

# mangal – making ecological network analysis simpler

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3 The study of ecological networks is severely limited by (i) the difficulty to access data, (ii) the lack of a  
4 standardized way to link meta-data with interactions, and (iii) the disparity of formats in which ecologi-  
5 cal networks themselves are represented. To overcome these limitations, we conceived a data specification  
6 for ecological networks. We implemented a database respecting this standard, and released a R package  
7 (`rmangal`) allowing users to programmatically access, curate, and deposit data on ecological interactions. In  
8 this article, we show how these tools, in conjunctions with other frameworks for the programmatic manipula-  
9 tion of open ecological data, streamlines the analysis process, and improves replicability and reproducibility  
10 of ecological networks studies.

# 1 Introduction

2 Ecological networks are efficient representations of the complexity of natural communities, and help discovering mech-  
3 anisms contributing to their persistence, stability, resilience, and functioning. Most of the “early” studies of ecological  
4 networks were focused on understanding how the structure of interactions within one location affected the ecological  
5 properties of this local community. They revealed the contribution of ‘average’ network properties, such as the buffering  
6 impact of modularity on species loss (Pimm *et al.* 1991, Yodzis (1981)), the increase in robustness to extinctions along  
7 with increases in connectance (Dunne *et al.* 2002), and the fact that organization of interactions maximizes biodiversity  
8 (Bastolla *et al.* 2009). New studies introduced the idea that networks can vary from one locality to another. They can  
9 be meaningfully compared, either to understand the importance of environmental gradients on the presence of ecological  
10 interactions (Tylianakis *et al.* 2007), or to understand the mechanisms behind variation itself (Poisot *et al.* 2012, 2014).  
11 Yet, meta-analyses of a large number of ecological networks are still extremely rare, and most of the studies comparing  
12 several networks do so within the limit of particular systems (Schleuning *et al.* 2011; Dalsgaard *et al.* 2013; Poisot *et al.*  
13 2013b; Chamberlain *et al.* 2014; Olito & Fox 2014). The severe shortage of publicly shared data in the field also restricts  
14 the scope of large-scale analyses.

15 It is possible to predict the structure of ecological networks, either using latent variables (Rohr *et al.* 2010; Eklöf *et al.*  
16 2013) or actual trait values (Gravel *et al.* 2013). The calibration of these approaches require accessible data, not only  
17 about the interactions, but about the traits of the species involved. Comparing the efficiency of different methods is also  
18 facilitated if there is an homogeneous way of representing ecological interactions, and the associated metadata. In this  
19 paper, we (i) establish the need of a data specification serving as a common language among network ecologists, (ii)  
20 describe this data specification, and (iii) describe `rmangal`, a R package and companion database relying on this data  
21 specification. The `rmangal` package allows to easily deposit and retrieve data about ecological interactions and networks  
22 in a publicly accessible database. We provide use cases showing how this new approach makes complex analyzes simpler,  
23 and allows for the integration of new tools to manipulate biodiversity resources.

## 24 Networks need a data specification

25 Ecological networks are (often) stored as an *adjacency matrix* (or as the quantitative link matrix), that is a series of 0  
26 and 1 indicating, respectively, the absence and presence of an interaction. This format is extremely convenient for *use*  
27 (as most network analysis packages, *e.g.* `bipartite`, `betalink`, `foodweb`, require data to be presented this way), but  
28 is extremely inefficient at *storing* meta-data (this can be done by adding attributes to the matrix objects in the language  
29 that support it). In most cases, an adjacency matrix informs on the identity of species (in cases where rows and columns  
30 are named), and the presence or absence of interactions. If other data about the environment (*e.g.* where the network  
31 was sampled) or the species (*e.g.* the population size, trait distribution, or other observations) are available, they are most  
32 either given in other files, or as accompanying text. In both cases, making a programmatic link between interaction data  
33 and relevant meta-data is difficult, time-consuming, and error-prone. Because of the lack of a common structure for these  
34 data, the process cannot be automated when different datasets needs to be processed.

