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Geographic conditioning in dietary, social, and health patterns in elderly population with disabilities

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ABSTRACT

Objective: The aim of this study was to identify the most relevant variables defining the dietary, social, and health patterns of elderly populations with disabilities, considering their geographic profile.
Methods: A cross-sectional study was carried out in a sample of 354 disabled, free-living elderly adults from three different geographic profiles (metropolitan, rural, and mixed profile). The dietary data were obtained through a validated food habit questionnaire. The data regarding health status, cohabitation unit, and social benefits were obtained through the public social services. A standardized principal component analysis was used to select the most relevant variables, by considering their contributions to each principal component and their relation with the geographic factor.
Results: From 131 variables, we highlighted 27 (57.37% of variability explained). The variables with more contribution are, in order, the calorie intake (especially from lipids), absence of home assistance, and the difference between intake and recommended calories. The procedure was validated by assessing the prediction using a multinomial logistic regression model (88.2% and 66.7% of success rate regarding the metropolitan and rural profiles, respectively). There is a differentiated behavior based on the geographic origin of individuals, specifically regarding caloric intake, number of diseases, and the requirement for home assistance.
Conclusions: Older adults living in a metropolitan are tend to have a greater number of diseases as well as a lower caloric intake. The increased rural caloric consumption comes from lipids. Better health status in rural areas is associated with a lower need for home assistance.

Introduction

Social welfare policies in addition to a healthy lifestyle have increased the life expectancy of the elderly population. In 2015, the average life expectancy at birth of the global population was 71.4 y but reached 82 y of age in European countries [1]. However, this healthier status of the older population is associated with multimorbidity [2] and polypharmacy [3], as well as functional limitations that restrict personal autonomy to carry out activities of daily living [4]. The incidence of functional limitations generates disabilities that require social assistance and affect both quality of life (QoL) and diet [5], thus precipitating a decline in physical functioning with or without mental frailty [2].

Some research suggests that social and health factors are conditioned by the geographic area of residence [6] as there are significant differences between metropolitan and rural lifestyles [7,8]. Generally, in developed countries, the rural lifestyle is linked to healthier patterns that are defined by a greater adherence to the Mediterranean diet or another healthy diet pattern [9], more physical activity [10], less stress [6], and consequently a better general health status. Therefore, this geographic dichotomy, based on lifestyle, induces trends toward pathological aging or healthy aging [11]. For this reason, it is interesting to study the relevance of the association between dietary, social, and health patterns and lifestyle (identified by the metropolitan, rural, or mixed profile of the geographic area) as these factors have been linked in only a few studies, to our knowledge.

We hypothesized that healthier aging, without disability or minimizing its prevalence, is achievable through a modification of the usual lifestyle from earlier ages. Additionally, this behavior is useful to preserve physical and mental function in older adults.

ML and FM designed the research. ML and LM conducted the research. JP analyzed the data. ML, LM, JP, and FM wrote the paper. FM had primary responsibility for final content. All authors read and approved the final manuscript. The authors have no conflicts of interest to declare.

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The aim of this research was to provide new data regarding the understanding of the affectation of the geographic environment on the QoL of older people residing in the family home.

To attain this overall objective, the following specific aims are proposed:

Identify the variables that most affect the population group (the most linked to geographic environment), considering the different causalities and magnitudes in each subset.

Assess the association between these selected variables and the geographic scope of reference.

Material and methods

Population sample

The sample consisted of 354 individuals, $\geq$65 y of age, with an average age of 81.6 $\pm$ 6.6 y. Of the participants, 75.4% were women. Social services of the municipality where consequently the participants receive social assistance previously classified them as disabled (unable to perform activities of daily living such as cooking, housework, shopping and management, medication, eating, getting in and out, personal care, leaving home, and interacting with other people). Participants were non-institutionalized, residents of any of the 17 municipalities in the east of Spain, and accessible to be interviewed.

The geographic environment of the municipality of residence also determined the classification of the sample for assessment, according to a geographic profile. The sample population was grouped into three geographic areas: metropolitan area (n = 203), rural area (n = 96), and mixed area (n = 55).

