Chapter 2
Functional Groups

Abstract The set of species co-existing in a given community constitute a functional group if they have similar functional characteristics related to one ecosystem service. This dependence on ecosystem service is defined by theoretical framework or by empirical evidence. Functional groups in vegetation science are known as plant functional types and in animal science as guilds. Functional groups may be defined externally using categories for key traits or generated from several traits using cluster techniques. In this chapter we show how to identify functional groups, selecting the appropriate measures to evaluate species similarity based on trait profiles, and choosing linkage algorithms to conform the functional groups. Changes in the relative abundance of each group in a sample may be used to interpret the relationship of community composition with environmental conditions.

Keywords Cluster analysis · Number of functional groups · Distance measures · Similarity measures · Trait types

2.1 Selecting Trait and its Relation With Ecosystem Services

Because a functional group is a collection of organisms with similar suites of co-occurring functional attributes they have similar responses to external factors and/or effects on ecosystem processes (de Bello et al. 2010). A functional group is often referred as plant functional type (PFT) in vegetation sciences or as a 'guild' when referring to animals. Ecosystem properties or processes determine the services an ecosystem provides. These properties are associated to functional attributes of individuals (or population): the traits. Thus, the PFTs or the guilds are defined based on sets of species traits useful to explain ecosystem properties.

Several species of organisms within a trophy chain or trophy network with similar feeding types have the same function and are considered as a guild. Several plant

species within an assemblage with similar photosynthetic strategy and foliar nutrient content (N and P) are considered as a PFT, possible related to wood density, which in turn affect the carbon sequestration service. Both, guild and PFT are associated to ecosystem services which make more suitable the human existence.

The idea of creating functional groups is to obtain a set of species having the same role in the ecosystem. These clusters of species are performed using a set of traits directly related to the ecosystem service. Several authors have summarized the relationship between traits and ecosystem services (MEA 2005; Carpenter et al. 2009; Lavorel et al. 2011; Polania et al. 2011).

The selected traits may include quantitative (continuous and discrete) and/or qualitative (nominal and ordinal) variables and the clusters are obtained by mean of a hierarchical algorithm. Hierarchical techniques are based on a dissimilarity matrix between species and a join procedure known as linkage strategy. The resulting hierarchy may be represented by a dendrogram, which allows grouping the species taking into account the level of the hierarchy and the aim of the study.

2.2 A Guide for Data Arrangement

The usual way to store data for further statistical processing is to arrange them in an $S \times t$ data table, where S represents the number of cases (in this context species) and t the number of traits. The traits may be continuous variables like leaf area, discrete quantitative variables like number of leaflets by leaf, or qualitative variables. If traits are qualitative, we should recognize if they are present-absent variables like evergreen or not, if they have more than two categories, or if they are ordinals. Additionally we should recognize if the categories are exclusive or not.

To calculate a dissimilarity matrix from a set of mixed type of traits it is convenient to express all of them in such a way that can be treated as quantitative. So the problem is how to re-express categorical variables. If a trait is categorical, having k exclusive categories, we may represent it as a set of $k - 1$ dummy variables (Box 2.1). To include the trait Reproductive system we have to use the two variables: Rep_Monoic and Rep_Dioic, which include all the information in the pairs (1,0) for Monoic, (0,1) for Dioic, and (0,0) for Hermaphrodite.

Box 2.1: Example of dummy transformation for an exclusive categorical trait

Species	Reproductive system	Rep_Monoic	Rep_Dioic
sp1	Monoic	1	0
sp2	Dioic	0	1
sp3	Dioic	0	1
sp4	Hermaphrodite	0	0
sp5	Hermaphrodite	0	0

When categories are not exclusive, like dispersal type (hydrochory, autochory, dispersed by mammals, etc.) we may represent the trait as a set of indicator variables (equals 1 if the category is present or 0 in contrary case), one for each observed category (Box 2.2). In future analysis we include the resulted four variables, in this example Hydrochory, Autochory, Zoochory and Wind.

