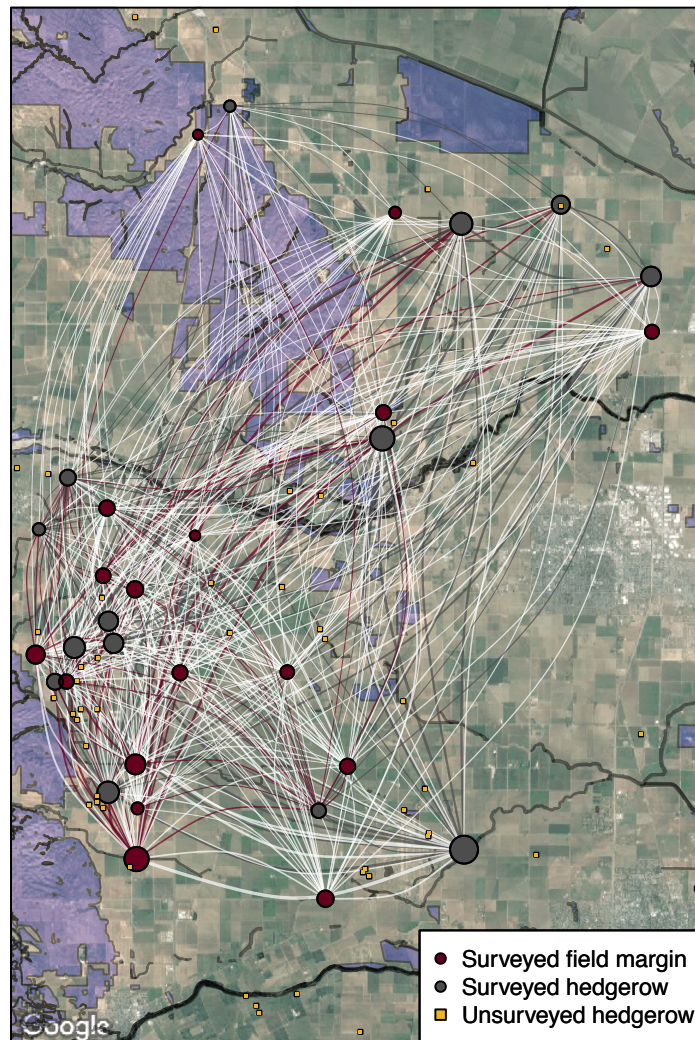


Plant diversity and pollinator niche breadth shape metacommunity dynamics in a 10-year study of wild bees in a agriculture landscape: a walk through of the models and analyses

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1 Overview

In our study we examine the metacommunity dynamics of plant-pollinator communities using variety of different methods including 1) occupancy modeling and 2) network analyses. We are committed to reproducible science and all analytical code will be maintained on github, along with this write up.

The entire analysis is executable from the main.sh file. All of the packages needed to run the analyses are listed in the packages.sh file. All analyses were run using R (version 3.5.1) and nimble (0.6-12).

Navigate to the analysis folder within the github repo (hedgerow_metacommunity) then the main.sh file can be selected and run (a warning, the occupancy analyses each take several hours on my 2.3 GHz imac pro, so all together they will take quite a while), you could run of the analyses in the study by running this line in BASH.

```
bash main.sh
```

This will somewhat helpfully print the results of each analysis and re-create any accompanying figures.

We will walk through each the main script for each analysis individually.

2 Occupancy model

The occupancy models are run through the main.R file in the analysis/occupancy folder. The script begins by setting the arguments for prepping the data. Run as is to reproduce the data use in the study. Prior analyses used the area of hedgerows in buffers weighted by log distance from a focal site instead of the Gaussian decay method, with similar results. In addition, the method for calculating the habitat quality of a patch can be toggled using the "col.name.div.type" argument. Other options are plant richness "Richness" or the diversity of flowers visited by pollinators "div.visits". All measures gave qualitatively similar results.

Importantly, "natural.decay" and "HR.decay" change the importance weighting of remnant and hedgerow proximity, respectively. Different combinations (350, 1000, and 2500) can be used to change the steepness of the decay rate from very steep ($\alpha = 350$ represents 98.5% reduction in weight by 1 km) to very shallow ($\alpha = 2500$ represents a 98.5% reduction in weight by 7 km). The main.sh script executes all combinations of decay rates. They are executed individually because the nimble models take a considerable amount of computer memory which is not cleared after the model is run. Running them all in a four loop within the same instance of R would overload most computers.