35 By contrast, a data specification (*i.e.* a set of precise instructions detailing how each object should be represented)  
36 provides a common language for network ecologists to interact, and ensure that, regardless of their source, data can be  
37 used in a shared workflow. Most importantly, a data specification describes how data are *exchanged*. Each group retains  
38 the ability to store the data in the format that is most convenient for in-house use, and only needs to provide export options  
39 (*e.g.* through an API, a programmatic interface running on a webserver, returning data in response to queries in a pre-

1 determined language) respecting the data specification. This approach ensures that *all* data can be used in meta-analyses,  
 2 thus increasing their long-term impact (Piwowar & Vision 2013). Data archival also offers additional advantages for  
 3 ecology. The aggregation of local observation can reveal large-scale phenomenon (Reichman *et al.* 2011), which would  
 4 be unattainable in the absence of a collaborative effort. Data archival in databases also prevents data rot and data loss  
 5 (Vines *et al.* 2014), thus ensuring that data on interaction networks – which are typically hard and costly to produce –  
 6 continue to be available and usable.

## 7 Elements of the data specification

8 The data specification (Fig. 1) is built around the idea that (ecological) networks are collections of relationships be-  
 9 tween ecological objects, each element having particular meta-data associated. In this section, we detail the way net-  
 10 works are represented in the mangal specification. An interactive webpage with the complete data specification can be  
 11 found online at <http://mangal.uqar.ca/doc/spec/>. The data specification is available either at the API root (*e.g.*  
 12 <http://mangal.uqar.ca/api/v1/?format=json>), or can be viewed using the `whatIs` function from the R package  
 13 (see *Supp. Mat. 1*). Rather than giving an exhaustive list of the data specification, this section serves as an overview of  
 14 each element, and how they interact.

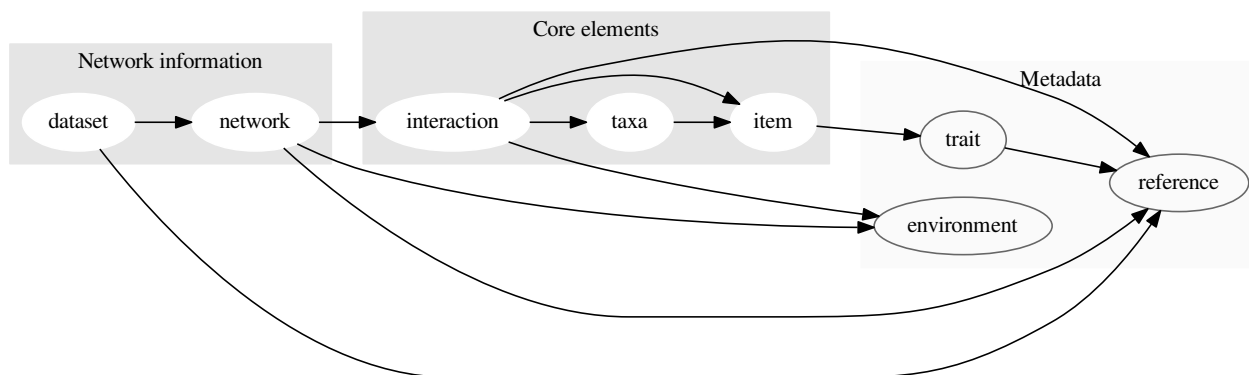


Fig. 1: An overview of the data specification, and the hierarchy between objects. Each box correspond to a level of the data specification, and arrows represent a relationship between objects. For example, `taxa` have associated `items`, and `interactions` have associated `taxa`, `items`, `references`. Not all relationships are mandatory, as we detail below.

15 We propose JSON as an efficient way to uniformise data representation for two main reasons. First, it has emerged as  
 16 a *de facto* standard for web platforms serving data, and accepting data from users. Second, it allows *validation* of the  
 17 data: a JSON file can be matched against a scheme, and one can verify that it is correctly formatted. Finally, JSON objects  
 18 representing individual items are easily and cheaply (memory-wise) parsed in the most common programming languages,  
 19 notably R (equivalent to `list`) and python (equivalent to `dict`). For most users, the format in which data are transmitted  
 20 is unimportant, as the interaction happens within R – as such, knowing how JSON objects are organized is only useful for  
 21 those who want to interact with the API directly. The `rmangal` package takes care of converting the data into the correct  
 22 JSON format to upload them in the database.