Box 2.2: Example of indicator variables to identify nonexclusive categorical traits

Species	Dispersion	Hydrochory	Autochory	Zoochory	Wind
sp1	Hydrochory, Autochory, Zoochory	1	1	1	0
sp2	Hydrochory, Autochory	1	1	0	0
sp3	Autochory, Zoochory	0	1	1	0
sp4	Zoochory, Wind	0	0	1	1
sp5	Autochory, Wind	0	1	0	1

Ordinal variables can be numerically codified by a sequence of integers which relate to the rank of the categories they represent. For example canopy strata in a forest with four layers may be codifying as: 1, 2, 3, 4; this codification is equivalent to apply rank transformation to a quantitative variable. However, if the assumption that categories are representing equally spaced points of a scale do not hold, the numerical coding using a sequence of integers could be discarding important biological information about the trait expression. In that case it should be preferable to represent those traits through indicator variables as in the case of non-exclusive categorical variable, coding the category observed and all ones below it in the ordinal scale as present (Box 2.3). See for example, that a species of the highest strata has a one in all the categories; while sp3 from lowest strata has a one only in the lowest or sp2 belonging to the medium strata has ones in lowest and in medium variables. The three variables Lowest, Medium and Highest should be used to represent the ordinal variable in further analysis.

Box 2.3: Example of indicator variables to identify non equidistance ordinal categorical traits

Species	Strata	Lowest	Medium	Highest
sp1	Highest	1	1	1
sp2	Medium	1	1	0
sp3	Lowest	1	0	0
sp4	Highest	1	1	1
sp5	Lowest	1	0	0

In some cases it is possible to recover the original quantitative scale. Researches should avoid the use of categorical variable when a quantitative trait is possible to measure, even when the precision of the measure is not quite well. For example the layers in the forest canopy can be defined as: lower layer from 0 to 10 m, middle layer from 10 to 30 m, high layer from 30 to 40 m, and emergent layer from 40 to 60 m. In this case coding as 1, 2, 3 and 4 indicates the relative order of altitude of layers, but this coding is based on the assumption of equidistance between layers. It should be better to take the mean point of each layer to represent the strata and represent the layer by 5, 20, 35 and 50 m. If the higher strata were defined as 'more than 40 m', there is not a mean value to represent the layer unless an estimation of highest species is available.

After having all variables in an appropriate numerical scale, the data-table will be $S \times k$ where k will be equal or greater than t because of coding. Moreover the data table will only contain numerical representations of the traits in such a way that a common procedure can be applied to the whole table in order to obtain a dissimilarity matrix between species.

2.3 Statistical Procedures to Define Functional Groups

2.3.1 The Selection of a Dissimilarity Measure

The selection of dissimilarity measures depends on the type of variables in the data set. If all the traits have been measured in continuous or discrete scale, Euclidean distance will be appropriated to represent differences between pair of species. In case of dichotomous variables (0–1 variables) there are several similarity measures that can be used to derive a dissimilarity matrix. The most widely used are Jaccard (1908); Simple matching (Sokal and Michener 1958) and Dice (1945) (Box 2.4).

Cluster algorithms are usually based on dissimilarity measures, so when likeness between species is obtained from similarity measures, they must be transformed into dissimilarities. There is more than one way to convert similarities into dissimilarities, but when similarity ranges in the interval [0,1], the simplest one is

to calculate d_{ij} (the dissimilarity between species i and j) as $d_{ij} = 1-s_{ij}$, were s_{ij} is the corresponding measure of similarity. Some specialized software like InfoStat automatically select the best (or most widely used) transformation for a given similarity measure.

When the data set has quantitative and qualitative variables the Gower similarity is one of the options (Gower 1971). This measure combines Euclidean distance with Jaccard similarity in a new similarity measure which can be converted into a dissimilarity using an appropriate transformation.

Box 2.4: Similarity measures for categorical variables

		Sp 1	
		Present (1)	Absent (1)
Sp 2	Present (1)	a	b
	Absent (0)	c	d

$$\text{Jaccard} = \frac{a}{a+b+c} \qquad \text{Dice} = \frac{2a}{2a+b+c}$$

$$\text{Single matching} = \frac{a+d}{a+b+c+d}$$

Another alternative to handle data sets with continuous and qualitative variables is to perform multidimensional scaling methods to summarize the qualitative variables in a set of new continuous variables (principal coordinates). In this case, it is possible to apply Euclidean distances to the set of continuous variables plus principal coordinates. One of the advantages using principal coordinates to summarize categorical traits is the possibility to use a multivariate analysis of variance or a cluster based mean comparison method (gDGC, Valdano and Di Rienzo 2007) to determine significance among resulted groups.

