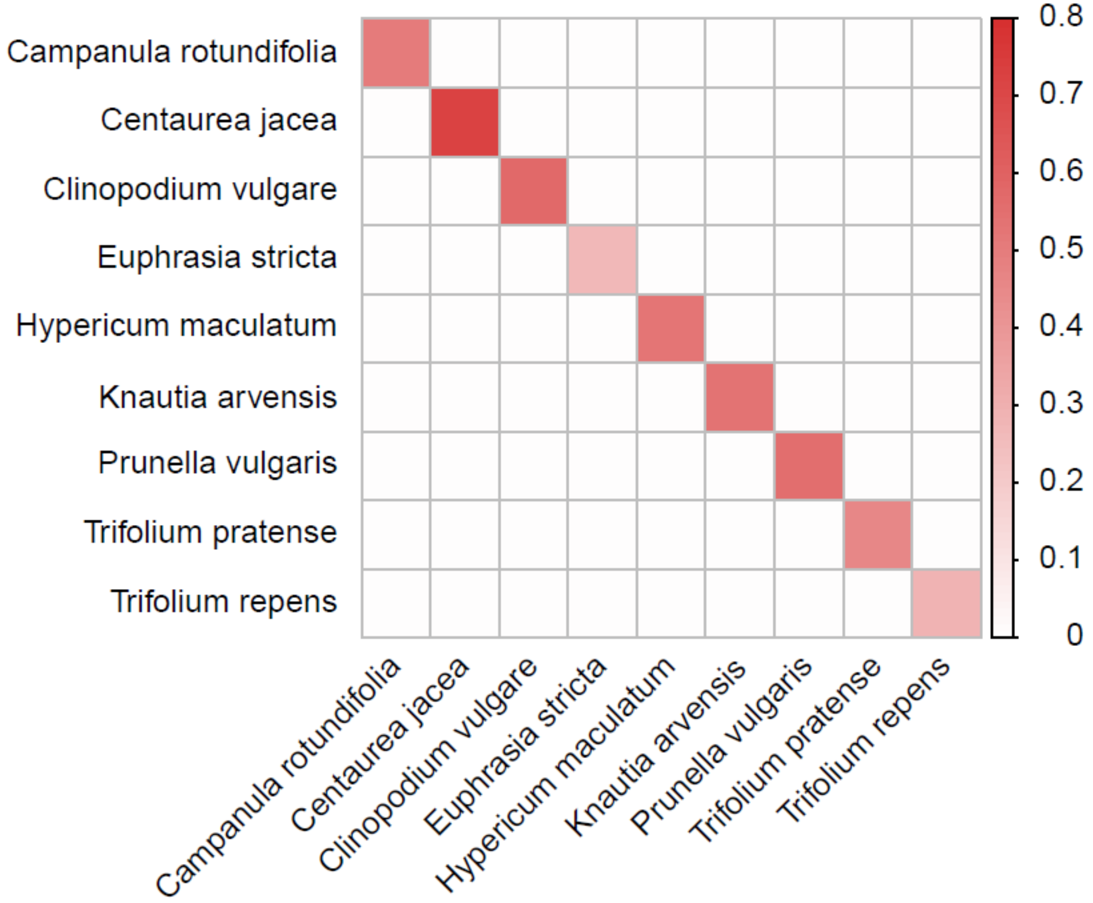
Plot level

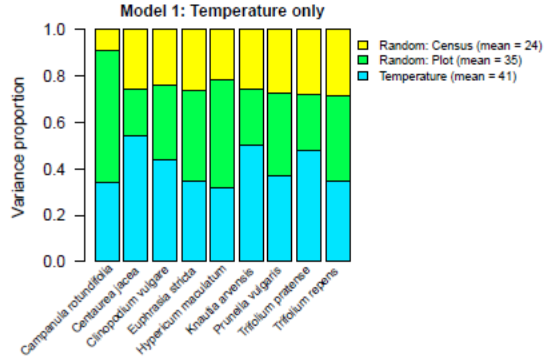


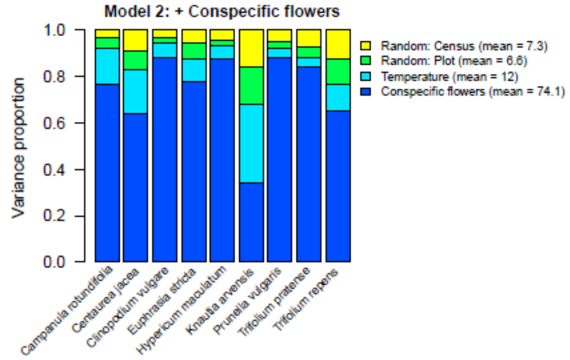