## 1 Node information

### 2 Taxa

3 Taxa are a taxonomic entity of any level, identified by their name, vernacular name, and their identifiers in a variety of  
4 taxonomic services. Associating the identifiers of each taxa allows using the new generation of open data tools, such  
5 as `taxize` (Chamberlain & Szöcs 2013), in addition to protecting the database against taxonomic revisions. The data  
6 specification currently has fields for `ncbi` (National Center for Biotechnology Information), `gbif` (Global Biodiversity  
7 Information Facility), `tsn` (Taxonomic Serial Number, used by the Integrated Taxonomic Information System), `eol`  
8 (Encyclopedia of Life) and `bold` (Barcode of Life) identifiers. We also provide the taxonomic status, *i.e.* whether a taxa  
9 is a true taxonomic entity, a “trophic species”, or a morphospecies. Taxonomic identifiers can either be added by the  
10 contributors, or will be automatically retrieved during the automated curation routine.

### 11 Item

12 An `item` is any measured instance of a taxon. Items have a `level` argument, which can be either `individual` or  
13 `population`; this allows to represent both individual-level networks (*i.e.* there are as many `items` of a given taxa as there  
14 were individuals of this sampled), and population-level networks. When `item` represents a population, it is possible to  
15 give a measure of the size of this population. The notion of `item` is particularly useful for time-replicated designs: each  
16 observation of a population at a time-point is an `item` with associated `trait` values, and possibly population size.

## 17 Network information

18 All objects described in this sub-section can have a spatial position, information on the date of sampling, and references  
19 to both papers and datasets.

### 20 Interaction

21 An `interaction` links two `taxa` objects (but can also link pairs of `items`). The most important attributes of `interactions`  
22 are the type of interaction (of which we provide a list of possible values, see *Supp. Mat. 1*), and its `ob_type`, *i.e.* how  
23 it was observed. This field help differentiate direct observations, text mining, and inference. Note that the `obs_type`  
24 field can also take `confirmed absence` as a value; this is useful for, *e.g.*, “cafeteria” experiments in which there is high  
25 confidence that the interaction did not happen.

### 26 Network

27 A `network` is a series of `interaction` object, along with (i) informations on its spatial position (provided at the latitude  
28 and longitude), (ii) the date of sampling, and (iii) references to measures of environmental conditions.

### 29 Dataset

30 A `dataset` is a collection of one or several `network(s)`. Datasets also have a field for `data` and `papers`, both of which  
31 are references to bibliographic or web resources describing, respectively, the source of the data, and the papers in which

1 these data have been significantly used. Datasets or networks are the preferred entry point into the resources, although in  
2 some cases it can be meaningful to get a list of interactions only.

### 3 **Meta-data**

#### 4 **Trait value**

5 Objects of type `item` can have associated `trait` values. These consist in the description of the trait being measured,  
6 the value, and the units in which the measure was taken. As traits may have been measured at a different time and/or  
7 location that the interaction was, they have fields for time, latitude and longitude, and references to original publication  
8 and original datasets.

#### 9 **Environmental condition**

10 Environmental conditions are associated to datasets, networks, and interactions objects, to allow for both macro and micro  
11 environmental conditions. These are defined by the environmental property measured, its value, and the units. Similarly  
12 to traits, they have fields for time, latitude and longitude, and references to original publication and original datasets.

### 13 **References**

14 References are associated to datasets. They accommodate the DOI, JSON or PubMed identifiers, or a URL. When  
15 possible, the DOI should be preferred as it offers more potential to interact with other on-line tools, such as the *CrossRef*  
16 API.

### 17 **Use cases**

18 In this section, we present use cases using the `rmangal` package for R, to interact with a database implementing this data  
19 specification, and serving data through an API (<http://mangal.uqar.ca/api/v1/>). It is possible for users to deposit  
20 data into this database, through the R package. Data are made available under a *CC-0 Waiver* (Poisot *et al.* 2013a).  
21 Detailed informations about how to upload data are given in the vignettes and manual of the `rmangal` package.