This study was reviewed by the Ethics Committee of the University of Valencia and all the participants gave their informed consent before inclusion in the study.

Collected data

The food consumption data was obtained through a semiquantitative eating habits food frequency questionnaire via personal interviews. This food frequency questionnaire was validated in a pilot study (N = 30), which was designed specifically for the population group due to the particular dietary information of the study area and the feeding limitations in people with functional disabilities. These data were complemented with the information about municipality of residence, age, sex, and anthropometric measures.

The dietetic data that was obtained through the eating habits questionnaire was quantitatively analyzed using DIAL software, version 2.12. The variable of estimated energy requirements, obtained from the formulas of the Institute of Medicine of the National Academy of Sciences [12], was also incorporated.

Data regarding health status (i.e., chronic diseases), chronic drug consumption, functional limitations, and autonomy level, as well as data on the cohabitation unit and social benefits received, were obtained through the public social services that take care of the participants. Whether the participant lives alone, only with a partner, or with descendants was specified.

There are several types of social services aimed at this population, such as funded home assistance (which can be in addition to private assistance), food service delivery, remote emergency care, and public economic aid for dependents. With all this information, we arrived at a data set conformed by 354 individuals and up to 131 variables. These variables were subdivided into different disciplinary subsets: anthropometrics, dietary, nutritional intake, chronic diseases, drug consumption, location, cohabitation, social care services, personal autonomy, and functional limitations (the complete variable set is available online at pages.uv.es/malore2/summary_variables.pdf).

Statistical analysis

The aim was to process the data in each subset of variables, differentiated by scientific disciplines, to respect the implicit causality in each of them (diet, chronic diseases, drug treatments, functional limitations, personal autonomy, cohabitation unit, and social assistance). A statistical procedure specifically designed for big data sets composed of several subsets from different scientific disciplines was applied. The different magnitudes between subsets were considered by standardizing the analysis. We used the selected variables to relate them with the geographic factor and identify which determine the geographic conditioning.

A central problem in multivariate data analysis is to reduce the dimensionality: If it is possible to describe accurately the values of the p variables by means of a small subset of size r ($r < p$), the dimension of the problem is reduced by only losing a small amount of information [13]. This allows the identification of the variables that are generating the data variability. Thus, considering 354 (n = 354) individuals and 131 variables (p = 131) we look for transform the original array $X_{(n,p)}$ in a new array $Y_{(n,r)}$ (where $r < p$).

To do this we used as a first step the standardized principal component analysis (PCA) on quantitative subsets or a multiple correspondence analysis (MCA) on categorical subsets, although we did not use them to interpret the principal components but to select a subset of variables. In both methods, the location variables were excluded in the analysis to use later as response variables in a regression model. In this way, we got the most relevant variables of each subset considering the contribution of each variable to each principal component, through a contribution index specifically designed by us, hence the number of variables is reduced.

In a second step, to further reduce the subset of selected variables in the first stage and to relate them with the geographic factor, we applied a new PCA using the selected variables of each subset. Note that in the first subset of variables, some quantitative and some qualitative variables coexist, and to latter apply the PCA again, each of them are transformed into as many dummy variables as many categories include minus one. To validate the selection, a multinomial logistic regression was used considering the selected variables of each subset as predictive variables and the geographic profile as the response factor. Finally, we used a stepwise method to identify the variables with higher geographic conditioning. This procedure was performed using R statistic software, version 3.1.2 [14].

A contribution index

When using PCA and MCA as reduction of the dimensionality techniques, we were not looking for a replacement of the set of original variables with a smaller set of principal components. Instead, our objective was to reduce the original set of variables. To do this, we defined an index for each variable Xi that measures its contribution to all principal components in which the variable is involved. We define this contribution index (CI) as a weighted mean of its contribution to each component with the explained variance of the components as weight. This is,

$$CI_i = \sum_{k=1}^{r} c_{k_i} v_k, \quad (1)$$

where c_{k_i} is the contribution to the component k and v_k is the explained variance for this component. The values of c_{k_i} are provided by PCA or MCA.