Census level



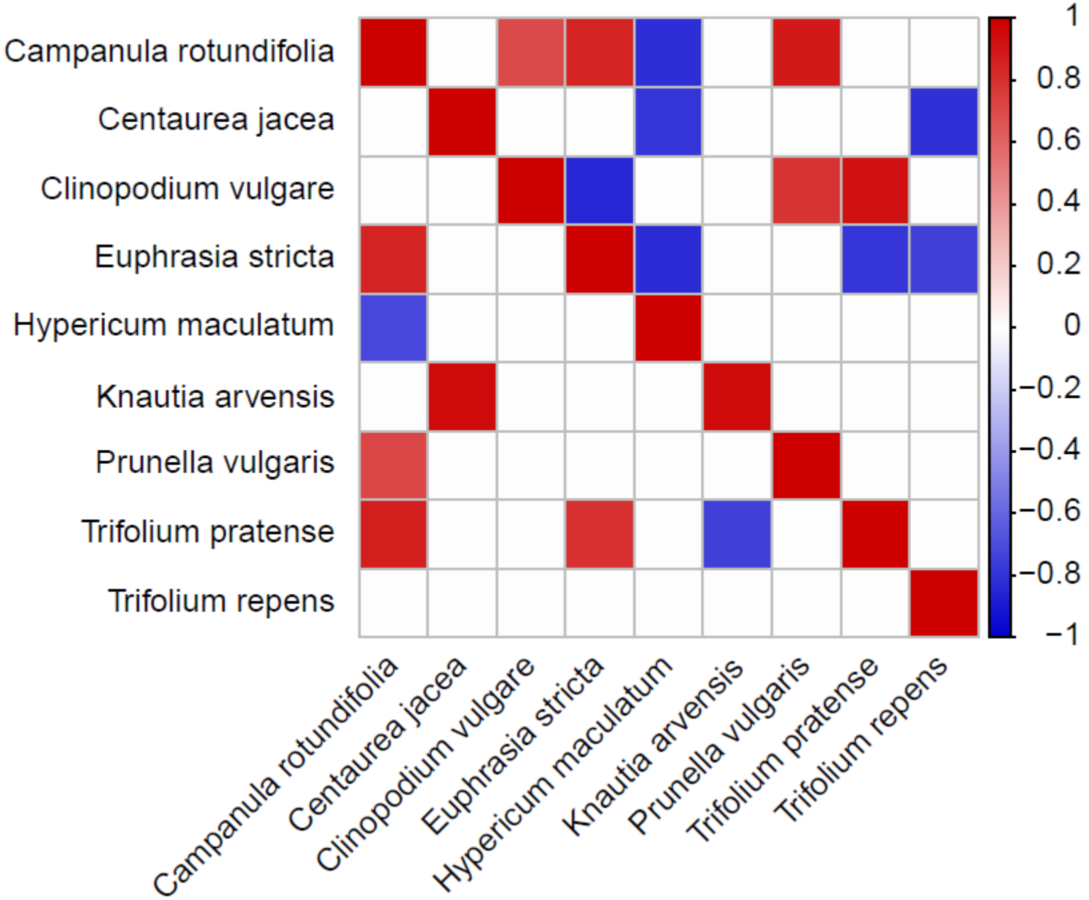
Model 2: Conspecific floral abundances

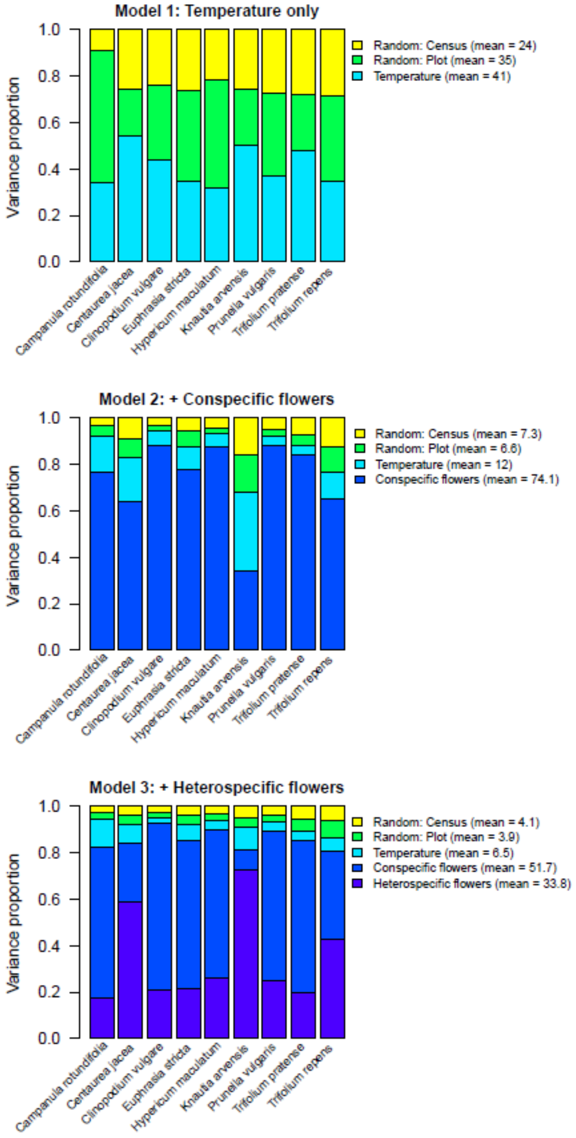