22 The data we use for this example come from Ricciardi et al. (2010). These were previously available on the *Interaction-*  
23 *Web DataBase* as a single `xls` file. We uploaded them in the `mangal` database at <http://mangal.uqar.ca/api/v1/dataset/1>.  
24 Before running the examples, users need to install the relevant packages and connect to the database:

### 25 **Link-species relationships**

26 In the first example, we visualize the relationship between the number of species and the number of interactions, which  
27 Martinez (1992) proposed to be linear (in food webs).

```
# Pull the dataset of interest
dataset <- getDataset(api, DSET_ID)
```

```

# Get each network in the dataset as a graph object
graphs <- alply(dataset$networks, 1, function(x) toIgraph(api, x))

# Make a data.frame with the number of links and species
ls <- ldply(graphs, function(x) c(S = length(V(x)), L = length(E(x))))
ls$X1 <- aaply(as.numeric(as.vector(ls$X1)), 1,
              function(x) getNetwork(api, x)$name)
colnames(ls)[1] <- 'Network'

# Now plot this dataset
plot(jitter(L)~jitter(S), ls, log='xy', pch=22, bg='lightgrey',
     lwd=1.5, cex=1.5, xlab='Species richness', ylab='Number of interactions')
# Constant connectance
X <- c(1:max(ls$S))
Y <- X^2 * mean(ls$L/ls$S^2)
lines(X, Y, lty=2)
# Best fit
bfit <- lm(L~S, ls)
Yf <- X * bfit$coefficients[2] + bfit$coefficients[1]
lines(X, Yf)
legend('bottomright', pch=c(22, NA, NA), lty=c(NA, 2, 1),
      pt.cex=c(1.5, 1, 1), lwd=c(1.5, 1, 1), pt.bg=c('lightgrey', NA, NA),
      legend=c('Data', 'Constant connectance', 'Best fit (linear model)'), bty='n')

```

- 1 Getting the data to produce this figure requires less than 10 lines of code. The only information needed is the identifier of
- 2 the network or dataset, which we suggest should be reported in publications as: “These data were deposited in the mangal
- 3 format at <URL>/api/v1/dataset/<ID>” (where <URL> and <ID> are replaced by the corresponding values), preferably
- 4 in the methods, possibly in the acknowledgements. So as to encourage data sharing and its recognition, we encourage
- 5 users of the database to cite the original dataset or publication.

## 6 Network beta-diversity

- 7 In the second example, we use the framework of network  $\beta$ -diversity (Poisot *et al.* 2012) to measure the extent to which
- 8 networks that are far apart in space have different interactions. Each network in the dataset has a latitude and longitude,
- 9 meaning that it is possible to measure the geographic distance between two networks.
- 10 For each pair of network, we measure the geographic distance (in km.), the species dissimilarity ( $\beta_S$ ), the network dissim-
- 11 ilarity when all species are present ( $\beta_{WN}$ ), and finally, the network dissimilarity when only shared species are considered
- 12 ( $\beta_{OS}$ ).

```

# We first retrieve all informations about the networks
Networks <- alply(dataset$networks, 1, function(x) getNetwork(api, x))

# Extract the lat/lon data