The analysis of the top five principal components is usually enough to cover the representativeness of data variability, although a cross-validation method can be used when this fact is not clear. Therefore, these first five components were used in the construction of CI, so $r = 5$ in Eq 1. Regarding the number of variables selected according to CI, it is advisable to establish a homogeneity criterion. The five variables with highest contribution of each block were chosen, and this number represented a balance between the loss of information and an effective reduction of the number of variables.

Association with geographic profile

Generalized linear models (GLM) are statistical tools that generalize the linear model, allowing non-normal response distribution of the data. GLM uses a link function that relates the change in the average of the evaluated response, Y, with the explanatory variables. For a binomial response variable, the GLM links the so-called logit transformation, $logit(\pi) = log(\pi/(1-\pi))$, with a linear combination of explanatory variables, that can be both categorical and quantitative variables. This can be expressed as:

$$logit(\pi) = log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p, \quad (2)$$

where $\pi = P(Y = i)$, and β_k, analogously to the linear model, represents the change in the logit per unitary change in the variable X_k, for any $k = 1, \ldots, p$. The model can also include transformed variables, combinations of variables, or interactions of variables.

When the response variable is multinomial (with more than two categories) the model consists of as many equations as categories minus one. Each equation relates a category with the one taken as reference. Thus, if by π_i, $i = \{0, 1, 2\}$ we represent the $P(Y = i)$, and the reference is the category $i = 0$, the two model equations are:

$$log\frac{\pi_1}{\pi_0} = \beta_{0,1} + \sum_{k=1}^{p} \beta_{k,1} X_k,$$
$$log\frac{\pi_2}{\pi_0} = \beta_{0,2} + \sum_{k=1}^{p} \beta_{k,2} X_k \;. \quad (3)$$

The relationship $\pi_0 + \pi_1 + \pi_2 = 1$ and Eq. 3 provide the direct expressions for the probabilities associated with each category, which are the following:

$$\pi_1 = \frac{exp(\beta_{0,1} + \sum_{k=1}^{p} \beta_{k,1} X_k)}{1 + exp(\beta_{0,1} + \sum_{k=1}^{p} \beta_{k,1} X_k) + exp(\beta_{0,2} + \sum_{k=1}^{p} \beta_{k,2} X_k)},$$
$$\pi_2 = \frac{exp(\beta_{0,2} + \sum_{k=1}^{p} \beta_{k,2} X_k)}{1 + exp(\beta_{0,1} + \sum_{k=1}^{p} \beta_{k,1} X_k) + exp(\beta_{0,2} + \sum_{k=1}^{p} \beta_{k,2} X_k)},$$
$$\pi_0 = \frac{1}{1 + exp(\beta_{0,1} + \sum_{k=1}^{p} \beta_{k,1} X_k) + exp(\beta_{0,2} + \sum_{k=1}^{p} \beta_{k,2} X_k)} \;.$$

Implementation of the validation model

The model was validated by checking the predictive ability of the selected variables with respect to the geographic factor. This was obtained by assessing the predictive ability of the multinomial model through its corresponding prediction table.

Also, if we consider a binomial response between the metropolitan and the rural profile, different models could be compared using area under the curve (AUC), the area under the corresponding receiver operating characteristics curves [15]. There is no equivalent of the AUC for a response variable with more than two categories. An overall measure M that, like AUC, measures the ability of the model to separate each class from the remaining categories [15]. For variables with s categories, its expression is:

$$M = \frac{2}{s(s-1)} \sum_{i=1}^{s-1} \sum_{j=i+1}^{s} A(i,j),$$

where

$$A(i,j) = \frac{A(i|j) + A(j|i)}{2},$$

and $A(i|j)$ is the probability that an individual of category j, randomly selected, would have an estimated probability of belonging to a category i less than an individual of category i, also randomly chosen. M takes values between 0 and 1.