To run the MCMC in order to estimate the model coefficients, we use the NIMBLE R package (NIMBLE Development Team, 2014; de Valpine *et al.*, 2017). "nimble" stands for "numerical inference for statistical models with Bayesian and likelihood estimation." It implements almost the same model language as BUGS and JAGS, but supports easy customization of MCMC algorithms, including writing new samplers, and user-defined functions and distributions, which opens up enormous flexibility in how models are written. This enabled us to integrate out the latent states, increasing computational efficiency by an order of magnitude in comparison to sampling every latent state.

The multi-species, multi-season occupancy model is as follows:

We assumed that the occupancy of the i^{th} species at the j^{th} patch in the t^{th} year is a Bernoulli random variable $z_{i,j,t} \sim \text{Bern}(\psi_{i,j,t})$ with probability $\psi_{i,j,t}$.

In the first year, we assumed that a species probability of occupancy, $\psi_{i,j,1}$, was equal to that species' equilibrium occupancy probability, based on the persistence and colonization probabilities for that patch:

$$\psi_{i,j,1} = \gamma_{ij} / (1 - \phi_{ij} + \gamma_{ij}). \quad (1)$$

After year 1, occupancy is determined by a species' ability to persist in an occupied patch or colonize a vacant patch. We let $\phi_{i,j,t}$ denote the probability that species i occupying patch j persists from years t to $t + 1$, and $\gamma_{i,j,t}$ denote the probability that species i , absent from patch j in year t , colonizes patch j in year $t + 1$. The probability of occupancy for species i at patch j in subsequent years is then

$$\psi_{i,j,t+1} = \phi_{i,j,t} * z_{i,j,t} + \gamma_{i,j,t} * (1 - z_{i,j,t}). \quad (2)$$

Patch-level intercept and slope parameters were modeled as species-specific but linked together by common community-level distributions (i.e., random intercepts and slopes).

$$\begin{aligned} \text{logit}(\phi_{i,j,k}) &= \phi[1]_i + \phi[2]_i * \text{HRwtProx}_j + \phi[3]_i * \text{RemnantWtProx}_j + \phi[4]_i * \text{frd}_{j,t} + \\ &\quad \phi[5] * k_i + \phi[6] * B_i + \\ &\quad \phi[7] * \text{frd}_{j,t} * \text{HRwtProx}_j + \phi[8] * \text{frd}_{j,t} * \text{RemnantWtProx}_j + \\ &\quad \phi[9] * k_i * \text{HRwtProx}_j + \phi[10] * B_i * \text{HRwtProx}_j + \\ &\quad \phi[11] * k_i * \text{RemnantWtProx}_j + \phi[12] * B_i * \text{RemnantWtProx}_j \\ &\quad \phi[s]_i \sim N(\mu_{\phi[s]}, \sigma_{\phi[s]}), s = 1 \dots 4 \\ \text{logit}(\gamma_{i,j,t}) &= \gamma[1]_i + \gamma[2]_i * \text{HRwtProx}_j + \gamma[3]_i * \text{RemnantWtProx}_j + \gamma[4]_i * \text{frd}_{j,t} + \\ &\quad \gamma[5] * k_i + \gamma[6] * B_i + \\ &\quad \gamma[7] * \text{frd}_{j,t} * \text{HRwtProx}_j + \gamma[8] * \text{frd}_{j,t} * \text{RemnantWtProx}_j + \\ &\quad \gamma[9] * k_i * \text{HRwtProx}_j + \gamma[10] * B_i * \text{HRwtProx}_j + \\ &\quad \gamma[11] * k_i * \text{RemnantWtProx}_j + \gamma[12] * B_i * \text{RemnantWtProx}_j \\ &\quad \gamma[s]_i \sim N(\mu_{\gamma[s]}, \sigma_{\gamma[s]}), s = 1 \dots 4 \end{aligned} \quad (3)$$

Here $\phi[1]_i$ and $\gamma[1]_i$ denote species-specific effects on persistence and colonization, respectively. The ϕ and γ parameters proceeding each of the explanatory variables represent the effect of those variables. All explanatory variables were centered.

