

Handling Missing Data in a Tree Species Catalog Proposed for Reforesting Mexico City

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Abstract: In this paper we present an application of handling missing attribute values for some data about urban forest in Mexico City. The missing attribute values are about pollution tolerance of the trees, around 42% of our observations are incomplete. Classical methods are non applicable without introducing noise. Our proposal is to use successive steps of multiple correspondance analysis. The estimations values are validated with a clustering approach. The complete data can be used for a variety of future applications.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

Trees are a vital component of the human environment and city landscape. Because of the many functions and benefits trees provide, it is impossible to imagine urban life without them (Burden, 2008). Even though trees have been a part of urban environments since cities began to develop, the study of urban trees is recent, and our knowledge about this important asset is limited. It wasn't until the second half of the 20th century, as urbanization increased, that city trees began to receive special attention, as evidenced by the emergence of such disciplines as urban forestry and arboriculture. The last comprehensive review of scientific literature about urban tree planting was in 1997 (Watson, 2011). Since that time, researchers have begun to focus on how to apply knowledge about plant biology, soil structure, and soil composition to improve tree survival in urban environments. In spite of those advances, our knowledge about urban trees remains incomplete and many questions stay unanswered (Carter, 1993).

Considering the importance of these valuable assets, many cities have adopted policies and strategic plans and initiated various programs for tree maintenance and planting. Highly populated Mexico City (Federal District and its metropolitan suburban area), long one of the most polluted regions of the world, is no exception. Mexico City's weather and geographic location offer ideal conditions for the

growth and adaptation of a great diversity of tree species. However, the characteristics of the city and its huge population are obstacles to tree survival. As is true in many cities, trees in Mexico City are located in both private and public spaces. In public spaces, they are planted along or in sidewalks, in road medians, and in gardens, sport fields, and cemeteries.

Unfortunately, it is common for urban trees to suffer severe injuries and diseases originated from their environment: air, soil and water pollution, insects, parasites, lack of water, impediments to growth, such as cabling, planting pits and soil compaction, and damage from vandalism. Because trees provide many benefits, one of the goals of authorities in charge of tree resources and green areas is to increase tree survival rates and improve conditions adequate for growth. Educating urban green areas' administrators, home owners and the general public about the benefits of trees and providing information about tree planting and care are among the ways to accomplish the goal – for example, the local secretary of the environment has published several technical manuals for the integral management of urban green areas (SMA, 2000). In particular, two of these manuals (one for pruning, felling, transplanting and an other to assess species' tolerance to pollution) include a catalog of species recommended for planting in the Federal District. For each species it is included information about appropriate planting sites and environmental conditions for growth, but they do not provide

comprehensive information about species' response to air pollution. Accordingly, the goal of the current study was to explore a method to replace missing data concerning species' response to air pollution through the use of multiple correspondence analysis (MCA). It is important to obtain these data because species tolerance to pollution might be a key factor for tree survival (EPA, 2010) in a city like Mexico City – where pollution levels vary depending on season, urban area, or even time of day.

Section 2 presents our data along with a brief description of various methods to replace missing values. Section 3 proposes an imputation-approach based on the MCA. The results of this method are detailed in section 4. Finally, conclusions and future work plans are presented in section 5.

2 TREE'S SPECIES DATA SET

The data set is generated from the fusion of attributes of recommended species included in two technical manuals. However, some attributes related to species' response to air pollution are missing. In this section data is described and briefly analyzed, followed by a short presentation of methods for handling missing values.