2.3.2 Standardization

Generally the traits values are expressed in their original scale of measurement, as for example: biomass (kg), leaf area (cm^2), wood density (mg cm^{-3}), maximum height (m), leaf carbon content (%), number of leaflets by leaf. When dissimilarity

measure is involve into the analysis, the scale and unit of measure will affect the results. Those variables having the largest scale will have the greatest impact on dissimilarity calculation. Standardization is the usual way to avoid the scale effect. Statistical software offers options to standardize data before performing analysis which are affected by the scale, like cluster analysis. Standardization can be also useful even when all the traits are expressed in the same units, because some traits can have more variance than others.

When the data set has mixture of quantitative and qualitative variables, previously transformed to zero–one variables, other options to avoid scale effects can be considered. For example, transform the variables to map the values into the zero–one interval [0, 1]. Thus, the minimum value in the original scale will be zero and the maximum will be one in the transformed scale.

2.3.3 Choosing the Linkage Algorithm Method

Widely used linkage clustering methods for cluster analysis are average linkage, single linkage, complete linkage and Ward, among others. Which of these methods is the best has not an easy answer. Although it depends on the purpose of clustering, the experience shows that the average linkage and Ward are the preferred methods. Average linkage is a linkage algorithm that maximized the cophenetic correlation. This means that the resulting hierarchy preserves in the best way possible the original dissimilarity structure. On the other hand, Ward method produces more clearly defined clusters which facilitate the definition of functional groups.

2.3.4 Assessing the Number of Functional Groups

Despite the existence of several proposals, Calinski and Harabasz (1974), Hartigan (1975), Sarle (1983), Kaufman and Rousseeuw (1990), Tibshirani et al. (2001), Pollard and van der Laan (2005), Fraley and Raftery (2002, 2006), Valdano and Di Rienzo (2007) and Pollard et al. (2009), to assessing the number of clusters in a data set, there are not statistical procedures or generally accepted rules to determine that number. Some times the number of clusters depends on the aim of the study, and it is determined by a heuristic criteria. For example if the main ecosystem property under study depends on acquisitive or conservative strategy of plants, two groups will be enough for the purpose of defining the corresponding PFTs. On the other hand, if the purpose of the research was to evaluate the effect of altitude on the composition of functional groups, a larger number of groups will be necessary.

As previously stated, each species in the data-set is represented by a single row-vector of traits values. Thus, no replicates are available at species level. This limit the use of assessing-number-of-clusters algorithms to those which do not need replicates. Within this class of algorithms, an approach to assessing the number of clusters in a data set is the comparison of the resulting clusters. This idea was

explored by Calinski and Harabasz (1974), who defined the number of clusters on the maximization of the between/within-cluster, of a generalized sum of squares ratio. Also Hartigan (1975), used the ratio between the within-cluster generalized sums of squares of k and (k + 1) clusters suggesting the selection of k ≥ 1 as the minimum k for which the ratio is lesser than 10. A model-based approach to the determination of the number of cluster is found in the MCLUS algorithm by Fraley and Raftery (2002, 2006). Unpublished simulation results (Di Rienzo, personal communication) shown that MCLUS is the best choice when no replicate are available. It must be warning that the same simulation study also shown that all algorithms tend to underestimate the true number of clusters in the data. Previous discussed procedures for assessing the number of clusters assume that traits are continuous variables, and in case of MCLUS, that they follow a normal-multi-variate distribution. When variables are categorical or a mixture of continuous and categorical, the previous methods could not be appropriate.

   The analysis of molecular variance (AMOVA) was introduced by Excoffier et al. (1992).The method implements a multivariable analysis of variance like analysis for haplotypes data which are usually coded as 0–1 variables. Hypothesis testing is based on the permutation test principles. Because the method operates on a distances matrix, it is ease to extend its application to more general cases provided a distance matrix can be derived from the original data. Another approach, based on similar ideas is the analysis of similarities (ANOSIM). This method provides a way to test statistically whether there is a significant difference between two or more groups of sampling units (Clarke 1993).

2.4 Functional Characterization of Coastal Sandy Plain Vegetation in Southeast Brazil

Coastal sandy plain vegetation (Restinga) grows on sandy plains along the Brazilian coast. Because its proximity to the sea and flat to undulate plains, it is a preferential zone to human occupation and it is being degraded rapidly in the last two decades. To illustrate the functional group definition, we use a data set collected in 2010 by Dra. Leda Lorenzo in Ilha do Cardoso State Park, SP, Southeast Brazil. Foliar traits were selected because they are related to plant strategies of acquisition and use of resources. These traits are associated to services such as provision of fruits and medicinal plants, soil formation and fertility (that may leads to a more complex ecosystem in some centuries or decades), land fixation and control of sea erosion, carbon sequestration, and indirectly climate regulation (Díaz et al. 2007).