```

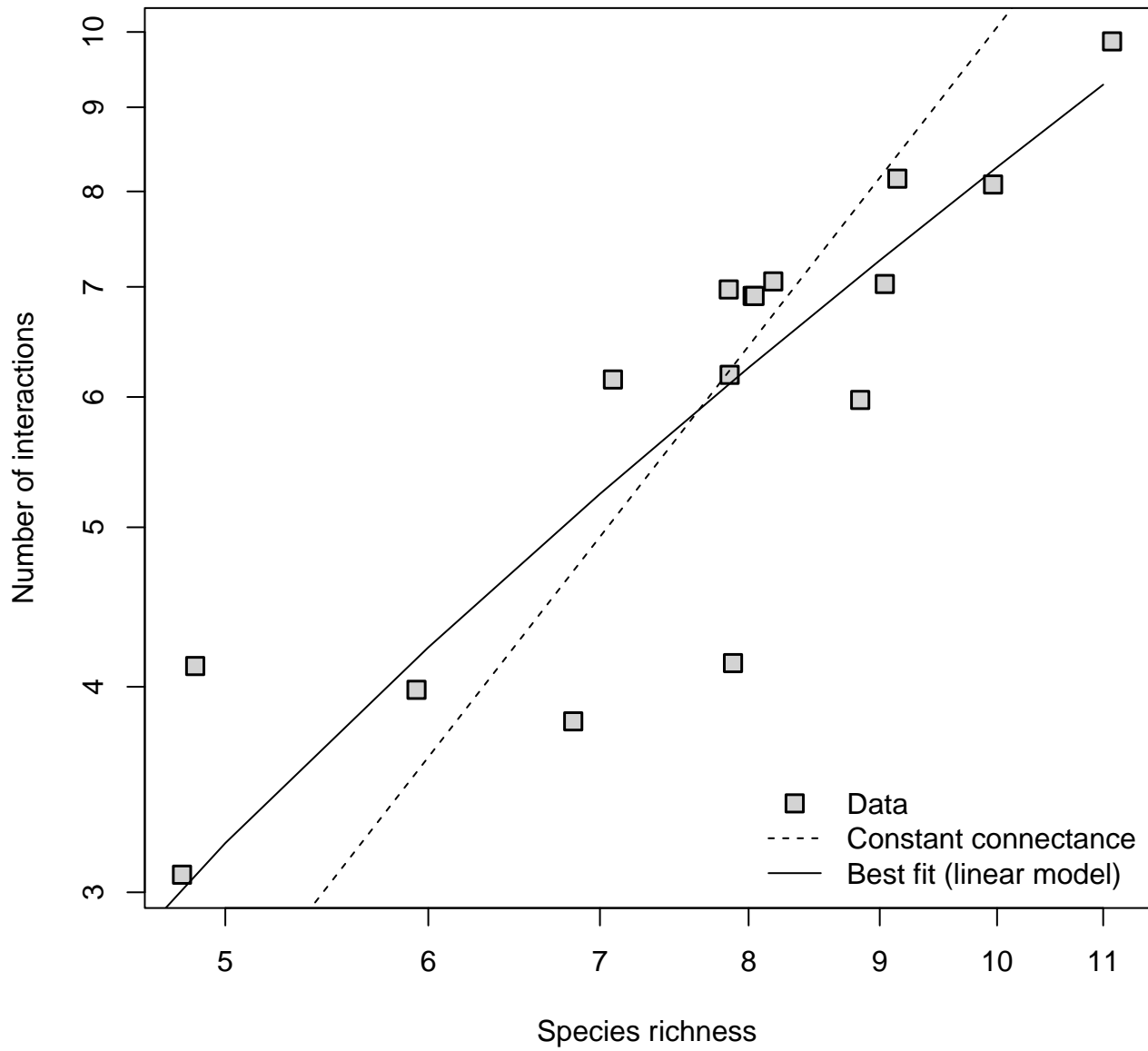


Fig. 2: Relationship between the number of species and number of interactions in the anemonefish-fish dataset. Constant connectance refers to the hypothesis that there exist a quadratic relationship between these two quantities.



```

LatLon <- ldply(Networks, function(x) c(name = x$name, lat = x$latitude, lon = x$longitude))
rownames(LatLon) <- LatLon$name
LatLon$lat <- as.numeric(LatLon$lat)
LatLon$lon <- as.numeric(LatLon$lon)
LatLon <- LatLon[,c('lat', 'lon')]

# Then we measure the distances between all pairs of sites
GeoDist <- spDists(as.matrix(LatLon, latlon=TRUE))
colnames(GeoDist) <- rownames(GeoDist) <- rownames(LatLon)
GeoDist <- as.dist(GeoDist)

# Now, we measure the beta-diversity of the networks
names(graphs) <- aapply(names(graphs), 1, function(x) Networks[[x]]$name)
# Finally, we measure the beta-diversity
BetaDiv <- network_betadiversity(graphs)

# We add the geographic distance
BetaDiv$GEO <- GeoDist

# And we do some plots
par(mfrow=c(2,2), pty='s')
with(BetaDiv,{
  plot(GEO, S, pch=22, bg='lightgrey', cex=1.5, lwd=1.5,
       xlab="Geographic distance", ylab="Species composition dissimilarity")
  plot(GEO, WN, pch=22, bg='lightgrey', cex=1.5, lwd=1.5,
       xlab="Geographic distance", ylab="Network dissimilarity (all species)")
  plot(GEO, OS, pch=22, bg='lightgrey', cex=1.5, lwd=1.5,
       xlab="Geographic distance", ylab="Network dissimilarity (shared species)")
})