We also assumed that detection was distributed according to a Bernoulli random variable such that $x_{i,j,t,r} \sim \text{Bern}(p_{i,j,t,r} * z_{i,j,t})$, where $p_{i,j,t,r}$ is the probability that the i^{th} species was detected at patch j in the r^{th} sample period of the t^{th} year, given that it was present. The detection probability of each species was allowed to vary over the season according species-specific phenologies. Specifically, the detection probability of the i^{th} species at the j^{th} patch in the r^{th} replicate of the t^{th} year was specified as

$$\text{logit}(p_{i,j,k,t}) = p[1]_i + p[2]_i * \text{date}_{j,k,r} + p[3]_i * (\text{date}_{j,k,r})^2 \quad (4)$$

where $p[1]_i$ denotes a species-specific effect and $p[2]_i$ and $p[3]_i$ denote the effect of day of the year on detectability of species i . We used orthogonal polynomials for the linear and quadratic terms on day. The inclusion of the quadratic term allowed species-specific rates of detection to have a seasonal peak.

The model code follows the notation above, except *HRwtProx* is abbreviated as *hr.area*, and *RemnantWtProx* as *nat.area*.

```
ms.ms.occ
## {
##   mu.p.0 ~ dnorm(0, 0.001)
##   mu.p.day.1 ~ dnorm(0, 0.001)
##   mu.p.day.2 ~ dnorm(0, 0.001)
##   sigma.p.0 ~ dunif(0, 100)
##   sigma.p.day.1 ~ dunif(0, 100)
##   sigma.p.day.2 ~ dunif(0, 100)
##   mu.phi.0 ~ dnorm(0, 0.001)
```

```

## mu.gam.0 ~ dnorm(0, 0.001)
## sigma.phi.0 ~ dunif(0, 100)
## sigma.gam.0 ~ dunif(0, 100)
## mu.phi.hr.area ~ dnorm(0, 0.001)
## mu.gam.hr.area ~ dnorm(0, 0.001)
## sigma.phi.hr.area ~ dunif(0, 100)
## sigma.gam.hr.area ~ dunif(0, 100)
## mu.phi.nat.area ~ dnorm(0, 0.001)
## mu.gam.nat.area ~ dnorm(0, 0.001)
## sigma.phi.nat.area ~ dunif(0, 100)
## sigma.gam.nat.area ~ dunif(0, 100)
## mu.phi.fra ~ dnorm(0, 0.001)
## mu.gam.fra ~ dnorm(0, 0.001)
## sigma.phi.fra ~ dunif(0, 100)
## sigma.gam.fra ~ dunif(0, 100)
## phi.k ~ dnorm(0, 0.001)
## gam.k ~ dnorm(0, 0.001)
## phi.B ~ dnorm(0, 0.001)
## gam.B ~ dnorm(0, 0.001)
## phi.hr.area.fra ~ dnorm(0, 0.001)
## gam.hr.area.fra ~ dnorm(0, 0.001)
## phi.nat.area.fra ~ dnorm(0, 0.001)
## gam.nat.area.fra ~ dnorm(0, 0.001)
## phi.hr.area.k ~ dnorm(0, 0.001)
## gam.hr.area.k ~ dnorm(0, 0.001)
## phi.nat.area.k ~ dnorm(0, 0.001)
## gam.nat.area.k ~ dnorm(0, 0.001)
## phi.hr.area.B ~ dnorm(0, 0.001)
## gam.hr.area.B ~ dnorm(0, 0.001)
## phi.nat.area.B ~ dnorm(0, 0.001)
## gam.nat.area.B ~ dnorm(0, 0.001)
## for (sp in 1:nsp) {
##   p.0[sp] ~ dnorm(mu.p.0, sd = sigma.p.0)
##   p.day.1[sp] ~ dnorm(mu.p.day.1, sd = sigma.p.day.1)
##   p.day.2[sp] ~ dnorm(mu.p.day.2, sd = sigma.p.day.2)
##   phi.0[sp] ~ dnorm(mu.phi.0, sd = sigma.phi.0)
##   gam.0[sp] ~ dnorm(mu.gam.0, sd = sigma.gam.0)
##   phi.hr.area[sp] ~ dnorm(mu.phi.hr.area, sd = sigma.phi.hr.area)
##   gam.hr.area[sp] ~ dnorm(mu.gam.hr.area, sd = sigma.gam.hr.area)
##   phi.nat.area[sp] ~ dnorm(mu.phi.nat.area, sd = sigma.phi.nat.area)
##   gam.nat.area[sp] ~ dnorm(mu.gam.nat.area, sd = sigma.gam.nat.area)
##   phi.fra[sp] ~ dnorm(mu.phi.fra, sd = sigma.phi.fra)
##   gam.fra[sp] ~ dnorm(mu.gam.fra, sd = sigma.gam.fra)
## }
## for (sp in 1:nsp) {
##   for (site in 1:nsite) {
##     for (yr in 1:nyear) {
##       for (rep in 1:nrep[site, yr, sp]) {
##         logit(p[site, yr, rep, sp]) <- p.0[sp] + p.day.1[sp] *
##           day[site, yr, rep, sp] + p.day.2[sp] * day.2[site,
##           yr, rep, sp]
##       }
##     }
##   }
## }