Results

The large number of evaluated variables (p = 131) grouped into different disciplines, which can be both qualitative and quantitative, recommended a preliminary analysis. The set of predictor variables (excluding the anthropometric and location variables) is subdivided into the following categories:

Quantitative variables:
39 nutritional variables (weight of satisfied nutrients through the diet).
18 dietary variables (servings of food groups consumed).
21 pharmacologic variables (average of drugs chronically consumed according to the International Classification of Diseases (ICD)-10).
19 pathologic variables (average of chronic pathologies according to the Anatomical, Therapeutic, Chemical (ATC) classification system).

Qualitative variables:

Disability variables: Functional limitations and autonomy level (17 variables in three severity degrees), family environment (unity and collaboration), and social assistance (five different services)

Preliminary selection of variables

The analysis of quantitative variables was carried out through a standardized PCA because of the different magnitudes of the evaluated variables in each subgroup. The geographic variables were not included in the analysis, observing later their behavior regarding the PCA and using them as response factor in a regression model. The first five principal components obtained through PCA and MCA for each subset were used to select those five original variables with higher CI (Eq. 1).

PCA and assessment of the CI of each subset

Table 1 shows the final selection of the variables with higher CI, obtained from the first five principal components of each of the subsets: dietary, basic nutrients, total nutrients, pharmacologic, pathological, and disability. Such selection was made up of 27 variables because 3 of them (caloric intake, total fat, and saturated fatty acids) were repeated in two subsets.

Assessment of the geographic association on the preselected variables

Due to the analysis by subsets, the procedure identified the main explicative variables in each of them. Each of these groups of variables explained part of the variability of the data set considering a different causality, based on the scientific disciplines studied in this paper that are related to lifestyle and QoL (dietary, nutritional, pharmacologic, pathological, and disability). In order to associate all these variables with the geographic factor, we implemented a new and single PCA for the 27 variables, and included the categorical ones as dummy. This PCA determined that the top five principal components explained $\leq$59.23% of the variability (the first two managed to explain 34.17%). Figure 1 shows that the election of the top five components was significant enough.

It can also been determined through the CI that the most relevant variables were those that defined the quality of the diet (caloric intake, total fat, or carbohydrates) and some of the disability categories (absence of home assistance and severe disorders), as can be seen in Table 2. The principal components obtained in this step were used to associate the variables with the geographic factor. In Figure 2, variables and factors are represented by means of their respective score for the four first principal components. From a health point of view, participants living in a metropolitan area

Table 1
Explained variability and preselected variables in each subset obtained through their CI

Subset	Percent explained variability	Preselected variables	CI
Dietary	46.80	Liquid food	485.05
		Water intake	434.78
		Vegetables	318.85
		Oily fish	279.61
		Dairy products	279.37
Basic nutrients	89.42	Caloric intake	621.76
		Difference caloric intake/EER	615.16
		Total fat	608.18
		Saturated fatty acids	595.91
		Carbohydrates	595.64
Total nutrients	79.82	Caloric intake	254.23
		Total fat	246.02
		Iron	244.68
		Saturated fatty acids	241.32
		Pantothenic acid	239.33
Pharmacologic	44.80	Total drugs	461.30
		CNS drugs	375.20
		Drugs that increase appetite	338.60
		Drugs that cause ulcers	311.02
		Digestive drugs	308.64
Pathological	40.22	Total diseases	510.80
		Ocular diseases	294.82
		Genitourinary diseases	279.44
		Musculoskeletal diseases	269.75
		CNS diseases	258.63
Disability	45.09	Severe confusion	158.38
		Severe conduct disorder	154.75
		Severe Alzheimer's disease or dementia	132.02
		Absence of private home assistance	129.10
		Absence of publicly funded home assistance	124.84

CI, contribution index; CNS, central nervous system; EER, estimated energy requirements.