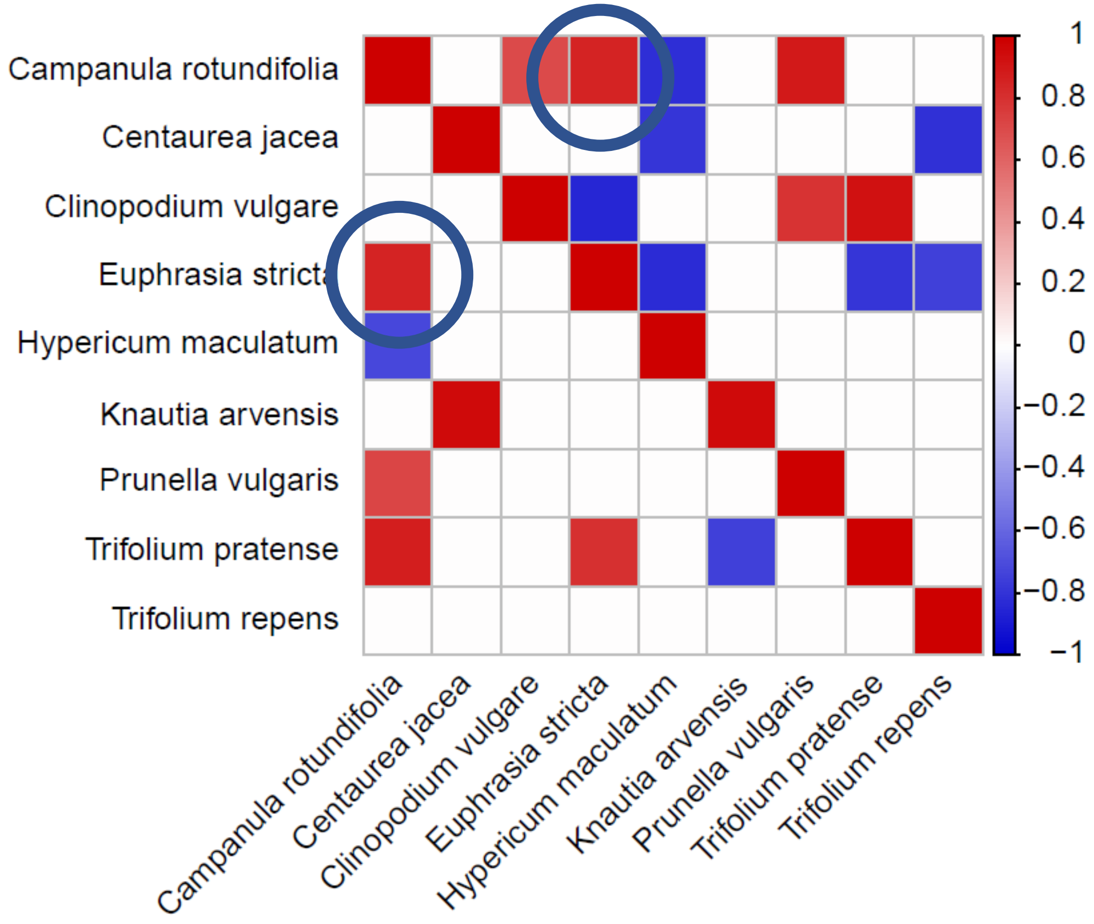
Model 3: All floral abundances





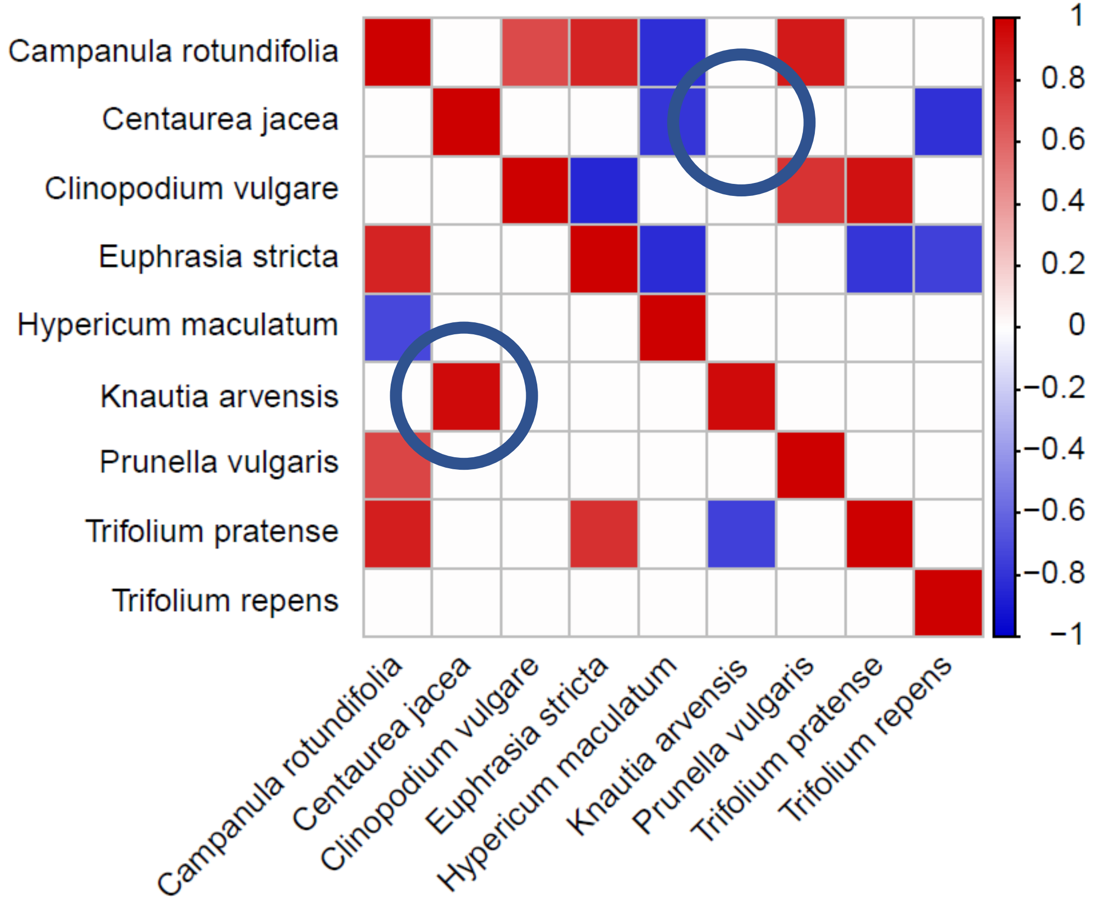