```

```

##      logit(phi.site.sp.mean[site, sp]) <- mean(phi[site,
##      1:(nyear - 1), sp])
##      logit(gam.site.sp.mean[site, sp]) <- mean(gam[site,
##      1:(nyear - 1), sp])
##      psi.1[site, sp] <- gam.site.sp.mean[site, sp]/(1 -
##      phi.site.sp.mean[site, sp] + gam.site.sp.mean[site,
##      sp])
##      psi[site, 1, sp] <- psi.1[site, sp]
##      for (yr in 1:(nyear - 1)) {
##        phi[site, yr, sp] <- phi.0[sp] + phi.k * k[sp] +
##        phi.B * B[sp] + phi.hr.area[sp] * HRarea[site] +
##        phi.nat.area[sp] * natural[site] + phi.fra[sp] *
##        fra[site, yr] + phi.hr.area.fra * fra[site,
##        yr] * HRarea[site] + phi.nat.area.fra * fra[site,
##        yr] * natural[site] + phi.hr.area.k * k[sp] *
##        HRarea[site] + phi.nat.area.k * k[sp] * natural[site] +
##        phi.hr.area.B * B[sp] * HRarea[site] + phi.nat.area.B *
##        B[sp] * natural[site]
##      gam[site, yr, sp] <- gam.0[sp] + gam.k * k[sp] +
##      gam.B * B[sp] + gam.hr.area[sp] * HRarea[site] +
##      gam.nat.area[sp] * natural[site] + gam.fra[sp] *
##      fra[site, yr] + gam.hr.area.fra * fra[site,
##      yr] * HRarea[site] + gam.nat.area.fra * fra[site,
##      yr] * natural[site] + gam.hr.area.k * k[sp] *
##      HRarea[site] + gam.nat.area.k * k[sp] * natural[site] +
##      gam.hr.area.B * B[sp] * HRarea[site] + gam.nat.area.B *
##      B[sp] * natural[site]
##    }
##  }
## }
## for (site in 1:nsite) {
##   for (sp in 1:nsp) {
##     X[site, 1:nyear, 1:max.nreps, sp] ~ dDynamicOccupancy(nrep = nrep[site,
##     1:nyear, sp], psi1 = psi[site, 1, sp], phi = expit(phi[site,
##     1:(nyear - 1), sp]), gamma = expit(gam[site,
##     1:(nyear - 1), sp]), p = p[site, 1:nyear, 1:max.nreps,
##     sp])
##   }
## }
## }

```

for those of you familiar with working in BUGS or JAGS, the main difference here is the call to 'dDynamicOccupancy'. This is the function allows us to numerically integrate over sequences of latent states to directly calculate model likelihoods, removing the need to perform MCMC sampling of these latent variables.

```

dDynamicOccupancy
## function (x, nrep, psi1, phi, gamma, p, log = 0)
## {
##   ProbOccNextTime <- psi1
##   ll <- 0
##   nyears <- nimDim(x)[1]
##   if (nyears >= 1) {
##     for (t in 1:nyears) {

```

```

##         if (nrep[t] > 0) {
##             numObs <- sum(x[t, 1:nrep[t]])
##             if (numObs < 0) {
##                 nimPrint("Error in dDynamicOccupancy: numObs < 0 but nrep[t] > 0\n")
##                 nimStop("Error in dDynamicOccupancy: numObs < 0 but nrep[t] > 0\n")
##             }
##             ProbOccAndCount <- ProbOccNextTime * exp(sum(dbinom(x[t,
##             1:nrep[t]], size = 1, p = p[t, 1:nrep[t]],
##             log = 1)))
##             ProbUnoccAndCount <- (1 - ProbOccNextTime) *
##             (numObs == 0)
##             ProbCount <- ProbOccAndCount + ProbUnoccAndCount
##             ProbOccGivenCount <- ProbOccAndCount/ProbCount
##             ll <- ll + log(ProbCount)
##             if (t < nyears)
##                 ProbOccNextTime <- ProbOccGivenCount * phi[t] +
##                 (1 - ProbOccGivenCount) * gamma[t]
##         }
##         else {
##             if (t < nyears)
##                 ProbOccNextTime <- ProbOccNextTime * phi[t] +
##                 (1 - ProbOccNextTime) * gamma[t]
##         }
##     }
## }
## if (log)
##     return(ll)
## else return(exp(ll))
## }
## <environment: 0x7f896defc958>