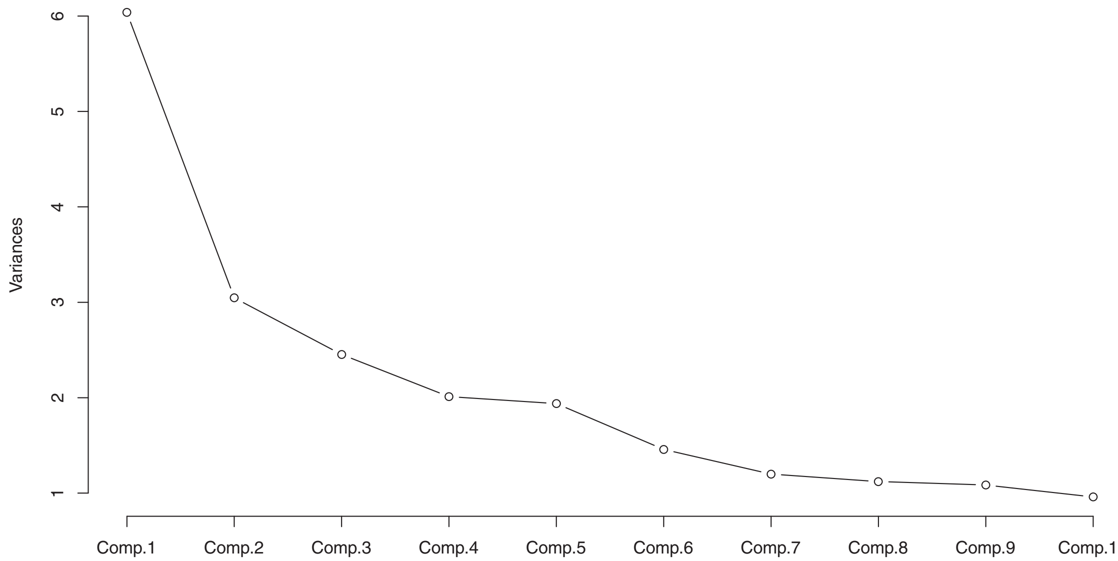

Fig. 1. Explained variance by the principal components in the implemented analysis on the preselected set of 27 variables.

Table 2
CI of all preselected variables in the top five components

Covariates	CI
Caloric intake	361.92
Total fat	330.70
Absence of home assistance	329.75
Absence of public funded home assistance	325.19
Difference caloric intake/EER	315.77
Severe confusion	311.33
Carbohydrates	310.09
Iron	303.77
Saturated fatty acids	287.72
Pantothenic acid	276.46
Severe dementia or Alzheimer's disease	274.63
Severe conduct disorder	272.85
Liquid food	243.64
Total drugs	239.19
Water intake	238.86
CNS drugs	219.49
Drugs that increase appetite	182.83
Total diseases	179.35
Vegetables	138.00
Digestive drugs	132.89
Musculoskeletal diseases	123.48
Oily fish	94.18
Drugs that cause ulcers	86.82
CNS diseases	59.01
Dairy products	46.31
Ocular diseases	43.18
Genitourinary diseases	9.19

CI, contribution index; CNS, central nervous system; EER, estimated energy requirements.

had agreater number of chronic diseases, central nervous system diseases, and severe disorders, as well as higher drug consumption. From a dietary point of view, metropolitan participants had a tendency to an increased consumption of water and liquid food. On the other hand, rural participants tended to a better health status without needing home assistance, as well as to an increased caloric intake from lipids and carbohydrates.

Validation model

It would be useful to check the predictive capacity of these 27 variables on the geographic factor, which has a polytomous nature (metropolitan, rural, and mixed profile) by implementing a multinomial logistic regression and assessing the predictive ability of the model through a prediction table. As can be seen in Table 3, there was limited predictive capability in the mixed area. However, the metropolitan and rural predictions were acceptable (88.2% and 66.7% of success, respectively).

Variable selection

The method of automatic variable selection (stepwise method) was applied to the set of 27 preselected variables. It aimed to find the variables that provided a better fit of the model based on a specific model, and comparing the models obtained by adding one more variable to finally select the model with less Akaike information criterion or Deviance criterion [13]. The final result (provided in Table 4) showed the associated regression coefficients.