2.1 Tree's Species Data Set

The data set is generated from the information contained in two technical manuals published by the local secretary of the environment of Mexico City:

- The first manual gives guidelines for pruning, felling and transplanting trees and shrubs (SMA, 2000). It includes relevant information about 134 species with key features such as:
 - *Group 1*: nominal characteristics (*species name, genus, origin*)
 - *Group 2*: basic characteristics (*tree, shrub, palm, fruit, evergreen*)
 - *Group 3*: tolerance to some general environmental conditions (to cold (*tcold*), to dryness (*tdry*), to mistreatment (*tmiss*) and to soil salinity (*tsal*))
 - *Group 4*: a recommended list of planting sites (streets and middle-roads (*s_street*), urban recreational parks (*s_urbrp*), parking lots (*s_parlot*), beneath electric lines (*s_beleclin*), cemeteries (*s_cem*), sport fields (*s_sportf*), urban forest (*s_urbf*))
- The second manual (SMA, 2001) offers information about environment and pollution

in México city and it includes information, about species' response to pollution (sensitivity = 1, tolerance = 2, resistance = 3, and adaptation = 4) to four levels of air pollution. Unfortunately this manual includes information for only 77 species of the 134 species listed in the first. Pollution levels are classified by primary component (SO_2 = sulphur dioxide, NO_x = nitrogen dioxides, CO = carbon monoxide and PST = total suspended particles) in metric tonnes per year. The four pollution levels form the following variables in *Group 5*:

- *veryhighpollution* = ($SO_2 > 500, NO_x > 2000, CO > 3000, PST > 2000$)
- *highpollution* = ($251 < SO_2 < 500, 500 < NO_x < 2000, 500 < CO < 3000, 500 < PST < 2000$)
- *mildpollution* = ($101 < SO_2 < 250, 100 < NO_x < 500, 100 < CO < 500, 100 < PST < 500$)
- *lowpollution* = ($SO_2 < 100, 10 < NO_x < 100, 10 < CO < 100, 10 < PST < 100$).

From these two sources a database resulted with 134 species, each of which has 4 columns (nominal variables) to account for general characteristics of *group 1*, 15 columns with 1 indicating presence and 0 indicated absence of the related characteristics of *groups 2, 3 and 4*, and four more columns to indicate response to one of the four pollution levels. Some codes names are based on the characteristics, for easy reference. These characteristics are not exclusive: the same species may have more than one characteristic of the same group (for example, a species that is both a shrub and fruit). In the case of species' response to pollution, a given species might have the same response to one or more pollution levels. Among responses to different pollution levels, there is an implicit order, this is to say, that if a given species is resistant to high pollution, it can be also resistant or adapted to lower levels of pollution, but it can't be tolerant or sensible to lower pollution levels. Given that all species are recommended for the urban forest (*s_urbf*) and are adapted to low pollution levels (*lowpollution*), these variables are not included in the analysis. Data can be obtained from the following address <http://www.emse.fr/~mathieu/data/trees/>.

The 134 species are from 65 genera. Of those genera, 72.39% are trees, 50% are shrubs, 4.48% are palms, 11.94% are fruit, 66.42% are evergreen, 82.84% resist cold, 49.25% resist dryness, 32.09% tolerate soil salinity, and 29.10% are tolerant to mistreatment. With regard to planting site, 52.99% of the genera are proposed for planting along, 97.01%

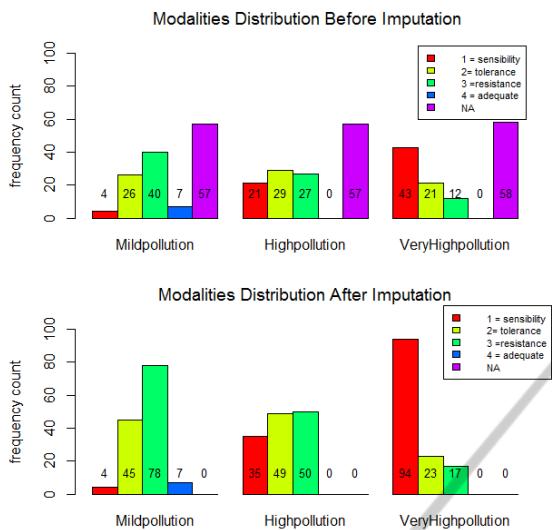


Figure 1: Distribution of modalities and missing values for variables related to pollution (the percentage of the 134 species is shown in parentheses).

in urban recreational sites, 54.48% beneath electrical lines, 86.57% in cemeteries, 78.36% in parking lots, and 89.55% at sport fields.