```

- 1 As shown in *Fig. 3*, while species dissimilarity and overall network dissimilarity increase when two networks are far
- 2 apart, this is not the case for the way common species interact. This suggests that in this system, network dissimilarity
- 3 over space is primarily driven by species turnover. The ease to gather both raw interaction data and associated meta-data
- 4 make producing this analysis extremely straightforward.

## 5 Spatial visualization of networks

- 6 Bascompte (2009) uses an interesting visualization for spatial networks, in which each species is laid out on a map at the
- 7 center of mass of its distribution; interactions are then drawn between species to show how species distribution determines
- 8 biotic interactions. In this final use case, we propose to reproduce a similar figure.

```

# We fill a community data matrix
sp_by_site <- llply(graphs, function(x) unlist(V(x)$name))

```

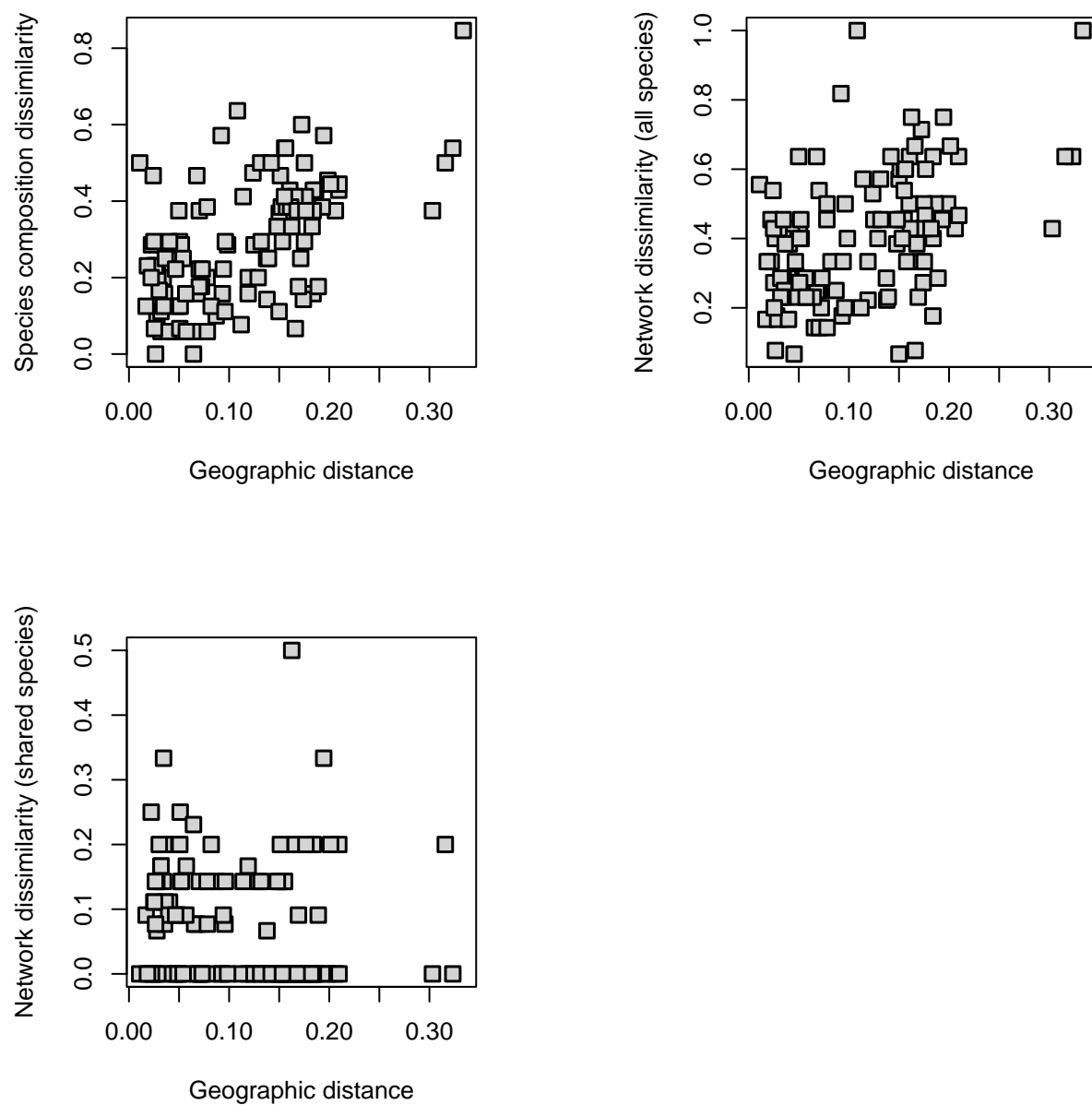


Fig. 3: Relationships between the geographic distance between two sites, and the species dissimilarity, network dissimilarity with all, and only shared, species.

```

sp_list <- unique(unlist(sp_by_site))
M <- matrix(0, ncol = length(sp_list), nrow = length(sp_by_site))
colnames(M) <- sp_list
rownames(M) <- names(sp_by_site)