```

The number of MCMC iterations, burnin, number of chains, etc. can be toggled by changing the value of the scale object. This script will also generate MCMC diagnostic figures (*src_plotting/checkChains.R*), interaction plots (*src_plotting/plotInteractions.R*), and posterior mean and credible internal plots and table (*src_plotting/posteriorPlotting.R*).

3 Metacommunity Network Analysis

The 'spTempMets.R' file executes the network analyses. The user can provide any network metrics taken by the function 'speciesLevel' in the bipartite package. The $y_{i,j,k}$ network metrics of the i^{th} species at the j^{th} site in the k^{th} year was modeled as:

$$\begin{aligned}
 y_{i,j,k} &\sim B_i + k_i + \text{site}_j + \text{site}_k \\
 \text{site}_j &\sim N(0, \sigma_{\text{site}}) \\
 \text{year}_k &\sim N(0, \sigma_{\text{year}})
 \end{aligned}
 \tag{5}$$

The results for how species traits effect the role of pollinators in the spatial metacommunity network:

```

lapply(mod.years.pol, summary)

## $k
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
## Data: specs.years.pol
##
## REML criterion at convergence: 557
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -3.0281 -0.4275 -0.0558 0.3588 3.4899
##
## Random effects:
## Groups Name Variance Std.Dev.
## GenusSpecies (Intercept) 0.09441 0.3073
## Site (Intercept) 0.01585 0.1259
## Residual 0.16260 0.4032
## Number of obs: 413, groups: GenusSpecies, 102; Site, 10
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) -0.05166 0.05682 20.54598 -0.909 0.3738
## r.degree 0.75945 0.04553 92.12789 16.680 <2e-16 ***
## MeanITD -0.09329 0.04015 115.53534 -2.324 0.0219 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) r.degr
## r.degree 0.169
## MeanITD 0.008 0.144
##
## $weighted.betweenness
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
## Data: specs.years.pol
##
## REML criterion at convergence: -1017.5
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -6.7043 -0.1604 -0.0414 0.1147 7.8436
##
## Random effects:
## Groups Name Variance Std.Dev.
## GenusSpecies (Intercept) 0.00151 0.03886
## Site (Intercept) 0.00000 0.00000
## Residual 0.00381 0.06173
## Number of obs: 413, groups: GenusSpecies, 102; Site, 10
##
## Fixed effects:

```

```

##           Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  0.025858   0.005359 110.137374    4.825 4.53e-06 ***
## r.degree     0.057224   0.006035  95.986259    9.481 1.94e-15 ***
## MeanITD      -0.005847   0.005419 124.159779   -1.079    0.283
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) r.degr
## r.degree  0.217
## MeanITD   0.014  0.150

```


And for how species traits effect the role of pollinators in the temporal metacommunity network:

```
lapply(mod.sites.pol, summary)

## $k
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
## Data: specs.site.pol
##
## REML criterion at convergence: 839
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -3.1765 -0.5764 -0.1379 0.3329 4.0470
##
## Random effects:
## Groups Name Variance Std.Dev.
## GenusSpecies (Intercept) 0.036829 0.19191
## Site (Intercept) 0.008274 0.09096
## Residual 0.368523 0.60706
## Number of obs: 429, groups: GenusSpecies, 98; Site, 17
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) -0.03852 0.04514 21.74320 -0.853 0.403
## r.degree 0.71464 0.04454 46.96095 16.046 <2e-16 ***
## MeanITD -0.05535 0.03911 97.36820 -1.415 0.160
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) r.degr
## r.degree 0.136
## MeanITD -0.022 0.221
##
## $weighted.betweenness
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
## Data: specs.site.pol
##
## REML criterion at convergence: -601.4
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -3.1409 -0.2313 -0.0816 0.1394 6.5257
##
## Random effects:
## Groups Name Variance Std.Dev.
## GenusSpecies (Intercept) 0.001316 0.03628
## Site (Intercept) 0.000000 0.00000
## Residual 0.012708 0.11273
## Number of obs: 429, groups: GenusSpecies, 98; Site, 17
##
```

```

## Fixed effects:
##           Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  0.038922   0.007243  97.667693   5.374 5.24e-07 ***
## r.degree     0.075158   0.008329  71.313326   9.024 2.04e-13 ***
## MeanITD      -0.007204   0.007262 137.218365  -0.992   0.323
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) r.degr
## r.degree   0.173
## MeanITD    -0.035  0.222