Figure 1 shows the distribution of modalities concerning species' response to the three different levels of pollution considered.

2.2 Classical Handling Missing Values

In the literature (Han and Kamber, 2006) different non exclusive options to handle missing values are proposed:

1. to ignore the values or the whole n-tuple
2. to replace missing values with a global value
3. to assign a value considering a statistical measure like: the tendency, the most probable value or the values generated, by simulating a given distribution
4. to establish relationships, models or groups obtained between non missing attributes of the data set and values of variables, where missing data is present. The use of statistical or data mining techniques might be applied to establish relationships and to obtain one or several estimations of the missing value.

The results obtained are then used to replace missing data. More details about all these methods can be found in (Grzymala-Busse and Grzymala-Busse, 2005).

Most of these methods are related to handle missing numerical information and suppose that information is missing due to error. Some of them

may delete information or add dummy information to account for missing values.

In the case of the trees species data set work, missing information is categorical and it is not due to error. As shown in Figure 1 there are 57 missing values (coded NA) on variables *mildpollution* and *highpollution*; and 58 missing values on variable *veryhighpollution*.

The simplest way to solve the problem of missing values is to delete the corresponding observations or the pollution variables (*group 5*) that have missing values (method 1). However, that information is an important factor, and eliminating it would result in 42.45% of observations deleted, or 20% of the pollution variables.

Another option is to assign missing modalities according to frequency (method 3). The variable *lowpollution* has just one modality (adequate), so it would be assigned to all species. For the other three variables in *group 5*, assigning the most frequent modality means defining all the trees as sensitive to very high pollution, tolerant of high pollution, and adequate in tolerance to mild pollution. The drawback to eliminating the missing values is homogenization of the variables. Furthermore, if random assignment of modalities is performed (even according to frequency distribution), it could result in instances, with not logic (without taking into account the implicit order discussed before), for example a tree may be categorized as sensitive to mild levels pollution and adapted to high levels. These drawback might be solved by considering just the distribution of the triplets (of the three pollution levels) observed in the instances with non missing values.

Finally a relationship might be established between one or all variables of the *groups 1 to 4*, and the three variables (*group 5*) related to pollution. The use of multiple correspondence analysis as a mean to find multiple relationships and to estimate missing data is an example of this approach.

3 HANDLING MISSING VALUES BY MULTIPLE CORRESPONDENCE ANALYSIS

Multiple correspondence analysis (MCA) is one of the most widespread methods for analyzing categorical multivariate data tables with I individuals in rows and J variables (with at least two modalities) in columns. Using the χ^2 distance helps to identify the primary sources of variability and to examine

v1	v2	...	vj	vj
tree	t1		t	a
tree	t4		s	b
shrub	t2		r	a
palm	t4		a	a
...
shrub	t3		Na	a

k1	k2	...	kj	kj
100	1000		0100	10
100	0001		1000	01
010	0100		0010	10
001	0001		0001	10
...
010	0010		?????	10

Figure 2: Indicator matrix generated from data.

and describe information contained in the original categorical data using a reduced number of variables (referred to as main factorial axes or components). Each individual observation, variable or modality can be represented by its coordinates relative to the factorial axes. Categorical information is thereby transformed through MCA into numerical form.

If $k_1, k_2, k_3, \dots, k_j, \dots, k_J$ are the number of modalities for each respective variable, then an indicator matrix X with I lines and K columns can be constructed, where $K = \sum_{j=1}^J k_j$. For this, each variable j in one column is decomposed in a group of k_j columns formed with $k_j - 1$ zeroes and one to indicate the presence of the modality. See figure 2 indicating this decomposition.

From X a Burt matrix $B = X^t \times X$ is constructed a contingency table from which classical correspondence analysis (CA) can be applied to find the factorial components (Lebart et al., 2006).

With non-missing data, it is possible to reconstitute 100% of the original data from the coordinates relative to the factorial components. However, as the number of components used to reconstitute original data is reduced, the error increases.