The territorial divergences among the selected variables stood out between metropolitan and rural profiles, as the obtained coefficients for the rural profile with respect to the metropolitan were larger than the coefficients for the mixed profile with respect to the metropolitan profile. This means that differences between rural and metropolitan profiles were more significant. This fact was been observed throughout the preliminary analysis. It is logical, as the participants of the mixed profile have shown characteristics of both profiles. Moreover, they are geographically located between both, as can be seen in Figure 2.

The stepwise method selected up to 15 variables as the most associated with the geographic profile. Among them, as can be seen in Table 4, are two groups of variables: those that define the quality of the diet and those that determine general health status. In the second group, the most important are home assistance, consumption of certain drugs related to feeding, and total number of chronic diseases. As can be seen, the rural profile is associated with better health patterns and higher caloric intake from fats. Also, higher drug consumption in rural profile is associated with non-pathological aging as digestive and blood diseases are related to primary physiological aging, common in the oldest population.

On the other hand, the ability of this model to separate the sample in each category of geographic profile can be assessed through a

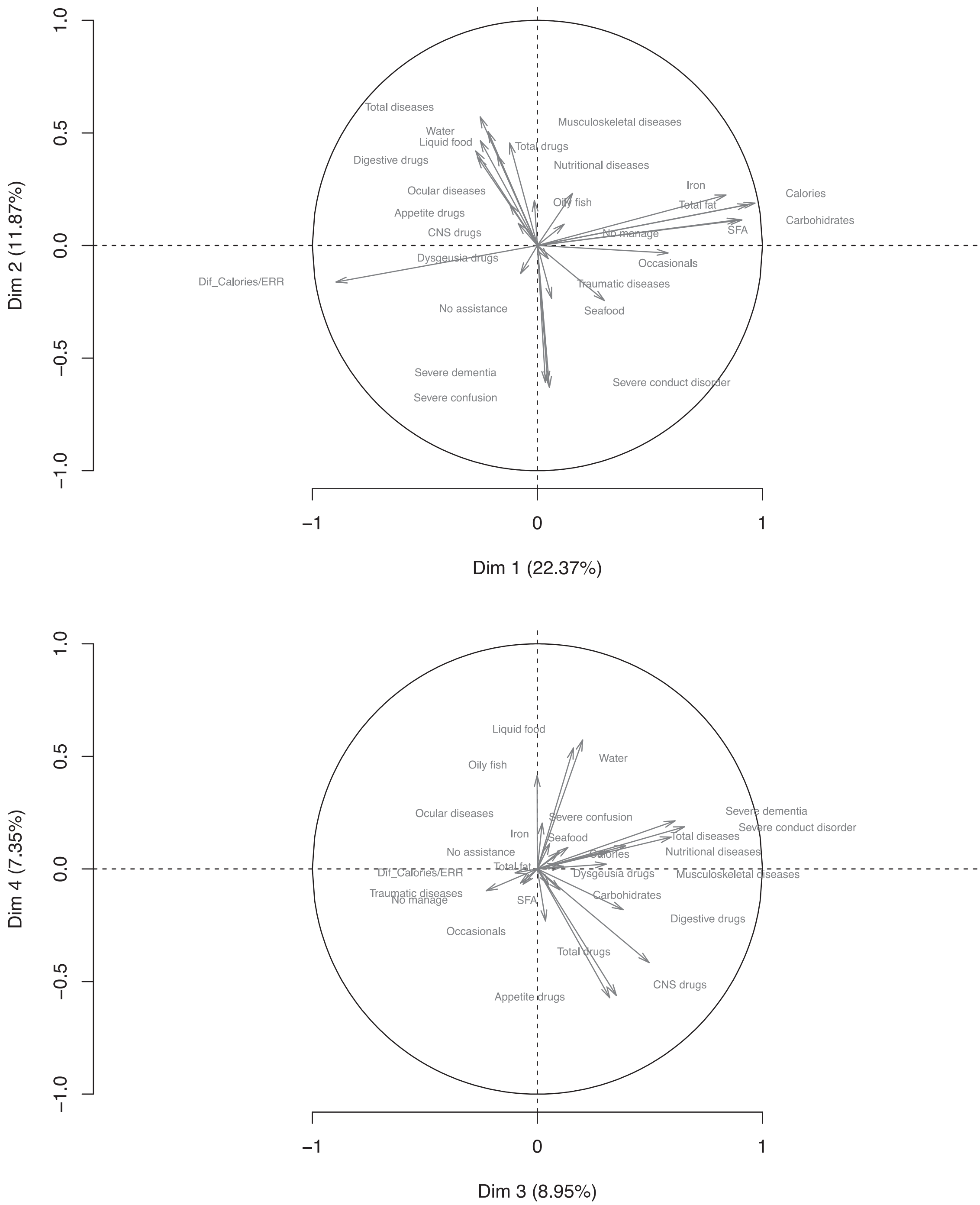

Fig. 2. Representation of the distribution of the predictor variables and the geographic factor (in bold), regarding the main components of the principal component analysis.

Table 3
Prediction table resulting of the multinomial logistic regression model

	Predicted profile			
Observed profile	Metropolitan	Mixed	Rural	Success % (%)
Metropolitan	179	11	13	88.2
Mixed	14	25	16	45.4
Rural	27	5	64	66.7