```

Lastly, for how patch "traits" effect their role in spatial metacommunity network:

```
lapply(mod.years.site, summary)

## $k
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
## Data: specs.years.site
##
## REML criterion at convergence: 398.3
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -1.8047 -0.6924 -0.1022 0.5191 2.7629
##
## Random effects:
## Groups Name Variance Std.Dev.
## GenusSpecies (Intercept) 0.3167 0.5627
## Site (Intercept) 0.0000 0.0000
## Residual 0.4947 0.7033
## Number of obs: 163, groups: GenusSpecies, 31; Site, 10
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 0.01499 0.11809 25.22235 0.127 0.900
## Div 0.28437 0.06903 157.27042 4.120 6.12e-05 ***
## natArea -0.02375 0.10887 28.87677 -0.218 0.829
## hrArea 0.16699 0.13577 21.48215 1.230 0.232
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) Div natAre
## Div 0.011
## natArea -0.060 -0.059
## hrArea 0.069 0.050 0.167
##
## $weighted.betweenness
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
## Data: specs.years.site
##
## REML criterion at convergence: -190.5
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -1.6527 -0.3194 -0.1939 -0.0430 6.1733
##
## Random effects:
## Groups Name Variance Std.Dev.
## GenusSpecies (Intercept) 0.003197 0.05655
## Site (Intercept) 0.000000 0.00000
## Residual 0.013625 0.11673
```

```
## Number of obs: 163, groups:  GenusSpecies, 31; Site, 10
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  0.048898   0.014083  29.699705   3.472  0.00161 **
## Div          0.023152   0.010796 154.423397   2.145  0.03355 *
## natArea      -0.002564   0.013378  37.990886  -0.192  0.84902
## hrArea        0.029587   0.015608  22.753103   1.896  0.07079 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr) Div    natAre
## Div      0.015
## natArea -0.046 -0.090
## hrArea   0.051  0.076  0.148
```

The plotting is then executed in the accompanying *plotting/spTempMets.R* script.