for (site in c(1:length(sp_by_site))) M[names(sp_by_site)[site], sp_by_site[[site]]] = 1

# Next, we get the center position for each species
# (i.e. the mean position of the sites it occurs at)
sp_center <- apply(M, 2, function(x) colMeans(LatLon[names(x)[x > 0], ]))
rownames(sp_center) <- sp_center[, 1]
sp_center <- sp_center[, -1]

# We now create a regional network using betalink::metaweb
Mw <- metaweb(graphs)

# Plot a map
center_point <- colMeans(sp_center)
vcolors <- c(brewer.pal(9, "Set1"), brewer.pal(8, "Set2"))

Layout <- matrix(c(1,2,2,2), 2, 2)
colSize <- c(1.3, 2.0)
rowSize <- c(1.2, 2)
layout(Layout, colSize, rowSize)

# Inset map is number 1
par(mar=c(4.5, 1, 1, 4))
map("worldHires", xlim=c(90,136), ylim=c(-15,15), col="gray90",
    fill=TRUE, resolution=0)
points(center_point[2], center_point[1], pch=1, cex=2, lwd=2)
box()

par(mar=c(4.1, 4.1, 4.1, 4.1))
map("worldHires", xlim=c(124.0,125.1), ylim=c(1.2,1.9), col="gray90",
    fill=TRUE, resolution = 0)
plot(Mw, layout = jitter(as.matrix(LatLon[,c('lon','lat')])),
    rescale = FALSE, add = TRUE, vertex.color = vcolors, vertex.size = 1,
    vertex.label = NA, edge.arrow.size = 0.25, edge.color = 1)
axis(1)
axis(4)
legend("bottomleft", fill = vcolors, legend = V(Mw)$name, inset = 0.02,
    cex = 0.7, bty = "n", ncol=2)