Model 3: All floral abundances

- Directionality:
- Two-way positive



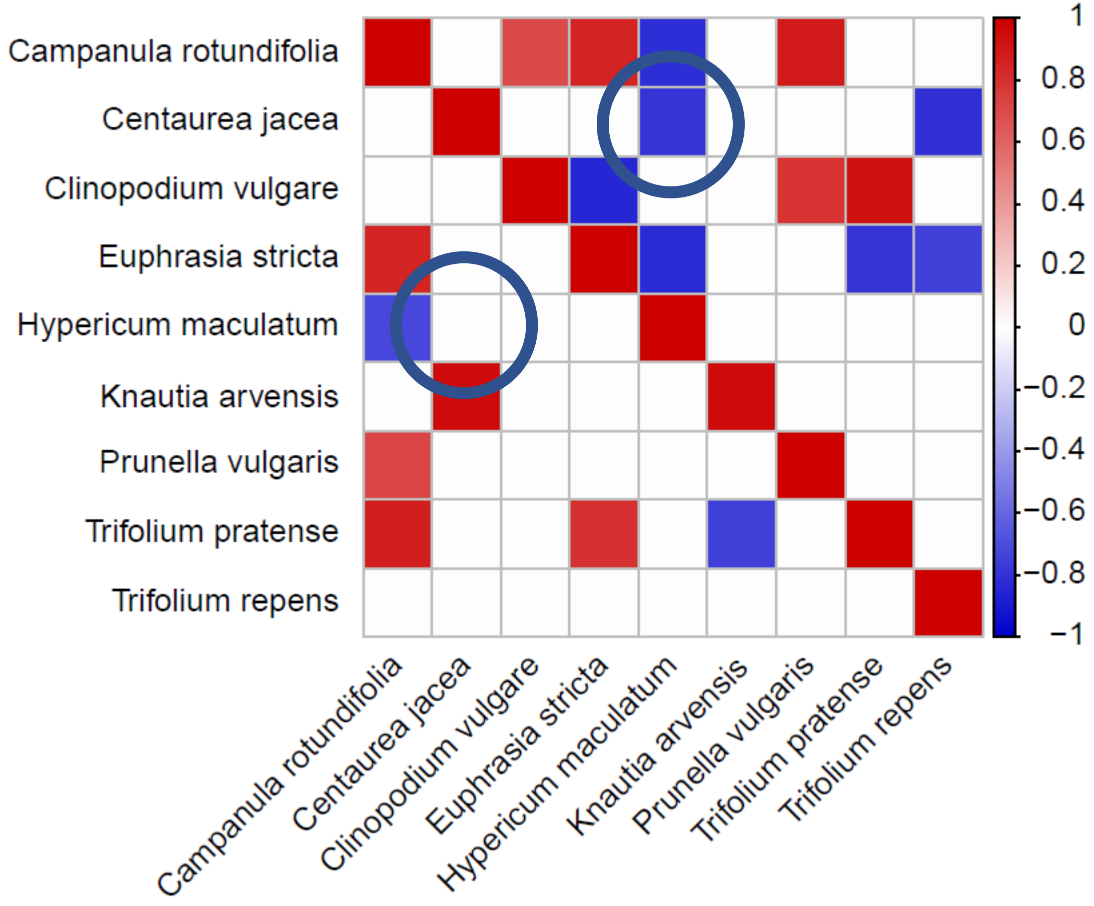
Model 3: All floral abundances