2.4.1 The Data Set

The five selected traits were leaf dry matter content (LDMC), leaf area (LA), leaf tensile strength (LTS), specific leaf area (SLA), and leaf nitrogen content (LNC).

In this survey, these leaf traits were evaluated according to Cornelissen et al. (2003) in two leaves of ten individuals by species.

One aim of the study is to defined plant functional groups, and then compares the abundance of each PFT in a gradient from the ocean coast. In Sect. 2.4.2 we present the analysis to cluster the 22 species founded in the study area, the procedures to select final number of clusters, and the characterization of PFTs.

2.4.2 Plant Functional Types from a Restinga Vegetation

All foliar trait measures were in a continuous scale and then the Euclidean distance is appropriate to evaluate the differences between species. We chose Ward as linkage criterion because the resulted dendrogram has compact groups and take into account the possible correlation among traits. We used InfoStat (Di Rienzo et al. 2010) to perform the analysis but similar results may be obtained with other statistical software.

From the dendrogram obtained (Fig. 2.1) it is clear that there are two main groups, one with six species and the other with 16 species. If we explore the mean trait values for each one (Table 2.1) we may recognize two plant strategies: group one with species allowing rapid acquisition of resource that have higher values of SLA, LA and LNC, and lower values of LTS and LDMC; and group two with species that conserve resources within well-protected tissues.

It could be interesting to interpret changes from sea coastal having more than two groups. Further inspection of the dendrogram of Fig. 2.1 allows differentiation among the 16 species of second group (see vertical line showing distance at which the dendrogram is splitting in Fig. 2.1). The resulting five clusters are characterized based on mean trait values (Table 2.2), and are referred as Plant Functional Type (PFT).

Plant functional types are named according to the species attributes. One group has three legume species with acquisitive attributes (Acq-Leg), other group has three non-legumes species with acquisitive attributes (Acq-non Leg). There are two groups of species with conservative attributes, one with six species in the transition to forest (Con-Forest) and the other with nine species in the transition to dunes (Con-Dune). The fifth PFT has only one species, *Clusia criuva* with high leaf tensile strength and latex contain, having maximum investment of resources in defense. Relationship among PFT and trait mean values are shown in a biplot (Fig. 2.2) resulted from a principal component analysis.

The biplot allows to relate traits mean values and species groups. The first two principal components explained 73.4% of the total variability; therefore the biplot presents a good synthesis for the relation among traits, groups and the interrelationships between PFT and traits.

The first principal component shows the maximum differentiation, in this case acquisitive strategies in the right, with high values of LA, SLA and LNC, and conservatives in the left, with low values for these traits. Between the both PFT
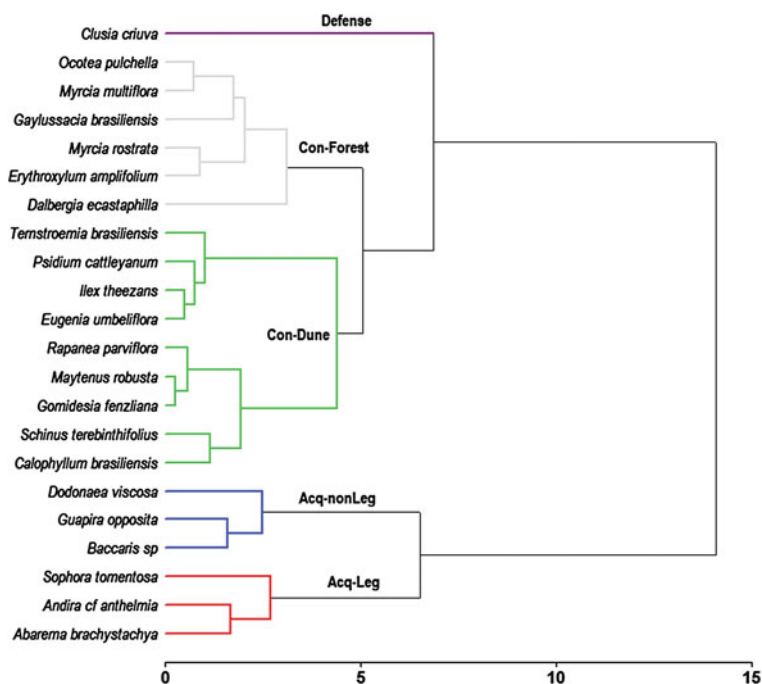
Fig. 2.1 Plant functional types in a Restinga vegetation survey. Five groups of species were defined using Euclidean distance and Ward linkage. *Acq-Leg* acquisitive legumes', *Acq-nonLeg* acquisitive non legumes', *Con-Dune* conservative of dune transition, *Con-Forest* conservative of forest transition, and *Defense* invested in defense