bootstrap test (Eq. 4). Table 5 shows the value of M for both models, the saturated with the 27 preselected variables and the stepwise with 15 variables, and their corresponding 95% confidence intervals obtained by bootstrap. There were no statistical differences between the models. Therefore, we determined the geographic conditioning through the simpler model, as we needed fewer variables to explain the dietary, social, and health patterns. Only 15 of the 131 original variables were needed.

Table 4
Result of automatic selection of variables in the multinomial logistic regression (Eq. 3)

	Regressions coefficients	
	Regarding mixed profile	Regarding rural profile
(Intercept)	−0.18	1.36
Total fat	−0.02	−0.14
Carbohydrates	0.01	0.01
Iron	0.14	0.45
Saturated fatty acids	0.03	0.24
Pantothenic acid	−0.02	−0.46
Vegetables	−0.11	0.07
Water intake	0.05	−0.02
Liquid food	−0.05	−0.02
Absence of home assistance	−0.20	−2.27
Absence of funded home assistance	−18.68	−0.63
Severe conduct disorder	−0.73	−3.03
Drugs that increase appetite	0.26	−0.52
Digestive drugs	0.30	0.39
Blood drugs	0.52	0.52
Total diseases	−0.56	−0.29
Deviance	443.07	
AIC	507.07	

AIC, Akaike information criterion.

Table 5
Bootstrap test applied on both the saturated and the selected model

Model	*M*	*Mean*	*SD*	*95%CI 95_inf*	*95%CI CI95_sup*
Saturated	0.8598	0.8596	0.0163	0.8271	0.8894
Selected	0.8447	0.8449	0.0156	0.8148	0.8745

SD, Standard deviation; 95%CI, Confidence interval 95%.

Discussion

Geographic conditioning in dietary, social, and health patterns is based on the specific lifestyle of each area. These lifestyles are habits, conduct, and behaviors that have an effect on health; depend on both individuals and the contexts in which they develop their life; and are susceptible to modification, which reinforces the objectives of this study.

The main factors affecting lifestyle are environmental, physical activity, and diet. These associations are supported by an extensive literature review conducted by Lopresti et al. [16]. These factors affect comorbidity, obesity, and malnutrition, which at the same time influence, as seen through the results of this research and in other studies, the progression of disability and dependence [17]. However, we have not found studies that consider together the disciplines involved in the present study as factors that affect QoL and their relation with lifestyle.