- Directionality:
- Two-way positive
- One-way positive



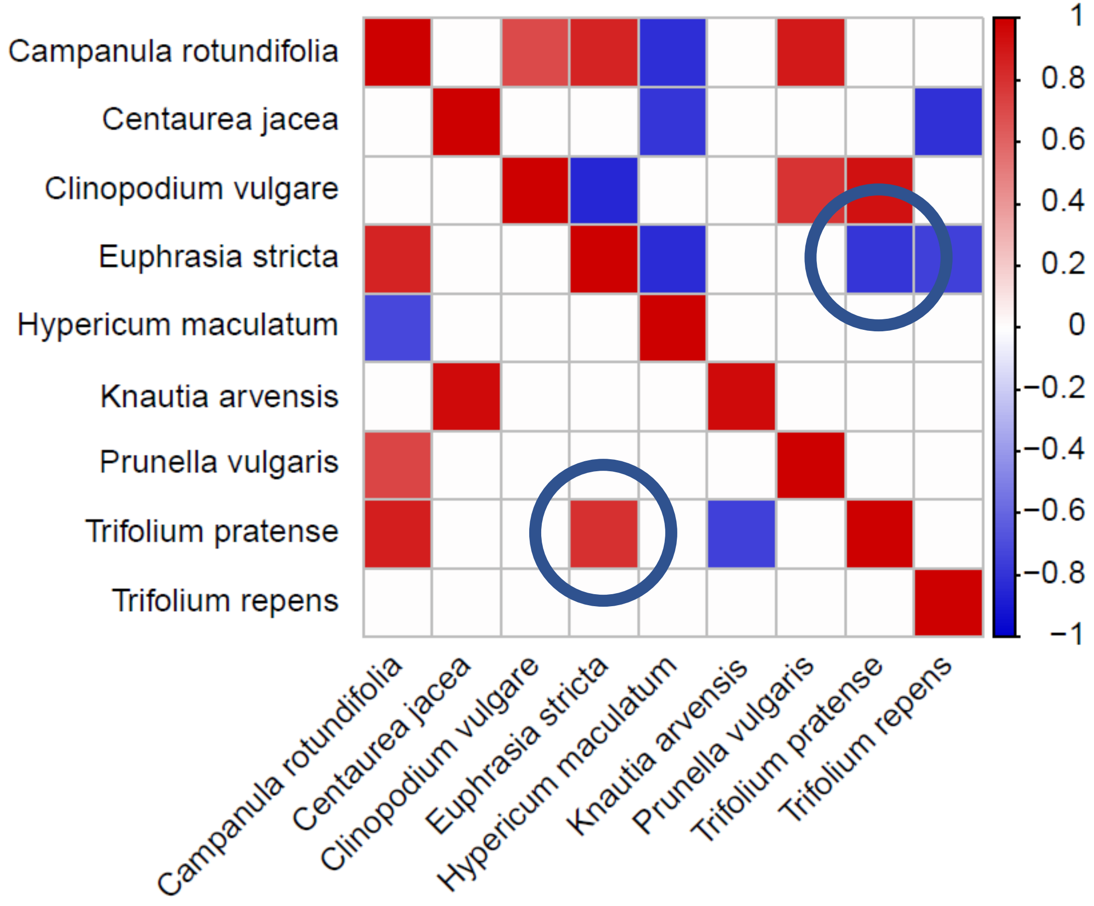
Model 3: All floral abundances