Table 2.1 Trait mean values when the species are splitting in two groups using Euclidean distance and Ward linkage algorithm

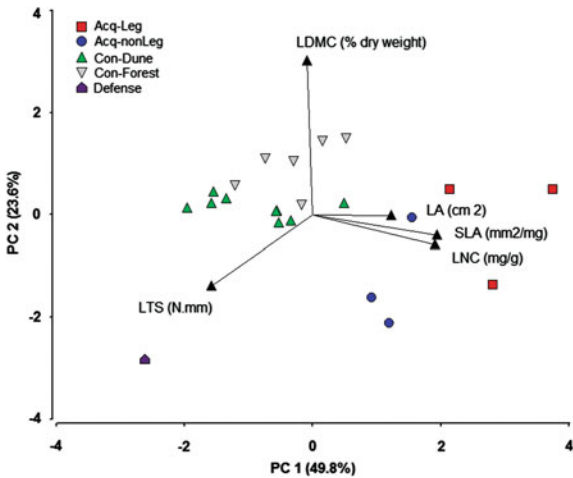| Trait	Cluster	S	Mean	SD	Min	Max
LTS (N.mm)	1	6	0.63	0.21	0.36	0.95
	2	16	1.07	0.47	0.67	2.62
LDMC (% dry weight)	1	6	36.05	9.50	26.25	47.20
	2	16	43.21	6.25	27.30	52.49
SLA (mm^2/mg)	1	6	9.28	1.09	7.70	10.63
	2	16	5.82	1.13	3.90	7.63
LA (cm^2)	1	6	67.76	63.24	9.02	153.24
	2	16	33.08	23.66	6.88	75.88
LNC (mg/g)	1	6	22.72	3.84	18.08	26.81
	2	16	12.35	3.35	8.49	19.83

S number of species in each group, *SD* standard deviation, *Min* minimum, *Max* maximum, *LTS* leaf tensile strength, *LDMC* leaf dry matter content, *SLA* specific leaf area, *LA* leaf area, *LNC* leaf nitrogen content

Table 2.2 Mean traits values for plant functional types (PFT) in a Restinga vegetation survey

PFT	S	LTS	LDMC	SLA	LA	LNC
Acq-Leg	3	0.60	41.55	9.81	123.22	24.41
Acq-nonLeg	3	0.66	30.54	8.75	12.30	21.03
Con-Dune	6	0.89	49.02	6.45	20.79	14.84
Con-Forest	9	1.02	41.11	5.49	38.56	11.05
Defense	1	2.62	27.30	5.04	57.53	9.24

S number of species in each PFT, *LTS* leaf tensile strength, *LDMC* leaf dry matter content, *SLA* specific leaf area, *LA* leaf area, *LNC* leaf nitrogen content, *Acq-Leg* acquisitive legumes', *Acq-nonLeg* acquisitive non legumes', *Con-Dune* conservative of dune transition, *Con-Forest* conservative of forest transition, *Defense* invested in defense

Fig. 2.2 First and second principal component using five traits and five plant functional types in a Restinga vegetation survey. *Acq-Leg* acquisitive legumes', *Acq-nonLeg* acquisitive non legumes', *Con-Dune* conservative of dune transition, *Con-Forest* conservative of forest transition, *Defense* invested in defense. *LTS* leaf tensile strength, *LDMC* leaf dry matter content, *SLA* specific leaf area, *LA* leaf area, and *LNC* leaf nitrogen content

with acquisitive strategy, the legumes are more acquisitive than the non legumes. The acquisition of resources is relatively cheaper for legumes since they have symbiosis with nitrogen fixers.