To better understand this approach to handling missing values, suppose that an individual species has no value (coded *NA*) for a given modality of a categorical variable with four modalities (*s, t, r, a*). For the sake of simplicity, we assume that there is not other more missing information. It then becomes possible, based on the proportion of each modality, to assign a missing value. Say, for example, that the guess is $[s = 0.3, t = 0.2, r = 0.1, a = 0.3]$. MCA is applied, and a number of $S < K$ components is retained to reconstitute the X matrix. To use MCA, it is necessary to fulfill certain conditions, such as having the same sum for all lines of the indicator matrix; therefore, some corrections should be made

on the run. Suppose that, after several iterations, the results are $[0.5, 0.1, 0.1, 0.2]$; *NA* is then substituted by the modality *s*.

The algorithm, based on the work of (Josse et al., 2012), is:

1.- *Initialization:*

$I \leftarrow 0$ imputation of missing modalities on the indicator matrix $X^{(0)}$ (i.e., with proportions);

Verify conditions to apply MCA

2.- *Iteration step for l*

a) *Estimation:*

Perform MCA on the indicator matrix $X^{(l-1)}$;

Obtain factorial components and retain $S < K$ components;

Get $\hat{U}^{(l)}$, size $J \times S$, and coordinates $\hat{F}^{(l)}$, size $I \times S$;

Estimate missing values with $\hat{X}^{(l)} \leftarrow \hat{F}^{(l)} \times (\hat{U}^{(l)})^t$;

b) *Imputation:*

Get the new indicator matrix $X^{(l)}$ by adding the new values to the X :

$$X^{(l)} \leftarrow W \times X + (1-W) \times \hat{X}^{(l)}$$

with $w_{ij} = 0$, if x_{ij} is missing, and $w_{ij} = 1$, if it is not missing;

Update proportions and verify conditions to apply MCA;

3.- Repeat step 2 until convergence, that is to minimize

$$C = \|W \times X^{(l)} - \hat{F} \times \hat{U}^t\|^2$$

S is chosen a priori, F are the coordinates, U are the factorial axes and W the weights

This algorithm is extended to multiple imputations to take data variability into account and to regularize eigenvalues to avoid overfitting. Further details about these modifications, validation tests with different percentages for missing values, and applications to other domains can be found in (Husson and Josse, 2013; Josse et al., 2012).

Once the indicator matrix is fully reconstituted and there are no more missing modalities, MCA is applied to examine and describe information, as discussed earlier, on a reduced number of components. The primary MCA results are a set of factorial axes (or components) that represent an important percentage of inertia and the coordinates for individuals, variables, and modalities with respect to those components. Data are examined by visualizing the distribution of projections on the coordinate plans generated by the factorial axes and are confirmed using indicators such as the contribution (individual, variable, or modality) to the axes, the quality of representation, and correlation.

Significant values are selected based on the *t.values*. Validation is performed by applying an algorithm such as agglomerative hierarchical clustering (AHC) to the retained coordinates. Algorithms to perform multiple imputation, MCA and AHC are, respectively in R libraries MissMDA and FactoMineR (R Core Team, 2014).

4 RESULTS

MCA is applied directly to the *Tree species data set* to assess the importance of missing values in terms of inertia, their variability and the degree of distinction from the individuals and variables without missing values. Then the algorithm described above is applied to estimate and to impute missing values. Finally MCA is applied to imputed data and the description of variables (as well as modalities) and species distribution is realized in function of the main components retained. AHC is used to define and to identify groups of species.