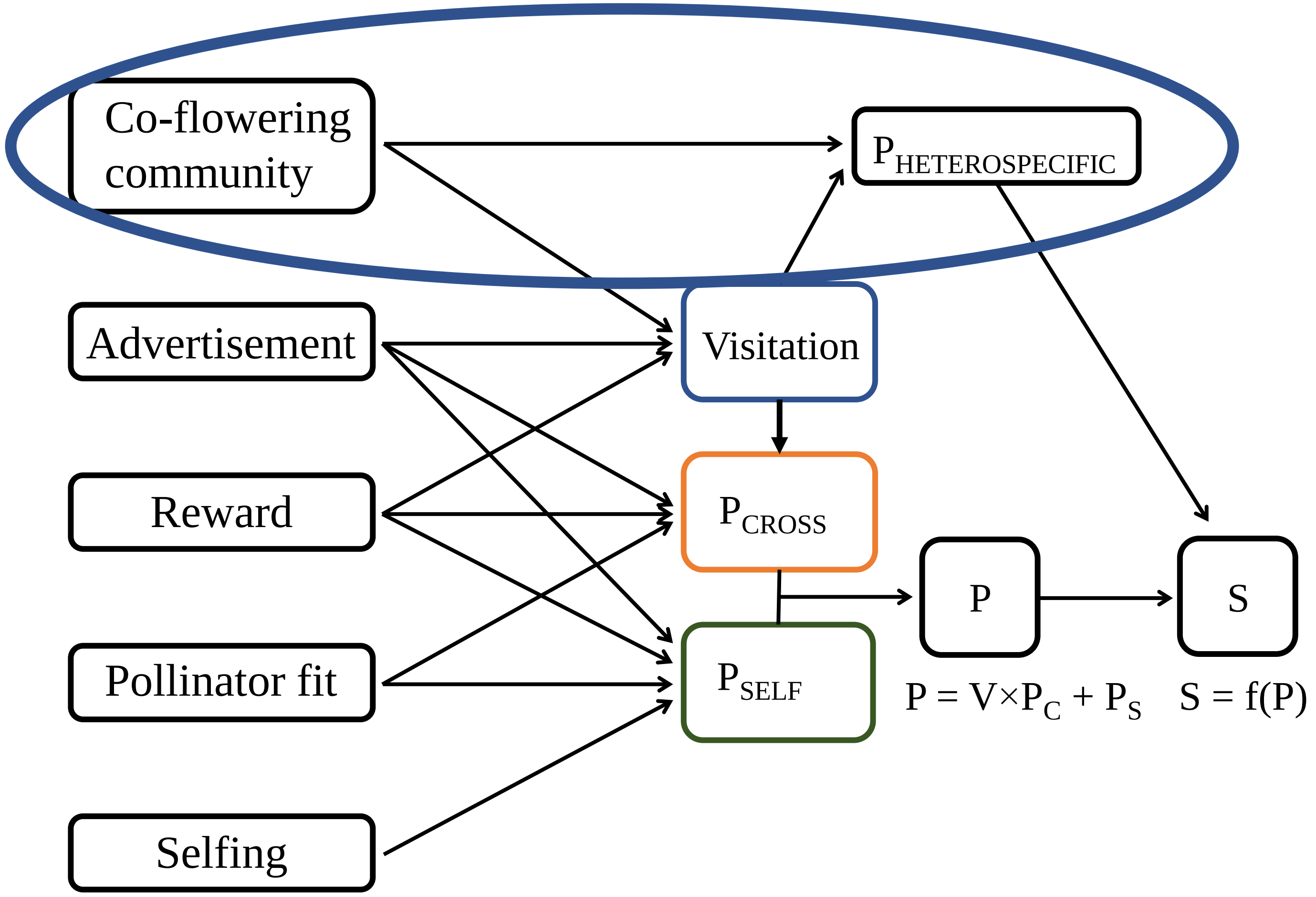
- Directionality:
- Two-way positive
- One-way positive
- One-way negative