For the PFTs with conservative strategy, the second principal component allows to separate between Con-Forest and Con-Dune through LDMC values, which are higher on the Con-Forest group. The Defense PFT is defined by extremely high values of LTS, associated to investments in defense against mechanical damage.

2.5 Functional Groups for Bird Species in Nicaragua

In this example we used a database with bird traits to define and characterize functional groups in tropical landscapes in Nicaragua to assess patterns of functional diversity in different land uses. We will define and characterize the

functional groups, and after that we will study the relative frequency of each group in six landscapes with different human intervention.

The concept of functional diversity links bird species diversity to ecosystem processes through resource-use patterns (Petchey and Gaston 2002; Tscharntke et al. 2007). In this case we are looking for patterns with respect to body mass, beak measures, diet, habitat and status (resident or migratory).

2.5.1 The Data Set

Six land-uses were identifying, from forest to pastureland: secondary forest, riparian forest, forest fallows, live fences, pastureland with high tree cover, and pastureland with low tree cover. Data in riparian forest and life fence were collected in four counting points every 100 m along linear transect, while data in other land uses were collected in 1 ha plots following the methodology by Vilchez et al. (2007). The data were collected for the project FRAGMENT (Developing methods and models for assessing the impacts of tree on farm productivity and regional biodiversity in Fragmented Landscapes).

The database used for this example comprises 56 species. Individuals of each species were inspected to record beak features (nares, width, and depth), wingspread and body weights. After identification, diet source were classified as primary, secondary, tertiary and fourth preference. Each species was classified as migratory or resident and the habitat in the study area were recorded using three categories: generalist, open areas, and covered areas (forests). These traits are associated to the provision of regulatory ecosystem services due to bird participation in biodiversity conservation and ecosystem services in fragmented landscapes.

Foraging guild classifications of each species is also part of the important information needed to interpret the role of functional groups. This variable was not used in the cluster procedure, which is based on individual bird characteristics like beak features that are associated with guilds.

To perform functional groups we used InfoStat software (website: http://www.infostat.com.ar, Di Rienzo et al. 2010). File 'Traits by bird sp Nicaragua.IDB2' (available for download via Springer's Extra Materials website: http://extras.springer.com/) has trait information for 56 species recorded, including status and feeding guild. The status variable is nominal with two exclusive categories, and habitat variable is also nominal with three exclusive categories. We transform them to dummy variables (see Sect. 2.2 and Box 2.2). For status we need one column (status_R), and for habitat we need two columns (habitat_G and habitat_OA). File 'Res traits by bird sp Nicaragua.IDB2' has extra columns with these new variables (available for download via Springer's Extra Materials website: http://extras.springer.com/).

File 'Bird sp by use Nicaragua.IDB2' (available for download via Springer's Extra Materials website: http://extras.springer.com/) has the abundance (number of

individuals) of each species in the six land uses. Double click the label of the column 'Land_use' to see the codification used for land-use.

2.5.2 Bird Functional Types from Nicaragua

In this example we have three types of numerical variables, those derived from the dummy transformation, those indicating the ordinal value of feeding preference and those measures in a continuous scale. To perform cluster analysis we used the same procedure as in previous example. We select Gower as a measure of similarity because we have continuous and dummy variables. The software selects automatically the appropriate transformation to distance measure and evaluate the distance matrix between species. We also select Ward as the linkage algorithm and ask for two clusters.

The resulted dendrogram has a clear difference between two main branches, but heterogeneity among species within the groups is still high. We run again asking for five groups and obtained the dendrogram shown the five groups left to the vertical line in Fig. 2.3. File 'Res traits by bird sp Nicaragua.IDB2' (available for download via Springer's Extra Materials website: http://extras.springer.com/) has the identification to which cluster each species belong.

2.5.3 Characterization of Bird Functional Types of Nicaragua

Traits nares, wingspread and weight are important to differentiate functional types, also the migratory species are cluster together and with the resource-use patterns we complete the characterization of groups. Mean values for continuous variables (Table 2.3), proportion of nominal categories and mean importance values for feeding categories (Table 2.4) allows the full characterization of the bird functional groups.