In other countries, some associations were studied. In a European and American consensus document developed by Morley et al. [18], the authors point to physical activity, diet, and reduction of drug treatments as preventive against fragility. It should be noted that geographic region determines cultural and socioeconomic factors. This fact establishes rural or metropolitan trends with worse or better lifestyle, depending on the development of each particular country. So, when the studies are conducted in less-developed regions where dietary pattern is deficient, metropolitan areas tend toward a balanced model, resulting in a reduced risk for functional disability, as was shown in a Taiwanese population [19]. In developed countries, this model is inverted, finding healthy patterns in the traditional rural environments.

From a dietary point of view, the results obtained in the present research regarding rural lifestyle are closer to the nutritional recommendations adapted to the elderly, as the socioeconomic footprint in this area leans food consumption toward the Mediterranean pattern. Still, the population group does not reach either dietary or nutritional recommendations. Regarding this, a recent review that included 43 235 elderly Spanish individuals in 47 different studies conducted by Mila et al. [20] confirms that malnutrition among the population was widespread and very variable, depending on the associated health problems or the residential area of population, as geographic profile determines lifestyle and the adherence to a traditional dietary pattern.

From a social and health point of view, there is a capacity of affectation of the lifestyle on the generation of dependence as Abellán et al. [5] warn that personal, family, and social factors also are involved.

Disability in the elderly population has a multifactorial origin assumed by several authors [4], especially when it is associated with sociodemographic factors such as the disadvantage of living in a metropolitan versus a rural environment [7]. This supports the results exposed here, as we found a similar preventive or palliative trend based on geographic area in both the accumulation of chronic diseases and functional impairment, dependency, and the need for social services. This fact, coupled with the positive trend that we found in the rural diet, enforces our hypotheses about the conditioning of the geographic area that is proposed here.

Some studies have explored, at least partially, the affectation of environmental factors on pathological aging. Sanchez-Rodriguez et al. [6] described how psychological stress and environmental pollution are associated with urban environment and oxidative stress, which is a risk factor for cognitive decline in older people. This study was developed in a Mexican population with an average age of 60 y, both metropolitan and rural, with increased risk in the first group.

Several studies enforce this geographic conditioning on social and health patterns. Thus, in an elder Finnish population, a direct link was found between rural areas and an increased prevalence of comorbidities, disability, and physical inactivity [21]. It should be noted that the same study indicates that in Finland the metropolitan lifestyle is positively considered compared with the rural one. These sociodemographic models do not represent the Spanish model, where the rural environment has positive connotations associated to lifestyle [6,7]. There are national studies that have investigated the territorial differences regarding the prevalence of chronic diseases or disabilities, considering rural areas as a protective or palliative factor. It is worth emphasizing the study of Pedro-Cuesta et al. [22] developed with 12 232 individuals ≥70 y of age.

Regarding dependence, we highlight the research conducted by Ayuso et al. [7] on a Spanish dependent population. It reflects the correlation between the geographic area and the prevalence of dependence, suggesting that individuals living in urban areas have three times more risk than those living in a rural area.

Finally, according to our results, direct association between functional disability and the use of assistance services is clear even when results are adjusted by age, comorbidities, and sociodemographic factors [23].

The present study had a sample size limitation compared with similar studies. The reduced sample size was due to the particular characteristics of the sample (people ages ≥65 y, non-institutionalized, officially classified as disabled by a public administration, and recipients of public services). Therefore, the convenience sampling used was limiting. In this sort of study, it could be interesting to introduce the sex factor, but we must consider that the study was based on the search for patterns based on the geographic profiles of the participants, so the sample must be firstly addressed divided in its three geographic profiles. The addition of this second factor would require a new subdivision of each geographic profile in two new ones (six in total), and this can produce an insufficient number of individuals in the category crossings, considering that only 24.6% from the total sample are men.

Conclusion

The metropolitan profile indicates a tendency to a greater number of chronic diseases (especially behavioral disorders), as well as a lower caloric intake. The increased rural caloric consumption comes from lipids (saturated fatty acids) and, to a lesser extent, from carbohydrates. The better health status found in rural areas is associated with a lower need for home assistance and a lower drug consumption pattern associated with increased longevity. This knowledge helps to provide improvement in their QoL.

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