4.1 Before Handling Missing Values

To evaluate the importance of missing values, an MCA data exploration was performed for all 134 species and the 18 associated categorical variables: *tree*, *shrub*, *palm*, *fruitful*, *evergreen*, *tcold*, *tdry*, *tmiss*, *tsal*, *s_street*, *s_urbrp*, *s_parlot*, *s_beleclin*, *s_cem*, *s_sportf*, *veryhighpollution*, *highpollution* and *mildpollution*. Given that all species are proposed for urban forest (*s_urbfor*) and are adapted to low pollution levels (*lowpollution*), these variables are not included in the analysis. Direct application of MCA with missing values requires addition of a new variable to code missing values. The primary results are as follows:

- The first three components represent, respectively 25.58%, 25.46% and 13.40% of total inertia, for an accumulated inertia of 64.44%.
- All 18 variables can be identified on the first two components, although the pollution variables appear to be outliers because they clearly separate from the group
- Contributions, of each group of variables, to the formation of the first three components are:
 - C1.- Group 2: 28.56%, Group 3: 7.05%, Group 4: 36.16% and Group 5: 28.22%.
 - C2.- Group 2: 2.53%, Group 3: 10.09%, Group 4: 18.19% and Group 5: 69.18%.
 - C3.- Group 2: 27.97%, Group 3: 40.68%, Group 4: 14.42% and Group 5: 16.91%.

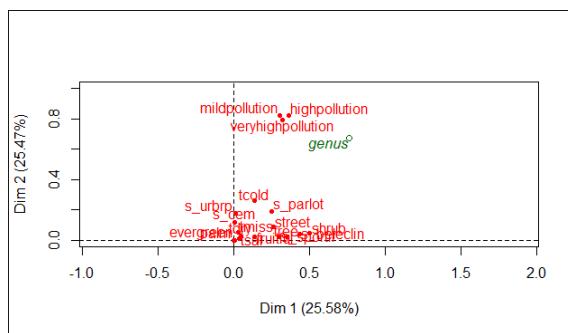


Figure 3: Results of MCA using initial data.

- The variables *veryhighpollution*, *highpollution* and *mildpollution* represent an important percentage of the inertia for each component.
- The missing modalities' contribution of the variables *veryhighpollution*, *highpollution* and *mildpollution* are respectively: 12.20%, 12.78% and 12.77%.
- Missing modalities are highly correlated and very well represented by the second axis; the quality of representation values are close to 1 (0.87, 0.87 y 0.86).
- The contribution of species with missing values to the formation of the first two components is respectively: 34.17 and 48.29.
- Almost all species with missing values, except one, form a very well defined cluster.

The major contribution of the missing values makes it difficult to analyze information with non-missing information, but the fact that all individuals comprise one cluster allows the possibility for handling them with the same approach. Figure 3 depicts the first application of MCA to the initial data with missing values.

Variable's projections on the first two MCA components show the pollution variables as outliers, which is the result of the high contribution of missing values.

4.2 MCA Handling Approach for Missing Values

The results of "cross validation" and "leave one out" tests suggest retaining five components to reconstruct the indicator matrix. From these components missing data are estimated and used to reconstruct the indicator matrix. Multiple correspondence analysis is then applied to reconstructed data, again for all 134 species and the 18 categorical associated variables. The distribution of modalities after MCA application

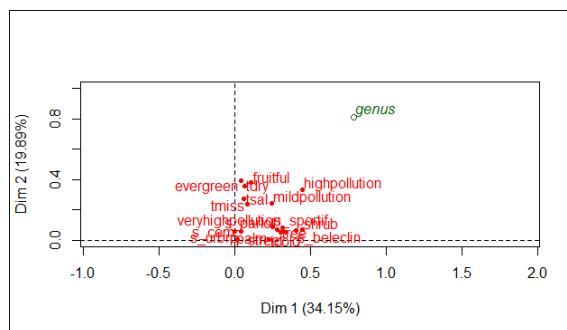


Figure 4: Results of MCA after handling missing values.

is presented in Figure 1. The primary MCA results are as follows:

- The first three components represent, respectively, 34.15%, 19.89% and 12.97% of total inertia, for an accumulated inertia of 67.01%. This is almost the same as the one obtained before handling missing values, but there is a slight increase in the first component with a corresponding decrease in the second.
- All 18 variables can be identified on the first two components, although pollution variables no longer appear to be outliers.
- Contributions of the groups of variables to the formation of the first three components are:
 - C1.- Group 2: 24.46%, Group 3: 11.86%, Group 4: 36.29% and Group 5: 27.38%.
 - C2.- Group 2: 33.81%, Group 3: 31.02%, Group 4: 11.92% and Group 5: 23.23%.
 - C3.- Group 2: 12.95%, Group 3: 14.59%, Group 4: 60.76% and Group 5: 11.69%
- The contribution of the variables *veryhighpollution*, *highpollution* and *mildpollution* has been reduced. No modalities were created to handle missing values.
- The contribution of species that had missing values to the formation of the first two components is 43.49 and 48.17, respectively. This means that no information was missing; therefore, the contribution to both axes was balanced.
- No particular cluster for species that had missing values was observed.
- No important change was observed when modalities with low percentages were removed.

Figure 4 displays the pollution variables mixed with the other variables.

These findings allow the components to be described, as presented in the following section.

4.3 Data Exploration with MCA and AHC

Description is based on variables correlation ($p.value < 0.05$) with each of the first three components (C1, C2 and C3) generated by MCA. Variables correlation is indicated between parenthesis and species are described according to the significant variables modalities ($t.value > 1.96$) on each side (positive or negative) of the specific component:

- **Component 1:** shrub (0.44), high pollution (0.44), below electric lines (0.40), streets and middle roads (0.33), tree (0.30), very high pollution (0.31), parking lots (0.28), sport fields (0.25), tolerance to cold (0.22) and genus (.79).
 - Positive side: Species that are shrubs but not trees; recommended for planting below electric lines; not recommended for planting in streets/medians, parking lots, and sport fields; tolerant to high pollution and very high pollution levels; not tolerant to cold.
 - Negative side: Species that are trees but not shrubs; recommended for planting in streets/medians, parking lots, and sport fields; not recommended for planting below electric lines; sensitive to high and very high pollution levels; tolerant to cold.
- **Component 2:** evergreen (0.39), fruitful (0.37), tolerance to dryness (0.35), high pollution (0.32), tolerance to soil salinity (0.27), genus (0.80), tolerance of mistreatment (0.23), tolerant of mild pollution levels (0.24)
 - Positive side : not evergreen; not fruit; not tolerant of dryness, soil salinity, and mistreatment; tolerant to mild and high pollution levels.
 - Negative side : evergreen; not fruit; tolerant to dryness, soil salinity, and mistreatment; resistant to mild pollution.
- **Component 3:** recreational parks (0.37), cemeteries (0.34), below electric lines (0.26), parking lots (0.24), tolerance to cold (0.18), very high pollution (0.19), shrubs (0.15), trees (0.11), tolerance of dry conditions (0.11), genus (0.69).
 - Positive side : not recommended for planting in recreational parks, cemeteries, and parking lots; not recommended for planting under electric lines.
 - Negative side : Species with characteristics opposite the positive characteristics.

Species identification is easier if cluster analysis, such as Agglomerative Clustering Analysis

(AHC) (Jain and Dubes, 1998; Grabmeier and Rudolph, 2002) is applied to the species coordinates generated by MCA. For example, AHC with the Ward method and Euclidean distance, pre-establishing four clusters (to identify observations on the four quadrants obtained with components C1 and C2), gives the results shown in Figure 4. For each cluster, 1 through 4, the following description can be made regarding genera:

- **Cluster 1** - Located on the second and third quadrants : *Abies*, *Alnus*, *Pseudotsuga*, *Quercus*, *Arbutus*, *Salix*, *Toxodium*, *Ulmus*, *Calocedrus*, *Cedrus*, *Celtis*, *Chamaecyparis*, *Chiranthoendrom*, *Cupressus*, *Fraxinus*, *Junglans*, *Legerstroemia*, *Liquidambar*, *Magnolia*, *Acer*, *Pinus*, *Alnus*, *Platanus*, *Podocarpus*, *Populus*.
- **Cluster 2** - Centered and spread through the first, third, and fourth quadrants: *Quercus*, *Araucaria*, *Robinia*, *Rosa*, *Schinus*, *Tamarix*, *Thuja*, *Washingtonia*, *Yucca*, *Acacia*, *Cedrus*, *Cupressus*, *Erythrina*, *Eucalyptus*, *Acacia*, *Ficus*, *Ginkgo*, *Grevillea*, *Jacaranda*, *Juniperus*, *Ligustrum*, *Magnolia*, *Olea*, *Phoenix*, *Acer*, *Pinus*, *Pittosporum*.
- **Cluster 3** - In the fourth quadrant: *Quercus*, *Schinus*, *Beaucarnea*, *Buddleia*, *Buxus*, *Calistemon*, *Cassia*, *Casuarina*, *Acacia*, *Eucalyptus*, *Juniperus*, *Acacia*, *Ligustrum*, *Nerium*, *Pittosporum*, *Populus*, *Prosopis*.
- **Cluster 4** - In the first quadrant: *Prunus*, *Citrus*, *Crataegus*, *Cydonia*, *Elaeagnus*, *Eryobotria*, *Ficus*, *Malus*, *Morus*, *Musa* and *Persea*.

These results provide insight into the validity of the approach presented in this work. For example, fruit species are found in *Cluster 4*. *Cluster 1* primarily includes large trees appropriate for planting along streets and in medians and that are tolerant of high levels of pollution. *Cluster 3* includes evergreen species (not fruit) that can tolerate dryness, soil salinity and mistreatment.

These results open the way for deeper data explorations. For example, it would be interesting to separate *Cluster 2* into a group of trees and palms and to evaluate the differences between species in *Cluster 1* and *Cluster 2* because they are the same genera. However, such an evaluation should be done with care, considering the diverse characteristics of *Quercus* and *Pinus* presented in this study.

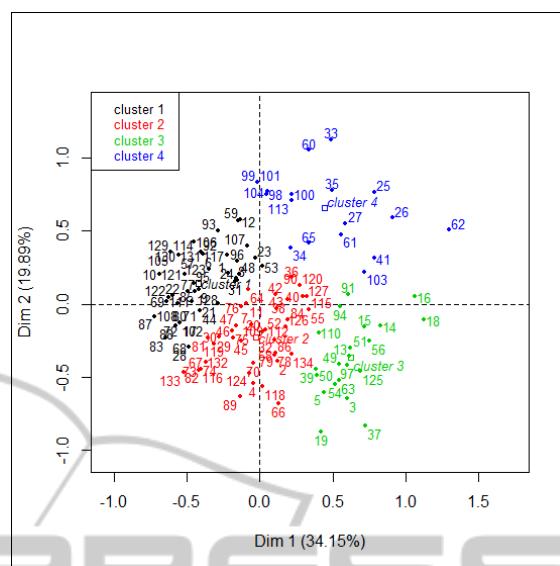


Figure 5: Application of hierarchical clustering with Ward method and euclidean distance, for 4 clusters.

5 CONCLUSIONS

After considering different options for handling missing values pertaining to trees species tolerance of and sensitivity to air pollution in Mexico City and given that it is not currently possible to obtain reliable information from official sources, this paper presents an option for estimating and imputing missing values of pollution related variables based on MCA.

The proposed approach has important advantages because MCA is an adequate and well proven technique for treating categorical variables. The approach to estimate missing information does not require to delete information, and it does not add spurious information to account for missing values. In theory basic data structure is not modified with this approach, for example, in terms of importance or possible associations between individuals and variables with non-missing information. However it would be worthwhile to apply other approaches to estimate missing information and to explore changes in data structure.

Further explorations with imputed missing values should be undertaken, changing the number of clusters generated, including the possibility of evaluating the results with the assistance of an expert in arboriculture in analysis of species similarities within a genus. Nevertheless, the exploratory results presented in this study agree with associated variables such as genus and some important species characteristics. These interpretations are, for the most part, validated by the clustering results.

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