```

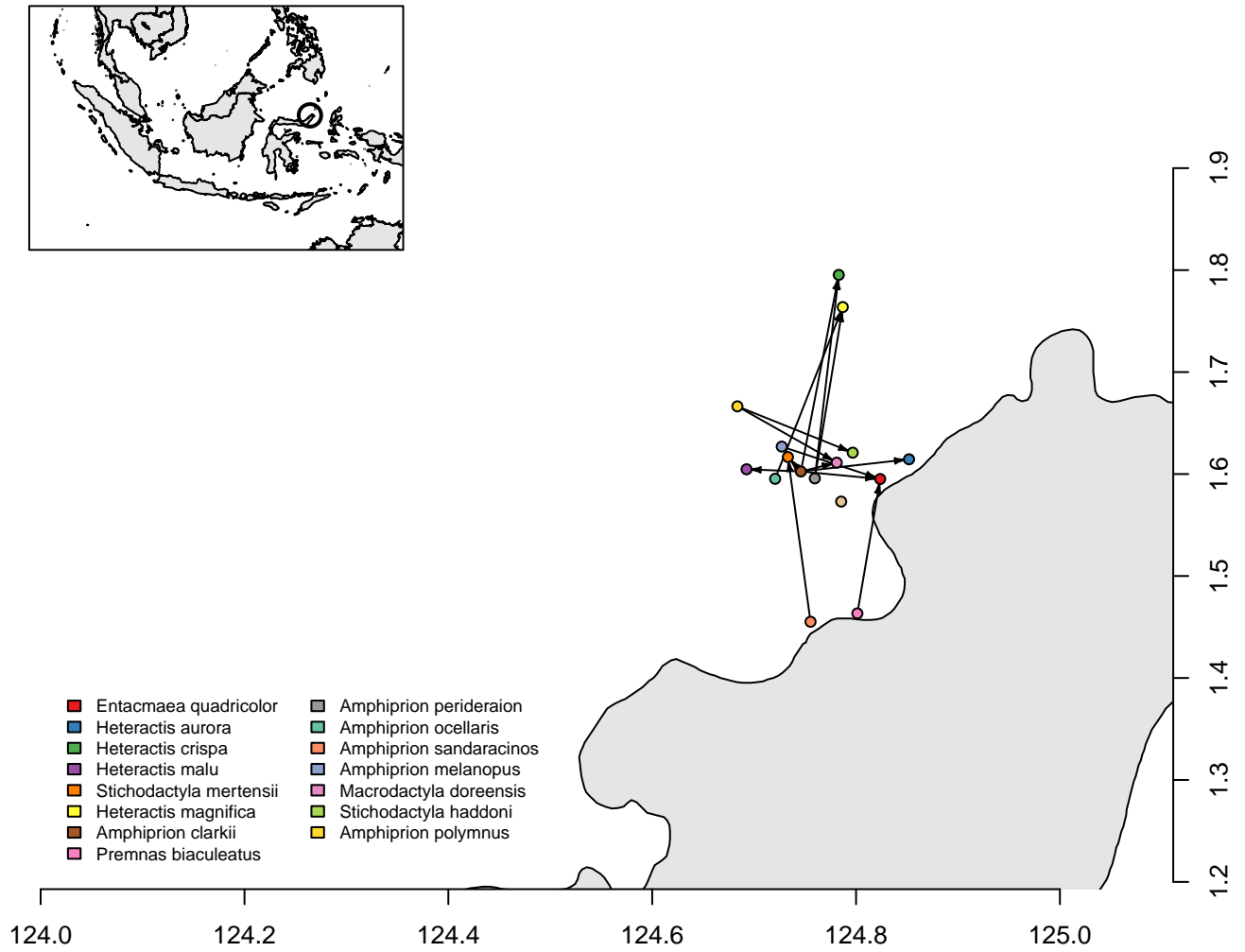


Fig. 4: Spatial plot of a network, using the maps and rmangal packages. The circle in the inset map show the location of the sites. Each dot in the main map represents a species, with (symbiotic mutualism) drawn between them. The land is in grey.

## 1 Conclusions

2 The mangal data format will allow researchers to put together dataset with species interactions and rich meta-data, that  
3 are needed to adress emerging questions about the structure of ecological networks. We deployed an online database with  
4 an associated API, relying on this data specification. Finally, we introduced rmangal, a R package designed to interact  
5 with APIs using the mangal format. We expect that the data specification will evolve based on the needs and feedback  
6 of the community. At the moment, users are welcome to propose such changes on the project issue page: <https://github.com/mangal-wg/mangal-schemes/issues>. A python wrapper for the API is also available at <http://github.com/mangal-wg/pymangal/>. Additionally, there are plans to integrate this database with GLOBI, so that data  
9 can be accessed from multiple sources (Poelen *et al.* 2014).

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