The functional groups are:

- Nectarivorous: Mainly nectar-feeding birds of the family Trochilidae (all species of hummingbirds) with beak and body size very small with the largest less nares.
- Migratory generalist (Migr-Gen): Birds of small and medium size, consisting mainly of migratory species with the larger ratio wing/weight but Nectarivorous. They prefer habitat generalist, these species that can live in forest edges, secondary growths but not in open areas. They feeding mainly on insects. All migratory species are in this group.
- Insectivorous specialists (Ins-Spec): Birds with small to medium sizes, composed of birds only of covered habitat. Most of these species feed on insects in the understory.
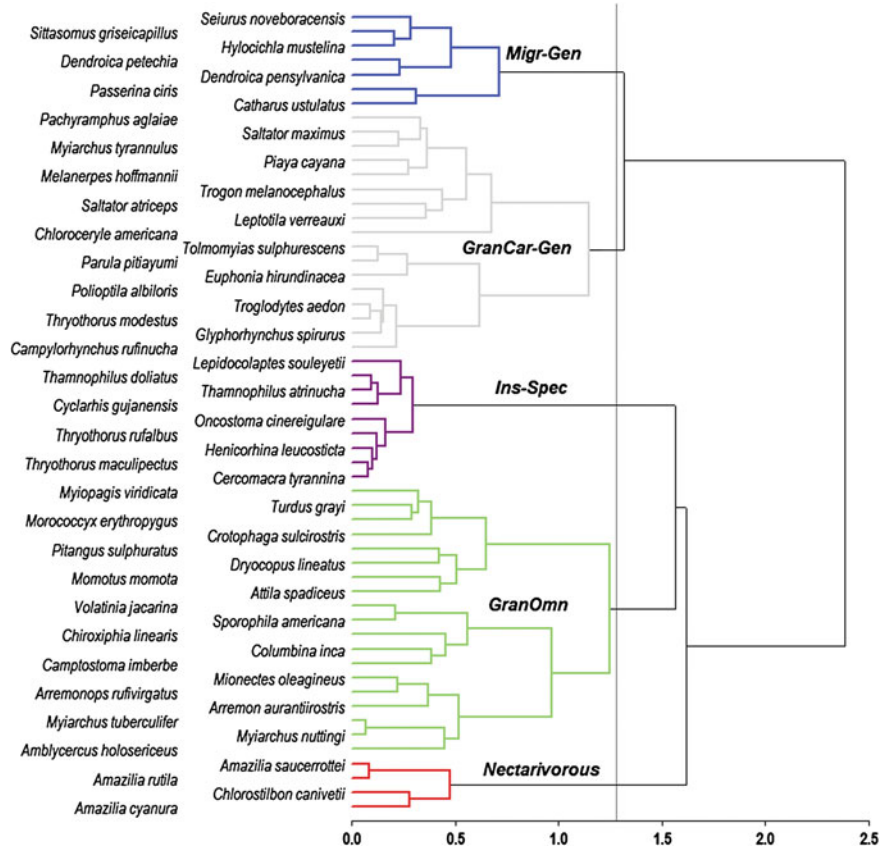
Fig. 2.3 Bird functional types in Nicaragua. Five groups of species were defined using Gower similarity coefficient transform to distance as square root of one minus Gower and Ward linkage algorithm. *Ins-Spec* insectivorous specialists, *GranCar-Gen* granivorous and carnivorous generalists, *GranOmn* granivorous and omnivorous, *Migr-Gen* migratory generalists, and *Nectarivorous*

- Granivorous and omnivorous (GranOmn): Bird species with the highest weight, wing and beak measures, except the nares; they are resident species with omnivorous feeding habits. This functional group has bird species foraging in open areas like pastures and crops, or species foraging in cover areas like forest.
- Granivorous and carnivorous generalists (GranCar-Gen): The birds of this group are generalist species of medium to large size, they can live in forest edges, secondary growths and advanced youth and scattered trees. The species of this group may be carnivores (fish), granivorous and insectivorous.