Model 3: All floral abundances

- Directionality:
- Two-way positive
- One-way positive
- One-way negative
- Two-way positive-negative



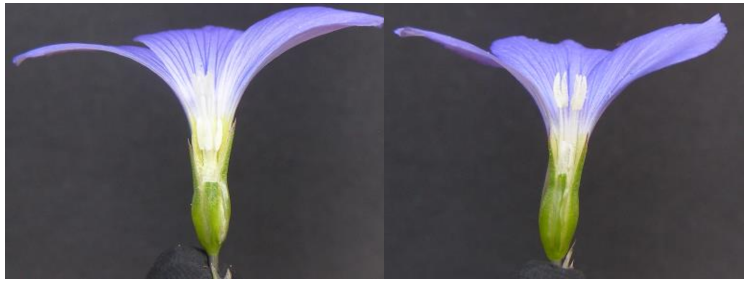


Co-flowering community
$P_{HETEROSPECIFIC}$
Advertisement
Visitation
Reward
P_{CROSS}
Pollinator fit
P_{SELF}
Selfing
P
S
$P = V \times P_C + P_S$
$S = f(P)$

Coflowering *Linum* species in southern Spain

Linum suffruticosum

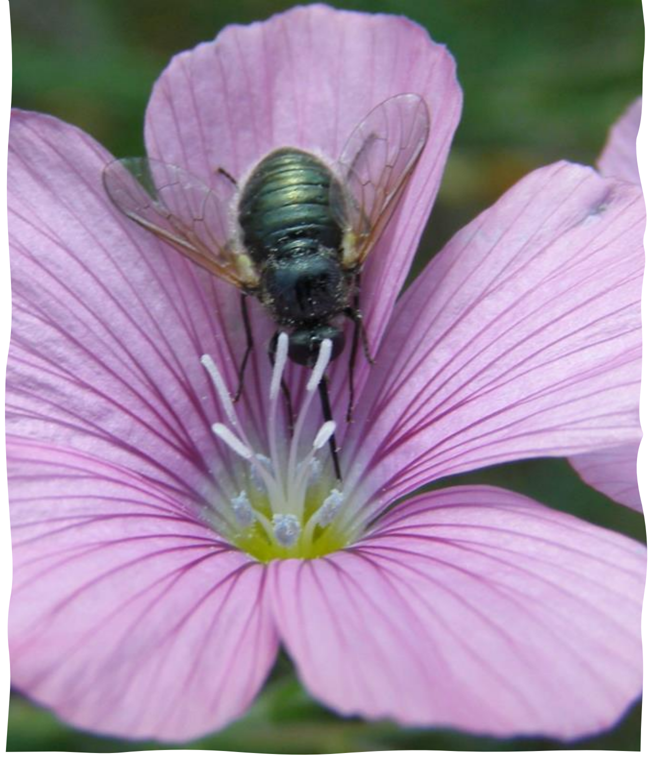
Linum suffruticosum



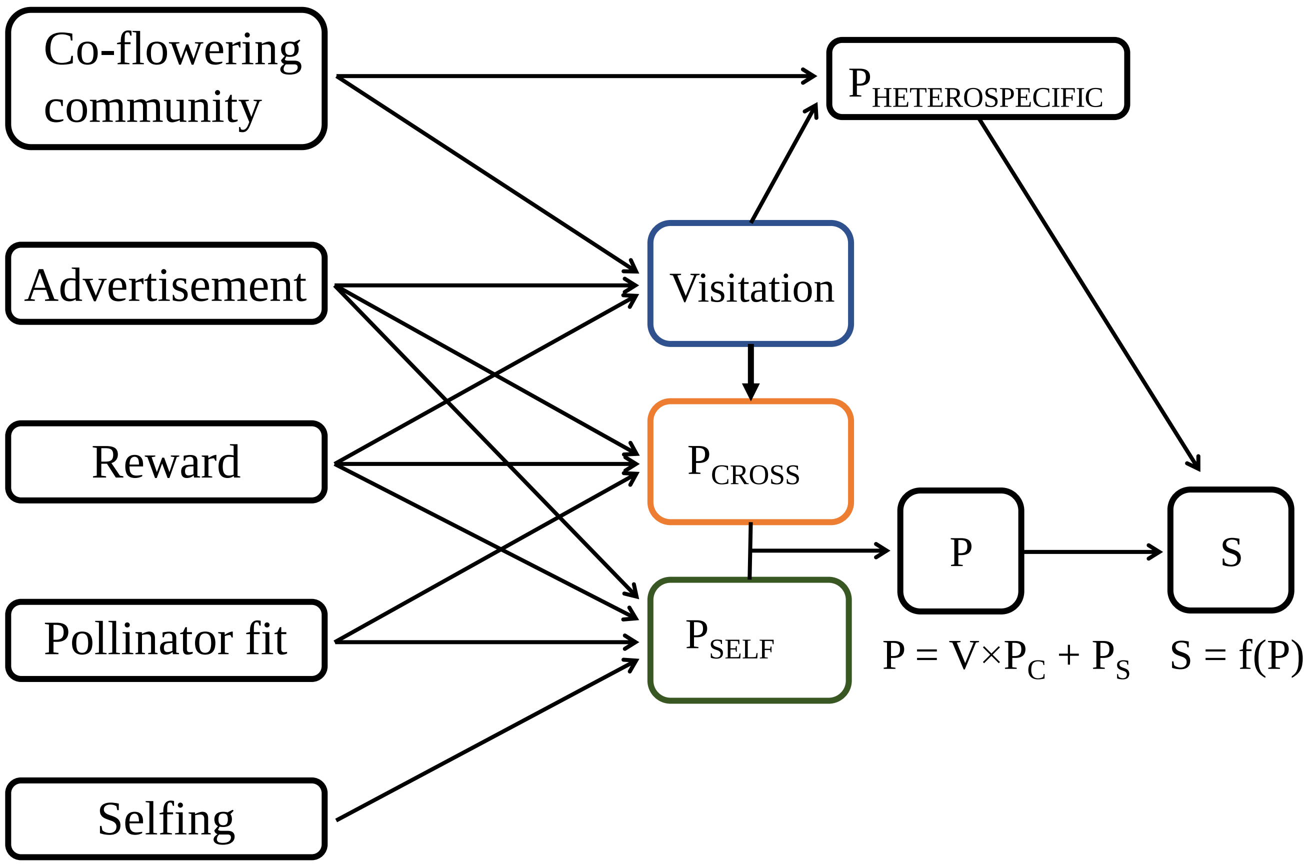
Linum viscosum

Ruiz-Martín et al. 2018
Pérez-Barrales & Armbruster, 2nd review

Rocío Pérez-Barrales et al.



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