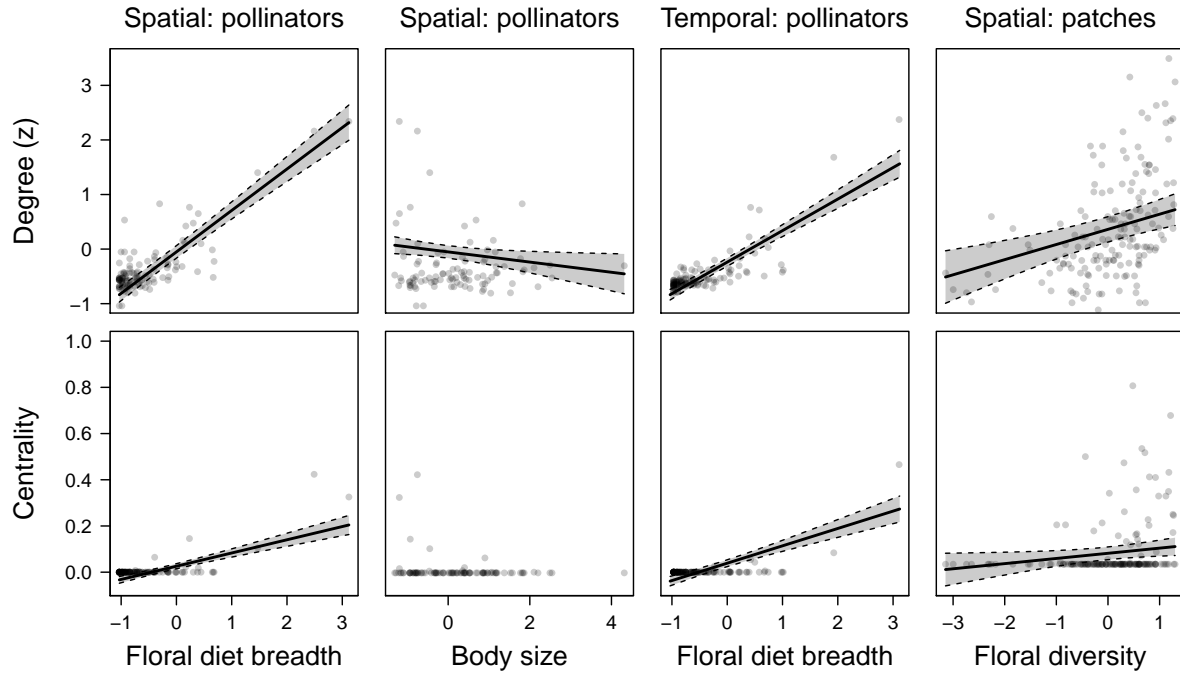


Figure 1: The relationship between species and patch traits and their position in the metacommunity network when the supergeneralists are not included in the community. Floral diet breadth was positively related to both species degree (standardized) and centrality and floral within a year across patches (spatial network) and within a patch across years (temporal network). Body size (mean intertegular distance, mm) was negatively related to species degree but not centrality in the spatial network. In addition, the floral diversity of a patch was positively related to its degree and centrality (marginally significant) within the patch network within a year. Points represent means for each species or patch. The solid line indicates the mean slope estimate and the dashed lines are the 95% confidence intervals around the estimate.

The results for how species traits effect the role of pollinators in the spatial metacommunity network without supergeneralists:

```
lapply(mod.years.pol, summary)

## $k
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
##   Data: specs.years.pol
##
## REML criterion at convergence: 767.9
##
## Scaled residuals:
##   Min       1Q   Median       3Q      Max
## -3.3223 -0.4184 -0.0923  0.3166  3.7501
##
## Random effects:
##   Groups             Name             Variance Std.Dev.
##   GenusSpecies (Intercept) 0.1755      0.41892
##   Site           (Intercept) 0.0093      0.09644
##   Residual                        0.3026      0.55012
## Number of obs: 393, groups:  GenusSpecies, 100; Site, 10
##
## Fixed effects:
##               Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  -0.06969    0.06361   34.03898  -1.096   0.2810
## r.degree      0.56697    0.05783  104.66451   9.804  <2e-16 ***
## MeanITD      -0.11872    0.05480  117.17997  -2.167   0.0323 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) r.degr
## r.degree 0.214
## MeanITD  0.003 0.012
##
## $weighted.betweenness
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
##   Data: specs.years.pol
##
## REML criterion at convergence: -1183.1
##
## Scaled residuals:
##   Min       1Q   Median       3Q      Max
## -3.6166 -0.1857 -0.0309  0.0624  7.3648
##
## Random effects:
##   Groups             Name             Variance Std.Dev.
##   GenusSpecies (Intercept) 0.002304 0.04800
##   Site           (Intercept) 0.000000 0.00000
##   Residual                        0.001805 0.04249
## Number of obs: 393, groups:  GenusSpecies, 100; Site, 10
```

```
##
## Fixed effects:
##           Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  0.023876   0.005808 106.531229   4.111 7.78e-05 ***
## r.degree     0.035537   0.006057 108.007658   5.867 4.93e-08 ***
## MeanITD      -0.005655   0.005648 118.283865  -1.001   0.319
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) r.degr
## r.degree  0.326
## MeanITD   0.004  0.002
```

And for how species traits effect the role of pollinators in the temporal metacommunity network without super generalists:

```
lapply(mod.sites.pol, summary)

## $k
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
##   Data: specs.site.pol
##
## REML criterion at convergence: 919.9
##
## Scaled residuals:
##   Min       1Q   Median       3Q      Max
## -3.1393 -0.5599 -0.1581  0.2961  3.4808
##
## Random effects:
##   Groups      Name      Variance Std.Dev.
##   GenusSpecies (Intercept) 0.06921  0.2631
##   Site         (Intercept) 0.00000  0.0000
##   Residual                0.62262  0.7891
## Number of obs: 372, groups:  GenusSpecies, 95; Site, 15
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept) -0.02572    0.05326   81.36366  -0.483    0.631
## r.degree     0.48541    0.05630   73.50603   8.623 9.04e-13 ***
## MeanITD      -0.06897    0.05278  100.38555  -1.307    0.194
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr) r.degr
## r.degree  0.141
## MeanITD  -0.034  0.059
##
## $weighted.betweenness
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: x
##   Data: specs.site.pol
##
## REML criterion at convergence: -496.9
##
## Scaled residuals:
##   Min       1Q   Median       3Q      Max
## -2.6593 -0.3989 -0.1419  0.0920  6.6031
##
## Random effects:
##   Groups      Name      Variance Std.Dev.
##   GenusSpecies (Intercept) 0.001649 0.0406
##   Site         (Intercept) 0.000000 0.0000
##   Residual                0.013291 0.1153
## Number of obs: 372, groups:  GenusSpecies, 95; Site, 15
```



```
##
## Fixed effects:
##           Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  0.036438   0.007956  99.335554   4.580 1.35e-05 ***
## r.degree     0.045370   0.008419  91.554906   5.389 5.47e-07 ***
## MeanITD      -0.012505   0.007865 122.245992  -1.590   0.114
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) r.degr
## r.degree   0.154
## MeanITD    -0.036  0.057
```