Table 2.3 Mean trait values of the five bird functional types in Nicaragua

Functional type	Richness	Wing	Weight	Nares	Width	Depth
Ins-Spec	9	64.72	20.97	12.35	5.53	4.97
GranCar-Gen	17	87.89	42.09	14.53	6.42	6.81
GranOmn	19	89.07	50.11	14.29	10.35	8.18
Migr-Gen	7	76.85	20.76	9.37	5.12	4.21
Nectarivorous	4	52.38	4.06	17.41	3.06	2.04

Ins-Spec insectivorous specialists, *GranCar-Gen* granivorous and carnivorous generalists, *GranOmn* granivorous and omnivorous, *Migr-Gen* migratory generalists, and *Nectarivorous*. Weights in grams, and beak measures and wing in millimeters

Table 2.4 Mean feeding preference for bird functional types in Nicaragua

FTypes	Fish	Invertebrates	Seeds	Small_fruits	Amphibians	Reptiles	Nectar
Ins-Spec	0.00	4.00	0.00	0.00	0.00	0.00	0.00
GranCar-Gen	0.24	3.29	0.65	2.12	0.00	0.12	0.12
GranOmn	0.00	3.26	1.42	1.89	0.42	0.53	0.00
Migr-Gen	0.00	3.14	1.00	2.29	0.00	0.00	0.00
Nectarivorous	0.00	0.00	0.00	0.00	0.00	0.00	4.00

Ins-Spec insectivorous specialists, *GranCar-Gen* granivorous and carnivorous generalists, *GranOmn* granivorous and omnivorous, *Migr-Gen* migratory generalists, and *Nectarivorous*. Scale of mean feeding preference follows variable codification: the highest value is four, when all the species of the functional type have the food category as first preference; lowest value is zero when no species eat that food in the functional type

2.5.4 *Relationship of Functional Types with Land Uses*

We performed a correspondence analysis to explore relationships between five functional types of birds with six land uses categories (Fig. 2.4). This analysis allows showing bivariate observations in a plane and identify the heaviest associations between patterns of two qualitative variables, in our case the functional types with the land uses. Correspondence analysis evaluates which are the combinations of modalities that have more inertia, which contributes most to reject the hypothesis of independence between the two variables. Points on the graph having a similar profile for land use are very close; those having similar functional type profiles are also very close. The distances from the origin indicate the discrepancy between the functional types from the average profile. The same applies to land uses categories. The distances between functional types and land use category's has no direct interpretation, but points in the graph fall in the same direction (relative to the origin) are positively correlated, while those that fall in opposite directions are negatively correlated. To perform this analysis we have to concatenate information from two data tables. The concatenated file 'Concat bird sp by use Nicaragua.IDB2' (available for download via Springer's Extra Materials website: http://extras.springer.com/) has the information of the species present in
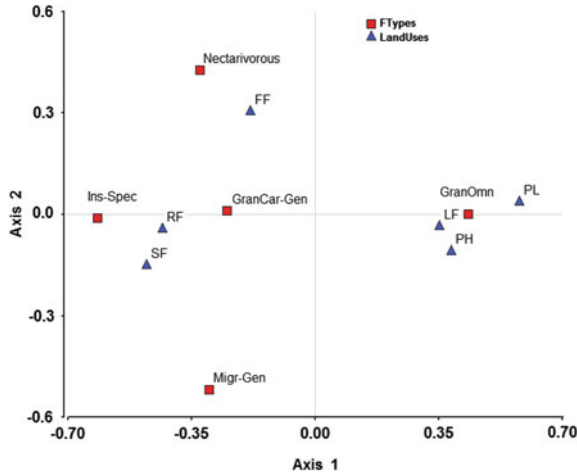
Fig. 2.4 First two axes from correspondence analysis between functional types of birds and land uses conditions in Nicaragua. The first axis explains the 85.50% of total variability and the second axis explains 11.65% of total variability. Five functional types: *Ins-Spec* insectivorous specialists, *GranCar-Gen* granivorous and carnivorous generalists, *GranOmn* granivorous and omnivorous, *Migr-Gen* migratory generalists, and *Nectarivorous*. Six land use conditions: *RF* riparian forest, *SF* secondary forest, *FF* forest fallows, *LF* live fences, *PH* pastureland with high tree cover, *PL* pastureland with low tree cover

each land use and the functional group to which the species belong. We used abundance (number of individuals) to weight the presence of each species in the land use categories.

The first two axes explain 97.15% (85.5% for axis one and 11.65% for axis two). There is a strong association of group GranOmn with pastures having high and low density of trees, and with live fences. Nectarivorous group has a strong association with secondary growths vegetation like forest fallows because this habitat provides pioneer plant species, increasing the availability of flowers for bird species of this group. Species of the functional type frugivorous and insectivorous specialists (Ins-Spec) are associated with secondary forests and riparian forests as expected because these bird species need to forage at understory. The GranCar-Gen type is mainly associated with riparian forests and species of Migr-Gen functional type prefer forest than pasture lands.

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