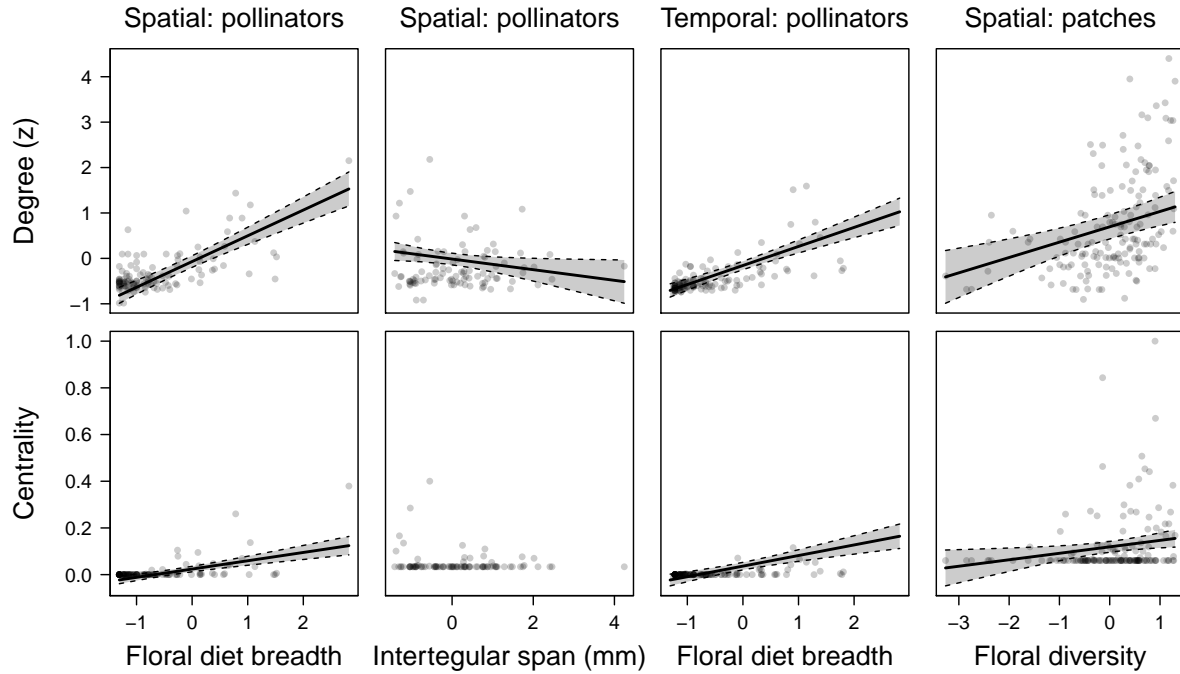


Figure 2: The relationship between species and patch traits and their position in the metacommunity network when the supergeneralists are not included in the community. Floral diet breadth was positively related to both species degree (standardized) and centrality and floral within a year across patches (spatial network) and within a patch across years (temporal network). Body size (mean intertegular distance, mm) was negatively related to species degree but not centrality in the spatial network. In addition, the floral diversity of a patch was positively related to its degree and centrality (marginally significant) within the patch network within a year. Points represent means for each species or patch. The solid line indicates the mean slope estimate and the dashed lines are the 95% confidence intervals around the estimate.

References

NIMBLE Development Team (2014). NIMBLE: An R package for programming with BUGS models, version 0.1.

de Valpine, P., Turek, D., Paciorek, C.J., Anderson-Bergman, C., Lang, D.T. & Bodik, R. (2017). Programming with models: writing statistical algorithms for general model structures with nimble. *Journal of Computational and Graphical Statistics*, 26, 403–413.